An Intelligent Framework for Pre-processing
Ancient Thai Manuscripts on Palm Leaves

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THE DEGREE OF DOCTOR OF PHILOSOPHY
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Declarations

I declare that this thesis is my own account of research and contains as its main content work which has not previously been submitted for any degree at any tertiary education institution.

Rapeeporn Chamchong
Abstract

In Thailand’s early history, prior to the availability of paper and printing technologies, palm leaves were used to record information written by hand. These ancient documents contain invaluable knowledge. By digitising the manuscripts, the content can be preserved and made widely available to the interested community via electronic media. However, the content is difficult to access or retrieve. In order to extract relevant information from the document images efficiently, each step of the process requires reduction of irrelevant data such as noise or interference on the images. The pre-processing techniques serve the purpose of extracting regions of interest, reducing noise from the image and degrading the irrelevant background. The image can then be directly and efficiently processed for feature selection and extraction prior to the subsequent phase of character recognition. It is therefore the main objective of this study to develop an efficient and intelligent image pre-processing system that could be used to extract components from ancient manuscripts for information extraction and retrieval purposes.

The main contributions of this thesis are the provision and enhancement of the region of interest by using an intelligent approach for the pre-processing of ancient Thai manuscripts on palm leaves and a detailed examination of the pre-processing techniques for palm leaf manuscripts. As noise reduction and binarisation are involved in the first step of pre-processing to eliminate noise and background from image documents, it is necessary for this step to provide a good quality output; otherwise, the accuracy of the subsequent stages will be affected. In this work, an intelligent approach to eliminate background was proposed and carried out by a
selection of appropriate binarisation techniques using SVM. As there could be multiple binarisation techniques of choice, another approach was proposed to eliminate the background in this study in order to generate an optimal binarised image. The proposal is an ensemble architecture based on the majority vote scheme utilising local neighbouring information around a pixel of interest. To extract text from that binarised image, line segmentation was then applied based on the partial projection method as this method provides good results with slant texts and connected components. To improve the quality of the partial projection method, an Adaptive Partial Projection (APP) method was proposed. This technique adjusts the size of a character strip automatically by adapting the width of the strip to separate the connected component of consecutive lines through divide and conquer, and analysing the upper vowels and lower vowels of the text line. Finally, character segmentation was proposed using a hierarchical segmentation technique based on a contour-tracing algorithm. Touching components identified from the previous step were then separated by a trace of the background skeletons, and a combined method of segmentation.

The key datasets used in this study are images provided by the Project for Palm Leaf Preservation, Northeastern Thailand Division, and benchmark datasets from the Document Image Binarisation Contest (DIBCO) series are used to compare the results of this work against other binarisation techniques. The experimental results have shown that the proposed methods in this study provide superior performance and will be used to support subsequent processing of the Thai ancient palm leaf documents. It is expected that the contributions from this study will also benefit research work on ancient manuscripts in other languages.
Acknowledgements

I would like to take this opportunity to express my most heartfelt gratitude and appreciation to my supervisor Associate Professor Dr. Lance Chun Che Fung for his support, advice, guidance and inspiration throughout the course of my study. Professor Fung always encourages the development of generic skills such as intellectual understanding and judgment, problem solving skills, and critical thinking skills during his supervision. His enthusiasm and practical views on research have made a deep impression on me. I owe him a lot in my development as a researcher and an academic. He is not only my mentor, but also a most valued friend whom I am forever grateful to have.

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Finally, without the support of my family, their understanding and patience, it would have been impossible for me to complete my study.
List of Publications

Journal


Book Chapter


Conference Proceedings


(P3) R. Chamchong, and C. C. Fung, "Text line extraction using adaptive partial projection for palm leaf manuscripts from Thailand," in the *Proceedings of the*


Contributions of the Thesis

Pre-processing of ancient Thai palm leaf manuscripts has been studied and solutions to the research questions have been proposed and developed. The main contributions of this thesis that have been published in refereed proceedings and book chapter are summarised in Table 1.

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<td>ADD</td>
<td>Adaptive Degrade Document</td>
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<td>ALL</td>
<td>Adaptive Logical Level</td>
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<td>APP</td>
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<td>AUC</td>
<td>Area under the ROC curve</td>
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<td>CBT-KSOM</td>
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<td>Document Image Processing</td>
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<td>DRD</td>
<td>Distance reciprocal distortion</td>
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<td>EGT</td>
<td>Estimated ground truth</td>
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<td>ETM</td>
<td>Eikvil et al.’s Method</td>
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<td>FCM</td>
<td>Fuzzy C-Mean</td>
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<td>FM</td>
<td>F-measure</td>
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<td>FP</td>
<td>False Positive</td>
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<td>G-mean</td>
<td>Geometric Mean</td>
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<td>GT</td>
<td>Ground Truth</td>
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<td>H-DIBCO</td>
<td>Handwritten Document Image Binarisation Competition</td>
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<td>IBT</td>
<td>The independence binarisation techniques</td>
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<td>ICDAR</td>
<td>The International Conference on Document Analysis and Recognition</td>
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<td>Abbreviation</td>
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<td>ICFHR</td>
<td>The International Conference on Frontiers in Handwriting Recognition</td>
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<td>IIF</td>
<td>Improvement of Integrated Function</td>
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<td>KKT</td>
<td>Karush-Kuhn-Tucker</td>
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<td>The Kohonen Self-organising Map</td>
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<td>LMM</td>
<td>Local Maximum and Minimum</td>
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<td>Misclassification penalty metric</td>
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<td>MSE</td>
<td>The mean square error</td>
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<td>OAA</td>
<td>One-Against-All</td>
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<td>PERR</td>
<td>Pixel error rate</td>
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<td>PR</td>
<td>Precision</td>
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<td>PS</td>
<td>Parameter Set</td>
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<td>PSNR</td>
<td>The peak signal-to-noise ratio</td>
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<td>QIR</td>
<td>Quadratic Integral Ratio Technique</td>
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<td>RBF</td>
<td>Radial Basis Function</td>
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<td>RC</td>
<td>Recall</td>
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<td>RGB</td>
<td>Red, Green and Blue</td>
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<td>ROC</td>
<td>Receiver Operating Characteristics</td>
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<td>Description</td>
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<td>SAU</td>
<td>Sauvola and Pietikainen</td>
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<td>SMOTE</td>
<td>Synthetic Minority Over-sampling Technique</td>
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<td>SNR</td>
<td>The signal noise ratio</td>
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<td>SVM</td>
<td>Support Vector Machine</td>
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<tr>
<td>SW</td>
<td>Stroke width</td>
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<td>THRAI</td>
<td>Thailand Herbal Repository Access Initiative</td>
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<tr>
<td>TN</td>
<td>True Negative</td>
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<tr>
<td>TP</td>
<td>True Positive</td>
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Chapter 1

Introduction

1.1 Significance of Ancient Thai Palm Leaf Manuscripts

In Thai history, over the past five hundred years, palm leaves were used as one of the most popular medium for written documents. The leaves were used to record information written by hand prior to the availability of paper. These ancient documents represent the history and heritage of Thai people that are passed down through many generations. Libraries and museums all across Thailand contain large collections of palm leaf manuscripts written in ancient local languages. These manuscripts contain knowledge about Buddhist teachings and doctrines, folklores, knowledge on the use of herbal medicines, stories of dynasties, laws, traditional arts and architectures, astrology, astronomy and techniques of traditional massages. Typically, only a few groups of people are allowed access to these collections due to concerns over the fragile state of these highly valued materials. With the passage of time, most of these documents, if left unattended, will deteriorate in the face of destructive environmental elements such as dampness, fungus, bacteria, and insect attacks.

Recently in Thailand, many projects have been initiated on the digitisation and preservation of these ancient documents. These projects are of great interest to the community including historians, traditional pharmacists, researchers, students,
scholars and people both local and foreign who are interested in Thai cultural heritage. The main goal of most of these projects is to preserve the content of the ancient manuscripts and to make the documents widely available to interested communities via electronic media. Typical projects were initiated by libraries, universities, and institutes such as medical departments and religious organisations. The list of organisations includes the National Library [1], Chiang Mai University [2],[3], and Mahasarakham University [4] which are involved in projects targeting the preservation of palm leaf manuscripts and the development of related database systems for access via the Internet. For example, two databases of digitised images of the manuscripts at the National Library, and the Centre for the Promotion of Arts and Culture [2] at Chiang Mai University [3] are readily available to the public. The volume of the collections is about 295 bundles and has kept increasing in number. Another example is the Thailand Herbal Repository Access Initiative (THRAI) at Kasetsart University [5]. The THRAI project aims at developing an ultimate database for the preservation and propagation of medical knowledge and wisdom from ancient manuscripts.

Unfortunately, digitised images alone are not sufficient to provide an easy access to the content in the manuscripts for useful research purposes. Laborious human involvement is required to search and read all the information contained in the documents. Although current storage systems can hold all these images and make them available for access, there is no specific system that is capable of searching and retrieving relevant information efficiently and allow for the extraction of knowledge from the documents.
This leads to the need of a system that is capable of providing features of search, retrieval, and knowledge extraction from the images of ancient documents. An essential component of such a system is an efficient module that should be able to carry out pre-processing of the images through background elimination line and character segmentation. This will help the process of knowledge and information retrieval from the ancient palm leaf documents. This therefore forms the key objectives of this study. The following section describes the problems of pre-processing associated with document recognition and information extraction from the ancient Thai manuscripts.

1.2 Problems of Pre-processing for Information Extraction and Recognition from Ancient Thai Documents

At present, there is no specific system that can satisfactorily process practical handwritten documents in Thai language because it is very different from other language systems. Also, there is not much reported work on the handling of horizontally overlapping lines in modern and ancient Thai handwriting. The use of specific tonal, vowel and consonant characters with multiple levels and no word spacing are the key challenges and obstacles against automatic processing of Thai language. Therefore, the main objective of this study is to develop an efficient image pre-processing system that could be used to extract components from ancient manuscripts for subsequent information extraction and retrieval purposes.
One obvious solution for knowledge extraction is by matching directly the image data using images of the words as queries or Optical Character Recognition (OCR). Word and character segmentation is generally seen as a pre-processing step for tasks such as document structure extraction, printed character or handwriting recognition. Most of the ancient manuscripts were handwritten while some printed characters have been identified in more recent manuscripts that are under fifty years old. Comparatively speaking, printed scripts can be separated easily using mechanism such as OCR. Despite much research, handwritten scripts still pose as a demanding challenge as they are difficult to segment. Handwritten pages with narrow spaced lines with overlapping and touching components, incomplete writings and blurred images are the typical issues and challenges. In addition, characters and words have unusual and varying shapes, and they are writer-dependent. Other issues are the periods and their places. Thai vocabulary is also very large and may include proper and unusual names and words. Full text recognition in most cases is therefore not yet available, except for printed documents for which dedicated OCR systems that have been developed.

In terms of Document Image Processing (DIP), it is desirable to have embedded tools to extract the knowledge by searching of specific blocks, lines and words and the inclusion of a dedicated handwriting recognition system. Interactive tools are generally offered for segmentation and recognition correction purposes. Several past projects in the discipline have been concerned with printed materials. However, solutions to tackle handwritten text perfectly are yet developed. In particular, there are several problems related to Thai handwritten segmentation. The main one is the different individual styles especially there is no stop words like the
English language. This is the main problem of the Thai writing system: the difficulty in separating the words or the sentences. In addition, in the Thai writing system, the characters could be located on one of the three levels; main text line, above and under main text line. This poses another challenge: the recognition of the position of a character at either below or above the main text line.

Although there are professional OCR software applications that are able to produce good results from high quality scanned document images, they are not applicable to the ancient palm leaf documents. Over the years, such documents have been deteriorating due to age and the lack of preservation facilities at the place of collection. In addition, palm leaf manuscripts are different from other printed documents. Information on these physical media is harder to extract because the formatting structure of the documents is looser. Also, many of these documents are of poor quality because of their fragility. The problems are due to issues such as spots and holes on the media, smearing, dirt, discolouration and blurriness as shown in Figure 1.1. These factors cause poor contrast and ghosting noise (seeping ink from the other side) as shown in Figure 1.1(b). In addition, text within the manuscripts often shows a certain amount of variation in terms of the stroke width, stroke brightness, and stroke connection as illustrated in Figure 1.1(c). These reasons reduce the accuracy of the automatic recognition results noticeably and can even render them useless. Moreover, due to limited space on the palm leaves, characters were written in narrow spaced lines with overlapping and touching components. The characters are non-uniformed, vary in shape and have different styles because of different writers. The Thai language by itself also imposes additional challenges caused by no word separation and the high number of consonants, vowels and tonal
indicators. Digital image pre-processing techniques are hence necessary to improve the readability of the manuscripts.

In this study, most of the manuscripts were acquired from the Project for Palm Leaf Preservation, Northeastern Thailand Division, Mahasarakham University [4]. The alphabets on these palm leaves are Thai-Noi, which is different from the modern Thai language. Also, there is no current system that can process the ancient handwritten document in Thai language because it is very different from other widely used languages such as English or Chinese. The use of specific tones, vowels and consonants with multiple levels and the lack of word spacing are the key challenges for the researchers to develop automated systems for the processing of Thai handwritten documents. The main purpose of this research is to develop an
intelligent framework for the pre-processing of ancient Thai manuscripts on palm leaves. The objective is to improve the quality of the documents before they are used by a recognition system for subsequent information extraction.

1.3 Objectives

This study aimed to achieve the following objectives:

(1) To study, design and develop a new intelligent framework of pre-processing ancient Thai manuscripts that have been handwritten on palm leaves.

(2) To study, design and develop a method in order to select an appropriate binarisation technique to eliminate background noise and generate an optimal output from multiple binarised images.

(3) To study, design and develop text line and character segmentation methodology to separate handwritten characters from ancient Thai manuscripts on palm leaves.

1.4 Organisation of the Thesis

The thesis is presented in seven chapters. Chapter 1 presents the introduction and overview of the research. As a background to this thesis, Chapter 2 introduces ancient Thai manuscripts, digital document image processing, and related research works on the pre-processing of ancient manuscripts. Data used in this thesis are also considered in this chapter.

Figure 1.2 shows the framework of the pre-processing steps that was implemented in this research study. Chapter 3 to Chapter 6 provide details of the framework design based on a pre-processing technique of image processing.
Figure 1.2 Proposed framework for the pre-processing of ancient Thai manuscripts for information extraction and OCR.

Chapter 3 proposes a methodology on the selection of binarisation techniques. The chapter begins by providing a review study of the different binarisation techniques that have been previously reported. The techniques have been compared and used to evaluate the proposed method. Support Vector Machine (SVM) is applied to select the binarisation techniques through classification. The features of manuscript images are extracted into two groups: global and local
features. Global features are the grey-level histogram and the moment of image. Local features are the contrast values and the moment in local area of decomposed matrices of image. These features are selected by using Principal Component Analysis (PCA). As the dataset from palm leaf images is imbalanced, this study also improves the performance of the selection processing by utilising the Synthetic Minority Over-sampling Technique (SMOTE) to address the issue.

Chapter 4 extends the work from previous chapter by considering the generation of an optimal output from multiple binarised outputs. The proposed approach is based on a majority vote approach used to combine binarised outputs from several techniques. Two new techniques of combination are proposed by considering the information of local neighbourhood around a pixel of interest. The two proposals are termed “local adaptation of majority vote” and “local adaptation of weighted majority vote”. The experimental results in this thesis have been compared to the combination of binarisation techniques based on Kohonen’s Self-organising Map (KSOM). This proposal has been evaluated with benchmark dataset from the Document Image Binarisation Contest (DIBCO). The proposed techniques are then applied to the palm leaf manuscripts with the results discussed in the chapter.

Chapter 5 describes the next stage of pre-processing - text line segmentation and it is an important step to separate the Thai handwritten text from a document image. In this thesis, two methods of text line segmentation have been proposed: Modified Partial Projection (MPP) and Adaptive Partial Projection (APP) methods. The MPP method is improved from the partial projection method by considering vowel analysis and touching components of two consecutive lines. The APP method
is improved from MPP by integrating an MPP with smooth histogram and adapts partial projections using divide and conquer strategies.

The final stage of image pre-processing for ancient Thai manuscripts is character segmentation. This issue is addressed in Chapter 6. The proposed technique for character segmentation in this thesis is based on a hierarchical approach. A contour tracing algorithm is first applied to segment the characters. If touching components are identified, they will be separated by a trace of the background skeleton, and a combined method of segmentation will then be performed.

Finally, conclusions are drawn from the work done in the study and they are discussed in Chapter 7. Suggestions for further development and possible extensions of this study are also discussed in this chapter. The thesis finally ends with appendices.
Chapter 2

Background

This chapter discusses the background and relevant research works for the intelligent framework for pre-processing of ancient Thai manuscripts on palm leaves. In this chapter, different types of palm leaf manuscripts and the Thai-Noi script systems are presented. In order to understand the concept of document image processing, the involved stages are described. This chapter also discusses the methods for pre-processing of image documents which are background elimination, optimal binarisation, text line segmentation and character segmentation.

2.1 Ancient Thai Manuscripts

Ancient manuscripts are documents recorded and produced in the past. They are heritage of human civilisation as they contain information and knowledge passed down from past to present. Thai ancient manuscripts recorded the history of Thailand and the daily lives of the societies during bygone eras. Examples of the recorded information are: Buddhist teaching and doctrines, folklores, knowledge and use of indigenous medicines, stories of dynasties, customary laws, traditional arts and architectures, astrology, astronomy and techniques of traditional massage.

In Thailand, ancient manuscripts were found only on stone inscriptions between the 13th and 16th centuries. After the 15th century, ancient Thai manuscripts were found on palm leaves and papers [5]. Thai manuscripts on palm leaves are on average have a width of either 30 or 55 centimetres, and a height of 5 to 6
centimetres. They are tied together in bundles to be viewed one page at a time. Manuscripts on papers are usually larger than on palm leaves, depended on the occasion of the recording. They are made in an accordion format which means the papers are often joined together along the width and can stretch to several yards if they are unfolded completely. Thai manuscripts on paper, named Samut Khoi or Samut Thai [6], consist of paintings and scripts. Paper-based ancient manuscripts are not considered in this study although the proposed techniques are equally applicable to them as well as palm leaf documents.

Thai scripts in stone inscriptions have been created by King Ram Khamhaeng during the Sukhothai era dated back to A.D.1283 [6]. The alphabet system was influenced by Cambodian and Khmers scripts around the 13th century. From historic evidence, Thai scripts on stone inscriptions were found from the 13th to 14th century. From the 15th century onwards, Thai scripts started to appear on palm leaves. The oldest palm leaf manuscript in Thailand is believed to have been engraved in A.D. 1498 using Dham-Lanna script in Pali language [5]. During the mid Ayudhaya era (16th century) until King Rama V of the Rattanakosin era (20th century), Samut Khoi was used. The oldest Samut Khoi was believed to have been produced in A.D. 1680.

According to archaeological evidence in Thailand, apart from stone inscriptions, palm leaf is supposed to be the oldest ancient written and recording materials found [5]. The palm leaf manuscripts are therefore invaluable and need to be preserved. For these reasons, this study focuses on palm leaf manuscripts. Further details of these manuscripts are described in the next section.
2.1.1 Palm Leaf Manuscripts in Thailand

Palm leaves had been used as one of the most popular medium for written documents in the past five hundred years [5]. They had been used to record information written by hand during the past prior to the availability of paper. These ancient documents represent the heritage of Thai people passed down through many generations. Libraries and museums all across Thailand contain a large collection of palm leaf manuscripts written in the ancient local languages.

The ancient palm leaves are mostly taken from the family of palm trees, “Corypha lecomtei” [7]. The young leaves from these species are suitable for engraving due to their dimensions. Each palm leaf has an average height of 5 to 6 centimetres and they could be as long as a meter. For engraving purpose, the length used is about 60 centimetres and the palm leaves are cut to size and tied up as a bundle. The components of a typical manuscript include covers, a title page, the main text, and possibly pagination. Information about the authors normally does not appear in the manuscripts, however, details of the transcriber and dates may have been recorded.

Generally, the inscribed text engraved about 4 to 5 text lines in both sides of the leaves within the boundary of 5 to 6 centimetres. Many palm leaves are included in each book and the bundle is known as “phuk” [7] in Thai. One or two punch holes are made at the middle of the palm leaves so as to allow a string to tie and hold the palm leaves together to form a bundle. The front and back covers of each bundle give the title of the book or a summary of the book.

In general, there are two sizes of Thai palm leaf manuscripts [7], [8] which are called Phuk book and Kom book.
• *Phuk* book (long palm leaf manuscript) is one that was made from long palm leaves with an average width of 55 to 60 centimetres and height of 5 to 6 centimetres. Phuk books are normally longer than Kom books. Each bundle has a pair of wooden covers and these books mainly recorded information about local literacy writing, folklore, Buddhist teaching and doctrines, and Buddhist fables. They are normally kept at community centres such as temples or education centres in the villages.

• *Kom* book - *Kom* means short, and they are made from shorter palm leaves. They use palm leaves of about 30 to 35 centimetres wide and about 5 to 6 centimetres in height. Each bundle has between ten to forty palm leaves and the average of most books is twenty to twenty five palm leaves. These books are normally owned by individuals and they were kept at homes. Most of the books contain information about incantation, astrology, ritual, auspicious occasions and local literary writing.

Since both types of books covered different aspects of the ancient manuscripts, samples from both books are therefore used in this experiment. The subjects under study were acquired from the Project for Palm Leaf Preservation in Northeast of Thailand, Mahasarakham University [4] and a total of 480 images have been used.

### 2.1.2 Thai-Noi Script System

In Thailand, there are many types of scripts written on palm leaf manuscripts. The ancient scripts include Thai, Thai-Noi, Dham-Isan, Dham-Lanna, Kmare and Mon which are based on Thai, Pali and Mon languages [5]. Dham-Lanna
and Mon scripts have been found in the northern Thailand while Thai-Noi and Dham-Isan scripts were found in the northeastern part of Thailand [9]. Kmare scripts were found in every region in Thailand.

Figure 2.1 Three levels of Thai-Noi writing.

In this study, palm leaf manuscripts were provided by the Project for Palm Leaf Preservation in Northeastern Thailand, Mahasarakham University [10]. Most of palm leaf manuscripts in the area are Thai-Noi and Dham-Isan scripts. This thesis focuses on Thai-Noi script only as it is almost similar to Thai script and Thai-Noi script is the root of Laos script. The Thai-Noi system [10] comprises three levels in a text line, which are the upper vowel, body, and lower vowel level as shown in Figure 2.1. Due to the characteristics that multiple levels are requested to form a text line, the line separation process is affected. Similar to modern Thai script, Thai-Noi writing starts from left to right and from top to bottom. It does not require any space between words and sentences.

The Thai-Noi character set consists of twenty-six isolate consonants, six double consonants, twenty-three vowels, two special vowels, four special symbols, and ten numbers as shown in Table 2.1 [4].
Table 2.1  Thai-Noi script set.

| Isolate consonants | | | | | |
|--------------------|--------------------|--------------------|--------------------|
|                     |                     |                     |

| Double consonants   | | | | | |
|--------------------|--------------------|--------------------|--------------------|
|                     |                     |                     |

| Vowels              | | | | | |
|--------------------|--------------------|--------------------|--------------------|
|                     |                     |                     |

| Special vowels      | | | | | |
|--------------------|--------------------|--------------------|--------------------|
|                     |                     |                     |

| Special symbols     | | | | | |
|--------------------|--------------------|--------------------|--------------------|
|                     |                     |                     |

| Numbers             | | | | | |
|--------------------|--------------------|--------------------|--------------------|
|                     |                     |                     |

2.2  Document Image Processing

In order to extract the relevant information from document images, pre-processing is needed to extract regions of interest, reduce noise from the image, and degrade irrelevant background. The image can then be processed for feature selection and extraction prior to the subsequent phase of character recognition. There are five steps involved [11], [12], which are described below.

2.2.1  Image Acquisition and Noise Reduction

The first step of processing a document on a computer is the conversion process by a digitiser which could be a scanner, a camera, or a tablet digitiser. An image is acquired in the form of either colour, grey-levels or binary format. In this research, all the palm leaf manuscripts were scanned in colour format by the Project for Palm Leaf Preservation, the Northeastern Thailand Division, Mahasarakham
University [4]. The colour images have to be converted to grey-level images, and then the images are converted to binary format for characters recognition and extraction. The process is described as follows.

The developed system in this study first of all imports an ancient document image in RGB (Red, Green and Blue) format as an input image, and the set of pixels is depicted as \( I(x, y) \). The image is then converted from an RGB image to a greyscale, \( g(x, y) \) by a commonly used expression as shown in equation (2.1) [13]:

\[
g(x, y) = 0.2989 \cdot I_R(x, y) + 0.5870 \cdot I_G(x, y) + 0.1140 \cdot I_B(x, y),
\]

(2.1)

where \( I_R(x, y) \), \( I_G(x, y) \) and \( I_B(x, y) \) are the intensity of red, green and blue channel at pixel \( (x, y) \), respectively.

During the scanning of the images and conversion to greyscale, noise may be generated and added to the images. Therefore, filtering techniques are needed to reduce the noise and to enhance the images. Noise from the image acquisition process may appear as salt-and-pepper-noise (impulse noise) [14]. Noise is a common problem in most of the image understanding processes. Noise reduction can be carried out by applying smoothing operations to grey level document images [11]. Smoothing and noise removal can be done by a neighbourhood operation, or “spatial filtering”.

Conventionally, average filtering and Gaussian filtering are commonly used [11], [15] for smoothing and noise removal. These techniques can remove salt and pepper noise in the grey level images and they can blur the images to remove the unwanted details [11], [16], [17].
Another category of spatial filtering is the nonlinear approaches such as Median filter and Weiner filter. The Median filter is a popular technique which is used to reduce speckle noise and impulse noise [14], [15]. This technique is useful to remove isolated lines or pixels while retaining the sharp edges of the image features [18]. The disadvantage of this technique mask is that it may cause discontinuation of thin lines and distorts the corners in the image [17].

![Figure 2.2](image.png)

Figure 2.2. Shape of an average filter and a Gaussian filter [15].

Alginahi [19] explained that Median filter, Average filter and Gaussian filter are proved to be able to eliminate the salt-and-pepper noise from grey level images. In addition, the Average filter and the Gaussian filter are better choices to provide a smoothened image. Comparing between the Average filter and the Gaussian filter, the Gaussian filter has a high point in the centre symmetrically tapering sections to both sides as shown in Figure 2.2. For this reason, the Gaussian filter provides smoother transitions and preserves the edges of the objects better than the average filter mask [20].

Spatial filtering structure is illustrated in Figure 2.3. The filter mask is applied to each pixel \( g(x, y) \) in an image. A pixel at location \( (x,y) \) is calculated by using a predefined neighbourhood and the filter mask.
For the spatial filtering, the output pixel is derived from a linear combination of filtering coefficients and the corresponding image pixels in the area of the filter mask. The linear filtering of an image \( g \) with size \( M \times N \) and a filter mask \( w \) of size \( W^2 \) is given by the expression [16]

\[
f(x, y) = \sum_{i=-a}^{a} \sum_{j=-a}^{a} w(i, j) g(x+i, y+j),
\]

where \( a = (W-1)/2 \), \( x = 0,1,2,\ldots,M-1 \) and \( y = 0,1,2,\ldots,N-1 \).

Some examples of smoothing filter masks are shown in Equation (2.3). An average filter assumes all the neighbouring pixels contribute equal weight to the process whereas a Gaussian filter mask has the form of a bell-shaped curve [15].
Gaussian filter is also called a weighted average as the central pixels add more significant weight to the result than pixels at the mask edges.

\[
\text{Average filter mask } = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}
\]

(2.3)

In this study, the Gaussian filter [11] is used to reduce noise from the images. This filter can smooth the image data and enhance the characters. This filtering technique consists of convolution between the greyscale image \( g(x, y) \) and a Gaussian filter with mask \( 3 \times 3 \) as given below.

\[
f(x, y) = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \otimes g(x, y).
\]

(2.4)

Next section explains the binarisation techniques which have been considered in this study.

## 2.2.2 Binarisation Techniques

Binarisation is the process of background elimination. This is an essential part of pre-processing in image processing that aims to convert a greyscale image to a binary image or to extract texts (foreground components) from the background, which could then be used for further processing such as document image analysis and OCR. Currently, scanners are able to binarise documents with a good contrast of foreground components and a uniform background [21]. However, most of the palm leaf manuscripts are of poor quality due to smeared or smudged characters, poor writing, and non-uniform changes in colours due to long term storage. Consequently, binarisation is necessary in order to process the document by identifying the
characters in the image. Figure 2.4 shows two binary images of palm leaf manuscripts which were acquired from the Digital Library of Lao Manuscripts [22]. They illustrated the issues related to the scanned images from the original palm leaf documents.

Figure 2.4 Binary images of palm leaf manuscripts acquired from Digital Library of Lao Manuscripts [22].

Binarisation can be categorised into two main techniques - global and local adaptive thresholding techniques [11], [21], [23], [24]. They are outlined in the following sections.

1) **Global thresholding techniques**

Global thresholding techniques attempt to find a suitable single threshold value, $T_t$, from the overall image. The pixels in the image are separated into two classes: foreground (black text) and background. This can be expressed as follows [17]:

$$b(x,y) = \begin{cases} 
0 & \text{if } f(x,y) \leq T_t \\
1 & \text{if } f(x,y) > T_t 
\end{cases}$$

(2.5)
where 0 and 1 represent foreground and background, \((x, y)\) is the coordinate of the pixel, \(f(x, y)\) is the pixel of the input image after noise reduction process and \(b(x, y)\) is the pixel of the binary image.

There are some popular techniques suitable for converting grey-level image into binary form [25] such as proposals by Otsu [26], Kittler and Illingworth [27], and Kapur et al. [28]. In this study, Otsu’s technique has been used to compare with other techniques. The technique is briefly described later in this chapter. Global thresholding has a good performance in a case where there is a uniform background and good contrast of foreground [29]. On the other hand, it is inappropriate for complex backgrounds [25]. Most ancient documents have poor quality and non-uniform background. In this case, local area information may provide better binarisation results.

2)  **Local adaptive thresholding techniques**

Local adaptive thresholding techniques [24] calculate the threshold values which are determined locally based on pixel by pixel or region by region. A threshold value \((T_a(x, y))\) can be derived for each pixel in the image by considering the greyscale information of neighbourhood pixels. The image can be separated into foreground and background as given in expression (2.6) [30].

\[
b(x, y) = \begin{cases} 
0 & \text{if } f(x, y) \leq T_a(x, y) \\
1 & \text{if } f(x, y) > T_a(x, y)
\end{cases}
\]

(2.6)

where \(T_a(x, y)\) in the above expression is different from \(T_i\) in expression (2.5) as the value varies according to the local region or neighbouring pixels.
These techniques have been widely used in document image analysis because they produced good performance in separating the characters in the image [29]. The conventional local adaptive thresholding techniques are Niblack’s technique [31], Sauvola and Pietikainen’s technique [32] and Bernsen’s technique [33]. The Sauvola and Pietikainen’s technique was used in this study and briefly described in this section.

Trier and Jain [24] proposed an evaluation methodology for low-level image analysis methods, called goal-directed evaluation. They tested 11 locally adaptive binarisation methods including Bernsen’s method [33], Chow and Kaneko’s method [34], Eikvil et al.’s method [35], Mardia and Hainsworth’s method [36], Niblack’s method, Taxt et al.’s method [37], Yanowitz and Bruckstein’s method [38], Parker’s method [39], Trier and Taxt’s method [40] and White and Rohrer’s Dynamic Threshold Algorithm [41]. They also experimented with four globally binarisation methods which are Abutaleb’s [42], Kapur et al.’s [28], Kittler and Illingworth’s [27], and Otsu’s methods [26]. Their experimental results indicated that Niblack’s method, Eikvil et al.’s method and Bernsen’s method with modified post-processing steps have good performance in the binarisation process respectively. However, their experiment results suggested that the original locally adaptive methods (Yanowitz and Bruckstein, Trier and Taxt, and Niblack) have the best performance.

Leedham et al. [43] compared five thresholding techniques by evaluating the precision and recall value of the words in the foreground. Chen and Leedham [44] proposed a decompose algorithm for an image and found the best approach was to apply different techniques for local areas instead of employing a single threshold technique. They compared their technique with six binarisation techniques using
word recognition from ancient documents. Six thresholding techniques were chosen: Yanowitz and Buckstein’s method, improved Niblack’s method [45], Bernsen’s method, Otsu’s method, Quadratic Integral Ratio technique (QIR) [46] and Eikvil et al.’s method (ETM). These methods have also been evaluated and compared by Trier and Jain. They have shown good performance on difficult images. From the experiments, their proposed method produced better recall result than the other six methods. They found that the improved Niblack’s method and the Bernsen’s method worked well on heavy handwriting image blocks while the other four methods provided acceptable results on faint handwriting images. Yanowitz and Bruckstain’s method gave promising results on various types of documents, but it was not good when there was seeping noise. ETM worked well for both faint and heavy handwriting images. Otsu’s method produced good performance with simple document images that were clearly separated between the background and foreground. QIR performed well for bimodal histogram images.

Sezgin and Sankur [47] surveyed 40 binarisation techniques and categorised them based on exploitation of their information content. They described different performance criteria for the binarisation techniques. They used five performance criteria including misclassification error, edge mismatch, region non-uniformity, relative foreground area error, and shape distortion penalty via Hausdorff distance [48]. They measured and ranked the techniques based on performance criteria. Their dataset was synthesised from a clean document image, which was considered as the ground truth image, and noise was then added to the original image. They found that even though the local binarisation techniques presented a better quality result, the global technique based on histogram or classification techniques (such as Otsu,
Kittler and Illingworth, and Kapur et al.) gave as good results as the local techniques. They concluded that the local based technique of Sauvola and Pietikainen’s technique and *Improvement of Integrated Function (IIF) Algorithm* by White and Rohrer [40], [49] were the best performance.

Badekas and Papamarkos [25] proposed a technique to combine the best binarisation results from the *independence binarisation techniques* (IBT) including Otsu’s technique, *Fuzzy C-Mean* (FCM) [50], Niblack’s technique, Sauvola and Pietikainen’s technique, Bernsen’s technique, *Adaptive Logical Level* (ALL) *technique* [51], [52] and *IIF Algorithm*. The best *Parameter Set* (PS) from the techniques was used and the *Kohonen Self-organising Map* (KSOM) neural network was applied in the final stage. Their paper explained that the best result was not known initially and this was the main problem of the validity of comparison. They used the ground truth image to estimate the best result, defined as *estimated ground truth* (EGT), and it was compared with IBT results using *Receiver Operating Characteristics* (ROC) analysis and *Chi-square* test. The evaluation was based on a variety of document images obtained from standard document databases such as the University of Washington database and the old Greek Parliamentary Proceeding [53]. The final binary image was produced by combining the binary information from independent binarisation techniques.

Stathis et al. [23], [54] evaluated thirty binarisation techniques and their performance on ancient documents. The evaluation images were synthesised. The evaluation metrics were *pixel error rate* (PERR), *mean square error* (MSE), *signal noise ratio* (SNR), and *peak signal-to-noise ratio* (PSNR). They found that on average, the local adaptive thresholding techniques were slightly better than the
global techniques. Good performance from the global thresholding techniques were found mainly due to histograms or classification techniques. They suggested that Sauvola and Pietikainen’s technique was the best technique for the document images.

Ntirogiannis et al. [55] proposed an objective evaluation methodology for document image binarisation as a semi-automated ground truth construction that aimed to reduce human involvement. They used the evaluation metrics of precision, recall, F-measure, broken and missing text, false alarms and deformation. The six most promising global and local adaptive binarisation techniques were found to be Otsu’s technique, Bernsen’s technique, Niblack’s technique [45], Sauvola and Pietikainen’s technique, ALL technique [51], [52] and Adaptive Degrade Document (ADD) technique [29]. Recently, benchmarking datasets for binarisation evaluation have been generated by this researcher group. The datasets were used in the Document Image Binarization Contest (DIBCO) [56], [57], [58] and the Handwritten Document Image Binarization Competition (H-DIBCO) [59]. Four evaluation measures had been used which were F-measure, Peak signal-to-noise ratio (PSNR), distance reciprocal distortion (DRD) metric and, misclassification penalty metric (MPM). These researchers have organised binarisation competitions in the International Conference on Document Analysis and Recognition (ICDAR) and the International Conference on Frontiers in Handwriting Recognition (ICFHR) since 2009.

In this research, binarisation techniques of the “classical” or the most commonly used approaches based on the global and local adaptive thresholding techniques were applied to palm leaf manuscripts. Otsu [26] of the global thresholding technique has been used, while local adaptive thresholding techniques
of Sauvola and Pietikainen [32], *Adaptive Logical Level (ALL) technique* [51], [52] *Improvement of Integrated Function (IIF) Algorithm* [49], *Background Estimation (BE) technique* [60], and *Local Maximum and Minimum (LMM) technique* [61] have been used to compare the results with global thresholding techniques.

Many researchers have applied different thresholding techniques to document images with both printed and handwritten text. Some of those techniques are more efficient for specific documents. In addition, most decisions on how to choose these techniques were subjectively decided by humans. There is no objective mean to decide whether an optimal result has been achieved. The next section discusses this issue.

In the local adaptive thresholding method, Sauvola and Pietikainen [32] improved Niblack’s method [31] gave the best performance in Sezgin and Sankur’s report. The Sauvola and Pietikainen’s technique also has been used to evaluate results in several research studies in local adaptive thresholding techniques such as Stathis et al.[23], Ntirogiannis et al.[55], Gatos et al.[62] and Badekas et al.[25]. Bernsen’s technique was used to compare with others in this study. This technique works well on clear background, high contrast images, and heavy handwriting image blocks [44]. This technique also yielded good performance in Trier and Taxt’s research [40]. The ALL technique was recently used to evaluate results from research works by Stathis et al.[23], Gatos et al.[62] and Badekas et al.[25]. This technique is based on stroke width. Badekas and Papamarkos reported that ALL techniques were very stable when they were applied to several types of document images. The IIF algorithm [40], [49] has also been used in recent binarisation research such as those research by Stathis et al., Trier and Taxt, and Badekas and Papamarkos. Two recent
techniques that provided the best performance in the binarisation technique competition during 2009 and 2010 are the Background Estimation (BE) technique [60], and the Local Maximum and Minimum (LMM) technique [61]. Both techniques are therefore used in this study.

The six binarisation techniques have been used in this study that describes in the following sections. The techniques comprise of

1. Otsu’s technique,
2. Sauvola and Pietikainen’s technique,
3. Adaptive Logical Level technique,
4. Improvement of Integrated Function algorithm,
5. Background Estimation technique,
6. Local Maximum and Minimum technique.

2.2.2.1 Otsu’s Technique

Otsu’s (OT) technique is the most popular global thresholding technique [11], [25], [44], [63]. It has been used in a wide range of image processing tools and libraries such as Matlab [64] and OpenCV [65]. This technique is one of the most used techniques for comparison and benchmarking in binarisation research [23]. This technique is based on nonparametric discriminant analysis of the histogram of the image intensity. It treats the task as a two class problem by maximising the class separability in order to determine the optimal threshold of binarisation. From the review undertaken by Trier and Tortex [40], the global thresholding technique based on Otsu’s method has been found to demonstrate good performance with simple documents and images with bimodal histogram.
The threshold selection is a clustering process which divides all the pixels of an image into two classes: $C_f$, is the foreground or text, with a grey-level value below or equal to threshold, $T_l$ and $C_b$ is the background with a grey-level value above $T_l$. This threshold selection is shown in Figure 2.5. By convention, the values below $T_l$ are black and those above are white.

![Threshold selection from the histogram of an image.](image)

Figure 2.5 Threshold selection from the histogram of an image.

The threshold selection is explained as follows: A measurement of the “goodness” of the threshold value ($T_l$) is based on the discriminant criteria maximising ($\eta$), which is the separability measure as shown below.

$$\eta(t) = \frac{\sigma_B^2(t)}{\sigma_T^2}, \quad (2.7)$$

$$T_l = \arg \min_{t \in \hat{G}} \left[ \eta(t) \right] = \arg \max_{t \in \hat{G}} \left[ \sigma_B^2(t) \right], \quad (2.8)$$

where $\eta$ is the ratio of between-class variance ($\sigma_B^2$) and total variance ($\sigma_T^2$) of the resultant classes in grey levels.
2.2.2.2 Sauvola and Pietikainen’s Technique

Sauvola and Pietikainen [32] applied a method by adapting the standard deviation based on a hypothesis of text pixels that have grey values close to zero, and background pixels with 8-bit grey values close to 255. This technique was an improvement on the Niblack’s method, especially for stained and badly illuminated documents. This technique is used in this research because it is one of the best among local adaptive thresholding techniques [47], [66].

The threshold $T_a$ at a pixel $(x, y)$ is determined by the equation below.

$$T_a(x, y) = m(x, y) \cdot \left[1 + k \cdot \left(\frac{s(x, y)}{R} - 1\right)\right], \quad (2.9)$$

where $m(x, y)$ and $s(x, y)$ are the average value and the standard deviation value of grey-level values in local area at a pixel $(x, y)$ respectively. The parameter $R$ is the dynamic range of standard deviation that is equal to 128, and parameter $k$ obtains positive value that is equal to 0.5. The local area has a $N \times N$ window where $N$ is the window size. In Bedekas and Papamarkos [67] experiment, they found that the proper values of their experiments were $k = 0.1$ and $R = 128$.

2.2.2.3 Adaptive Logical Level (ALL) Technique

The Adaptive Logical Level (ALL) technique was proposed by Yang and Yan [52]. This technique was improved from the Logical Level (LL) technique which was suggested by Kamel and Zhao [51]. The technique was based on stroke width (sw) analysis and character geometry properties. This local technique gives good performance and it has been widely used for comparison purposes.
The LL technique processes each pixel \( (x, y) \) of the image \( f(x,y) \) by simultaneously comparing its grey level or its smooth grey level values \( g(x,y) \) with four local averages in windows centred at the four points \( P_i, P'_i, P_{i+1}, P'_{i+1} \) as shown in Figure 2.6 and explains in Equation (2.10). The size of neighbourhood window is \((2sw+1) \times (2sw+1)\).

\[
b(x,y) = \begin{cases} 1 & \text{if } \bigcup_{i=0}^{3}(L(P_i) \land L(P'_i) \land L(P_{i+1}) \land L(P'_{i+1})) \text{ is true} \\ 0 & \text{otherwise} \end{cases}, \quad (2.10)
\]

where 1 represents character/object and 0 represents background in the result binary image, \( b(x,y) \) and

\[
\begin{align*}
P'_i &= P_{(i+4) \mod 8} \quad \text{for } i = 0,1,...,7, \\
L(P_i) &= \begin{cases} \text{true} & \text{if } |\text{mean}(P_i) - g(x,y)| > T \\ \text{false} & \text{otherwise} \end{cases}, \quad (2.12)
\end{align*}
\]

where \( T \) is a predetermined global parameter and

Figure 2.6 The processing window of the LL technique.
where \( x_i, y_i \) are the coordinates of \( P_i \), \( g(x, y) = f(x, y) \) or its smooth value.

Yang and Yan proposed to improve this technique by determining the mean of maximal stroke width \((sw)\) automatically. It was defined as the run-length with the highest frequency of the histogram in the selected local region of the image.

### 2.2.2.4 Improvement of Integrated Function (IIF) Algorithm

Another popular stroke analysis technique for local adaptive thresholding is the Improvement of Integrated Function (IIF) algorithm [68]. IIF was proposed by Trier and Taxt [49] and it was improved by Badekas and Papamarkos [68].

This technique is based on a gradient from a Laplacian operator [49]. Firstly, the smoothed image of the original image is processed by a median filter. The gradient image is then separated by using the Laplacian operator, and an activity threshold \( T_A \) which is calculated from Otsu’s algorithm. The three level image, \( L(x, y) \), is used to extract the objects as follows:

\[
L(x, y) = \begin{cases} 
0 & \text{if } \nabla f(x, y) < T_A \\
- & \text{if } \nabla f(x, y) \geq T_A \text{ and } \nabla^2 f(x, y) < 0 \\
+ & \text{if } \nabla f(x, y) \geq T_A \text{ and } \nabla^2 f(x, y) \geq 0
\end{cases}
\]  

(2.14)

\( \nabla^2 f \) is the Laplacian [16] for all pixels of the smoothed image, \( \nabla f \) is the gradient at every point of an image.

The post-processing step is used to remove false print objects. The mean filter is used to smooth the input image, and the gradient image is then calculated. An
average gradient of the edge pixels is then calculated to determine the object by using a threshold \( T_p \) where \( T_p \) is a predetermined threshold by trial.

### 2.2.2.5 Background Estimation (BE) Technique

Lu et al. [60] in 2010 proposed another technique by using background estimation and it was evaluated based on the DIBCO 2009 benchmark dataset. This technique provided the best result among the 43 submitted techniques in DIBCO 2009.

This technique first estimates the document background surface through an iterative polynomial smoothing process. The polynomial order is adaptively increased as the following estimation of the document background surface

\[
d_n = d_0 + f_{rd}(k_t \cdot n),
\]

where \( n \) refers to the iteration number and \( f_{rd} \) denotes a rounding function. \( d_0 \) and \( d_n \) are the order of the initial smoothing polynomial and the smoothing polynomial at the \( n^{th} \) iteration, respectively. Parameter \( k_t \) specifies the increase speed of the polynomial order that can be set between 0.1 and 0.2.

The text stroke edge is then detected by combining L1-norm image gradient in horizontal \( V_h(x, y) \) and vertical \( V_v(x, y) \) directions as follows:

\[
V(x, y) = V_h(x, y) + V_v(x, y)
\]

The text on the document is segmented by a local threshold that is estimated from the detected text stroke edges as follows:
where 1 and 0 are set to be foreground (text) and background, respectively. \( \tilde{I}(x, y) \) refers to the normalised image from the estimation of document background surface. 

\[ E_{\text{mean}} \] is the mean of the image intensity of the detected stroke edge pixels in the neighbourhood window. \( N_e \) is the number of detected stroke edge pixels that lie in the local neighbourhood window, and \( N_{\text{min}} \) is the minimum number of the detected stroke edge pixels within the neighbourhood window.

### 2.2.2.6 Local Maximum and Minimum (LMM) Technique

This technique was proposed by Su et al. [61]. It was ranked first among the 17 submissions of the H-DIBCO 2010 competition held at the 2010 International Conference on Frontiers in Handwriting Recognition (ICFHR’10). LMM used the image contrast that evaluated by the local maximum and minimum of the image intensity.

An image contrast is performed based on the local image intensity maximum and minimum as follows:

\[
D(x, y) = \frac{f_{\text{max}}(x, y) - f_{\text{min}}(x, y)}{f_{\text{max}}(x, y) + f_{\text{min}}(x, y) + \varepsilon},
\]

where \( f_{\text{max}}(x, y) \) and \( f_{\text{min}}(x, y) \) denote the maximum and the minimum image intensities within a local \( N \times N \) window. The local neighbourhood window is defined as \( 3 \times 3 \). The \( \varepsilon \) is a positive value which should be a small number that is added in case the local maximum equals to 0.
The high contrast image pixels around the text stroke boundary are then detected through the global thresholding by using Otsu’s technique. The text image is degraded based on the local thresholds that are estimated from the detected high contrast image pixels. The binary pixel of the image is then classified from its intensity and its neighbouring high contrast pixels as follows,

\[
B(x, y) = \begin{cases} 
1 & \text{if } \left( N_e \geq N_{\text{min}} \land I(x, y) \leq E_{\text{mean}} + \frac{E_{\text{std}}}{2} \right), \\
0 & \text{otherwise}
\end{cases}
\]  

(2.19)

where 1 and 0 are set to be foreground (text), and background, respectively. \( E_{\text{mean}} \) and \( E_{\text{std}} \) are the mean and the standard deviation of the image intensity of the detected high contrast image pixels in the neighbourhood window respectively. \( N_e \) is the number of high contrast image pixels that lie in the local neighbourhood window, and \( N_{\text{min}} \) is the minimum number of the high contrast image pixels within the neighbourhood window.

In this study, a selection of the binarisation techniques is proposed by using machine learning and the techniques are explained in the next section.

### 2.2.3 Optimal Binarisation

Although there exist several good binarisation techniques, researchers (Trier and Jain [40], Leedham et al.[43], Chen and Leedham [44], Sezgin and Sankur [47], Badekas and Papamarkos [67]) have proved that there is no single binarisation technique that can be applied effectively to all kinds of digital documents, even in a single application domain. The overall performance of different binarisation systems may vary according to different datasets.
Due to this reason, a few researchers pointed to the need of selecting the optimal binarisation technique or combining binary results from multiple binarisation techniques for an image. Chen and Leedham [44] proposed the decompose algorithm for an image by using local information to analyse and select an appropriate algorithm to determine the threshold for the sub-regions in a document. Their techniques worked well on handwriting documents which contained text, but it did not work well on document images with big patterns or pictures.

Badekas and Papamarkos [25] proposed a technique to combine the best binarisation results from IBT by using KSOM. Their techniques performed as a semi-automatic approach by selecting the most appropriate binarisation methods and applied them to the KSOM. This technique worked well on document images with complex background but it could be time consuming [69].

Gatos et al. [70] presented a binarisation technique based on a combination of multiple binarisation techniques and adapted edge information. Three binarisation techniques (Otsu, ALL, and ADD) were selected to combine the results and the majority vote approach was used. The authors compared their methods with six well-known binarisation techniques from Otsu, Bernsen, Sauvola and Pietikainen, ALL, and ADD. F-measure was used to evaluate their proposal and they reported that the combined binary results from the multiple binarisation techniques gave the best performance.

Another approach based on combination of binarisation was proposed by Su et al.[69]. The combination technique was performed by classifying each pixel into three classes; background, foreground and uncertainty, from results of the candidate binarisation techniques. The classifier first attempted to determine whether a pixel
was either foreground or background. If the result was uncertain, the classifier would then use the global foreground and background information to determine the status of the pixel. The proposed technique incorporated self-training strategy on existing binarisation methods. Evaluation of this technique was compared with the performance of Otsu’s, Sauvola and Pietikainen’s, Gatos’s, Lu’s and Su’s methods. The four evaluation measures from DIBCO’s report were used. The authors found that most of the text strokes in the result were preserved while most of the noise pixels were removed. This proposed method was based on combining two techniques at a time and then the result was combined with a subsequent technique one after another in a cascading fashion. This technique caused time consuming if a large number of binarisation techniques were used.

From literature, the selection of optimal thresholding method, and the determination of an optimal binary image are challenging topics and they are subsequently addressed in Chapters 3 and 4 in this thesis respectively.

The performance of the binarisation techniques has critical effects on the output from subsequent text line and character segmentation, and the recognition processes. The principles of text line and character segmentation are discussed in the next section.

### 2.2.4 Text Line Segmentation

The text line segmentation is required to separate the text lines from a document image. For English or similar languages, processing of character segmentation consists of three steps; text line segmentation, word segmentation and character segmentation. However, the ancient Thai writing system is slightly
different because there is no word separator. So the process consists of only two steps; text line segmentation and character segmentation. In the optical character recognition process, flow of text components (characters or alphabets) cannot be read unless they are in proper sequence. Therefore, text line segmentation is an essential process in document processing and it must be include in this study.

Zahour et al. [71] proposed the partial projection profile for text line segmentation. The image was divided into eight vertical strips. The vertical profile of each strip was based on the histogram along the horizontal axis. The baselines were analysed by using maximum and minimum values of the histogram in each strip. The vertical gaps among two consecutive text lines were determined according to the vertical profiles. This method worked well for text with overlapping lines, incomplete lines and change in text orientation, but it did not deal with touching lines. An improved version of the partial projection profile method was explained by Pal and Datta [72], and Tripathy and Pal [73], for handwritten Bangla scripts. Their technique computed the width of the stripes by using four characters of Oriya that were calculated the width from 7500 Oriya words. The baselines were determined by using peak and valley points, and the baselines of each strip were connected to form a long line. In this approach, false text line separation might occur when several neighbouring text lines were connected significantly and there were diacritical points through letters.

The review by Likforman-Sulem et al. [74] on historical documents described and compared six categories of text line separation methods (projection-based, smearing, grouping, Hough-based, repulsive-attractive network and stochastic methods) for separating printed or handwritten documents, broken and touching
characters. They reported that piecewise projections proposed by Zahour et al. [71], and Pal and Datta [72] were suitable for overlapping or touching lines. However, the stochastic method [75] was more robust and suitable for overlapping lines. They summarised that there was no single line segmentation technique that suited all documents. The particular technique depended on the characteristics of the writings such as script size, stroke width and average spacing.

Surinta [76] proposed an algorithm based on sorting and distinguishing the histograms of projection profiles in order to select the baselines. This experiment worked with Thai handwritten documents and the accuracy achieved was 97.11%. However, the reported experiment did not consider overlapping consecutive lines and fluctuating lines.

Arivazhagan et al. [77] proposed a statistical approach to line segmentation. Their approach was also based on partial projection profile. The width of strip size was calculated by using 5% of the image width. Histograms of each strip were computed and then the baselines were determined by using bivariate Gaussian densities. When there were some connected components between consecutive lines, a decision would be performed by traversing lines around the obstructing components. It was reported that their technique could preserve the dot above and below a word. Most of the errors occurred because of two reasons; normal component which spans across two or more lines, and normal component lying in between two lines.

Although those techniques deal quite well with overlapping lines, incomplete lines, change in text orientation and a touching component of two consecutive lines (as shown in Figure 2.7), they will have issues when dealing with the research problem in this thesis. Palm leaf manuscripts could have one or two
holes between the lines and character components between text lines as shown in Figure 2.8. All the above techniques are not able to deal successfully with the separation of vertically connected text lines which could be crucial for word or character recognition [78].

Figure 2.7 Illustration of touching, overlapping and fluctuating lines.

Figure 2.8 Illustration of character components and holes on palm leaf manuscript.
2.2.5 Character Segmentation

Character segmentation is another important topic in image document processing system as the performance of this process could significantly affect the overall accuracy of the recognition system. Casey and Leolinet [79] reported a survey of four methods and strategies in character segmentation; classical approach, recognition-based segmentation, hybrid approach and holistic methods.

The classical approach is based on character-like or image features [79]. The technique, called “dissections”, cuts an image into a sequence of sub-images. A number of popular methods under this category are the white space and pitch, projection analysis, connect component processing and dissection with contextual post-processing graphemes techniques. It has been reported that these techniques provided promising results but they may fail to separate the handwriting character and touching characters [80].

Recognition-based segmentation is based on pattern recognition [79] without the image content. The system searches the image for components that match classes of alphabets. This technique can be divided into two methods; windowing process and feature-based. Although there are other strategies that use intelligent techniques to determine touching segmentation points and they have reported high accuracy of segmentation, they however need a large volume of training data and overhead of time. In addition, the segmentation accuracy depends on the robustness of the recogniser [80].

The hybrid approaches are performed by a process of preliminary segmentation based on image features. If the letters are dissected into multiple paths,
a correct segmentation are combined and processed using the recognition-based segmentation [79]. This technique can improve the accuracy of over-segmenting.

The Holistic method is a searching and matching approach to recognise whole words, and avoids separation of characters [79]. This method performs feature extraction and global recognition. The global recognition is done by comparing the representation of the unknown word with those of the references stored in the lexicon. Consequently, this method uses the “classical approach”, with complete words as symbols to be recognised. For instance, the scale space technique [81] and holistic word recognition [82] are normally used on Roman scripts. These methods are restricted in applications with a predefined lexicon.

Many techniques have also been proposed for segmentation of touching characters. In the literature, many character segmentation approaches have low performance when dealing with touched characters [80]. Although there are a number of approaches to segment touching characters, most techniques deal with touching handwritten numeral strings [83], [84], [85] and printed touching characters [86]. Most of the segmentation approaches for handwriting scripts are applied to Roman [87], Arabic [88], Indian [89], [90] Chinese [91], [92] and Japanese [93], [94] languages, but there are only limited researches on Thai handwriting segmentation. Many papers concerning Thai handwritten segmentation used the classical approaches to segment characters [95], [96], [97], and the demonstrations were based on controlling the writing styles of the writers which is not practical. In addition, all those studies were based on the modern Thai language which is far different from ancient Thai language.
Surinta and Chamchong [98] applied the recursive strip for line segmentation and connected components for character segmentation on Thai palm leaf manuscripts. Their experiment found several components fell into wrong lines and several ancient Thai characters cannot be separated due to overlapped components and connected characters. While it was found that these techniques could be applicable, they however were not useful for practical documents.

Contour tracing technique [11], [99], [100] is applied to digital images for extracting the boundary of an object such as character. This technique is performed by using connected components, either 4-connected components or 8-connected components. The premising approaches of this algorithm are Square-Tracing algorithm [11], Moore-Neighbour tracing [99], and Theo Pavlidis’s algorithm [100]. This technique is suitable for extracting over-segmented character images and slant writing styles but the technique cannot separate connected or touching components.

In terms of document image processing, it is desirable to have embedded tools for searching of blocks, text lines, words and characters, and the inclusion of a dedicated handwriting recognition system. Interactive tools are generally offered for segmentation and recognition correction purposes. Several projects in the past were concerned with printed materials. However, solutions to tackle Thai handwritten text accurately are yet to be developed. Furthermore, there is no OCR system tool or development currently widely available for the processing of ancient Thai handwriting and documents. This leads to the motivation of this study.

The following section provides a description of the datasets used in this study.
2.3 Description of Datasets

Datasets of this study are based on practical data from palm leaf manuscripts, and the DIBCO benchmarking datasets [56].

2.3.1 Palm Leaf Manuscripts

![Example 1](image1)

(a) Example 1

![Example 2](image2)

(b) Example 2

![Example 3](image3)

(c) Example 3

Figure 2.9 Samples of palm leaf images.

This study focuses on ancient manuscripts provided by the Project for Palm Leaf Preservation [4]. The palm leaf manuscript images have been converted to RGB format of $200 \times 200$ dpi resolution. Most of the palm leaf manuscripts in Northeast Thailand are Thai-Noi and Dham-Esan. This research focuses on the Thai-Noi script as it is closer to modern Thai script, and it is also the root of Lao script. Dham-Esan has mainly been used in Buddhist documents only while Thai-Noi
was more commonly used in all other documents. Hence, this study used Thai-Noi for the initial investigation and development. The study used totally 480 palm leaf images from ten bundles that were written by different writers. Some samples of the palm leaf images are shown in Figure 2.9.

2.3.2 The Binarisation Benchmark Data

In 2009, the first International Document Image Binarisation Contest (DIBCO2009) was established and organised by Gatos et al. [56]. In the contest, evaluation of document image binarisation methods was based on a variety of scanned machine-printed and handwritten documents. Ntirogiannis et al. [55] developed the ground truth of the binary images by using an objective evaluation methodology for document image binarisation techniques. The datasets from the DIBCO series have been used to evaluate the binarisation techniques since 2009. In this study, the datasets used are the DIBCO2009 [58], H-DIBCO2010 [59] and DIBCO2011 [57]. They were used to evaluate and compare the results from the proposed combination technique. The categories of the benchmarking datasets in each contest are shown in Table 2.2.

<table>
<thead>
<tr>
<th>Benchmark dataset</th>
<th>Machine-Printed Document Images</th>
<th>Handwritten Document Images</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>DIBCO2009</td>
<td>5</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>H-DIBCO2010</td>
<td></td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>DIBCO2011</td>
<td>8</td>
<td>8</td>
<td>16</td>
</tr>
<tr>
<td>Total</td>
<td>13</td>
<td>23</td>
<td>36</td>
</tr>
</tbody>
</table>

Chapter 3 discusses background elimination and selection of binarisation techniques in this study.
Chapter 3

Background Elimination and Selection of Binarisation Techniques

Challenges for text processing in ancient document images are mainly due to the high degree of variations in the foreground and background composition. Image binarisation is one of the image segmentation techniques that has been used to separate the image into text and background components. Binarisation technique is crucial to the removal of unrelated artefacts and background noises in document images. If this step is inefficient, the original characters from the image may not be recognised, or more noise may even be added. Subsequently, this technique is deeply essential to improve the readability of the document and the overall performance of the process.

Refer to the previous survey of binarisation techniques; it is observed that there is no single technique that is effective for all kinds of digital documents, even in the same problem domain. The performance of different binarisation techniques may vary due to different datasets. This chapter therefore proposes a new method for the selection of the most appropriate binarisation technique for the extraction of text from the background.

The following Section (3.1) shows the example results from the noise reduction process, and the subsequent Section (3.2) investigates the binary results from six binarisation techniques that have been reported in the literature and they were used in this study. Then Section (3.3) introduces a selection framework of the
binarisation techniques. Finally, the nominated appropriate binarisation techniques have been evaluated, and a summary of this chapter is given in the last Section (3.4).

3.1 Experiments with Noise Reduction

Before the evaluation of the selection of binarisation, the input images in RGB format were first converted to greyscale images and then noise was reduced by using the Gaussians filtering technique with a mask of $3 \times 3$ dimension. The input samples of palm leaf images in RGB format, greyscale images and filtered images are shown in Figure 3.1 to Figure 3.3.
Figure 3.1 Five samples of original palm leaf images in RGB format.
Figure 3.2 Sample results of the digitised images in greyscale.
Figure 3.3 Sample results of filtered images.

Figure 3.3 shows the filtered images that have been smoothed by Gaussian filtering. Figure 3.4 shows the example result without noise reduction and noise.
reduced by Gaussian filtering. This example illustrates that noise is reduced after the filtering technique.

Figure 3.4 Binarised image results illustrating no noise reduction and noise reduction by Gaussian filtering.

The sample results in Figure 3.4 show that noise reduction is needed in order to reduce spatial noise from the grey-scale images. Figure 3.4(b) is the original binarised image without noise reduction when Figure 3.4(c) shows the binarised image after done with noise reduction by Gaussian filtering technique.

### 3.2 Experiments with Binarisation Techniques

Although there are several efficient binarisation techniques, they produce different results. Some techniques may generate more noise in the background but provide good result for the foreground while others generate less noise but may provide inappropriate foreground. The overall performance of different binarisation
techniques may vary according to different datasets. Consequently, six binarisation techniques reported widely in prior literature have been implemented in this study.

After noise reduction, the palm leaf images were applied using six binarisation techniques; Otsu’s (OT) technique, Sauvola and Pietikainen’s (SAU) technique, ALL technique, IIF algorithm, BE technique and LMM technique. In this experiment, the initial parameters of SAU, ALL and IIF were set as follows:

SAU: \( R=128, k=0.1 \),

ALL: threshold was calculated automatically, and

IIF: \( T_A \) was set automatically by Otsu’s technique, \( T_p =60 \).

Some example results of palm leaf manuscripts are shown in Figure 3.5 to Figure 3.10. On average, OT only worked well on bimodal histogram images and it did not perform well on palm leaf images. SAU could retain details of the strokes but it was sensitive to noise, especially ghosting noise as shown in Figure 3.6 (d).
Figure 3.5 Sample results of binary images from the OT technique.
Figure 3.6 Sample results of binary images from the SAU technique.
Figure 3.7 Sample results of binary images from the ALL technique.
Figure 3.8 Sample results of binary images from the IIF technique.
Figure 3.9 Sample results of binary images from the BE technique.
The ALL technique retained details of the strokes in the text. However, noise still occurred surrounding the text. It also added some noise to the background as a result of ghosting noise as shown in Figure 3.7(d). This is due to ghosting noise.
On the other hand, IIF did not retain the details of the strokes in the text, and some of the texts had even been lost. This technique, yet, suppressed the noise on the background. Both ALL and IIF techniques were suitable for palm leaf image that has cracks or lines between text as shown in Figure 3.8(a).

BE and LMM techniques suppressed noise better than other techniques. However, if the image has cracks or lines on the text, these techniques will have difficulties in extracting the text. If there are no lines or cracks, both techniques will be able to extract the text properly. The BE technique could reduce more noise surrounding the text better than the LMM. Besides, it reduced ghosting noise and isolates characters better than others. LMM could extract text better than BE. However, LMM is unsuitable for the image has lines of crack on the text because connected components could occur and it could not suppress ghosting noise.

In conclusion, there is no single binarisation technique that suits all images although LMM has shown the acceptable result. The characteristics of practical datasets may greatly differ; it is, thus, difficult to claim a single algorithm or a suitable threshold value for all datasets.

### 3.3 Selection Framework of Binarisation Techniques

This section explains the selection process based on the machine learning technique - classification. The selection is performed by classifying the appropriate technique considering the features extracted from the image. In this study, the issue of imbalanced data was addressed in order to improve the accuracy of the method. Finally, the Support Vector Machine (SVM) [101], [102], [103], [104], [105] was
used to select the most appropriate binarisation technique for generating the binary image.

Figure 3.11 Overall process of the proposed method for selecting the optimal binarisation technique.

Figure 3.11 illustrates the overall process of the proposed method for selecting the optimal technique for binarising an image. The dataset was separated into a training set and a test set for the learning and evaluation processes,
respectively. The overall process is divided into three steps: (i) feature extraction: feature patterns are extracted from greyscale images based on global intensity, and local contrast and local intensity; (ii) treatment of imbalanced data: imbalanced dataset are addressed and balanced by using the Synthetic Minority Over-sampling technique (SMOTE) [106], [107], [108], [109] to improve the performance of prediction; and (iii) selection: SVM is applied with the feature patterns in order to select the appropriate binarisation techniques. Detailed discussion of the proposed process is given in the sections below.

3.3.1 Feature Extraction

Feature extraction is an essential step in any learning methods which transforms the characteristics of original data to feature patterns for decision making. This section explains the feature pattern of the images used in the dataset, and Principal Component Analysis (PCA) [16], [105], [110] is used for dimensionality reduction of the feature space.

3.3.1.1 Feature pattern

Intensity histograms are the most commonly features for global binarisation techniques. They are used to convey the grey distribution information. This forms a compact representation of the colour feature. Apart from that, the mean, standard deviation, minimum and maximum of intensity are also used as global features.

For local binarisation techniques, intensity and contrast have been the most frequently used features [111]. A contrast feature has also been used and modified by Su et al. [69]. If there is significantly change of intensity between the boundary of the foreground text and the background, the contrast of grey-level indicates the
characteristics differentiation between the foreground and background. In this study, the contrast feature was used for feature extraction and it was modified by decomposing the image into sub-images. In addition, this study also applied the intensity values by using mean, standard deviation, maximum and minimum of intensity of the sub-areas. The features of an image used in this study are explained below:

1) **Global features**

The image histogram represents the relative frequency of occurrence of the various grey levels in the image. It gives a global description of the image, and the shape of the histogram reveals significant contrast information. A discrete function of the histogram [11], [16], $H$, is given by the relation

$$H = \{h_0, h_1, \ldots, h_{L-1}\},$$  \hspace{1cm} (3.1)

where

$$h_l = \frac{n_l}{N},$$  \hspace{1cm} (3.2)

while $l$ is the level of greyscale such that $0 \leq l \leq L-1$, $n_l$ is the number of pixels in the image with the $l^{th}$ level of greyscale, and $N$ is the total number of pixels in the image.

The image histogram carries important content of the image. For global binarisation techniques, this content is useful to distinguish between foreground and background of an image.
In this study, sixty-four bins of greyscale histogram of the image were extracted and used as features for the selection module. This represents the global characteristic of the image and it could be used to assist the decision on selecting the appropriate technique.

The mean \((f_{\mu})\) and standard deviation \((f_{\sigma})\) of the intensity of an image [18] represent the compact features. These expressions are shown as follows:

\[
f_{\mu} = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} f(x, y)
\]

and

\[
f_{\sigma} = \sqrt{\frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} (f(x, y) - f_{\mu})^2},
\]

where \(f(x, y)\) is the intensity value of the grey pixel at \((x, y)\) axis, while \(M\) is the number of columns and \(N\) is the number of rows of image.

The other two intensity features are minimum, \(f_{\min}(i,j)\) and maximum, \(f_{\max}(i,j)\) intensity values of image which were also used in this study.

2) **Local features**

For these features, an image is decomposed into sub-images with \(C \times R\) of column and row matrices as shown in Figure 3.12. The contrast and intensity features of an image are then applied to describe the characteristics for each sub-image. In this study, \(9 \times 5\) sub-images were considered for each feature.
Figure 3.12 Image decomposition.

a. Contrast feature

This feature is used to describe the characteristics of the text and background in the sub-area. It illustrates the difference between text and background information. The contrast feature in local neighbourhood from Su et al.’s study [69] is defined as follows:

\[
Cont(x,y) = \frac{f_{max}(x,y) - I(x,y)}{f_{max}(x,y) + \epsilon},
\]

where \(I(x,y)\) and \(f_{max}(x,y)\) denote the intensity of pixel \((x,y)\) and the maximum intensity values within local area. \(\epsilon\) is an infinitely small positive number, which is added in case the local maximum is equal to 0. \(Cont(x,y)\) refers to the contrast value of the estimating pixel \((x,y)\).

This feature is calculated from the high contrast responses at the area near the boundaries between the text strokes and document background. The contrast
feature preserves the ability to suppress the background variation and assigns a more accurate contrast value to the document pixels.

In this study, the contrast feature is calculated in each sub-image, and this feature is then modified as expression (3.6).

\[
\text{Cont}(i, j) = \frac{f_{\text{max}}(i, j) - f_\mu(i, j)}{f_{\text{max}}(i, j) + \epsilon}
\]  

(3.6)

where \( f_\mu(i, j) \) and \( f_{\text{max}}(i, j) \) denote the average intensity of sub-image \((i, j)\) and the maximum intensity value of sub-image \((i, j)\). \( \epsilon \) is an infinitely small positive number, which is added in case the maximum intensity values is equal to 0.

\( \text{Cont}(i, j) \) refers to the contrast value of the estimating sub-image \((i, j)\), with \( 1 \leq i \leq C \) and \( 1 \leq j \leq R \), where \( C \) and \( R \) is the number of columns and rows of decomposed image.

b. Intensity feature

Another local feature commonly used in binarisation is the intensity feature. However, the feature for classification should form a compact representation and mean, standard deviation, maximum and minimum value of intensities are also used to extract the feature from each sub-image in this study.

Acharya stated that the mean and standard deviation of sub-image [19] characterise the compact representation of the intensity feature. The mean \((f_\mu(i, j))\), and the standard deviation of the sub-image \((f_\sigma(i, j))\) are expressed as follows:

\[
f_\mu(i, j) = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} f(x, y)
\]

(3.7)

and
where \( f(x, y) \) is the value of the grey pixel in the \( x^{th} \) column and \( y^{th} \) row of the sub-image, while \( M \) is the number of columns and \( N \) is the number of rows.

Two other intensity features are minimum \( f_{\min}(i, j) \) and maximum \( f_{\max}(i, j) \) intensity values of sub-image which were also used in this study.

As 45 sub-images were considered in this study, 225 feature vectors from five features (contrast, mean, standard deviation, maximum and minimum) were then extracted from an image. The number of overall features is 293 feature vectors including 68 feature vectors from the global feature. These feature vectors were applied to the learning process described in the next subsection which explains the selection module that recommends the appropriate binarisation technique based on the feature space model.

### 3.3.1.2 Principal Component Analysis

In machine learning, it is common to deal with data having high dimensionality input features. In order to improve the prediction performance, dimensionality reduction may be applied through a transformation of the original data.

*Principal Components Analysis* (PCA) is a powerful tool [112] and the most widely used technique [104] for feature selection in the transformed space for dimension reduction. This technique is an unsupervised method based on a
correlation or covariance matrix that has been used in applications such as face recognition and image compression [112].

PCA [16], [105], [110] is calculated from the eigenvectors and eigenvalues of the data covariance matrix. The process is to find the axis system where the covariance matrix is diagonal. This technique can reduce the dimension of the representation. On the other hand, the original information content is preserved as much as possible.

As the number of overall features of this work is 293 feature vectors that have high dimensionality input features, the PCA is then applied to reduce the dimension of feature patterns. The next section addresses the problem of imbalanced data for machine learning.

3.3.2 Treating Imbalanced Data with SMOTE

Real world datasets usually have the problem of imbalanced data. It is a significant problem affecting learning algorithms. It associates with the situations that some classes have much larger number of instances than the others. This is shown in Figure 3.13. Examples of real world cases with an imbalanced dataset are biomedical applications, fraud detection and network intrusion [107], [113].

![Figure 3.13: A dataset with a between-class imbalance](image)

Figure 3.13 A dataset with a between-class imbalance [114].
The issue of imbalanced data needs to be approached at data-level with an objective to balance the training data before learning process is applied. Approaches to deal with imbalanced data can be separated into three categories; under-sampling, over-sampling and combined techniques. The under-sampling technique aims to balance the dataset by removing instances of majority class while over-sampling balance the dataset by adding the minority class. In addition, the combined technique is a combination of both under-sampling and over-sampling techniques.

In this study, there are cases that contain only a few instances in the dataset, over-sampling technique is therefore adopted. There are several over-sampling techniques such as the Random Over-sampling technique and Synthetic Minority Over-sampling technique (SMOTE) [106]. SMOTE has shown to be a successful method in many applications [107] and the SMOTE algorithm generates synthetic data based on the feature space similarities between minority examples. Other technique such as Random Over-sampling technique performs over-sampling by replicating minority class instances randomly. For this reason, the SMOTE algorithm may avoid the over-fitting problem [114]. The SMOTE algorithm is shown in Algorithm 3.1 below.
Algorithm 3.1 SMOTE algorithm [106]

$I$ is the input dataset
$M$ is the set of minority class instances
For each instance $x_i$ in $M$

Find the $k$-Nearest Neighbours (minority class instances) to $x_i$ in $M$
Obtain $\hat{x}_i$ by randomising one from $k$ instances
$\delta = \text{random number between zero and one}$
$x_{new} = x_i + (\hat{x}_i - x_i) \times \delta$
Add $x_{new}$ to $I$
End for

The number of new minority class instances is increased by the above algorithm and the synthetic instances are generated by the Euclidian distance technique [107]. The minority class instances that are close together are firstly considered before they are employed to form new minority class instances. Figure 3.14 shows the data generation by the SMOTE algorithm.

![Figure 3.14 Example of the k-nearest neighbours for the $x_i$ instance (k = 6) and data generation based on Euclidian distance [107].](image)

In this study, the class imbalanced problem in multi-class data was addressed with the One-Against-All (OAA) scheme [115], [116]. The OAA scheme is a promising technique of multi-class problem and is suitable for small sized training
data [109]. This scheme can be used to deal with the data balancing issue in multi-classes and it can also reduce the complexity in the machine learning process. As some of the datasets in this study contain fewer instances, the OAA scheme was therefore applied.

### 3.3.3 Selection Module

This study aims at proposing a selection process for the most appropriate binarisation technique by machine learning. In particular, the selection is based on Support Vector Machine (SVM) [101], [117], [118], due to its appropriateness for classification problems. The SVM is a classification technique based on statistical learning theory which was introduced by Vapnik [101], and its applications have provided good results. In this study, SVM was used to select the appropriate binarisation technique by learning from feature patterns of a training dataset. The binarisation technique is then used to generate the binary image.

The decision function of SVM is calculated from a training dataset. Four basic concepts of SVM [102], [103], [104], [105] are the separating hyperplane, the maximal margin hyperplane, the soft margin and the kernel function.

The separating hyperplane is used to separate objects into two classes in which the objects are treated as points in a high-dimensional space. A linear decision function is given by

$$f(x) = w \cdot x + b.$$  \hspace{1cm} (3.9)

The training data of $n$ samples $\{(x_1, y_1), \ldots, (x_n, y_n)\}$, $y \in \{+1,-1\}$ can be expressed by the hyperplane decision function as follows:
\[ y_i (w \cdot x + b) \geq 1, \quad i = 1, \ldots, n, \]  

where \( w \) is the weight vector, and \( b \) is a bias. The decision function specifies a hyperplane separating the points of two classes as shown in Figure 3.15. The distance between the points of two classes closest to the hyperplane \( \left( \frac{2}{\|w\|} \right) \), which is called the maximum margin of the hyperplane.

![Hyperplane classifier for binary classification and the margin](image)

Figure 3.15 Hyperplane classifier for binary classification and the margin [11].

In many instances, the classes may not be linearly separable and Kernel functions are then used to separate the classes [119]. In this study, radial basis functions (RBFs) [102] were used to separate the classes. The RBF kernel for the SVM is flexible models for nonlinear discriminant analysis and provides good performance in pattern recognition applications [104]. For building this module, the LIBSVM library [103] has been used in the implementation. The next section discusses the experimental results from the proposed method on the selection of binarisation technique.
3.4 Experimental Results from the Proposed Method

The next section describes the datasets that were used in this experiment. Sample results of the candidate of binarisation techniques are then illustrated and finally, the evaluation of the selection is given.

3.4.1 Dataset Used in This Experiment

This chapter deals with training hence there is a need for a large set of data in the learning process. A dataset of palm leaf manuscripts is used to evaluate the proposed method in this study. The dataset is first split into training and test set by applying \textit{k-fold cross-validation} [104]. The dataset is partitioned into \( k \) (randomly selected) subsets and the holdout method is repeated \( k \) rounds. For each iteration, one subset is used as the test set and \( k-1 \) subsets are a training set. The advantage of this method is that every data point will be in a test dataset, and it will be in a training set of \( k-1 \) rounds. Typical choice for \( k \) are 5 or 10 [120]. In this experiment, 10-fold cross validation was used.

In this study, the dataset of the experiment was separated into two types which are:

1. \textit{Imbalanced dataset} – the dataset comprises 480 instances, divided into four classes which are LMM 280 instances, ALL 96 instances, BE 58 instances and IIF 46 instances (Ratio of instances, LMM: ALL:BE:IIF=58:20:12:10).

2. \textit{Balanced dataset by SMOTE} – as class distribution of this dataset is imbalanced, SMOTE technique was applied to synthesise the minority classes. LMM
is a majority class, and ALL, BE and IIF are minority classes. The number of instances of minority classes in ALL was increased 100%, BE 200% and IIF 200%. The number of instances after synthesis were 784 instances, with 280 instances in LMM, 192 instances in ALL, 174 instances in BE, and 138 instances in IIF. (Ratio of instances, LMM: ALL:BE:IIF=36:24:22:18).

3.4.2 Evaluation Measures

In general, the accuracy is used to explain the overall classification performance. In case of an imbalanced dataset, it has been widely premised that if the number of prior classes are very different, this measure may be unsuitable because misclassification may occur [114]. Other evaluation measures of the imbalance problem like $F$-measure, the Geometric Mean (G-mean) and the area under the ROC curve (AUC) [107], [121], [122], [123] have been proposed. These indicators aim to maximise the accuracy between the minority class and the majority class so they are good for the class imbalanced problem. These measures were therefore applied to evaluate the performance of the selection of the binarisation techniques in this study.

These measures are calculated from a confusion matrix. The confusion matrix of a multi-class application of $k$-classes is presented in Table 3.1 [121].
Table 3.1 A confusion matrix of \( k \)-classes.

<table>
<thead>
<tr>
<th>Actual class</th>
<th>Predicted class</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_1 )</td>
<td>( n_{11} )</td>
</tr>
<tr>
<td>( C_2 )</td>
<td>( n_{21} )</td>
</tr>
<tr>
<td>( \vdots )</td>
<td>( \vdots )</td>
</tr>
<tr>
<td>( C_k )</td>
<td>( n_{k1} )</td>
</tr>
</tbody>
</table>

The metrics of this study are defined as follows [121]:

The accuracy (AC) is the proportion of the total number of predicted instances that were correct and it is shown as below.

\[
\text{Accuracy (AC)} = \frac{\sum_{i=1}^{k} n_{ii}}{\sum_{i,j=1}^{k} n_{ij}} \tag{3.11}
\]

Recall (RC) values or True Positive (TP) rate is the proportion of positive instances that were correctly identified: This value is calculated as follows:

\[
RC_i = TP_i = \frac{n_{ii}}{\sum_{j=1}^{k} n_{ij}} \tag{3.12}
\]

Precision (PR) is the proportion of the predicted positive instances that were correct. This value is determined by Equation (3.13) below.

\[
PR_i = \frac{n_{ii}}{\sum_{j=1}^{k} n_{ji}} \tag{3.13}
\]

F-measure (FM) combines precision (PR) and recall (RC) as a measure of the effectiveness of classification. This value is calculated as follows:

\[
FM_i = \frac{2 \cdot RC_i \cdot PR_i}{RC_i + PR_i} \tag{3.14}
\]
*G-mean* is the geometric means of recall values of every class. It has been introduced to measure the balanced performance among the classes of a classification output [121]. This measure evaluates the degree of inductive bias in terms of the ratio of positive accuracy (true positive rate) and negative accuracy (true negative rate) [107]. This value is calculated by Equation (3.15) below.

\[
G\text{-}mean = \left( \prod_{i=1}^{k} RC_i \right)^{1/k}
\]  
(3.15)

Another measure of imbalanced data is the *area under the ROC curve (AUC)* [124]. The ROC curve is the trade-off between True Positive (TP) rate and False Positive (FP) rate. The curve is a plot the TP rate on the y-axis against the FP rate on the x-axis as shown in Figure 3.16. The best classification model should plot the ROC curve that is equal to one of TP rate and zero of FP rate. In general, the ROC curve can be used to explain the performance of a classification technique.

![Figure 3.16 The ROC curve [114].](image)

However, when two or more classification models are compared, the AUC is needed as it provides a single scalar value that represents the total area falling under the ROC curve. The advantage of AUC is that it can be used to evaluate the
classification performance even if the class distribution of minority and majority instances is highly imbalanced [114]. If AUC has higher value, the better performance of the classification will be provided.

The next section discusses the evaluation result of the proposed method.

3.4.3 Evaluation

For the experiment of optimal selection of binarisation techniques, 10-fold cross-validation was applied to two datasets (imbalanced data and balanced data). The overall features comprised of 68 global features (64 bins of histogram, a minimum, a maximum, a mean and a standard deviation values of intensity of image), and 225 local features (45 sub-images of contrast, 45 sub-images of mean, 45 sub-images of standard deviation, 45 sub-images of maximum, and 45 sub-images of minimum).

PCA was applied to the dataset in order to reduce the features and LIBSVM [103] was used with RBF kernel function (Gaussian) to select the optimal binarisation technique. The RBF parameters are estimated using the parameter selection tool of the LIBSVM that gives the highest cross validation accuracy.

The confusion matrices by classes of the selection method are given in Table 3.2 and Table 3.3 for imbalanced dataset and balanced dataset by SMOTE, respectively.
Table 3.2 Confusion matrix of the selection of binarisation techniques on imbalanced dataset.

<table>
<thead>
<tr>
<th>Classify as →</th>
<th>ALL</th>
<th>LMM</th>
<th>BE</th>
<th>IIF</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALL</td>
<td>15</td>
<td>80</td>
<td>1</td>
<td>0</td>
<td>96</td>
</tr>
<tr>
<td>LMM</td>
<td>14</td>
<td>266</td>
<td>0</td>
<td>0</td>
<td>280</td>
</tr>
<tr>
<td>BE</td>
<td>2</td>
<td>55</td>
<td>1</td>
<td>0</td>
<td>58</td>
</tr>
<tr>
<td>IIF</td>
<td>3</td>
<td>43</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>Total</td>
<td>34</td>
<td>444</td>
<td>2</td>
<td>0</td>
<td>480</td>
</tr>
</tbody>
</table>

Table 3.3 Confusion matrix of the selection of binarisation techniques on balanced dataset by SMOTE.

<table>
<thead>
<tr>
<th>Classify as →</th>
<th>ALL</th>
<th>LMM</th>
<th>BE</th>
<th>IIF</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALL</td>
<td>166</td>
<td>24</td>
<td>1</td>
<td>1</td>
<td>192</td>
</tr>
<tr>
<td>LMM</td>
<td>23</td>
<td>240</td>
<td>11</td>
<td>6</td>
<td>280</td>
</tr>
<tr>
<td>BE</td>
<td>0</td>
<td>10</td>
<td>164</td>
<td>0</td>
<td>174</td>
</tr>
<tr>
<td>IIF</td>
<td>1</td>
<td>6</td>
<td>0</td>
<td>131</td>
<td>138</td>
</tr>
<tr>
<td>Total</td>
<td>190</td>
<td>280</td>
<td>176</td>
<td>138</td>
<td>784</td>
</tr>
</tbody>
</table>

The performance of selection of binarisation techniques on the imbalance data is tabulated in the results for comparisons from Table 3.2 and Table 3.3 as shown in Table 3.4.

Table 3.4 Performance of the selection of binarisation techniques on imbalanced dataset and balanced dataset by SMOTE.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Class</th>
<th>Imbalanced dataset</th>
<th>Balanced dataset by SMOTE</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-measure</td>
<td>ALL</td>
<td>0.231</td>
<td>0.865</td>
</tr>
<tr>
<td></td>
<td>LMM</td>
<td>0.735</td>
<td>0.857</td>
</tr>
<tr>
<td></td>
<td>BE</td>
<td>0.033</td>
<td>0.943</td>
</tr>
<tr>
<td></td>
<td>IIF</td>
<td>0.000</td>
<td>0.949</td>
</tr>
<tr>
<td>Accuracy</td>
<td></td>
<td>0.588</td>
<td>0.980</td>
</tr>
<tr>
<td>G-mean</td>
<td></td>
<td>0.000</td>
<td>0.902</td>
</tr>
<tr>
<td>AUC</td>
<td></td>
<td>0.683</td>
<td>0.980</td>
</tr>
</tbody>
</table>
With respect to the selection of imbalanced dataset, the performances of class LMM are significantly better than those from classes ALL, BE and IIF, which have smaller instances. By applying SMOTE technique to imbalanced dataset (balanced dataset by SMOTE), performance of class LMM increased slightly, while performances of class ALL, BE and IIF improved dramatically. The selection accuracy of balanced dataset by SMOTE, G-mean and AUC of imbalanced dataset is significantly improved by 40.8%; 90.2% and 29.7%, respectively.

3.5 Summary

This chapter describes the experiments on background elimination, and proposed a framework for an automatic selection from multiple binarisation techniques. The background elimination consists of two main steps; noise reduction and binarisation techniques in order to extract texts from document images. This chapter has applied noise reduction by using Gaussian mask and original binarisation techniques (OT, SAU, ALL, IIF, BE and LMM), and the results from experimental studies have been reported. This chapter also recommends a framework for an automatic selection of binarisation techniques by using SVM with imbalanced and balanced datasets by applying SMOTE technique. The proposed measurement is based on F-measure, Accuracy, G-mean and AUC. From the evaluation of the proposed framework, all terms of measures of imbalance dataset have been improved. The evaluation result indicates that if the classes of dataset are imbalanced, the over-fitting problem may occur.

With regard to the key points in this study, the automatic selection of binarisation techniques used in this framework will be beneficial to the users in
recommending the appropriate technique. In order to balance data, the SMOTE technique is applied to up-sample the instances of minority classes. As this method needs learning from a large dataset, the method may be unsuitable for large dataset as it could be time consuming.

An optimal binarisation output could be generated by combining multiple binarised images. It is another module in the proposed framework and the details will be discussed in the next chapter.
Chapter 4

Generation of an Optimal Binarisation Output

Chapter 3 discussed the selection of an appropriate technique for the binarisation of images. Another approach to provide improved results is to generate an optimal binary image from multiple binarised images with different binarisation techniques.

The proposed techniques in this study are based on the majority vote scheme from the information based on local areas of the binarised image. To combine multiple binarised images, an output pixel can be defined as foreground, background and uncertain pixels. The uncertain pixel is then determined as either foreground or background by extending the size of neighbouring window. The benefits of this technique could be applied to both even and odd numbers of binary images. This proposed method has been applied and compared with six original binarisation techniques as explained in Section 2.2.2. The proposed techniques have also been compared with the combination of binarisation technique by KSOM [25], [67].

In this research, the benchmark datasets of DIBCO series and evaluation measures from DIBCO 2011’s report were used to evaluate the combination techniques. The benchmark datasets of DIBCO series was used in Section 2.3.2. The proposed techniques were also applied to palm leaf manuscript images.

This chapter is organised as follows: Section 4.1 provides the detail of the combination of binarisation technique using KSOM. This technique was then used to
compare with the proposed techniques. Section 4.2 explains the proposed techniques for combining binarised images. The technique applied a majority vote scheme and local adaptation. Section 4.3 demonstrates the evaluation of the experiment based on benchmark dataset and the palm leaf manuscripts. A summary of this chapter is then given in Section 4.4.

4.1 Background of Combination of Binarisation Techniques by KSOM (CBT-KSOM)

Combination of Binarisation Techniques by KSOM (CBT-KSOM) was proposed by Badekas and Papamarkos [25], [67]. The technique combines the best results of binarisation from independent binarisation techniques (IBT). To combine binarised results, the technique optimises the best values of Parameter Set (PS) from individual binarisation techniques and the Kohonen Self-organising Map (KSOM) [125] was then used to obtain the final results. Specifically, the best parameter values for each independent binarisation technique were estimated in the first stage. In order to take advantage of the binarisation information given by the independent techniques, a neural network was then fed with the binarisation results obtained by those techniques using their estimated best parameter values. Ground truth images were estimated as proposed by Yitzhaky and Peli [126] for edge detection evaluation. The evaluation was performed using ROC analysis and Chi-square test [25].

In previous work, an IBT was designated as a set of binarisation techniques comprising with Otsu’s [26], Fuzzy C-Mean (FCM) [50], Niblack’s [31], Sauvola and Pietikainen’s [32], Bernsen’s [33], Adaptive Logical Level (ALL) [51], [52] and Improvement of Integrated Function (IIF) [41], [49] techniques. The entire
application was implemented in the BDI application [127]. The image data were
digital document images obtained from standard document databases such as the
University of Washington database and the old Greek Parliamentary Proceeding [53].
Even though their proposed technique provides promising results on the document
images with complex background, manual-based generation of IBT inhibits fully
automatic document image processing systems. In the next section, the proposed
technique of automated generation of IBT is explained. The proposed technique
combines a set of binarisation techniques using voting scheme approaches [69] based
on local information.

4.2 Combination of Binarised Images using

Majority Vote Scheme

Recently, a number of binarisation techniques have been proposed. Several
binarisation techniques have revealed good performance on the evaluation of
degraded document images. This section proposes a technique to combine the
existing binarisation technique in order to produce the final results. The proposed
combining method is performed based on majority vote schemes [69], [128], which
is explained in the following sections. In this study, two new majority vote-based
techniques for image combination have been proposed. The proposed techniques are
based on the information of local interaction/neighbourhoods of a pixel in order to
determine a pixel’s class. These techniques can be applied to both odd and even
number of binarised images so that the techniques will not be limited to only odd
number of input images as in the paper [70]. In case of even number of input images,
the decision cannot be done if the result of combination may be equal in all classes.
For this reason, pixels can be assigned to the appropriate classes by using information from their local neighbourhood. The technique of deploying local neighbouring information of pixels can be achieved by applying local adaptive majority vote and adaptive weighted majority vote, which are described in Sections 4.2.2 and 4.2.3, respectively. Both proposed techniques are applied to combine binarised images and the results are given in the next section.

4.2.1 Combined Images Based on Majority Vote

To apply the majority vote in order to derive a combination of binarised images, the input images $B_i(x,y)$ from multiple binarisation techniques are defined as follows [70]:

$$
B_i(x,y) = \begin{cases} 
0 & \text{(foreground)} \\
1 & \text{(background)} 
\end{cases}, \quad (4.1)
$$

where $i = 1, 2, \ldots, N$, $N = 2n + 1$, $N$ is the number of binarised images which is selected as odd number, $(x,y)$ is the coordinate of a pixel and $n$ is a threshold value of classes (foreground and background).

Having defined the input images, a combined image $C_B(x,y)$ from $N$ binarisation results is determined by

$$
C_B(x,y) = \begin{cases} 
1 & \text{if } \sum_{i=1}^{2n+1} B_i(x,y) > n \\
0 & \text{otherwise}
\end{cases}. \quad (4.2)
$$
Figure 4.1 An example of a combined image obtained from the majority vote from three binarised images.

An example of a combined image from three binarised images is shown in Figure 4.1. The key problem of applying the majority voting scheme for binarising images (where pixels are classified into background or foreground) is a final decision cannot be made when the number of accumulated votes of a pixel to background and foreground are equal. In this study, the problem is usually found when the number of images used in the resemble step is even. Therefore, this work aims to improve the outcomes of the image binarisation by considering the number of input images in even number and determining uncertain pixels using neighbouring information to derive final decisions. This technique is described in the next section.
4.2.2 Local Adaptation of Majority Vote for Uncertain Pixel

To avoid the problem of using the even number of input images such that summation of binarised images of foreground and background are equal, in this case, the result of combination is defined as uncertain pixels. In addition, as the information surrounding a pixel may affect it, the local neighbourhood of a pixel is used in this method to determine its status. The combination is then determined by

$$C_B(x, y) = \begin{cases} 
0 \text{(foreground)} & \text{if } \frac{\sum_{i=1}^{N} V_i}{N} < 0.5 \\
1 \text{(background)} & \text{if } \frac{\sum_{i=1}^{N} V_i}{N} > 0.5 \\
-1 \text{(uncertain)} & \text{otherwise}
\end{cases}$$

(4.3)

and $V_i$ is a voting within neighbouring window from binarised images:

$$V_i = \sum_{y=-m}^{m} \sum_{x=-m}^{m} B_i(x, y),$$

(4.4)

where $M = 2m + 1$, $M$ is a size of window and $N$ is a number of binarised images.

To resolve an uncertain pixel, the information in the neighbouring area of the pixel is used. The combination is then applied iteratively to determine the status of the uncertain pixels into either foreground or background by extending the size of the neighbouring window. This technique is called Local Adaptation of Majority Vote (LAMV). This algorithm is described in Algorithm 4.1.
Algorithm 4.1  **LAMV**: Combining binarised images and determining uncertain pixels by local adaptation of majority vote.

(1) Generate a result image from $N$ binarised images by using voting of neighbouring window as given in Equation (4.3) and (4.4).

(2) If an uncertain pixel occurs from step (1), a size of neighbouring window is increased by $m = m + 1$.

(3) The process is then repeated from step (1) to step (2) until the uncertain pixel is resolved to either foreground or background. Otherwise, stop the process.

In this study, $M$ starts from three, and the number of iterations is under five.

Figure 4.2 shows an example of the combination method by using LAMV from three and four binarised images. Figure 4.2 (b) illustrate that the result of combination from four binarised images fall in the case of uncertain pixel, and then a size of neighbouring window is increased.
(a) Three binarised images

(b) Four binarised images

Figure 4.2 An example of a combined image by LAMV from three and four binarised images
4.2.3 Local Adaptation of Weighted Majority Vote for Uncertain Pixel

This is an improvement of the LAMV technique. As the majority vote from exact label does not consider the significance of a pixel and neighbouring pixels, weighted majority vote of the pixel in neighbouring window is then applied. This technique is performed as follows:

1. Normalised weight values of background \((\sigma_{1,i})\) and foreground \((\sigma_{0,i})\) in the neighbouring window of each image are defined by:

\[
\sigma_{1,i} = \frac{\sum_{y=-m}^{m} \sum_{x=-m}^{m} B_i(x,y)}{M^2},
\]

(4.5)

\[
\sigma_{0,i} = -(1 - \sigma_{1,i}),
\]

(4.6)

where \(M = 2m + 1\) and \(M\) is a size of window.

The normalised weights are defined as + and − to avoid the product of zero in the next step. A sample normalised weight value of background and foreground in neighbouring window of each binarised image is illustrated in Figure 4.3.

2. Normalised weight values in the neighbouring window of an input image are adjusted by using a Gaussian distribution mask [17], \(g(x,y)\), which is calculated by

\[
g(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}},
\]

(4.7)

where \(\sigma\) is the standard deviation of the associated probability distribution.
Gaussian distribution mask provides more significance in its pixel and the nearest neighbouring pixels. The Gaussian weight, \( GW_i(x, y) \), is then given by

\[
GW_i(x, y) = \sum_{y=-m}^{m} \sum_{x=-m}^{m} \sigma_i(x, y) \times g(x, y).
\]  
(4.8)

(3) Combined pixel is determined by applying Equation (4.9) as follows:

\[
C_B(x, y) = \begin{cases} 
0 \text{ (foreground)} & \text{if } \frac{\sum_{i=1}^{N} GW_i(x, y)}{N} < 0 \\
1 \text{ (background)} & \text{if } \frac{\sum_{i=1}^{N} GW_i(x, y)}{N} > 0 \\
-1 \text{ (uncertain)} & \text{otherwise}
\end{cases}
\]  
(4.9)

where \( N \) is a number of binarised images.

If uncertain pixels still occur, the size of the neighbouring window will be increased and determination of the uncertain pixels is executed iteratively until the pixel is resolved to either foreground or background.

This technique is called the *Local Adaption of Weighted Majority Vote* (LAWMV) and the algorithm is described in Algorithm 4.2.
Algorithm 4.2 **LAWMV**: Combining binarised images and determining uncertain pixels by local adaptation of weighted majority vote.

1. Generate a result image from $N$ binarised images by
   - normalising the weights of voting of neighbouring window as given in Equation (4.5) and (4.6).
   - adjusting the normalised weight of voting by using Gaussian distribution as explained in Equation (4.7) and (4.8).
   - determining the optimal result as given in Equation (4.9).
2. If an uncertain pixel occurs from step (1), the size of neighbouring window is increased by $m = m + 1$.
3. The process is then repeated from step (1) to step (2) until the uncertain pixel is resolved to be either foreground or background. Otherwise, stop the process.

In this study, $M$ starts from three and the number of iterations is fixed at five.

![Diagram](image)

Figure 4.3 An example of combined image by LAWMV from three binarised images.
In this study, both proposed techniques with local adaptation based on majority vote were compared with CBT-KSOM. The evaluation measures and results of this study are discussed in the next section.

4.3 Experimental Results

These proposed techniques were evaluated over benchmark datasets (DIBCO2011, H-DIBCO2010 and DIBCO2009) and tested with palm leaf images.

The DIBCO2011, DIBCO2009 and H-DIBCO2010 datasets contain 36 historical document images that suffer from different kinds of degradations. The different well-known binarisation techniques including Otsu’s (OT), Sauvola’s (SAU), ALL, IIF, BE and LMM techniques which are described in Section 2.2.2.

4.3.1 Evaluation Measures

Recently, a few researchers have proposed various evaluation measures for binarisation techniques. A competition of binarisation techniques was established in 2009, the evaluation measures and benchmark dataset for this competition have been proposed by Gatos et al. [56], [58] for DIBCO. Researchers in this area also used evaluation measures and the dataset from the competitions. Such researchers included Lu et al. [60] and Su et al. [61].

The evaluation measures in this study consist of $F$-measure, Peak Signal to Noise Ratio (PSNR), Distance Reciprocal Distortion (DRD) and Misclassification Penalty Metric (MPM). In particular, these measures are described in the sections of this chapter.
4.3.1.1 F-measure

*F-measure* measures how well a technique can detect text and background pixels in the image. A high *F-measure* value indicates a better match, and it is defined by integrating precision and recall as follows:

\[
F - \text{Measure} = \frac{2 \times RC \times PC}{RC \times PC},
\]

(4.10)

where

\[
RC = \frac{TP}{TP + FN}
\]

(4.11)

and

\[
PC = \frac{TP}{TP + FP}.
\]

(4.12)

*RC* and *PC* refer to the binarisation *Recall* and the binarisation *Precision*, respectively. *TP*, *FP* and *FN* denote the *True Positive*, *False Positive* and *False Negative* values, respectively.

4.3.1.2 Peak Signal to Noise Ratio (PSNR)

*PSNR* is a measure of the difference between two images. A higher *PSNR* indicates a better match. This metric was used in both DIBCO [56] and Statis [23] and *PSNR* is computed by

\[
PSNR = 10 \log_{10} \left( \frac{C^2}{MSE} \right)
\]

(4.13)

and the *Mean Square Error (MSE)* is calculated from

\[
MSE = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} (f(x,y) - gt(x,y))^2,
\]

(4.14)
where $C$ is the difference between the foreground and background colours. In this study, all images were converted to binary $(0, 1)$, thus $C = 1$. $f(x, y)$ and $gt(x, y)$ are the pixel of the result image $(M \times N)$ and the ground truth image.

### 4.3.1.3 Distance Reciprocal Distortion (DRD)

$DRD$ has been proposed to measure visual perception in binary document images [129]. This metric properly correlates with the human visual perception, and it measures the distortion for all the flipped pixels as follows:

$$DRD = \frac{\sum_{k=1}^{S} DRD_k}{NUBN},$$  \hspace{1cm} (4.15)

where $NUBN$ is the number of the non-uniform (not all black or white pixels) $8 \times 8$ blocks in the ground truth image and $DRD_k$ is the distortion of the $k^{th}$ flipped pixel and it is computed using a $5 \times 5$ normalised weight matrix ($W_{Nm}$). $DRD_k$ is the weighted sum of the pixels in the $5 \times 5$ block of the ground truth that differ from the centred ($k^{th}$) flipped pixel at $(x, y)$ in the binarisation result image. The $DRD_k$ is calculated by the following equation:

$$DRD_k = \sum_{i=-2}^{2} \sum_{j=-2}^{2} |gt_k(i, j) - b_k(x, y)| \times W_{Nm}(i, j).$$  \hspace{1cm} (4.16)

### 4.3.1.4 Misclassification Penalty Metric (MPM)

This technique evaluates the prediction against the Ground Truth (GT) on an object by object basis. This metric provides a comparison of the contour of the character between the result and ground truth image. A low $MPM$ value denotes that
the technique is good at identifying a boundary of objects. The $MPM$ is defined as follows:

$$MPM = \frac{MP_{FN} + MP_{FP}}{2}.$$ (4.17)

where

$$MP_{FN} = \frac{\sum_{i=1}^{N_{FN}} d_{FN}^i}{D}$$ (4.18)

and

$$MP_{FP} = \frac{\sum_{j=1}^{N_{FP}} d_{FP}^j}{D}.$$ (4.19)

$d_{FN}^i$ and $d_{FP}^j$ denote the distance of the $i^{th}$ false negative and the $j^{th}$ false negative pixel from the contour of the $GT$ segmentation. The normalisation factor $D$ is the sum over all the pixel-to-contour distances of the $GT$ object.

### 4.3.2 Evaluation Results of Benchmark Datasets

To evaluate the benchmark datasets, the binarisation techniques were performed and produced corresponding results. The results from the binarisation were then combined to produce the optimal result. The combination were categorised into four groups as follows:

- **Group 1 (G1)** ALL, IIF, Otsu’s (OT) and Sauvola’s (SAU) techniques.
- **Group 2 (G2)** BE and LMM techniques.
- **Group 3 (G3)** BE, LMM and ALL techniques.
- **Group 4 (G4)** BE, LMM, ALL and Otsu’s techniques.
Having defined the combination groups, the evaluation was performed and the results of the evaluation were compared to the binarisation implemented by CBT-KSOM. The evaluated results are given in Table 4.1 to Table 4.6.
Table 4.1 Evaluation results of individual binarisation techniques on the dataset of DIBCO2011.

<table>
<thead>
<tr>
<th>Measures</th>
<th>Binarisation techniques</th>
<th>OT</th>
<th>SAU</th>
<th>ALL</th>
<th>IIF</th>
<th>BE</th>
<th>LMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-Measure</td>
<td></td>
<td>77.4611</td>
<td>73.8697</td>
<td>80.2972</td>
<td>80.4826</td>
<td>81.6674</td>
<td>85.5594</td>
</tr>
<tr>
<td>DRD</td>
<td></td>
<td>25.819</td>
<td>18.1682</td>
<td>11.9148</td>
<td>8.0187</td>
<td>11.2353</td>
<td>5.0244</td>
</tr>
</tbody>
</table>

Table 4.2 Evaluation results of combination binarisation techniques on the dataset of DIBCO2011.

<table>
<thead>
<tr>
<th>Group</th>
<th>Measure</th>
<th>Binarisation techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1 (combine OT, SAU, ALL and IIF)</td>
<td>F-Measure</td>
<td>80.197</td>
</tr>
<tr>
<td></td>
<td>PSNR</td>
<td>14.8095</td>
</tr>
<tr>
<td></td>
<td>DRD</td>
<td>8.7599</td>
</tr>
<tr>
<td></td>
<td>MPM</td>
<td>10.1772</td>
</tr>
<tr>
<td>G2 (combine BE and LMM)</td>
<td>F-Measure</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>PSNR</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>DRD</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MPM</td>
<td>-</td>
</tr>
<tr>
<td>G3 (combine BE, LMM and ALL)</td>
<td>F-Measure</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>PSNR</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>DRD</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MPM</td>
<td>-</td>
</tr>
<tr>
<td>G4 (combine BE, LMM, ALL and OT)</td>
<td>F-Measure</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>PSNR</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>DRD</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MPM</td>
<td>-</td>
</tr>
</tbody>
</table>
Table 4.1 and Table 4.2 show the evaluation results of the DIBCO2011 dataset, which consists of eight handwritten and eight machine-printed documents. Based on the six independent binarisation techniques in Table 4.1, the LMM technique provided the best results of all measures while SAU technique had the lowest performance in terms of \( F\)-Measure and PSNR. Considering DRD and MPM; on the other hand, Otsu’s technique resulted the lowest performance. Table 4.2, the two proposed algorithms of combination binarisation techniques were compared to the binarisation results obtained by CBT-KSOM. CBT-KSOM was only compared with the proposed ensemble of binarisation algorithms-decomposed in group 1 (OT, SAU, ALL and IIF). The experimental results show that the ensemble algorithms of group 1 were superior to CBT-KSOM for the all measurements. In addition, CBT-KSOM did not obtain the best result when it was compared with the four individual binarisation techniques. Based on the algorithms of the proposed techniques, LAWMV gave better performance than LAMV in data groups 1, 3 and 4, while LAMV had better performance than LAWMV in group 2. Overall, LAWMV provided better performance than other techniques for this dataset. In addition, the proposed techniques of combining binarisation in each group were superior results than each single technique in the group.
Table 4.3  Evaluation results of individual binarisation techniques on the dataset of H-DIBCO2010.

<table>
<thead>
<tr>
<th>Measures</th>
<th>Binarisation techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OT</td>
</tr>
<tr>
<td>( F\text{-Measure} )</td>
<td>85.3844</td>
</tr>
<tr>
<td>( PSNR )</td>
<td>17.4906</td>
</tr>
<tr>
<td>( DRD )</td>
<td>4.0745</td>
</tr>
<tr>
<td>( MPM )</td>
<td>1.6068</td>
</tr>
</tbody>
</table>

Table 4.4  Evaluation results of combination binarisation techniques on the dataset of H-DIBCO2010.

<table>
<thead>
<tr>
<th>Group</th>
<th>Measure</th>
<th>Binarisation techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>CBT-KSOM</td>
</tr>
<tr>
<td>G1 (combine OT, SAU, ALL and IIF)</td>
<td>( F\text{-Measure} )</td>
<td>78.6165</td>
</tr>
<tr>
<td></td>
<td>( PSNR )</td>
<td>15.6947</td>
</tr>
<tr>
<td></td>
<td>( DRD )</td>
<td>6.6868</td>
</tr>
<tr>
<td></td>
<td>( MPM )</td>
<td>1.9609</td>
</tr>
<tr>
<td>G2 (combine BE and LMM)</td>
<td>( F\text{-Measure} )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>( PSNR )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>( DRD )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>( MPM )</td>
<td>-</td>
</tr>
<tr>
<td>G3 (combine BE, LMM and ALL)</td>
<td>( F\text{-Measure} )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>( PSNR )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>( DRD )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>( MPM )</td>
<td>-</td>
</tr>
<tr>
<td>G4 (combine BE, LMM, ALL and OT)</td>
<td>( F\text{-Measure} )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>( PSNR )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>( DRD )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>( MPM )</td>
<td>-</td>
</tr>
</tbody>
</table>
Table 4.3 and Table 4.4 present the evaluation results of the H-DIBCO2010 dataset which was collected from ten handwritten documents. Based on the independent binarisation techniques in Table 4.3, LMM technique was the best result of all measurements while IIF and SAU techniques produced poor results. In Table 4.4, the two proposed algorithms of combination binarisation techniques were compared to binarisation results obtained by CBT-KSOM. The experimental results show that the ensemble algorithm of group 1 was superior to CBT-KSOM for all measurements. In addition, CBT-KSOM did not obtain the best result when it was compared with the four individual binarisation techniques. Based on the algorithms of the proposed techniques, LAWMV and LAMV were not much different based on the data in all the groups. Overall, the proposed techniques of combining binarisation in each group provided better results than each single technique in the group.
Table 4.5  Evaluation results of individual binarisation techniques on the dataset of DIBCO2009.

<table>
<thead>
<tr>
<th>Measures</th>
<th>Binarisation techniques</th>
<th>OT</th>
<th>SAU</th>
<th>ALL</th>
<th>IIF</th>
<th>BE</th>
<th>LMM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>78.1917</td>
<td>80.7447</td>
<td>74.7886</td>
<td>79.8307</td>
<td>91.1333</td>
<td>91.0604</td>
</tr>
<tr>
<td>F-Measure</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PSNR</td>
<td></td>
<td>15.0586</td>
<td>15.1427</td>
<td>14.854</td>
<td>15.3695</td>
<td>18.6557</td>
<td>18.66</td>
</tr>
<tr>
<td>DRD</td>
<td></td>
<td>22.7551</td>
<td>11.3118</td>
<td>9.6019</td>
<td>10.4706</td>
<td>3.0528</td>
<td>2.8197</td>
</tr>
<tr>
<td>MPM</td>
<td></td>
<td>13.8624</td>
<td>7.9245</td>
<td>3.1703</td>
<td>3.2536</td>
<td>0.5496</td>
<td>0.4571</td>
</tr>
</tbody>
</table>

Table 4.6  Evaluation results of combination binarisation techniques on the dataset of DIBCO2009.

<table>
<thead>
<tr>
<th>Group</th>
<th>Measure</th>
<th>Binarisation techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>CBT-KSOM</td>
</tr>
<tr>
<td>G1</td>
<td>F-Measure</td>
<td>83.244</td>
</tr>
<tr>
<td>(combine OT, SAU, ALL and IIF)</td>
<td>PSNR</td>
<td>16.2702</td>
</tr>
<tr>
<td></td>
<td>DRD</td>
<td>8.3716</td>
</tr>
<tr>
<td></td>
<td>MPM</td>
<td>3.4057</td>
</tr>
<tr>
<td>G2</td>
<td>F-Measure</td>
<td>-</td>
</tr>
<tr>
<td>(combine BE and LMM)</td>
<td>PSNR</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>DRD</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MPM</td>
<td>-</td>
</tr>
<tr>
<td>G3</td>
<td>F-Measure</td>
<td>-</td>
</tr>
<tr>
<td>(combine BE, LMM and ALL)</td>
<td>PSNR</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>DRD</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MPM</td>
<td>-</td>
</tr>
<tr>
<td>G4</td>
<td>F-Measure</td>
<td>-</td>
</tr>
<tr>
<td>(combine BE, LMM, ALL and OT)</td>
<td>PSNR</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>DRD</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MPM</td>
<td>-</td>
</tr>
</tbody>
</table>

100
Table 4.5 and Table 4.6 demonstrate the evaluation results from the DIBCO2009 dataset, which comprises five handwritten and five machine-printed documents. Among the independent binarisation techniques, BE gave the best results in terms of \textit{F-Measure} while LMM drove the best performance in terms of \textit{PSNR}, \textit{DRD} and \textit{MPM}. In this dataset, ALL generated less-promising results and obtained the lowest performance in terms of \textit{F-Measure} and \textit{PSNR}. In terms of \textit{DRD} and \textit{MPM}, Otsu’s technique had the lowest performance. CBT-KSOM was only compared with the proposed ensemble of binarisation algorithms-decomposed in group 1. The experimental results show that the ensemble algorithm of group 1 was superior to CBT-KSOM for the all measurements. In addition, CBT-KSOM did not obtain the best result when it was compared with the four individual binarisation techniques. Based on two algorithms of the proposed techniques, LAWMV derived better performance than LAMV in data group 2, while LAWMV and LAMV were not much different. Overall, the proposed techniques of combining binarisation in each group provided better results than each single technique in the group.

In summary, the proposed techniques demonstrated that they were superior performance than independent binarisation techniques in the DIBCO2011 and DIBCO2009 dataset, while in HDIBCO2010, they derived poor results. Due to the dataset from DIBCO2011 and DIBCO2009 comprises of handwritten and machine-printed documents, they include a variety kinds of documents. The proposed technique can perform well over DIBCO2011 and DIBCO2009 because the combined output is based on local information of the input images.

Furthermore, it is found that the CBT-KSOM did not perform well in all datasets as LAMV and LAWMV. As CBT-KSOM uses global information of input
images to determine a final result while LAMV and LAWMV are ensemble technique using local information of input images.

4.3.3 Sample Results of Benchmark Datasets

This section shows sample results of binarised images from independent binarisation techniques (OT, SAU, ALL and IIF), combined images from CBT-KSOM and the proposed techniques (LAMV and LAWMV).

Figure 4.4 shows samples of the original image, ground truth image and the results of binarised images performed by independent binarisation techniques. Figure 4.7 shows the samples of the combined images using CBT-KSOM and the proposed techniques (LAMV and LAWMV), respectively. The problem of this document is the existence of marginal noise, which is one of the major problems of extracting texts from the background.
Figure 4.4 Binarised image of independent technique from DIBCO 2011.

Figure 4.4 shows that OT, BE and LMM suppressed noise on the left hand side of the image; however, LMM generated foreground better than OT and BE. SAU, ALL and IIF techniques were able to reduce background noise on the right hand side of the image better than other techniques (OT, BE and LMM); however; SAU generated more noise scattering around the image. In this case, IIF did not
reveal promising results as the technique eradicated some text fragments, whereas ALL technique extracted text properly and performed good results. These example results show that one technique may be applied effectively for some document images but they may not be suitable for all kinds of digital documents even it may achieve the best performance of those datasets.
Figure 4.5 Binarised image of independent technique from H-DIBCO2010.
The binarisation results of the sample document image from H-DIBCO2010 are illustrated in Figure 4.5. LMM and BE suppressed noise better than the other techniques. LMM technique extracted the text properly, while BE technique produced few noises from seeping noise. In contrast, the other techniques often produced a certain amount of noises due to ghosting noise within the background. SAU, ALL and IIF generated more noise from ghosting noise while the OT technique revealed noises less than those techniques. As SAU and ALL techniques perform based on stroke width, this may affect the process to generate the result.
Figure 4.6 Binarised image of independent technique from DIBCO2009.
The binarisation results of the sample document image from DIBCO2009 are shown in Figure 4.6. The OT technique of global thresholding could not classify text from background if the document image has high contrast background. The ALL technique suppressed high contrast of the background, but this technique still generated salt and pepper noise. The BE technique suppressed noise better than other techniques. ALL, BE and LMM techniques extracted the text properly. In contrast, the other techniques often produced a certain amount of noise due to the variation within the background.
Table 4.7 Summary of advantages and disadvantages of independent binarisation techniques.

<table>
<thead>
<tr>
<th>Binarisation Techniques</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>OT</td>
<td>- fast and suitable to separate uniform distribution of background</td>
<td>- cannot extract texts from marginal noise and high contrast of background</td>
</tr>
<tr>
<td>SAU</td>
<td>- extract texts properly - reduce marginal noise better than other techniques</td>
<td>- there are more noises that distribute over the document such as in Figure 4.4 (d) and Figure 4.5 (d) - noise distribution in the dark area of background and some parts nearby texts such as in Figure 4.6 (d)</td>
</tr>
<tr>
<td>ALL</td>
<td>- high contrast of background can eliminate clearly</td>
<td>- in the dark area of the image that has high contrast background can extract texts properly but salt and pepper noise may occur such as Figure 4.6 (e) - Not good for the image that has ghosting noise such as in Figure 4.5 (e).</td>
</tr>
<tr>
<td>IIF</td>
<td>- extract texts properly - high contrast of background can eliminate clearly</td>
<td>- cannot extract texts properly - losing detail of interior characters such as in Figure 4.4 (f) and Figure 4.6 (f) - texts are eliminated in the dark area of background as they fades out such as in marginal noise area in Figure 4.4 (f) - even high contrast of background can be eliminated clearly but texts are also eliminated in this area such as in Figure 4.6 (f)</td>
</tr>
<tr>
<td>BE</td>
<td>- extract texts properly - work well with ghosting noise such as Figure 4.5 (g) - texts are sharp and clear</td>
<td>- some texts are eliminated in dark area of background and some texts are faded in area of high contrast background such as in Figure 4.6 (g)</td>
</tr>
<tr>
<td>LMM</td>
<td>- extract texts properly - work well with ghosting noise Figure 4.5 (i)</td>
<td>- there are a few noises that occur surround texts in the dark area of high contrast background such as in Figure 4.6 (i)</td>
</tr>
</tbody>
</table>
Figure 4.7 Sample results of combined images from DIBCO 2011.
Figure 4.8 Sample results of combined images from H-DIBCO2010.
Figure 4.9 Sample results of combined images from DIBCO2009.
Figure 4.7 to Figure 4.9 show sample results of combined images from DIBCO2011, H-DIBCO2010 and DIBCO2009. The combined results will depend on the original binarised images. Both proposed techniques performed better than CBT-KSOM. The combined results from LAMV and LAWMV were marginally different.

The next section presents the sample results of combined techniques on palm leaf manuscripts.

4.3.4 Sample Results of the Combined Techniques on Palm Leaf Images

This section shows the sample results of combined images using the binarisation techniques on palm leaf manuscripts. The proposed method was applied to generate the optimal output from ancient Thai manuscripts on palm leaves. Some sample results of the combined image are shown in Figure 4.10 to Figure 4.12.

From the sample results of three images, the results reveal that the proposed techniques could provide better output from multiple binarised images. The results from the proposed techniques were not significantly different. Furthermore, the result depends on the selected binarised-images obtained from the prior combining process.
Figure 4.10 Sample results of combined images on palm leaf manuscript from filtered image in Figure 3.3(a).
Figure 4.11 Sample results of combined images on palm leaf manuscript from filtered image in Figure 3.3(b).
Figure 4.12 Sample results of combined images on palm leaf manuscript from filtered image in Figure 3.3(d).
4.4 Summary

This chapter proposes an approach for the generation of the optimal binarisation output by combining different binarised images. This study has developed two combination techniques called LAMV and LAWMV. Both methods have been implemented based on voting scheme and local adaptation of neighbouring window. LAWMV is an improved version of LAMV that utilises the Gaussian of weight majority vote in the neighbouring window of its pixel. The dataset from DIBCO’s series has been used in this chapter to evaluate both techniques. They have been compared with six independent binarisation techniques and a combination of binarisation techniques by CBT-KSOM. LAMV and LAWMV signify better performance than six independent binarisation techniques and the combination of binarisation technique by CBT-KSOM. Performance of LAMV and LAWMV is marginally different. Both techniques has been applied to generate the optimal binarisation output with palm leaf manuscripts. These approaches are able to provide promising results than independent binarisation techniques.

The key contribution of this chapter is the proposal of a novel technique that can be used to combine different binarised outputs from different techniques to produce an optimal output. Experimental results show that the proposed techniques can improve the reported binarisation methods significantly. This method also has been applied to practical documents, namely, ancient Thai manuscripts from palm leaves. The results illustrate that the proposed method can provide the optimal binarised output.

After background elimination, text line segmentation is then performed and the details will be explained in the next chapter.
In automatic ancient document processing, text line segmentation is one of the processes usually performed before character segmentation. Line segmentation extracts lines and locates the text regions in the document images. As a consequence, text line segmentation algorithms can potentially improve the performance of character segmentation and recognition. In previous literature, there are many methods for text line segmentation in ancient document data. However, there are still rooms for improvement in order to achieve better accuracy. Although partial projection methods [71], [72], [90] have been reported that are suitable for overlapping or touching lines, such techniques do not deal successfully with the separation of vertically connected text lines which is a significant issue associated with word or character recognition [87]. The partial projection approach proposed by Zahour et al. [71] works correctly on overlapping texts, tabulations, incomplete lines and changes in text orientation; however, inability to deal with touching lines is the major drawback of the technique [130]. An improved version of this method was proposed by Tripathy and Pal [90] for Indian scripts. Their technique computed the width of the stripes from a character dataset. The baselines were determined by using peak and valley points, and the baselines of each strip were connected to form a long line. This technique however may produce false segmented lines due to the use of diacritical points [130]. In addition, a number of touching neighbouring text-lines in document images may cause the technique to generate poor outcomes.
In order to improve those techniques, two text line segmentation algorithms based on partial projection profiles have been proposed in this study. To improve the partial projection profile for text line segmentation, this study determines the touching components of two consecutive lines, and analyses the components of the texts at vowel levels in order to identify the lines in the image. This approached is termed the Modified Partial Projection (MPP) in this thesis. In addition to the MPP, this study proposes an adaptive technique of partial projection profile, called the Adaptive Partial Projection (APP) method. The technique applies the MPP method with the smoothened histogram and adapts partial projections using divide and conquer strategies.

This chapter is organised as follows: Section 5.1 outlines the details of the proposed method of the MPP while Section 5.2 describes the APP method. Finally, experimentations and evaluation are illustrated in Section 5.3.

5.1 Modified Partial Projection (MPP) Method

The MPP is a line segmentation technique based on the partial projection profile techniques [131]. To separate text lines, the partial projection method [71], [72], [90] is applied in the first step by dividing a text image into vertical strips. A width of strip is defined by a pre-determined width parameter. The width parameter governs the size of strips. There are a number of techniques that have been used to determine this parameter. Tripathy and Pal [90] examined a strip width by using statistical mode of the width of the bottom reservoirs obtained from texts as described in Section 2.2.4. The overall process of the MPP method is shown in Figure 5.1.
In order to implement the MPP method, pre-defined parameters are firstly defined by using the mean of the characters from a dataset of palm leaf manuscripts. Then an image is cropped to reduce the unrelated information. After defining the width strip parameter, unrelated artefacts are removed before the MPP is carried out in the final step. The overall description of the MPP method is explained in the following sections.

Figure 5.1 Overall process of the MPP method.
1) **Pre-defined parameters**

A vertical strip width is a preliminary parameter that is initiated before performing consequent processes in the MMP. To determine this parameter, there are two super-parameters that are taken into account: (i) the average width \( WC \) and (ii) the height \( HC \) of the isolated characters from the dataset. This dataset was collected by using Connected Component (CC) on forty-eight random images from the dataset of 480 palm leaf manuscripts. In the MPP method, the width of the vertical strips is defined as the value of \( WC \).

2) **Image cropping**

To reduce unrelated information on palm leaf images, that is, separation of the artefacts located near the boundary of the images and noise, the images are cropped by checking the first and final valleys of global horizontal and vertical projection profile of the images. This information is then used to separate the two components as described in the next step.

3) **MPP approach**

After the two parameters are defined, the MPP approach to separate the lines is performed as follows:

(1) **Divide the images into vertical strips:**

\[
N = \frac{W}{WS},
\]

where \( N, W \) and \( WS \) denote the number of strips, the width of the images and the width of strips, respectively.
In case that the width of the last strip \( (WS_N) \) differs from \( WS \) as shown in Figure 5.2 then \( WS_N \) is defined as below:

\[
WS_N = W - WC \times (N - 1). \tag{5.2}
\]

(2) In each vertical strip, find the base lines as follows:

(2.1) compute the horizontal projection profile, \( P_y(i) \), which is obtained by summing the pixel values along the horizontal axis for each \( y \) value as shown in Equation (5.3) [74].

\[
P_y(i) = \sum_{1 \leq x \leq \text{columns}} f(x, y), \tag{5.3}
\]

where \( 1 \leq y \leq \text{rows} \) and \( i = 1, 2, \ldots, N \).

A sample of horizontal projection profile is shown in Figure 5.3

Figure 5.3 An example of horizontal partial projection in the second partial strip.
(2.2) Find the minimum value (equal to 0) of the projection in each strip. This minimal value of horizontal partial projection or histogram of projection indicates the top line \((L_T (i, j))\) and the bottom line \((L_B (i, j))\). A bottom line is chosen as a base line as follows:

\[ L_T (i, j) = \min P_y (i), y = 1, 3, 5, \ldots \]  

(5.4)

and

\[ L_B (i, j) = \min P_y (i), y = 2, 4, 6, \ldots , \]  

(5.5)

where \(j\) is a line number.

(3) Define the height of the characters of each line in each strip for vowel analysing as shown below:

\[ L_H (i, j) = |L_T (i, j) - L_B (i, j)|. \]  

(5.6)

(4) Check the size of the height in each line.

(4.1) If \(|L_B (i, j-1) - L_B (i, j)| < HC\), \(L_B (i, j)\) are then removed as they should be vowels or noise. Adjust \(L_H (i, j)\) and set \(j = j - 1\).

(4.2) Isolated vowels appearing above or below characters (illustrated in Figure 5.4(a)) are analysed. The positions of these vowels occupy certain distance from the characters. This significantly affects line separation because Thai language has three levels (i.e. upper level, body level and lower level as shown in Figure 5.4 (b)) of texts, and some vowels belong to the upper level of the next line or the lower level of the current line. To calculate distances of vowels from the upper and
lower lines as shown in Figure 5.4(b), the value of \( d_1 \) defines the distance between the bottom of the upper line and the top of vowels. \( d_2 \) defines the distance between the bottom of vowels and the top of lower lines.

![Diagram of vowel lines](image)

(a) Consonants with vowel

(b) Analysing the distance of the vowels

Figure 5.4 Sample of vowel and vowel analysing.

(4.2.1) If \( (d_1 \geq d_2) \) then the vowels belong to the lower lines, \( L_B(i, j-1) \) is then removed where \( j-1 \) is the base line of the vowels. Adjust \( L_H(i, j) \) and set \( j = j - 1 \).

(4.2.2) If \( (d_2 > d_1) \) then the vowels belong to the upper line, \( L_B(i, j) \) is then removed where \( j \) is the base line of this upper line. Adjust \( L_H(i, j) \) and set \( j = j - 1 \).
(5) Calculate the average value based on the number of lines ($L_{n_{avg}}$) of all strips, and use this value to check the number of lines in each strip ($L_n(i)$) before checking the base line, $L_B(i, j)$, as follows:

(5.1) If ($L_n(i) < L_{n_{avg}}$), $L_B(i, j)$ is added from the same line of the closest left strips which is lower than the base line. Adjust $L_H(i, j)$ and set $j = j + 1$. In case of the first strip, it may have the number of lines less than the number of lines in the strip of the text body so this needs to estimate the number of lines and base line from the first strip of text body that has $L_n(i) = L_{n_{avg}}$.

(5.2) If $|L_B(i-1, j) - L_B(i, j)| \leq HC$, the current line of this strip is assumed to be the base line of vowels or non-base line.

(5.3) If the components of two lines are connected, they can be separated by checking the gap between the two lines as shown in Figure 5.5. Touching consecutive lines can be separated into two lines by setting the base line position of the upper line as in Equation (5.7).

$$L_B(i, j) = L_B(k, j) + \frac{|L_B(i, j) - L_B(k, j)|}{2}, \quad (5.7)$$

where $i$ is the current strip, $j$ is the current line position, and $k$ is the current line position of the left strip.

(6) Join the horizontal line from each strip and then form individual lines.
The process of the MPP method can detect the base line of each text line from the documents, and individual lines (separated based-on the gap between lines) can be extracted from the document images. The next section describes a new proposed method that integrates the MPP method and smooth histogram of profile, and adaptive width-strip.

### 5.2 Adaptive Partial Projection (APP) Method

The proposed technique, called APP, is derived from the MPP method by integrating the smooth histogram of the profile. The improvement from the MPP method is to adapt the width of the strip based on the characters in each image and divide the strips based on divide and conquer strategies. Although the MPP method uses information related to vowels and touching components of two consecutive lines to detect the lines, the technique does not consider the prolonged part of the characters. Incorrect estimation of vowels may occur if the lower vowel and upper vowel of two consecutive lines are touching. In addition, if the upper vowel of current line is closer to upper lines than the current line, or the lower vowel of current line is closer to lower line than the current line, line estimation may be defined to the wrong line as shown in Figure 5.6.
Figure 5.6 Problems of text line segmentation from the MPP method.

The APP technique applies a smooth histogram of the profile that can combine upper and lower vowels along the body line of texts. If there are some obstructive components between two consecutive lines, the technique traverses baselines along the partial histogram of profile to the upper or lower position of the characters. Another improvement concerns obstacles. After traversing the baseline, if the position of the baseline cannot be defined, divide and conquer strategy will be performed by dividing the strip into two. The process of baseline detection is then re-calculating until the position of baselines is defined or the size of strip is less than the average width of characters. Applying divide and conquer strategy is useful for eradicating obstructive components as shown in Figure 5.6. The overall process of the APP method is shown in Figure 5.7.
Figure 5.7 Overall process of the APP method.

The adaptive size of the width is flexible for all scripts of all types of documents because the width-strip of all methods based on partial projection profile is fixed. In addition, Pal and Datta’s [89], Tripathy and Pal’s [73] method and the MPP have to determine the width of characters from the dataset. If the size of the partial strip is dependent on the width of the character from the dataset, it may not be suitable for some documents – as the width of the characters is varied. In general, the
size of the characters is varied and comes from several handwritten documents written by many writers; therefore, applying a global character size for all documents is not practical.

This section outlines the underlying techniques of the *Adaptive Partial Projection* (APP) to detect lines in document images. In this method, pre-defined parameters are obtained automatically by finding the average width of characters in each image data. The image is then cropped by the global vertical and horizontal projection profile. Finally, the APP method is performed to separate the lines.

1) **Pre-defined parameters**

An advantage of the APP is the width of vertical strips and the height of characters are initiated automatically while other techniques (based on partial projection profile) are fixed or calculated from a dataset. Unlike the MPP, these two parameters are pre-defined automatically from a calculation based on the average width \( WC \) and height \( HC \) of the isolated characters of each image. The isolated characters are separated by using CC on the image of palm leaf manuscripts. The size of the width and height of characters are varied and adapted themselves according to the information in the images. Furthermore, these pre-defined parameters can be used with other scripts and do not need to determine the isolate characters before the processing.

2) **Image cropping**

To reduce the unrelated information on a palm leaf image, which are the boundary of an image and noise, an image is cropped by checking the first and final valleys of global horizontal and vertical projection profile of the image.
3) **APP method**

Text images are divided into vertical strips and then the histogram of the projection profile is applied by smoothing the histogram of profile to separate lines. Smoothing is used to remove spurious peaks and valleys of the histogram. A moving average filter is implemented to smooth the histogram of profile based on the average value of the height of characters ($HC$), which has been defined previously. The size of a partial strip uses three characters which are the common length of words in Thai-Noi scripts. The width of characters ($WC$) is calculated from the average value of the width of the isolated characters in each image as explained above. If the lines cannot be separated, divide and conquer strategy will then be applied to divide the strips into two parts and this process is iterated to find the baselines until the strip size are less than 75% of the width of characters. The approach to separate the lines by this technique is described as follows:

1. Find the number of lines ($Ln$), the line position of each line ($L_p$) and the average height of lines ($HL$) from the global horizontal projection profile. These values are calculated as given below:

   1.1) Calculate the global horizontal projection profile of an image and smooth the histogram of profile by moving average filtering with $HC$.

   1.2) Find the peaks of the histogram and then define $Ln$ as the number of lines from the number of peaks and then define the line position ($L_p$) from the peak position of the histogram, where $p = 1, 2, ..., Ln$.

   1.3) Calculate the average value of the height of lines, ($HL$) as follows:
\[
HL = \frac{\sum_{p=2}^{Ln} |L_p - L_{p-1}|}{Ln}
\]  

(5.8)

(2) Divide the image into vertical strips as the following Equation:

\[
N = \frac{W}{WS},
\]

(5.9)

\[
WS = 3 \cdot WC,
\]

(5.10)

where \( N, W \) and \( WS \) denotes the number of the strips, the width of the image and the width of the strips, respectively.

If the width of the last strip \( WS_N \) differs from \( WS \) then \( WS_N \) is defined as below:

\[
WS_N = W - WC \times (N-1).
\]

(5.11)

(3) Compute horizontal projection profile, \( P_y(i) \), which is obtained by summing the pixel values along the horizontal axis of each row \( (y) \) as shown in Equation (5.12).

\[
P_y(i) = \sum_{1 \leq x \leq \text{columns}} f(x, y),
\]

(5.12)

where \( 1 \leq y \leq \text{rows} \) and \( i = 1, 2, \ldots, N \).
Figure 5.8 Samples of smooth histogram of profile and baselines in each strip.

(4) Smooth the histogram, $SP_j(i)$, $SP[y]$twice by moving average filtering with $HC \times 0.9$ which were calculated automatically in each image as shown Figure 5.8(a). The moving average filtering is applied twice because the spurious peaks and valleys in the projection can be found after the first smooth of the histogram.

(5) Find the estimation point of base lines ($\beta_j, j \in \{1, 2, \ldots, M\}$) where $M \leq N$ in each strip by using the following rules:
(5.1) Find the valleys of the smooth histogram as shown in Figure 5.8(b). The valley of a histogram is the lowest point between two peaks. These valleys are defined as the estimation points of baselines in each strip. In Figure 5.8(b), four valley values are shown and they are used together with the final lowest value at the bottom of the diagram.

(5.2) However, some obstructive components may occur at the estimation points of baselines and all valleys need to be tested. If two consecutive valleys are very close \( ((\beta_{j+1} - \beta_j) < \frac{4}{5}HC) \), it can be assumed that it is the baseline of the vowel. To select candidate valleys, projection profile \((P_y(i))\) tested as follows:

(5.2.1) If \( P_y(\beta_j) > 0 \) and \( P_y(\beta_{j+1}) > 0 \) then go to (5.2.2), otherwise go to (5.2.3).

(5.2.2) If \( SP_y(\beta_j) < P_y(\beta_{j+1}) \) then delete \( \beta_j \), otherwise delete \( \beta_{j+1} \).

(5.2.3) If \( P_y(\beta_j) = 0 \) and \( P_y(\beta_{j+1}) = 0 \) then go to (5.2.4), otherwise go to (5.2.5).

(5.2.4) If \( (\beta_j - \beta_{j-1}) < HC \) then delete \( \beta_j \),

else if \( (\beta_{j+2} - \beta_j) < HC \beta_{i+2} - \beta_{i+1} < Ht \) then delete \( \beta_{j+1} \)

otherwise set \( \beta_j = \beta_j + (\beta_{j+1} - \beta_j) / 2 \) and delete \( \beta_{j+1} \).

(5.2.5) If \( P_y(\beta_j) = 0 \) then delete \( \beta_{j+1} \), otherwise delete \( \beta_j \).
(6) An incorrect top line (this may be the upper vowels of the first or unnecessary information) and bottom line (this may be the lower vowels of the last line or unnecessary information) are examined as follows:

(6.1) For the top line: if \( \beta_j < L_1 \) then delete \( \beta_j \).

(6.2) For the bottom line: if \( \beta_{j+1} > L_{Ln} \beta_{i+1} > u_k \) then delete \( \beta_{j+1} \).

A hole among text lines

A gap among text lines

The gaps at the left and right borders of image

Figure 5.9 A hole and gap among text lines, and the gaps at left and right borders of image.

(7) Test the number of base lines \( (M - 1) \) as palm leaf manuscripts may have one or two holes and gaps among text lines, and the gaps at the left or right borders of the image as shown in Figure 5.9. Some base lines may occur due to vowels on the top and bottom of characters. These need to be checked, and insert or delete the correct base line to each strip. In each strip, therefore, correct base lines are inserted to text line or deleted otherwise. This can be achieved by the following procedure.

(7.1) If \( (M - 1) < Ln \), a baseline will be inserted by checking against \( L_p \).
(7.2) If there is no baselines belonging to $L_p$, a baseline at this position will be inserted by $\beta_j = \beta_j + HC$.

(7.3) If $(M-1) > Ln$, a baseline will be deleted by checking against $L_p$. If there are more than baselines belonging to $L_p$, then baselines between mid of $L_p$ and $L_{p+1}$ will be deleted.

![Figure 5.10 Sample of recursion if connected components occurs.](image)

(a) Vowels and prolong problems  (b) Recursion when vowels and prolong occur

(c) Connected component  (d) Recursion when connected component occurs

(8) Examine touching components, upper/lower vowel levels or prolonged parts of consonants at all baseline positions (shows in Figure 5.10) as follows:
(8.1) If \( P_y[\beta_j] > 0 \) \( \text{and} \ P[\beta_i] > 0 \) then traverse the projection up and down from \( \beta_j \) position to the size of vowels \((HV)\), which is estimated at the half of the height of characters \((HV=\frac{HC}{2})\). Go to step (8.1.1).

(8.1.1) If the first position \((F)\) of \( P_y[\beta_j]=0 \) is \((P[\beta_i]=0)\) then between up traverse and down traverse, and if \(|F-\beta_j| > \frac{1}{2} HV\) then the height \((H)\) is tested between \(\beta_{j-1}\) and \(F\).

(8.1.2) If \( \frac{1}{2} HL < H < \frac{1}{2} HL \) then the new position is set to \( \beta_j \). A sample result is shown in Figure 5.10(b).

(8.2) If \( P_y[\beta_j] \neq 0 \) then it is a touching component as shown in Figure 5.10(c), go to step (8). A sample result after separate this touching component is shown in Figure 5.10(d).

(8.3) If a baseline overlaps one or more touching components, then divide the strip into two and repeat step (3) to step (8) to each of the strip. The recursion is halted when the width of the strips is less than 75% of the width of characters.

(9) Join the horizontal lines from each strip and then form separate lines.

The process can detect the baseline of each text line from the documents, and individual text lines can be extracted from the document images. The next section presents the assessment of the proposed method.
5.3 Assessment of the Proposed Methods

The experimental results based on two line extraction techniques are presented in this section, (a) MPP and (b) APP. In the experiment, 552 text lines from 120 palm leaf manuscripts were sampled. To check whether a text line is extracted correctly, a boundary is drawn between two lines. The results of line extraction are measured by the rules presented in [89]. Sample results are shown from Figure 5.11 to Figure 5.13 and the results of the experiments are given in Table 5.1. The experiment shows that the MPP and the APP technique correctly segmented 158 lines (28.62%) and 351 lines of all lines (63.59%), respectively. There is one component (alphabet or vowel) out of the correct 144 lines of all lines (26.09%) and 124 lines of all lines (22.46%) by using MPP and APP, respectively. For the lines with two components out of the correct lines, the number was 84 (15.22%) and 43 (7.79%) by using MPP and APP, respectively. The rest are more than two out of the correct lines.

The APP method can be used to separate some touching characters from consecutive lines. The APP method integrates the MPP method and smooth histograms with recursion so that the proposed method can employ with vowels, like in the MPP. The proposed method also varies the window size of the partial strip and window size of the height of characters according to the images. This method adjusts the size of characters automatically in each image. The APP also reduces the time for the line extraction process because the method determines three-character widths instead of one-character widths used in the MPP. In addition, the APP re-executes only some required partial strips. This technique also checks the prolonged characters during the process. However, false detection may result due to
overlapping characters. Furthermore, some binary images are vague and they have major effects on the accuracy of text line extraction.

Table 5.1 Results from text line extraction.

<table>
<thead>
<tr>
<th>Number of components out from their correct line</th>
<th>Percentage of components segmented within the correct line</th>
<th>MPP</th>
<th>APP</th>
</tr>
</thead>
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<tr>
<td></td>
<td></td>
<td>Number of correct lines</td>
<td>Percentage of correct line</td>
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<td>100%</td>
<td>158</td>
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<td>144</td>
<td>26.09%</td>
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<td>84</td>
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</tr>
<tr>
<td>≥4</td>
<td>≤95.99%</td>
<td>102</td>
<td>18.48%</td>
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</tbody>
</table>
Figure 5.11 Sample result 1 of line extraction.

Figure 5.12 Sample result 2 of line extraction.
5.4 Summary

This chapter describes the experiments on text line segmentation, and proposed two applied techniques based on partial projection profile; the MPP and APP methods. The MPP is based on analysis of vowels while the APP is improved by using smooth histogram of projection profile and it is able to define the size of strip automatically.

From the evaluation of the proposed framework, it was found that the APP method generated dramatically higher accuracy than the MPP method. The APP method also reduced the time required because this technique will separate the strips wider than the MPP method. The APP method will divide each strip if obstructive components exist at the estimated points of baselines. The APP technique is an
improvement based on partial projection profile and it is anticipated that this work is significant for text line segmentation on palm leaf manuscripts.

The final pre-processing step for recognition systems is character segmentation and this is described in the next chapter.
Chapter 6

Character Segmentation

After text line segmentation, the next stage of automatic ancient document processing is character segmentation. Character segmentation has been proposed in literature for many years. In general, there are four approaches: classical approach, recognition-based segmentation, holistic approach, and hybrid methods [79].

Touching characters is the main issue of character segmentation. Therefore, a number of segmentation techniques have also been proposed to solve the problem. Character segmentation of Roman, Arabic, Indian, Chinese and Japanese handwritten has been published but there are few research reports on Thai handwritten documents. Concerning the research on Thai handwritten segmentation, mainly the classical approaches have been used [95], [96], [97] and demonstrations based on controlling the writing styles of the writers are not practical. Furthermore, all the reported studies were based on modern Thai language and it is different from ancient Thai languages. While it was found that touching component techniques could be applicable, they are not useful when dealing with practical ancient documents [98].

In terms of document image processing, it is desirable to have embedded tools for searching of blocks, lines and words, and the inclusion of a dedicated handwriting recognition system. Interactive tools are generally offered for segmentation and recognition correction purposes. Several projects in the past have mainly been concerned with printed materials. However, solutions to tackle Thai handwritten text accurately are yet to be developed. Furthermore, there is no OCR
systems, or tools currently available for the processing of ancient Thai handwriting and documents.

Most of the past studies have focused on specific scripts. The proposed methods are difficult to apply to other scripts due to different characteristics in the scripts. This study developed a system for extracting scripts from palm leaf manuscripts composing with Thai-Noi script of ancient Thai language. To this date, there is no effective system for automatic separation of the characters in these scripts. To extract characters from the manuscript, a framework of character segmentation for ancient Thai handwriting has been proposed by applying the Contour Tracing algorithm [11], [99], [100], a trace of the background skeleton [132], and a combined method of segmentation.

The background of these approaches is described in Section 6.1, the proposed framework of character segmentation is addressed in Section 6.2, and the subsequent section is an assessment of the proposed framework. The last section is the summary of this chapter.

6.1 Background of Character Segmentation

After the text line is extracted, isolated characters are then segmented. In this study, the Contour Tracing algorithm, trace of background skeleton, and a combined method of separation were applied to separate the characters. The related concepts of these techniques are explained in the following sections concerning contour tracing algorithm, thinning algorithm and Hough transform.
6.1.1 Contour Tracing Algorithm

Contour tracing [11], [99], [100] is an algorithm applied to digital images for extracting the boundary of objects. These algorithms are also applied to separate characters. The boundary of an object $P$ is defined as the set of border pixels of $P$. There are two types of boundary pixels which are 4-connectivity and 8-connectivity as shown in Figure 6.1.

![Connectivity patterns](image)

(a) 4-connectivity  
(b) 8-connectivity

Figure 6.1 Connectivity patterns.

From relevant literature, the most common algorithms frequently used are the Square Tracing algorithm [11] and the Moor Neighbouring Tracing algorithm [99]. Both algorithms are easy to implement, but each of these algorithms has some deficiency and weak in stopping criterion [99].

Another algorithm proposed recently is the Theo Pavlidis’s algorithm [100]. This algorithm cited by Ghuneim [99] that is superior to both algorithms (Square Tracing and Moor Neighbouring Tracing). An example result of contour tracing algorithm is shown as Figure 6.2.
The Theo Pavlidis’s algorithm is used in this study. The main idea of this algorithm is to set the three pixels \((P1, P2\) and \(P3)\) in front of current pixel as shown in Figure 6.3. \(P2\) denotes the pixel in front of the current position (arrow), \(P1\) is the pixel adjacent to \(P2\) from the left and \(P3\) is the right adjacent pixel to \(P2\).

![Figure 6.3 Starting point (arrow) of the Theo Pavlidis’s algorithm.](image)

Figure 6.4 demonstrates the three rules to keep track of the direction and all moves with regard to current orientation.

![Figure 6.4 Three rules to keep track of the direction and move [99].](image)
The first rule, pixel $P_1$ is checked. If pixel $P_1$ is black, pixel $P_1$ is defined to be the current boundary pixel as shown in Figure 6.4(a).

The second rule, pixel $P_2$ is checked if pixel $P_1$ is white and pixel $P_2$ is black, pixel $P_2$ is defined to be the current boundary pixel as shown in Figure 6.4(b).

The third rule, pixel $P_3$ is checked if pixel $P_1$ and $P_2$ is white. If pixel $P_3$ is black, pixel $P_3$ is defined to be the current boundary pixel as shown in Figure 6.4(c).

The algorithm terminates the trace in two cases:

1) If all three pixels in front of current pixel are white, then it needs to rotate 90 degrees clockwise to face a new set of three pixels in front of the current pixel, and three rules are then applied. This indicates that the pixel is an isolated pixel.

2) When the current boundary pixel is the start pixel and the trace is completed.

The next section describes the thinning algorithm.

### 6.1.2 Thinning Algorithm

Thinning [118] is a process for finding the skeleton of an object. After the pixels have been peeled off, the pattern will be recognised. Hence, the obtained skeleton should have the following properties: it must be as thin as possible; it should be connected and centred. An example result of thinning algorithm is shown in Figure 6.5. There are many algorithms that can be used for skeletonisation of binary patterns in digital images and two examples are the Hilditch’s [133] and Zhang-Suen [134] thinning algorithms. These algorithms are easy to implement and the Zhang-
Suen algorithm produces less distortion than the Hilditch’s algorithm. The Zhang-Suen algorithm keeps the connectivity but it does not support images with two pixels thick. The Hilditch’s algorithm has a problem of extracting straight lines. This study applies Zhang-Suen thinning algorithm in the process of foreground and background skeleton for separation.

(a) Original image  (b) Result image

Figure 6.5 An example result of thinning algorithm.

Zhang-Suen thinning algorithm [134] has two sub-iterations and background region pixels (white pixels) is set to “0”, and the object regions (black pixels) is assigned to “1”. Figure 6.6 shows that P is current pixel; P1,P2,P3,...,P8 are the neighbouring pixels of P.

Figure 6.6 A 3 by 3 window that shows the pixels around P and its neighbouring pixels.

In the first sub-iteration, the south or east boundary pixels, or the north-west corner pixels are removed as illustrated in Figure 6.7(a), (b) and (c) respectively. In
the second sub-iteration, the north or west boundary pixels, or the south-east corner pixels are removed as shown in Figure 6.7(d), (e) and (f) respectively.

![Thinning Algorithms](image)

(a) South boundary pixel  
(b) East boundary pixel  
(c) North-west corner pixels

(d) North boundary pixel  
(e) West boundary pixel  
(f) South-east corner pixels

Figure 6.7 Zhang-Suen thinning algorithm [11].

### 6.1.3 Hough Transform

Hough transform [11], [117] is applied in order to detect lines in horizontal direction for path of components and vertical direction for junctions. Hough transform is calculated in the parameter space as expressed in Equation (6.1).

$$
\rho = x \cos \theta + y \sin \theta
$$

(6.1)

where $\rho$ is the length from the origin to the line as shown in Figure 6.8, and $\theta$ is the angle of $\rho$ with respect to the $x$-axis.

Therefore, a line in the image space is mapped to a unique point, $(\theta_0, \rho_0)$.  

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The following section gives the details of a framework of character segmentation for ancient Thai handwriting.

6.2 A Framework of Character Segmentation for Ancient Thai Handwriting

After the text line is extracted, isolated characters are then segmented. The process of hierarchical character segmentation comprises of the contour tracing algorithm, and touching components are separated by a trace of background skeleton and combined method of segmentation. The proposed framework of the hierarchical character segmentation is illustrated in Figure 6.9.
Firstly, the contour tracing algorithm is executed as described in Section 6.1.1. This method is suitable for extracting over segmented characters in images and slant writing styles. The characters of text line are then separated. Although most of the components are isolated, touching components may still occur.
The criteria of segmented components are described in the next sub-section.

6.2.1 Criteria of Segmented Components

After the characters are isolated, the mean and standard deviation width of all the segmented components ($\mu$ and $\sigma$) in each manuscript are calculated. The values are then used for the analysis of the width of the segmented components.

If the width of the segmented component is greater than the width threshold ($T_w$) value which is shown in Equation (6.2), it will be separated again by using a trace of the background skeleton. If the components are still connected, the combined method of separation is used to separate touching components again.

\[
T_w = \mu + \frac{1}{2} \sigma
\]  

(6.2)

The width of the segmented components from this process is checked. If the width is greater than the threshold value of the average width of the components, this means there are some connected characters are not separated.

6.2.2 A Trace of Background Skeleton

A trace of background skeleton approach [132] is applied to separate the touching components. Background skeleton technique was used to segment the connected characters. It is processed by the Zhang-Suen thinning algorithm that described in Section 6.1.2. Contour tracing algorithm is then applied to extract the skeleton of the background. An example result after this process is shown in Figure 6.10.
6.2.3 A Combined Method for Segmentation

After a trace of background skeleton has been processed, some touching components may not be separated by this technique. To improve the segmentation results, a combined method for connected handwritten segmentation has been proposed. However, the application of only one method may not be able to separate the characters precisely. The proposed method is based on foreground and background skeleton [119], line detection for path of touching components and path of background in vertical direction, and junction detection for path of foreground.
The overall process of the proposed method is shown in Figure 6.11, and the details of this method are explained in the following section.

![Diagram](image)

Figure 6.11 The combined method of segmentation for connected components of handwritten segmentation.

### 6.2.3.1 Points of Foreground Detection

To identify the points of connected character (foreground), the three steps are outlined as follows.

- **Foreground skeletons**: To detect touching component, foreground skeletons are extracted by the Zhang-Suen thinning algorithm.

- **Path and junction detection**: This step is to identify the path and junction of the object. The process is given as follows.
Define area of path: In this step, the first and last columns of the process are defined by begin with a half of width of character, and end before a half of width of the character. This is shown in Figure 6.12(a). To find the junction points of path, the area of path is defined by applying histogram of projection profile to the horizontal axis. The first and last column of the sub-area are then redefined by considering the change of density values of black pixels on horizontal axis which are greater than $\Delta d$, where $\Delta d$ is the different values of the density. In this case, $\Delta d = 3$. The area of path is then defined as shown in Figure 6.12(b).

(a) At the first step  
(b) After apply histogram of projection profile

Figure 6.12 Define the first and the last column.

Line detection: the purpose is to detect the lines in the horizontal direction for path of components and vertical direction for junctions, Hough transform is applied and $\rho$ values (Equation (6.1) in Section 6.1.3) is then calculated by using two rules as follows:

- **Lines in horizontal direction for paths:** The parameter for horizontal direction is the degree of angle ($\theta$) of lines. In this case, $\theta$ is more than $0.25\pi$ and less than $0.75\pi$ where $\pi = 3.1415$. 

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6.2.3.2 Points of Background Detection

For character segmentation, background information of image is considered in order to identify the position of connected path as the foreground information alone cannot identify precisely. The process of points of background detections described as follows.

- **Background skeletons**: To find the path of background in vertical direction, the background skeletons are extracted by using Zhang-Suen thinning algorithm.

- **Top and bottom path detection**: This step is to detect the path of top and bottom between connected characters in vertical direction. The path is detected as the same as path and junction as explained in points of foreground detection (Section 6.2.3.1). Hough transform is used to detect the lines in vertical direction, by setting $\theta$ to less than 45 or greater than 135 degrees.

6.2.3.3 Point Estimation and Separation

The purpose of this step is to estimate the possible points of separation. Junctions and paths from the points of foreground detection are then identified as shown in Figure 6.13(c) between two characters, and top and bottom path is detected as shown in Figure 6.13(e). If there is an intersection point between the path (inside junction) from the foreground detection and path from the background detection, the
path between top and bottom point of background is used to separate the components.

(a) Original component

(b) Foreground skeletons

(c) Path and junction detection

(d) Background skeletons

(e) Top and bottom path detection

Figure 6.13 A sample of points of foreground and background detection.

6.3 Assessment of the Proposed Framework

After line segmentation, character segmentation is processed to separate individual components. Ten images, which have 100% correction of text line segmentation, were investigated for character segmentation. The performance of the character segmentation is presented in Table 6.1. The dataset consists of 2702 characters from ten palm leaf manuscripts. The correct character segmentation rate by using the contour tracing algorithm was 81.24%. After the contour tracing algorithm, the touching components occurred. Figure 6.14 and Figure 6.15 show examples of connected components from the dataset.
Figure 6.14 Examples of two connected components of this dataset.

Figure 6.15 Examples of three or more connected components of this dataset.

The connected components were separated by tracing background skeleton and the correct rate of segmented characters had improved at 82.57%. After the combined method of segmentation for touching components from the second step was processed, the correct rate of segmented characters was 83.83%. After the contour tracing algorithm was applied and touching components from this step was separated by a trace of background skeleton and combined method of segmentation, the correct rate had increased 2.59%. This process could improve the segmentation method for touching components shown as Figure 6.16.
Figure 6.16 A sample result of a proposed framework of character segmentation for ancient Thai handwriting.
Table 6.1  Accuracy of character segmentation.

<table>
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<th>Manuscripts</th>
<th>Total components</th>
<th>Correct segmentation by using contour tracing algorithm (1)</th>
<th>Correct segmentation after using tracing background skeleton (2)</th>
<th>Correct segmentation after using combined method (3)</th>
<th>Difference between after (1) and (3)</th>
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<tbody>
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<td>Components</td>
<td>Rates (%)</td>
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<tr>
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<td>2195</td>
<td>81.24</td>
<td>2231</td>
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</table>
6.4 Summary

This chapter describes the technique of character segmentation for ancient Thai Handwriting, and the proposed framework is based on hierarchical character segmentation. The proposed framework of hierarchical character segmentation is to improve the performance of connected components by applying the trace of background skeleton and the combined method of segmentation after the contour tracing algorithm.

From the evaluation of the proposed framework, it was found that the touching components occurred after the contour tracing algorithm. The touching components are difficult to separate due to the writing style and smearing from ink. Moreover, some of the binary images are unclear and they have a major effect on the accuracy of text line and character segmentation. After the trace of background skeleton and the combined method of segmentation have been applied, the approach can improved the performance of separating connected components. A main problem of segmentation is the touching characters and the proposed techniques applied in this system have separated most characters correctly.

The next chapter provides the conclusion and discussion on future work.
Conclusion and Future Work

7.1 Conclusion

In Thailand, there is an increasing demand to access the visual content of documents stored in ancient and cultural archives. In order to extract information from ancient documents, it is essential to develop efficient image pre-processing and processing techniques in the recognition systems. The ancient manuscripts in this study are palm leaves from Thailand. The study focuses on the pre-processing techniques for information extraction. To obtain optimum binary outputs from multiple binarisation techniques, this study proposes a novel technique for the selection of binarisation-technique candidates in Chapter 3 and a novel method for combining multiple binarisation technique in Chapter 4. In addition, an intelligent approach for text line and character segmentation has also been proposed in Chapter 5 and Chapter 6.

In this study, the pre-processing framework of ancient Thai manuscripts improves the performance of the information extraction approaches and generates better results for the recognition or information extraction system. A conclusion of this study is described in the following sections.
7.1.1 Framework for the Selection of Binarisation Techniques

There are several techniques for binarising text in image documents. The performance of these techniques is differing and depended on the image characteristics. Some techniques require certain datasets while the others work in different way. In order to improve the document image analysis performance, an approach for selecting the appropriate binarisation technique is then necessary.

This study has proposed a selection framework for multiple binarisation techniques using SVM. The proposed framework aims to selecting the optimum binarisation technique from multiple binarisation techniques. The performance of the proposed techniques is evaluated based on F-measure, Geometric Mean and area under the ROC curve, by using a dataset of palm leaf images. This study has also improved the performance of the proposed framework by treating imbalanced data using the SMOTE technique. Results from the techniques have demonstrated that the selection framework of binarisation techniques is useful for the recommendation of appropriate binarisation techniques. In order to deal with unbalanced data, the SMOTE technique has been applied to up-sample the instances of minority classes.

This framework can be applied to select the optimum binarisation technique from multiple binarisation techniques. However, it is unsuitable for real world dataset as it is necessary to treat imbalanced data before learning method. In addition, it also requires a large prior dataset for learning.
On the other hand, an optimal binarisation output can be generated by combining multiple binarised images. Summary of this technique is described in the following section.

### 7.1.2 Generation of Optimal Binarisation Output

This study has suggested a combination of multiple binarised images to generate an optimal output based on majority vote scheme using information of local pixels in the images. The objective is to select the optimal output pixels in order to produce the most likely binarised image. The proposed technique can be used to combine different binarised outputs from different techniques to produce an optimal output. The differences between the proposed technique and the selection framework of binarisation techniques using SVM are:

1) the combination method does not need learning mechanisms,

2) the combination method does not depend on neither the dataset nor prior dataset,

3) the combination method determines the output pixel from the input pixels of multiple input images - using the information of local interaction between the pixels in the images.

The key advantages of the proposed technique are simplicity and it does not require a large prior dataset. The results from the proposed technique have been compared with those from different independent binarisation techniques, and those from the combination of binarisation technique using KSOM (CBT-KSOM). The benchmark dataset (DIBCO series) from the competition of binarisation technique (DIBCO) is used in this evaluation. The evaluation methods consist of F-measure,
Peak Signal to Noise Ratio (PSNR), Distance Reciprocal Distortion (DRD) and Misclassification Penalty Metric (MPM). The performance of the proposed technique is better than those from other binarisation techniques. This method also has been applied to practical ancient Thai manuscripts on palm leaves and the results have been shown in previous chapters.

7.1.3 Text Line Segmentation

The objectives of line segmentation are to extract precise lines and locate text regions in document images. Text line segmentation can potentially improve the performance of character segmentation and recognition. In this study, text line segmentation algorithms based on partial projection profiles have been proposed. In order to improve the partial projection profile segmentation, this study has proposed a Modified Partial Projection (MPP) approach to address issues due to touching components of two consecutive lines, and analyse the components of texts at vowel levels. In addition, an Adaptive Partial Projection (APP) method has been proposed by applying the MPP method with smooth histogram, and adapting partial projections using divide and conquer strategies.

The proposed technique aims to extract text lines from the images in order to identify the characters or alphabets in proper sequences. The APP technique is an improvement based on partial projection profile and this work addresses issues associated with text line segmentation on palm leaf manuscripts. The contributions of the study are still the development of analysis techniques for touching components between two consecutive lines and the analysis of the components of texts at vowel. Moreover, the APP technique adapts the partial projections using divide and conquer
strategies based on the size of characters in each image. The size of strip is flexible for each images and the APP can reduce the time for the line segmentation process as it re-executes only some required partial strips due to obstructive objects. Furthermore, some binary images are vague and they have major effects on the accuracy of text line extraction.

7.1.4 Character Segmentation

This study has proposed the framework of hierarchical character segmentation. The framework consists of three steps; (i) a contour tracing algorithm for the identification of individual characters, (ii) a separation of touching components using a trace of background skeleton, and (iii) a separation of touching components using combined method. The applied technique aims to extract characters from the text line images for the identification of individual characters.

The major contribution of this study is the development of techniques that consider touching components by a trace of background skeleton, and combined method of segmentation. The proposed method can successfully segment characters from text line images. Although some of touching components can be separated, some complex connected components are still difficult to be segmented.

The overall contributions of this study are summarised as follows:

- An investigation on palm leaf manuscripts dataset with ancient Thai-language which have received little attention from researchers.
- A study of candidate binarisation techniques for background elimination.
• Addressing the problem of background elimination as there is no single effective technique for all kinds of digital documents, even in the same problem domain.

• Proposal and development of a selection framework of binarisation technique using SVMs and treatment of imbalanced data.

• Proposal and development of a combination technique for generating an optimum output from multiple binarised images based on majority vote scheme and local pixel information. The performance of the proposed technique is better that the binarised images from different binarisation techniques and the combination of binarisation technique using KSOM.

• Proposal and development of the Adaptive Partial Projection method for text line segmentation by applying the Modified Partial Projection method with smooth histogram and adapting partial projections using divide and conquer strategies with significant results.

• Proposal and development of the hierarchical approach for character segmentation by applying contour tracing algorithm and separating touching components using a trace of the background skeleton, and a combined method with significant results.

Future work on this study is described in the next section.

### 7.2 Future work

Future work of this study may be extended as follows:

1) The pre-processing framework of this study can be integrated with a number of document image analysis applications such as Optical Character
Recognition (OCR) systems and Text-Based Image Retrieval (TBIR) systems for information extraction. With respect to these systems, there are no specific off-line OCR systems capable of dealing with handwritten Thai or ancient Thai scripts, and there are also no TBIR systems for Thai scripts. This is a challenge for researchers working on OCR system for Thai handwritten documents, ancient Thai scripts and TBIR system for Thai scripts.

2) On the selection framework of binarisation techniques, this study developed a prototype for future research in this area. This framework can be improved to provide selections to be ranked by the user in a semi-automatic approach.

3) As regard to text line segmentation based on Partial Projection Profile, the APP technique can be improved by considering the position of touching components of consecutive lines and prolong the path of characters by using blocks of characters. This technique could be compared with other text line segmentation approaches such as smearing and grouping methods. In addition, the hit-rate may be used as evaluation measures.

4) In character segmentation, dealing with touching components remains an issue in this problem domain. This is a challenge for researchers in developing techniques to separate touching components by determining the possible positions of connected characters due to smearing, water reservoir and falling path. However, this research does not consider the touching characters in vertical direction such as touching components between upper vowel and body consonant, and between lower vowel and the body consonant.
5) The major public benchmark datasets used in this study is obtained from Roman scripts of ancient documents as there is no benchmark dataset in Thai scripts. It is necessary to generate benchmark datasets for Thai scripts on ancient document for future research in this problem.
References


[124] T. Landgrebe and R. Duin, "A simplified extension of the area under the ROC to the multiclass domain," in *Seventeenth Annual Symposium of the Pattern Recognition Association of South Africa, 2006*.


Appendices
**Table A.1 DIBCO2011 dataset.**

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Appendix B. Sample Results of Combined Image (Sub-section 4.3.4)

Figure B.1 Binarised image from DIBCO 2011.
Figure B.1 Binarised image from DIBCO 2011 (continue).
Figure B.2 Binarised image from H-DIBCO 2010.
Figure B.3 Binarised image from DIBCO 2009.
Figure B.3 Binarised image from DIBCO 2009 (continue).
Appendix C. Sample Images of Text Line Segmentation using MPP and APP

(Section 5.3)

Figure C.1 Text line segmentation using MPP.
Figure C.1 Text line segmentation using MPP (continue).
Figure C.2 Text line segmentation using APP.
Figure C.2 Text line segmentation using APP (continue).
Appendix D. Sample Results of Character Segmentation (Section 6.3)

Figure D.1 Character segmentation.