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A Simple Method for Automatically Locating the Nipple on Mammograms

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Abstract—This paper outlines a simple, fast, and accurate method for automatically locating the nipple on digitized mammograms that have been segmented to reveal the skin-air interface. If the average gradient of the intensity is computed in the direction normal to the interface and directed inside the breast, it is found that there is a sudden and distinct change in this parameter close to the nipple. A nipple in profile is located between two successive maxima of this parameter; otherwise, it is near the global maximum. Specifically, the nipple is located midway between a successive maximum and minimum of the derivative of the average intensity gradient; these being local turning points for a nipple in profile and global otherwise. The method has been tested on 24 images, including both oblique and cranio-caudal views, from two digital mammogram databases. For 23 of the images (96%), the rms error was less than 1 mm at image resolutions of 400 μm and 420 μm per pixel. Because of its simplicity, and because it is based both on the observed behavior of mammographic tissue intensities and on geometry, this method has the potential to become a generic method for locating the nipple on mammograms.

Index Terms—Automatic nipple location, computer vision, image processing, mammograms.

I. INTRODUCTION

MAMMOGRAMS are X-ray images of the breast. At present, they are the method of choice for screening asymptomatic women for early detection of breast cancer. Such screening will necessarily generate a large number of mammograms which must be viewed and interpreted by a limited number of expert radiologists. Automatic analysis of mammograms by computer, as the first stage in analyzing mammograms, could serve to reduce the workload on radiologists.

Before mammograms can be analyzed by machine, they must be digitized with adequate greyscale and spatial resolution. It is also vital to ensure that low-intensity features such as the skin-air interface and the nipple are preserved with fidelity during digitization. Assuming that this has been done, the first stage of preprocessing is segmentation of the image into background and object. This should yield a clear and smooth skin-air interface.

The next logical step would be to locate the nipple on the mammogram. There are several reasons why this should be done. Anatomically, the nipple is the only landmark on the breast [1, p. 119]. The glandular structures comprising the lobules, ductules, lobes, and ducts hierarchically converge onto the nipple. Because cancer arises in the glandular tissue of the breast [1, p. 121], it would be sensible for any automatic search strategy for detecting cancer to begin at the nipple and fan out into the “cone” or “triangle” of glandular tissue that has the nipple as its apex. Moreover, given its singularity, radiologists pay specific attention to the nipple as part of their examination of a mammogram [2, p. 22]. [3, p. 123]. Radiologists also compare corresponding regions of the right and left breasts to detect relative anomalies [2, p. 22]. Computer methods that attempt the same task rely heavily on the nipple as an alignment pivot [4], [5].

This paper reports on a simple method for locating the nipple on a mammogram. It has been tested on a total of 24 images. Sixteen of these are oblique-view mammograms from a digital database made available to researchers by the Mammographic Image Analysis Society (MIAS) of the United Kingdom [6], [7]. The remaining eight images are cranio-caudal views from another database of digitized mammograms distributed by the University of California, San Francisco, CA (UCSF), and the Lawrence Livermore National Laboratory (LLNL), Livermore, CA [8]. These two databases shall henceforth be referred to by the acronyms MIAS and UCSF/LLNL, respectively.

II. REVIEW OF PREVIOUS WORK

There are relatively few reports in the literature on automatic nipple location. The problem was first discussed by Semmlow et al. [9] in their paper on the automated screening of xeromammograms. They used a special shape-sensitive spatial filter to generate measures of roughness and directionality to locate the central region of the breast boundary. The lowest point on this boundary was then taken to be the nipple—a debatable geometric assumption. A more recent account of automatic nipple location is that by Yin et al. [5], reported

1While the present paper was under review, Mendez et al. [10] published a paper on automatic detection of the breast border and nipple. Their work was motivated by observations similar to ours, although the nipple detection method described therein is different from that presented here. Interested readers are referred to the original paper for details.
as part of a bilateral-subtraction technique to detect masses in mammograms. They extracted the breast border and averaged the grey values in small 10 by 40 pixel regions for points along the border. They then plotted the relative average intensity value against location along the border and identified the nipple at the location of the maximum on the plot. They reported that for images digitized at 400 μm per pixel, the nipple position found by computer differed on average by 10 mm from that located by a radiologist. In their study, no mention was made of whether or not the nipple was in profile in any of the segmented images, but we believe that their method would fail for a mammogram in which the nipple is in profile.

III. OUTLINE OF METHOD

The method we describe here is based principally on the observed behavior of the pattern of intensities on the mammogram adjacent to the skin-air interface. It was observed that the iso-intensity contours there follow the direction of the skin-air interface and run more or less parallel to it. Near the region of the nipple, however, the iso-intensity contours slope rather sharply toward the skin-air interface. A form of intensity aliasing may be used to demonstrate this. For example, on a byte image where each pixel may take a value from 0–255, an $m$ cycle intensity ramp may be applied to each original intensity value, $I_\text{org}$, to yield the new intensity, $I_n$, given by

$$I_n = (m I_\text{org}) \mod 256$$

(1)

where $p \mod q$ stands for the remainder when $p$ is divided by $q$, both $p$ and $q$ being integers. Fig. 1 shows an original mammogram and the images obtained by ramping the intensities for eight and 64 cycles, to better display low-intensity levels. It is clear from Fig. 1(b) that the iso-intensity contours are more closely packed as they slope toward the nipple.

If the nipple appears in profile on the mammogram, the intensity of the nipple is always comparatively low and varies little in the region of the protuberance. This is most easily seen by displaying the mammogram in color using a random colormap. It may also be seen by intensity-ramping the image as shown in Fig. 1(c). Note also the marked nonuniformity of the background made apparent in this image although not obvious in the original.

Based on these two observations, we framed the following hypothesis.

1) The nipple is located on the mammogram close to where the intensity gradient in the direction normal to the skin-air interface and directed inside the breast is a maximum.

2) In cases where the nipple is in profile, its relatively unchanging, low intensities mean that it would be located close to a minimum of the intensity gradient in the normal direction.

Two assumptions underlie this hypothesis.

1) The nipple, whether in profile or not, is situated on or very close to the skin-air interface.

2) The nipple points in the direction of the normal to the skin-air interface.

Experiments were performed on 24 mammograms from two databases to ascertain whether this hypothesis was justified, and if so, whether it could be used to locate the nipple reliably on a mammogram.

IV. NOTATION

The image is treated as a discrete-valued function, $I(x,y)$, of two integer variables, $x$ and $y$, with the origin at the top left-hand corner of the image, orientated as shown in Figs. 1(a) and 2. This means that the $y$ value runs positive from top to bottom, anomalously. Because the breast sometimes can and does curve in on itself in the oblique-view, the $y$ value is used to index position rather than the $x$ value. We will denote the original image as $I(x,y)$. The number of pixels in the image in the $x$- and $y$-directions are denoted by $n_x$ and $n_y$, respectively. The resolution of the image in both the $x$- and $y$-directions is $\tau$ mm per pixel.

Where the word gradient is used without qualification, it means the first derivative in the conventional sense. Where
Fig. 2. The breast is orientated so that the nipple always faces the right. The coordinate axes are directed as shown with the origin corresponding to the top left corner of the image. The normal to the breast at the point \( (B(y), y) \) on the skin-air interface is directed breastwards in the direction \( ON \) as shown. The intensity gradient along the normal is computed using the pixels lying on \( ON \). The angle \( \theta \) made by the normal with the positive \( x \)-direction is also shown.

**V. Detailed Description of Algorithm**

The detailed description of the algorithm is given below.

1) The breast is segmented from the background, either interactively (semiautomatically) or automatically, special care being taken to preserve with fidelity as much as possible of the breast portion of the skin-air interface, including the nipple, if it is in profile. Because of the variation in the background, [see Fig. 1(c)], and the possibility that the same intensity could represent breast tissue in one region of the image and background in another, simple thresholding would not necessarily work always. Another precaution is to ensure that the extracted skin-air interface is smooth to the eye at the resolution of the image. This results in a labeled binary image, \( I(x, y) \), showing the breast and background [see Fig. 3(b)].

2) The border of the breast, representing the skin-air interface, is extracted from the labeled image. We denote this by \( B(y) \), defined for all integer values of \( y \) running from 0 to \( n_y - 1 \). \( B(y) \) gives the \( x \) value of the skin-air boundary for a given \( y \). Implicit in this is the assumption that \( B(y) \) is well defined. This may not hold at the inferior portion of the breast, near the infra-mammary crease and the chest wall, but those regions will usually be excluded from our search as explained below.

3) We restrict the search for the nipple to values of \( y \) lying between \( 0.3n_y \) and \( 0.9n_y \). For convenience, these values of \( y \) will be denoted by \( y_i \) and \( y_n \), respectively, the general \( y \) value lying within these limits being denoted by \( y_i, i = 1, \ldots, n \). This restriction avoids unnecessary computation as well as edge artifacts (such as tapes) that sometimes appear at the edges of the digitized images. It also circumvents problems arising from \( B(y) \) not being well defined in the inferior portion of the breast. A similar restriction is also imposed on the allowable \( x \) values by requiring \( B(y) \) to be greater than \( 0.1n_x \), again to avoid edge effects and artifacts such as skin folds.

4) For each of the \( n \) test points, \( (B(y_i), y_i) \), on \( B(y) \), we estimate the tangent to \( B(y) \) by the straight line that best fits (in the sense of least squared error) a neighborhood of \( p \) points on the border, centered on \( y_i \). The gradient of this line is denoted by \( m_i \).

5) The gradient (and hence direction) of the normal at \( (B(y_i), y_i) \) is estimated as \( -1/m_i \), taking into account the anomalous coordinate system described above. Associated with this normal is the angle \( \Theta_i \) that it makes with the positive \( x \)-direction (see Fig. 2).

6) Pixels lying on the normal at various integer distances \( j, (j = 1, \ldots, k) \), from the test point \( (B(y_i), y_i) \) are identified, and for each of these, \( I(x, y_j) \), the intensity gradient along the normal direction is computed simply as

\[
G_{ji} = \frac{I(x, y_j) - I(x, y_i)}{j} 
\]

for \( j = 1, \ldots, k \) and \( i = 1, \ldots, n \). (2)

We call \( k \) the depth of the normal. The average of these \( k \) intensity gradients is defined to be the average intensity gradient along the normal, \( G_i \):

\[
G_i = \frac{1}{k} \sum_{j=1}^{k} G_{ji} \quad \text{for} \quad i = 1, \ldots, n. \quad (3)
\]

7) The sequence \( G_i \) is smoothed by a smoothing filter \( S \), and the resulting sequence is normalized to yield the zero mean, unit variance sequence, \( g_i \). This latter sequence is passed through a differentiator \( D \), to yield \( g'_i \). Likewise, \( \Theta_i \) is smoothed and normalized to yield \( \theta_i \) and differentiated to give \( \theta'_i \).

8) Graphs of \( g_i, \theta_i \) and their derivatives are then plotted against \( y_i \) for \( i = 1, \ldots, n \). For convenience, we shall refer to the graphed variables without explicitly mentioning the index \( i \). Thus the “\( y-y \) curve” shall refer to the graph of \( g_i \) as dependent variable plotted against \( y_i \) [see, for example, Fig. 3(d)].
9) The maximum value of \( g_k \) is then found. It is denoted by \( g_{\text{max}} \) and its index by \( i_{g_{\text{max}}} \). The minimum value of \( \theta_{g_{\text{min}}} \) is also found and its position denoted by \( i_{g_{\text{min}}} \).

10) If \( \theta_{g_{\text{max}}} \) is less than a predefined negative threshold \( \theta_\theta \), the nipple is inferred to be in profile; otherwise, it is not. Because the \( \theta_\theta \) vary across a predictable range of values in all images, it was possible to use an absolute threshold on \( \theta_\theta \) without sacrificing generality. (Occasionally, because of poor segmentation or an image with an uneven skin-air interface, the value of \( \theta_\theta \) can lie below the threshold even when the nipple is not in profile. To exclude such cases, we check to see if the indexes \( i_{g_{\text{max}}} \) and \( i_{g_{\text{min}}} \) lie within a certain distance of each other, called the \textit{nipple window} \( \psi \), If they do, the nipple is in profile; otherwise it is not.)

11) The algorithm \textit{automatically} bifurcates here depending on whether or not the nipple is in profile (as determined above)

\[ a) \text{ Nipple is not in profile:} \] The indexes of the global maximum, \( g_{\text{max}} \) and minimum, \( g_{\text{min}} \) of the derivative curve \( g' \) are located and denoted by \( i_{g_{\text{max}}} \) and \( i_{g_{\text{min}}} \). The \( y \) value of the computed nipple position is given by \( y_c \) where

\[ c = \frac{(i_{g_{\text{max}}} + i_{g_{\text{min}}})}{2} \]  \hspace{1cm} (4)

and the nipple position is then \( B(y_c), y_c \). One comment is in order here: we have found that \( i_{g_{\text{max}}} \) is often a good first estimate for \( c \). Therefore, if the global maximum and minimum lie within \textit{one nipple window} of \( i_{g_{\text{max}}} \), the estimate may be considered more reliable than otherwise. Although this reliability measure is not used in these results, through its use, the algorithm may itself estimate the reliability of its nipple detection and pass that information on to other program segments, in the context of a more ambitious automatic global segmentation of mammograms. It could also be used to improve the performance of this algorithm adaptively.

\[ b) \text{ Nipple is in profile:} \] The local minimum on \( g' \) immediately preceding \( \theta_{\text{min}} \) is found. Let us call it \( g_{\text{min}} \) and its position \( i_{g_{\text{min}}} \). The local maximum, \( g_{\text{max}} \), that occurs immediately after \( i_{g_{\text{min}}} \) is then found and its position, \( i_{g_{\text{max}}} \), ascertained. The \( y \) value of the computed nipple position is given by \( y_c \) where

\[ c = \frac{(i_{g_{\text{max}}} + i_{g_{\text{min}}})}{2} \]  \hspace{1cm} (5)

and the nipple position is again \( B(y_c), y_c \).

VI. EXPERIMENTAL METHOD

A. Preliminary

Our algorithm was developed and tested using oblique-view images from the MIAS database. However, since that database lacks cranio-caudal views, we subsequently used images from the UCSF/LLNL database to test our method on cranio-caudal views as well. The images in the two different databases were acquired and presented differently. Accordingly, they were preprocessed differently.

The MIAS images are distributed as 8-bit-per-pixel greyscale images at 50 \( \mu \)m per pixel spatial resolution in each orthogonal direction. The images were simultaneously shrunk and lowpass filtered by averaging within an \( 8 \times 8 \) window and assigning the result to the new pixel value. The resolution of the test images was, therefore, 400 \( \mu \)m per pixel in each direction. It is noteworthy that pixel values in the MIAS database were assigned using a detector that was \textit{linear in the optical density} (O.D.) range of 0 to 3.2 [6], [7].

The UCSF/LLNL images are distributed as 12-bit-per-pixel greyscale images at 35 \( \mu \)m per pixel in each orthogonal direction. These images were likewise averaged and shrunk within a \( 12 \times 12 \) window to yield working images having a resolution of 420 \( \mu \)m per pixel in each direction. We note however, that during digitization, the pixel values for the UCSF/LLNL database were assigned \textit{linearly with transmitted intensity} [11] (rather than optical density as in the MIAS database). To test images from this database on the same software, the 12-bit images were transformed into 8-bit-per-pixel images by retaining the 256 lowest levels in each image and clipping all higher pixel values to 255. We felt justified in doing this since we were concerned with the low-intensity end of the image in our algorithm.

The method was tested on 16 oblique-view images from the first 80 in the MIAS database. The images were selected to include cases where the nipple was in profile and where it was not. The latter category included three images where the nipple was noticeably recessed. Eleven of the fifteen test cases were normal mammograms which ranged from fatty to glandular to dense, as classified by the MIAS. Of the remaining five, two exhibited benign changes and three were malignant.

The algorithm was also tested on 18 cranio-caudal images from the UCSF/LLNL database. These images were not selected by us, but had been used by other researchers working on a different project. We report on the results for eight of the images here. The results for some of the remaining images were not as good and point to the need for additional preprocessing—a subject that we have dealt with elsewhere [12], because it raises larger issues such as the effect of method of digitization on algorithm performance across databases.

All images used for these experiments were rotated so that the nipple always faced the right, whether of a right- or left-breast mammogram. The labeled binary image, \( \widetilde{L}(x,y) \), was generated by modeling the image background as a polynomial, subtracting it out, thresholding the subtracted image and region-filling the resulting image to obtain a smooth, contiguous border. This step was semiautomatic, with the user selecting two parameters interactively for the MIAS images, and entirely automatic for the UCSF/LLNL images. The details of this preprocessing are beyond the scope of this paper and have been described in full elsewhere [12], [13].

B. Choice of Parameter Values

Although the nipple and the nipple-areolar complex vary in size across individuals, they are anatomical structures with
characteristic dimensions. It was decided, therefore, to express parameters in terms of such dimensions wherever possible. For example, the “diameter” of the nipple in profile was taken to be typically 10 mm (based on preliminary experiments with the MIAS database) and this value was used to determine the lengths of the smoothing and derivative filters. By expressing the filter length of 10 mm in terms of the pixel-resolution \( r \) of the image in mm per pixel, this value was automatically scaled with the image. To avoid dependence on “magic numbers” and give the method generality, we have expressed most parameters in terms of \( r \) or in terms of \( n_y \), the \( y \) length of the image, which is inversely proportional to \( r \); these values are shown in Table I.

### C. Filters

A raised cosine smoothing filter was chosen because it was analytic, differentiable, had compact support, and was zero at both extremes. The sine filter used to differentiate the smoothed data was chosen because it was analytically the derivative of the smoothing filter. Both filters were normalized so that the sum of the absolute values of their coefficients was unity. The sine filter functions as a smoothing filter for half its length and, thereby, distorts the derivative values at either end of the input sequence. For this reason, the number of data points at the beginning and end, equal to the filter length, were discarded from the derivative data. As explained earlier, the filter lengths themselves were chosen to match the size of the structure being detected, namely the nipple. The derivative data were scaled five times to occupy a similar range as the smoothed data.

### D. Effect of Varying Parameters

The method was tested out on MIAS images at resolutions of 800 \( \mu m \) per pixel and 1200 \( \mu m \) per pixel and found to yield results consistent with those from the images at 400 \( \mu m \) per pixel.

The depth parameter \( k \) was also varied. In cases where the nipple was in profile, \( k \) could be varied from about 5 mm (i.e., \( 5r/r \)) to 10 mm, to yield consistent results; varying it above 10 mm led to the normal transecting the nipple and going beyond the extent of the object region in \( L(x, y) \). However, in cases where the nipple was not in profile, and especially in the case of image 051 (discussed below) where the nipple is recessed from the skin-air interface by a distance greater than \( k \), increasing \( k \) gave results of similar accuracy to the other images.

### E. Reference Data

The position of the nipple was manually identified by a radiologist using a mouse and the \( \chi \nu \) Interactive Image Display program (version 3.10a) [14]. The Sun display terminal used was 1152 \( \times \) 900 pixels at 83 \( \times \) 82 dots per inch. The MIAS images at 400 \( \mu m \) per pixel, and the UCSF/LLNL images at 420 \( \mu m \) per pixel were used for this purpose.

The reference data and the results of the experiments are given in Table II. The positions of the superior/inferior or medial/lateral extents of the nipple were identified by the radiologist; the \( y \) coordinates of these positions were used as the \( y_{ref} \) range values. The radiologist also identified the position of the nipple on the skin-air interface three times and the average of these \( y \) values gave the \( y_{ref} \) value in Table II.

In three images, the nipple was noticeably recessed from the skin-air interface. In these cases, the actual nipple position was different from the three values on the skin-air interface used to obtain the \( y_{ref} \) values. These images are considered in more detail later.

### VII. RESULTS AND DISCUSSION

The test mammograms fell into two main classes:

1) nipple fully or partly in profile;
2) nipple not in profile.

In Table II, the column labeled \( y_c \) gives the computer-detected nipple location in accordance with (4) or (5). The column labeled \( \varepsilon \) gives the error in pixels between \( y_c \), the computer-identified position, and the reference nipple position, \( y_{ref} \). The column headed by \( g_{\text{glob-max}} \) gives the \( y \) values of the midpoint of the positions of the global maximum and minimum of \( g' \). The columns headed by \( g_{\text{max}} \) and \( \theta_{\text{min}} \) give the \( y \) values corresponding to \( g_{\text{max}} \) and \( \theta_{\text{min}} \), respectively. The last column pertains to the nipple and the abbreviations stand for

### TABLE I

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r )</td>
<td>varies</td>
<td>Resolution of image in mm per pixel in either direction.</td>
</tr>
<tr>
<td>( n_y )</td>
<td>varies</td>
<td>Length of image in pixels in ( y ) direction.</td>
</tr>
<tr>
<td>( y_1 )</td>
<td>0.3 ( n_y )</td>
<td>The search for the nipple is restricted to values of ( y ) lying between ( y_1 ) and ( y_n ).</td>
</tr>
<tr>
<td>( y_n )</td>
<td>0.95 ( n_y )</td>
<td></td>
</tr>
<tr>
<td>( p )</td>
<td>( 10/r )</td>
<td>Number of points in the neighborhood of each test point used to estimate the tangent at that point. Set to the number of pixels in 10 mm.</td>
</tr>
<tr>
<td>( k )</td>
<td>( 10/r )</td>
<td>Depth to which intensity gradients along the normal are computed before being averaged. Set to the number of pixels in 10 mm.</td>
</tr>
<tr>
<td>( l )</td>
<td>( 10/r )</td>
<td>Length of smoothing and derivative filters. Set to the number of pixels in 10 mm.</td>
</tr>
<tr>
<td>( t_0 )</td>
<td>(-0.4 )</td>
<td>The absolute threshold against which the minimum value of ( \theta' ) is tested. If ( \theta_{\text{min}} &lt; t_0 ) the nipple could be in profile; not otherwise. If ( \theta' ) is scaled by 5, the test becomes ( \theta_{\text{min}} &lt; -2.0 ).</td>
</tr>
<tr>
<td>( w )</td>
<td>( 20/r )</td>
<td>Length of nipple window within which both ( g_{\text{max}} ) and ( \theta_{\text{min}} ) should lie if the nipple is in profile. Set to the number of pixels in 20 mm.</td>
</tr>
</tbody>
</table>
the following: P: nipple fully or partly in profile; S: nipple not in profile, but close to or at the skin-air interface; R: nipple noticeably recessed from skin-air interface; I: inverted nipple.

A. Nipple in Profile

A nipple in profile is seen in MIAS image 003, illustrated in Fig. 3. The labeled image is shown in Fig. 3(b) where the skin-air interface is defined by the white border adjacent to the black region. This border is used to estimate the tangent and normal directions at every \( y \) value on the border between \( y_1 \) and \( y_m \). The normals are shown drawn on Fig. 3(a). The average value of the intensity gradient along the normal is plotted against the \( y \) coordinate at the left of Fig. 3(a). Note the clear dip in the average intensity gradient at \( y \) values close to where the nipple is. This behavior is characteristic of the nipple in profile and results from the normals traversing tissue corresponding to the protruding nipple, which we have observed is an almost uniform, low-intensity region on the mammogram. However, the absolute magnitudes of the minimum and the two maxima that abut it vary across images, precluding thresholding of \( y \) values close to where the nipple is. This change is bounded: at most, it is of the order of \( \pi \) across a region that is about 10 mm. In other words, we may justifiably set an absolute threshold for \( \theta' \) to detect the nipple in profile, which is what we do. However, although \( \theta'_{\min} \) is a well-behaved parameter, it tends to over estimate the position of the nipple as shown in Table II. This is because, \( \theta' \) is a geometric parameter that is affected by the orientation of the nipple in profile. A characteristic based on tissue intensity will not suffer this drawback. If we use the position of \( \theta'_{\min} \) as an anchor, we observed that there was always a local minimum of \( g' \) preceding the minimum of \( \theta' \). This is \( g'_{\min} \) and the local maximum following it is \( g'_{\max} \). The nipple was always located between the positions defined by \( g'_{\min} \) and \( g'_{\max} \). We have consistently found that for our test images, the nipple position may be estimated reliably and accurately by the midpoint between the positions of \( g'_{\min} \) and \( g'_{\max} \). We note in passing that these two turning points define the two steep drops in \( g \) that enclose the trough, i.e., their midpoint roughly indicates the middle of the trough corresponding to the nipple.

The results for cranio-caudal images from the UCSF/LLNL database follow the same pattern as for the oblique-view mammograms from the MIAS database. An example is shown in Fig. 4. Note that although the trough on the \( g-y \) curve corresponding to the nipple in profile is not as pronounced in this case as in Fig. 3(d), the average of the \( y \) positions of \( g'_{\min} \) and \( g'_{\max} \) again gives a good estimate of the nipple position.

B. Nipple Not in Profile

MIAS Image 072, shown in Fig. 5, is a case of a nipple that is not in profile. In such images, the position of the nipple...
may be grossly estimated by the position of \( g_{\text{max}} \). Indeed, in this case, the midpoint of the positions of \( g'_{\text{max}} \) and \( g'_{\text{min}} \), the global maximum and minimum, respectively, of \( g' \), equals the position of \( g_{\text{max}} \) at \( y = 344 \), which again is close to the reference position at \( y = 343 \). We have chosen to use the midpoint of \( g'_{\text{max}} \) and \( g'_{\text{min}} \) in preference to \( g_{\text{max}} \) because the former better reflects the rapid change in the intensity gradient \( g \) associated with the nipple. The maximum, being a single value, may or may not be located symmetrically about these rapid changes in intensity gradient. The results in Table II bear this out for the images tested. Note that the position of \( \theta'_{\text{min}} \) is not relevant here, and in any case, \( \theta'_{\text{min}} \neq \theta_0 \).

Even if the nipple is in profile in the original image, if the labeled image is the result of over-thresholding (i.e., the boundary on \( L(x,y) \) represents not the skin-air interface, but rather some interface between tissues in the breast) the plot of \( g \) etc., will be similar to Fig. 5(d).

It is noteworthy that the maximum we are dealing with here is the maximum of the average intensity gradient in the direction normal to the skin-air interface, whereas the maximum used by Yin et al. [5] is the maximum of the average intensity directed along the border.

The one mammogram that exhibited an inverted nipple (MIAS no. 063) could also be treated as an image in this category.
The cranio-caudal view UCSF/LLNL images showed behavior similar to that of the oblique-view images when the nipple was not in profile. A typical example is shown in Fig. 6. Comparison of Fig. 5(d) with Fig. 6(d) shows a remarkable similarity in pattern between the two sets of curves.

C. Recessed Nipple

In three images, numbers 043, 051, and 074, the nipple was noticeably recessed from the skin-air interface, by distances of 2.4, 10.9, and 2.2 mm, respectively. The results of Table II show that only the results for image number 051 were adversely affected. This is also the image where the nipple is farthest from the skin-air interface: by about 11 mm, which is in excess of the depth parameter $k$, set at 10 mm. In this case, if the value of the depth parameter $k$ were increased from 10 mm through 12–20 mm, the value of $y_k$ changes from 395 through 416–421, the latter value being in accord with the value of 422 determined by the radiologist. We conclude that the results from our method are accurate in cases where the distance of the recessed nipple from the skin-air interface is less than the value of the depth parameter, $k$. Bearing this in mind, the error analysis below has been done both with image 051 included and excluded, although for purposes of comparison, we feel justified in leaving image 051 out.

D. Accuracy of Results

The indexes $\hat{\xi}$ and positions $y_k$ are necessarily integers because of digitization. Intermediate results such as the index
of the maximum or minimum were taken to be integers, or rounded to the nearest integer as well. This would result in some loss of precision and accuracy as rounding errors propagate. There is a possibility, therefore, that results could be in error by at least one pixel in either direction. This is not a serious shortcoming because the method is intended to be simple and its results are constrained in accuracy by the image resolution in any case.

Because the $y$ coordinate is used as the independent variable, the error will be higher when the slope of the skin-air interface gives rise to large changes in nipple position for small changes in $y$. This occurs where the skin-air interface makes a small angle with the positive $x$-direction. The solution to this would be to use test points that are located at unit increments along the border rather than along the $y$ axis. Again, in the interests of simplicity, this was not done.

Although we have distinguished between the nipple being in profile and the nipple not being in profile, there is actually a gradual transition from one to the other where the nipple may be in profile in varying degrees across different images. On the $g-y$ curve, this would represent the gradual merging of the two separate peaks as in Fig. 4(d) to the single peak as in Fig. 5(d).

In such “transitional” images, the change in $\theta$ may be too small for $\theta'_{\text{min}}$ to be less than $\theta_0$. In these cases, it will be incorrectly inferred that the nipple is not in profile, and the
result, computed from the positions of the global maximum and minimum of $g'$, may not be reliable.

E. Error Analysis

Because of the different image resolutions, the error analysis is done separately for the MIAS and UCSF/LLNL images. For the MIAS images, with image 051 included the mean error is −2.56 pixels or −1.03 mm and the rms error, 7.08 pixels or 2.83 mm. With image 051 excluded, the mean error is −0.93 pixels or −0.37 mm; and the rms error, 2.22 pixels or 0.89 mm. For the UCSF/LLNL images, the mean error is zero pixels and the rms error is 1.66 pixels or 0.70 mm. Thus, in 23 out of 24 images (96%) across two databases and two views, at resolutions of 400 or 420 μm per pixel, the rms error in the $y$-direction between the radiologist-located nipple position and the computer-estimated position was less than 1 mm. This is an order of magnitude better than the results reported by Yin et al. [5] on images of similar resolution.

F. Timing of Program

The algorithm, implemented in ANSI C, takes less than 500 ms to run on a Sun Sparcstation 2. This makes it suitable for use in systems performing on-line processing of mammograms by computer.
G. Exceptions

In cases where imaging conditions, image quality or abnormality due to benign or malignant processes modify the intensity profile or lead to an ill-defined skin air interface, this method could fail.

H. Likely Reasons for the Observed Intensity Changes

The observed intensity pattern and its behavior near the nipple invite comment. The discussion in this section is conjectural in that it is not substantiated by a model based on experimental or calculated values of the attenuation coefficients for different types of breast tissue. Rather, it is a qualitative analysis that seeks to reconcile the observed pattern with what would be expected given the anatomy, geometry and position of the breast during mammography.

The increase in intensity at the nipple could be anticipated from the convergence of the lactiferous ducts (glandular tissue) draining into it. Also, if the nipple were not in profile, it would be lying atop other tissue and adding to the attenuation (and, therefore, intensity) at that point. Anatomically [15, p. 1447] there is no fat immediately beneath the skin of the areola and nipple. If it is recalled that fat is more radiolucent than glandular tissue, this is one more reason for brighter intensities being observed near the nipple.

If the nipple were in profile, the brightening due to the ductal convergence and absence of fat would still be observed close to the nipple, directed toward the breast. However, the geometry and position would dominate the behavior of intensities at the very edge of the nipple. A nipple in profile would represent a very thin layer of tissue projecting from the rest of the breast. The attenuation of X-rays by this thin tissue layer would be comparatively small, leading to a rather faint image at that point. This is in accord with what is observed—nipples in profile are faintly imaged at their outer extremes.

I. Possible Improvements

The method is sensitive to lack of smoothness in the skin-air interface. If this interface were fitted to smooth functions such as splines, and the fitted boundary used, the results would be less dependent on the fidelity of the initial segmentation.

The use of other features, in addition to the mean of the intensity gradients along the normal [see (2)], such as their variance, needs to be investigated. The reliability measure mentioned in Section V could also be used to drive a feedback loop that would confer greater robustness on the algorithm, which at present is open-loop and cannot iteratively improve on a poor first estimate.

Moreover, the simple algorithm we have described cannot accommodate all the variations that naturally occur across mammograms. The threshold $t_0$, for example, has already been identified as one source of potential weakness.

The patterns of maxima and minima on the smoothed curves of $g, g', \theta,$ and $\theta'$ plotted against $y$ are clear enough for a human observer to guess the correct nipple location from them without difficulty in most cases. This means that the smoothed sequences $g_s, g'_s, \theta_s,$ and $\theta'_s$ are discriminating features. Because we are essentially recognizing maxima and minima in the two-dimensional neighborhood of smoothed curves, an adaptive, automatic pattern classifier (rather than a set of hierarchical rules) is likely to succeed in this task of learning from examples and generalizing reliably.

VIII. Conclusions

We have described a simple method for automatically locating the nipple on mammograms. It has been tested out on 24 images from the MIAS and UCSF/LLNL databases—at resolutions of 400 and 420 $\mu m$ per pixel—representing a spectrum of images: oblique-view, cranio-caudal-view, nipple in profile, nipple not in profile, benign, malignant, normal, fatty, glandular, and dense. It located the nipple correctly and with minimal error in 23 images or 96% of the cases. The rms error for these 23 images was less than 1 mm which is an order of magnitude better than a previously reported result in the literature [5] with images of similar resolution. The results justify the hypothesis and its underlying assumptions made at the beginning of this paper. Because of its simplicity, and because it relies both on the tissue characteristics in the nipple region and on geometry, we believe this method has the potential to be a generic means of locating the nipple automatically, especially when coupled with an automatic classifier. It is fast enough to be part of on-line processing of mammograms by computer.

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