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# Identification of Secondary Flow Pattern in a Heated Curve Rectangular Channel using Image Processing Technique

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***Abstract*** ***– This paper introduced a new application of pattern recognition technique to the problem of automatic identification of secondary flow patterns in a heated curve rectangular channels. The proposed algorithm is based on two observations. Firstly, in the study of secondary flow patterns, it is found that a smaller pair of secondary vortices is generated when the flowrate of a fluid in a curve passage is beyond certain threshold value. Secondly, human can easily identify the centre of the vortex by visual inspection. This paper proposes an algorithm that can automatically realise the existence and location of such vortices. Such information can be used to provide feedback signal for the control of the flow within the channel.***

***Keywords*** ***– Image Processing, Pattern Recognition, Process Control***

## I. INTRODUCTION

This paper describes a novel approach based on an image processing technique for the automatic identification of secondary flow patterns in a curved channel. When a fluid is forced through a passage with a curvature, a secondary flow appearing in spiral motion is superimposed on the main flow. Such phenomena are commonly found in radiators, compressors, centrifugal pumps, turbine blades and many heat exchange equipment.

While secondary flow is expected to promote the mixing of fluids, limited attempts have been made to improve the heat exchange process through the control of the secondary flows. This is mainly due to the fact that many aspects and the nature of the secondary heat transfer are highly complex. Hence, much research and investigations have concentrated on the examination and the study on the understanding of the underlying mechanisms and other characteristics of the secondary flows.

In this paper, it is hypothesised that if the existence of the secondary vortices are identified and quantified correctly, then it is possible to provide feedback information to the control of the main flow for improving the heat exchange process. One possible identification of the secondary vortices is the use of pattern recognition where transparent fluids are involved. Once the understanding on the transparent fluids is developed, outcomes may be applied to other fluids.

Pattern recognition has interested scientists and researchers because of the sheer potential application of such technology. Many successful applications of the pattern recognition have been developed in other areas such as voice recognition, optical character recognition and biometric identification systems, so and so forth. This paper extends the horizon by applying the image pattern recognition technique to a flow control system. This paper reports the first phase of the study, which tackles the problem of identifying the secondary flow patterns. Once the patterns can correctly be identified and quantified, the information can be used as feedback for the control of the flowrates.

## II. PRELIMINARIES

### A. *Application*

Recently, analysis of heat and fluid flow has become an important field of research due to the increasing awareness of environmental issues and the need for high efficient heat transfer appliances such as electronic cooling and heat recovery systems. While it is understood that when a fluid flows in a curved passage a secondary flow will occur when the flow rate is increased, however. beyond certain threshold, an unstable flow condition will occur. A smaller pair of secondary vortices will be generated under such conditions, known as the Dean's Instability. Also, the additional vortices are called Dean Vortices [1-4]. Such occurrences are related to the physical constructions of channels, the characteristics and flowrates of fluids.

It has been reported that external heating in the vicinity of vortices can significantly affect the secondary flows [5-6]. The induced temperature is capable to influence the formation and dimension of the vortices and allowing higher flowrates by countering the centrifugal forces. By controlling the external heating, it would be possible to permit a higher flowrate while maintaining symmetry of the secondary vortices without entering the region of the unstable behaviour.

In most of the process control systems, feedback information is gathered by using various sensors. The selection of the exact sensors suitable for the application is dependent on the nature of the information required. However, it is difficult to measure the secondary flow in a non-intrusive manner. If the dynamic patterns are captured in the form of visual images, image recognition technique can then be used as an alternative and more efficient way of analysing the system. Therefore, the intention of this paper is the investigation and development of a visual-based system to identify and quantify the secondary flow patterns. The information can then be used to control the external wall heating, thereby improving the main heat exchange process.

### B. *Similarities and Differences*

In this study, an image processing mechanism has been designed and implemented overseeing a heated curved-rectangular channel carrying transparent fluid. It was found that unlike many other object recognition applications, the system did not face problems such as background illumination, spurious data and object occlusion. However, different types of problems have been encountered such as the existence of noise, uncertainty due to point of invariance, and problems due to weak and non-continuous edge identification. An algorithm is therefore proposed in this paper to overcome these issues.

## III. THE THEORY

### A. *Image Recognition Process*

Fig. 1 shows the overall process of object recognition. The process starts with a captured image as the input. The input data in the form of digitized bit-map image is then processed by the image processing. The process may include noise filtering and data normalisation. These processes are essential for the extraction of important features from the image. Typical features may include colour or grey-level, texture and edge of the image. These features are then further processed for the extraction of relevant information needed for the classification of the object. The process will be dependent on the object model or template that is stored in the system's database. Performance of the classification process is also dependent on the representation of the object in the database and the search algorithm. The last two processes, the pre-processing and classification, form the core components of any object recognition system and they are the focuses of most researches in the discipline of object recognition.

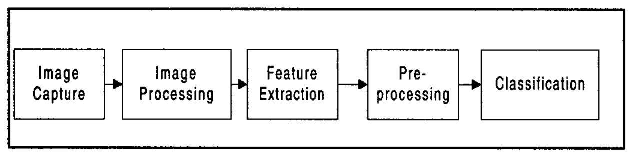


Fig. 1: Image Acquisition and Classification system

### B. *Proposed Algorithm*

A typical vortex pattern is shown in Fig. 2(a). By visual inspection, it is not difficult to identify the centre of the vortex. The challenge is to develop an algorithm that will enable a machine vision system to automatically recognise the existence and location of such vortices.

(a) (b)

Fig. 2: (a) A typical image of a vortex in a secondary flow (b) The processed image after applying an edge detection algorithm.

It is apparent that the centre of the vortex is surrounded by layers of edges in circular patterns. One possible technique that can be applied is to perform an edge detection process first. Following that, the number of edges in the image can be counted by scanning the image line by line. An initial algorithm has been developed for counting the number of edges. From the results, it has been found that the number of edges peak at the centre of the vortices. Based on this observation, a vortex centre location algorithm particularly suitable in this type of applications may be formulated as follows:

Step 1. Applying an edge detection algorithm to sharpen the image.
Step 2. Scan through the image in a horizontal and vertical direction.
Step 3. The centre of the vortex can then be located where the horizontal and vertical edge counts peak.

In the actual implementation, the processed image will be transformed into a two-level representation. As demonstrated in Fig. 2(b), each edge is represented by a white colour pixel with the pixel value of 1 in a black and white image. To avoid treating straight line as multiple edges, Step 2 of the above algorithm for the vertical scan become:

$$E(x) = E(x) + 1;$$
$$\text{for} \quad P(x, y) <> P(x + 1, y) \ \& \ P(x, y) = 1$$

Where x and y are the position of an image, E(x) is number of edges found in the scanned line and P(x, y) is the value of a given image pixel at location (x, y).

It has been found that due to noise and presence of weak edges inherent in the pattern, the output from the edge detection algorithm may not be always be consistent. To eliminate such inconsistencies, the application of the best-fit technique, as illustrated in Fig. 3, was found to be useful. In this manner, by finding the maximum in points in the curve and based on a given threshold value, the vortex or any other area of interest in the pattern can then be located. It is also found that the data is best represented by graph exerts polynomial behaviour. The accuracy of the data representation can be improved by increasing the polynomial degree. This is further discussed in the later section of the paper. Fig. 3 below illustrates a typical result from such process.

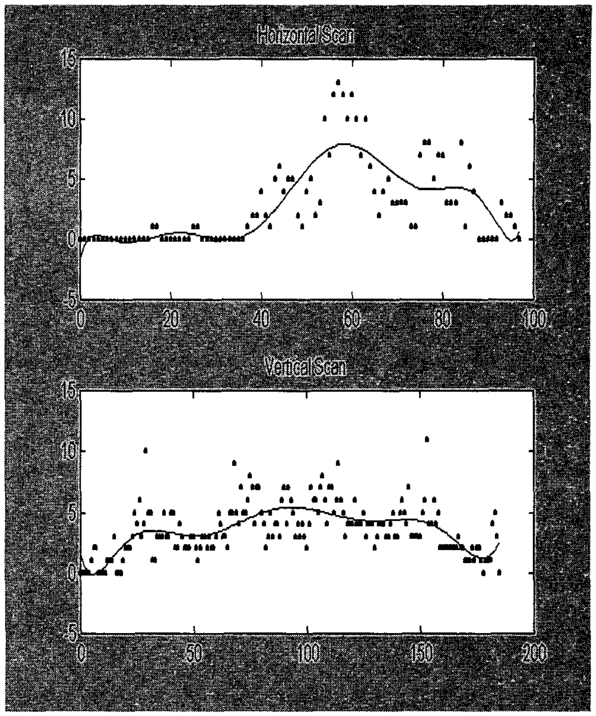


Fig. 3: The result obtained from scanning Fig. 2(b) along the horizontal and vertical axes.

## C. *Assumptions*

It should be noted that the algorithm developed in the previous section is based on the following assumptions:

(a) The edges found in most of the images are in general very weak and non-continuous. Thus, the assumption is made that algorithm applied to extract the edges from the image are always robust enough to be able to extract most of the weak edges but without the unnecessary noise. This assumption can be limiting, as most of the edge detection algorithms such as Canny Operator [4], that are robust to weak edges are also sensitive to noise.

(b) The shape of the best-fit curve is accurate enough to represent the data sample. Again, this assumption can be simplistic. Further details are discussed in the later sections.

(c) The centre of vortex is always at the maximum point on the best-fitted curve.

(d) The resolution of the image is always high enough such that the noise level in the image is minimal. Hence, no error correction is required in processing the image.

## IV. THE RESULTS

### A. Simulated Result

The proposed algorithm was tested with a number of simulated situations. Additional noise signals were introduced to test the performance of the algorithm. It is found that the outcomes can be affected by a number of factors. They are:

(a) The threshold value used in the edge detection algorithm - this is demonstrated in Fig. 4. It should be noted that the fine details of the image that includes possible noise detected by the smaller threshold value, whereas the larger threshold values are only capable for detecting the global feature of the pattern. Table I shows the accuracy of the algorithm along with different threshold value. Based on Table I, it is found that in general, the threshold values are needed to be small enough to be able to detect all the weak edges existing in the pattern. However, if the value is too large, too much information may be lost.

(b) Accuracy of the curve-fitting function – which determines the centre of the vortex. As the centre is located by finding the maximum point of the approximated curve of the data samples, the curve-fitting algorithm will be crucial to the accuracy of the curve. The curve is also affected by the amount of noise that exists within the image. In addition, the dimension of the polynomial function of the best-fit curve is another contributing factor to the accuracy.

Fig. 4: Edge detected Images from different threshold value. (a) Sobel operator with threshold = 0.05. (b) Sobel operator with threshold = 0.1

Table I: Simulated results from processing Fig. 2(a) with different threshold parameters. The vortex centre is located at x = 93 and y = 54

| Calculated X | Calculated Y | Difference In X | Difference In Y | Threshold |
|---|---|---|---|---|
| 113 | 44 | -10 | 20 | 0.03 |
| 115 | 44 | -10 | 22 | 0.05 |
| 117 | 45 | -9 | 24 | 0.07 |
| 120 | 46 | -11 | 27 | 0.09 |
| 119 | 45 | -9 | 26 | 0.11 |
| 121 | 47 | -8 | 28 | 0.13 |
| 120 | 49 | -5 | 27 | 0.15 |
| 120 | 53 | -1 | 27 | 0.17 |
| 121 | 55 | 1 | 28 | 0.19 |
| 119 | 53 | -1 | 26 | 0.2 |
| 118 | 60 | 6 | 25 | 0.22 |
| 119 | 60 | 6 | 26 | 0.24 |
| 119 | 65 | 11 | 26 | 0.26 |

### B. Discussions

As discussed in the previous section, the accuracy of the vortex location is partly dependent on the degree of the best-fit polynomial function. Fig. 5 shows the best-fit curves extracted from the same data set but based on different polynomial degrees. Noise signals are also introduced to appear at the upper-left-hand corner as indicated in the diagram. It can be observed that the functions with a high polynomial power have provided a closer approximation to the original data and the noise. In particular, the appearance of the a peak on the left-hand-side of the curve. In the cases of (c) and (d), this peak may appear as the maximum value thereby causes errors in the location of the centre. On the other hand, functions with smaller polynomial power are less accurate in data approximation but they are more robust against the noise within the image.

The above discussion suggested that the source of problem using the line of best-fit approach is the inability of controlling the outcome of the function approximation. One suggestion is to predefine function's characteristic, that is, the shape of the curve but still provides the flexibility of scaling and translating. Such approach may reduce the sensitivity to the noise and produce a more predictable result. For instance, images with one vortex should in theory consist of only one maximum point. Thus, function's characteristic for data shown in Fig. 5 should be defined as:

$$P(x) = A( x*x + 30x + B) \qquad (1)$$

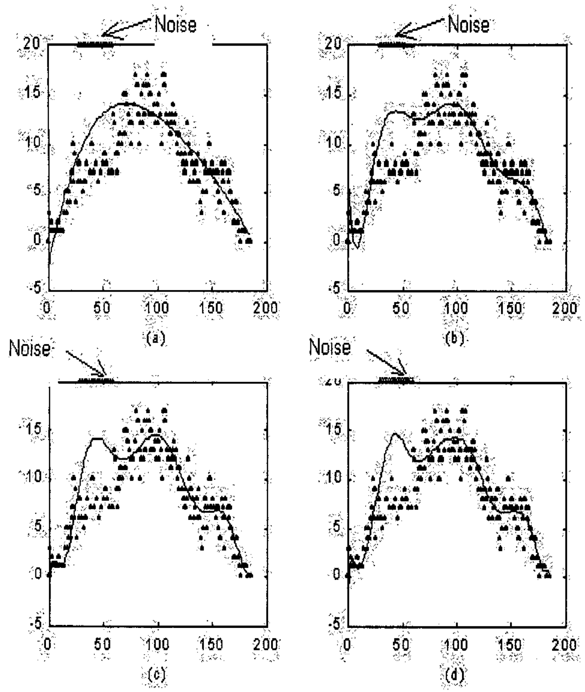


Fig. 5: Results from curve fit function using different polynomial functions. (a) Polynomial power = 4, (b) power = 8, (c) power = 12, (d) power = 16

Where x is the number of edges scanned, P(x) is the simulated best-fit function, A and B are the scaling and translating factor. Fig. 6 shows the simulated result from applying Eq. (1). It could be observed that the noise now has minimal effect on the final curve.

Since noise has an adverse effect on the accuracy of the vortex location, it is also suggested to reduce the noise level by totally reconstructing the image. This is, through the image reconstruction process, only the relevant features from the image will be extracted while filtering any unnecessary noise. Algorithm such as Hough Transform [9] is a well-known image processing theory that provides the ability for any image object to be reconstructed with a higher precision.

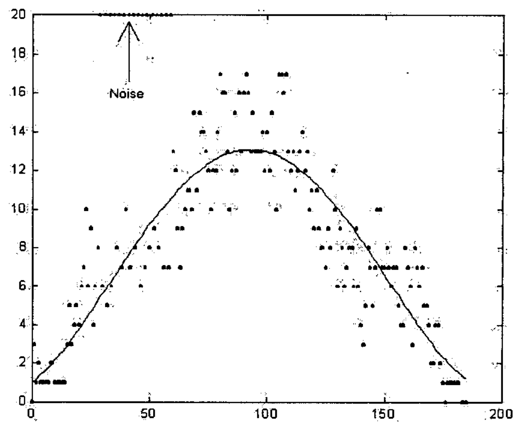


Fig. 6: Line of best fit with predefined function characteristic. The minimum error is found at A = 322 and B = 319.

### C. *Further Developments*

The proposed algorithm in this paper is only in the preliminary stage. It has only tested under several restricted assumptions. Only images with one vortex are tested. In the case of secondary flow study, this may be sufficient as the location of the patterns are localised at specific regions. Hence the processing can be applied to limited region within the image.

Further work is continuing to improve the algorithm for the detection and quantifying of images with multiple vortices. Hence, the development of more advanced algorithms for processing of the images with multiple vortices, recognition of the patterns, and relating them to the control parameters are the next stage of the project.

## V. NOVELTIES

A novel approach for the measurement of the secondary flow patterns based on image processing is presented. The application of the edge detection methods and development of the supporting algorithms are the main themes of this paper. This is an initial stage of the study in the development of vision-based close-loop control system for a heat exchange process.

## VI. CONCLUSION

In this paper, a new application of image recognition system to the recognition of fluid flows has been introduced. This proposed approach identifies the existence of secondary flow vortex in a curved channel and locates them appropriately for subsequent control purposes. The success of achieving the objectives of the pattern recognition, as applied in here, is expected to provide a new and alternate approach to the heat exchange and fluid flow control problems.

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