Problems Related to Automatic Nipple Extraction

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Abstract. Computerized analysis of mammograms can serve as a secondary opinion, improving consistency by providing a standardized approach to mammogram interpretation, and increasing detection sensitivity. However, before any computer aided mammography algorithm can be applied to the nipple, one of several important anatomical features, need to extracted. This is challenging since the contrast near the border of the breast, and thus the nipple in mammograms, is very low. Therefore, in order to develop more robust and accurate methods, it is important to restrict the search area for automatic nipple location. We propose an automatic initialization of the search area of the nipple by combining a geometrical assumptions verified against the MIAS database regarding the location of the nipple along the breast border and a geometrical model for deciding how far into the breast region the nipple can occur. In addition, the modelling reduces the need for parameters determining the search area and thus making the method more general. We also investigate the variance between the medical experts often use as ground truth when determining performance measures for developed medical methods.

1 Introduction

Mammography, x-ray imaging of the breast, is currently the best method for early detection of breast cancer. During screening mammography, the radiologist may fail to detect cancer and the lack of detections may be due to the subtle nature of the radiographic findings (i.e., low conspicuousness of the lesion), poor image quality, eye fatigue, or oversight by the radiologists. Therefore it is the practise that two radiologists should analyze the mammograms to increase the sensitivity [7]. To minimize the necessity of attention by two radiologists, computerized analysis of mammograms can serve as a secondary opinion, improving consistency by providing a standardized approach to mammogram interpretation, and increasing detection sensitivity. In computerized mammography, the need to automatically detect anatomical features, such as the background (the non-breast area), pectoral muscle, fibroglandular region, adipose region and the

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nipple is very high. These entire anatomical landmarks are either direct or indirect necessary during judging mammogram in the search for abnormalities in tissue, which might be breast cancer. The first segmentation procedure involves extracting the principal feature on a mammogram; the breast border (also known as the skin-air interface). This is performed by segmenting the breast and the nonbreast into distinct regions and during this segmentation procedure it is important to preserve the nipple if it is positioned in profile. As stated, the nipple is another important anatomical feature to extract and due to positioning it does not always occur on the breast border and can be depicted inside breast tissue. The extraction of such cases is a particularly challenging image analysis task.

Our aim is to develop robust automated extraction methods for extracting the anatomical features required for an automatic patient positioning assessments in mammography. It is our intention to develop a fully automatic and generic algorithm to extract the position of the nipple. For this reason, we have in this paper developed a robust extraction of the region of interest (ROI) as an initial search area for the nipple, both along the breast border and into the breast tissue. Thereafter, we have implemented a known automatic nipple localization method and applied to our search area. Since many known techniques in medical imaging often are compared to medical expert (i.e. in our case a radiologist) we found it interesting to investigate the variance between the positions of the nipple marked by different experts.

2 Existing Approaches

There are several approaches to segment the breast region from mammograms reported in the literature. However, only a few of them also cover the locations of the position of the nipple. One of the earliest approaches to segmentation of the breast contour was presented by Semmlow et al. [5].

Méndez et al., [2] report a fully automatic technique to detect the breast border and the nipple. The proposed algorithm finds the breast contour using a gradient based method. Furthermore, Chandrasekhar and Attikiouzel, [1] outline a simple, fast and promising method (based on 24 images) for automatically locating the nipple in mammograms. Their method search for the nipple along the entire breast border except for 30% of pixels at the top and 5% of pixels at the bottom, this for avoiding artefacts, in these area, to interfere with the automatic method and produce inaccurate result.

We have noticed two interesting issues regarding existing methods. 1) In the methods where a region of interest is chosen for locating the position of the nipple the motivation for the selected area, is to our understanding not clearly stated. 2) The evaluation of the performance of the algorithms are compared to one or several experts in mammography, however, the effect the variance between them might have on the performance measure are not explicitly considered.

3 The Method of Finding the Position of the Nipple

The search area for the position of the nipple along the breast border need to be restricted for two reasons; (1) due to edge effects and artefacts that may occur at the inferior portion of the breast, near the infra-mammary fold and the chest wall and (2) due to the development of a more robust and accurate method. For this last reasons, it is also necessary to investigate how far into the glandular tissue the nipple may be imaged. By modelling the geometry of the breast, suitable initialisation of the search area can be done automatically, reducing the need for fixed numbers in the algorithm.

The dataset in this study consisted of 322 digitized mammograms from the MiniMammographic Image Analysis Society's (MIAS) Digital Mammography Database[1]. According to Suckling et al. [6], all the mammograms have been carefully selected from the United Kingdom National Breast Screening Programme to be the highest quality of exposure and patient positioning. In this method all images were low-pass filtered and reduced in resolution to 400^2 μm per pixel.

3.1 Search Region Along the Breast Border

In addition, the investigation of the geometrical approach presented in [4] based on automatically finding the pectoralis muscle and the maximum distance perpendicular to the muscle is integrated into this algorithm. The main idea is to perform the Hough transform on a gradient image. Once the line P, representing the pectoralis muscle is found a normal line N, passing through the estimated nipple $MAM = (x_{mam}, y_{mam})^T$ is approximated. To find the point, $MAX = (x_{max}, y_{max})^T$, the orthogonal maximum distance between the calculated line P and a point MAX on the breast border is estimated.

Based on 305 mammograms, the mean of euclidean distance, e, between the points MAX and MAM is 17.5 pixels with a standard deviation of 23.8 pixels. Since the nipple has an extension in area, estimates of the position of the nipple could be valid even if they are not right on the given position. In the MIAS database the mean extension of the nipple is estimated to $\ell =$ 25.3 pixels [4]. Based on this investigation we can expect to find the nipple with 99% certainty in the interval defined as $(MAX \pm 4\ell)$ along the breast border.

However, the approximation of the position of the nipple, based on the geometrical assumption, is dependent on two features: the angle of the pectoralis muscle and the shape of the breast border. The investigation of how perturbations in these two features effects the final approximation of the position of the nipple shows that the extracted angle of the pectoralis is not critical to estimate the position of the nipple by this geometrical approach. The critical aspect of the algorithm is the extraction of the breast border [4].

[1] http://www.wiau.man.ac.uk/services/MIAS/MIASweb.html

3.2 Search Region into the Breast Tissue

In order to set boundaries to the problem of how far inside the breast region the nipple can be expected to appear, some assumptions regarding the geometry of the breast were done. The main assumption is that the bulge of the breast between the compression paddles is a half-circle with radius r. Other assumptions are that the nipple is considered to be point and that the compression paddles are parallel with the image plane. With reference to Fig. 1 the geometry is approximated and under these assumption it is trivial to calculate the projected position of the center of the nipple. The values for a and b are the same for all examinations performed with a specific x-ray machine and can easily be estimated ($a \approx 60$ cm, $b \approx 1$ cm). The values of r and c is dependent on the anatomy of the particular woman under examination and we have chosen to use typical values for these parameters ($r \approx 3$ cm, $c \approx 10$ cm). The angle β is dependent on the skill of the radiographer and we have assumed that the values of β are described by a probability density function $p(\beta)$, see Fig. 1 Top Right. Based on the model and the values of the parameters the distribution of the distances of the projected nipple to the breast border was estimated, see Fig. 1 Bottom Right. Based on this distribution the distance between the projected nipple p in Fig. 1 and the breast border p_{max} in Fig. 1 was estimated at a confidence level of 99%. Depending on the choice of distribution for $p(\beta)$ the following distances were obtained: $p(\beta) = \Pi(-\frac{\pi}{2}, \frac{\pi}{2}) \rightarrow 3.73cm$, $p(\beta) = \Lambda(-\frac{\pi}{2}, \frac{\pi}{2}) \rightarrow 3.65cm$ and $p(\beta) = N(0, 0.5) \rightarrow 2.13cm$. Since it is reasonable to assume that a trained radiographer manages to position the nipple close to halfway between the compression paddles most of the times the uniform distribution ($\Pi(-\frac{\pi}{2}, \frac{\pi}{2})$) is a rather pessimistic assumption. Thus it is concluded that with a high degree of certainty, the nipple is not projected further into the breast than about 3 cm.

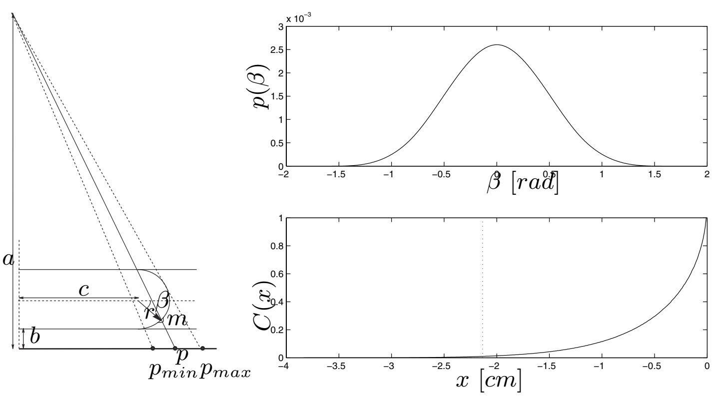

Fig. 1. Left: The geometry of nipple projection. **Right Top**: An example of a probability density function for β used in simulations. **Right Bottom**: The cumulative distribution of the probability of $x = p_{max} - p$. The dotted line marks the 99% confidence ($x = 2.13$ cm)

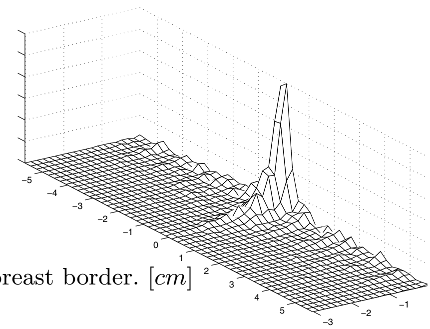

Fig. 2. Combined PDF of the position of the nipple. The mode of the distribution is located at MAX, i.e. the point on the breast border with the furthest distance to the pectoralis muscle

A perturbation analysis gives that the estimated solution is stable in the sense that errors are not magnified. This is important since this show that the error of the estimated distance is not larger than the estimation error of any of the parameters. The most critical parameter is the radius r. The empirical information presented in [4] were combined with the simulated information to generate an approximation of the 2D PDF of the position of the nipple. In order to do this it was assumed that the position of the nipple along the breast border is independent of how far into the breast the nipple was projected. The result is presented in Fig. 2. Based on the PDF it is possible to derive a narrower ROI for the nipple. For instance, we can say that with 86% certainty that the nipple is within 3 cm from the point denoted MAX.

3.3 Locating the Nipple

The breast is segmented from the background with special care taken to preserve as much as possible of the breast portion of the skin-air interface, including the nipple, if it is in profile [3]. A original mammogram (is shown to the left in Fig. 3) and to the right (in Fig. 3) the same mammogram after the breast border extraction method was applied is shown. For location of the nipple, a method developed by Chandrasekhar and Attikiouzel [1] was implemented, however, modified to search only in our defined ROI.

The breast border is denoted $B(y)$. Due to the investigation of the maximum distance MAX presented in Sect. 3.1 the search areas along the border, is restricted to all integer values of y running from $(MAX \pm 4\ell)$. The y values lying within these limits is denoted y_i, $\{i = 1, \ldots, n\}$. $B(y)$ gives the x value of the skin-air boundary for a given y in the image. To each of the n points, $(B(y_i), y_i)$ the tangent to $B(y)$ is estimated by the straight line that best fits (in the sense of least squared error) a neighbourhood of p points on the border, centred on y_i. The

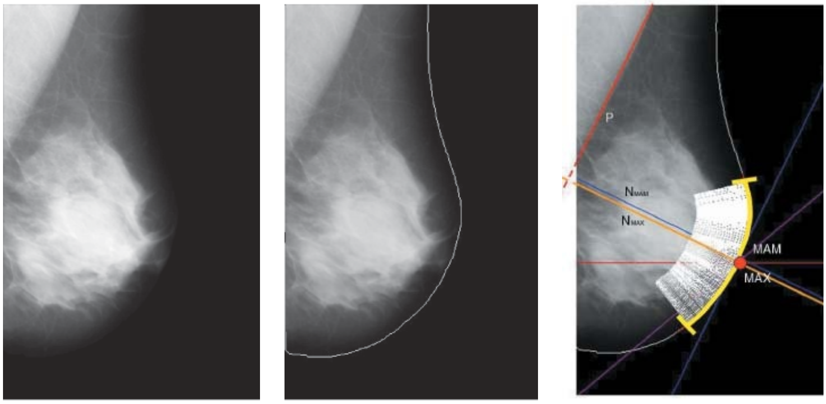

Fig. 3. Mammogram (No. 1). To the left is the original mammogram and the middle with the border outlined. To the right, the intensity gradient along the normal is plotted, the pectoralis line P and the normal to P, N passing through the point MAX and the point MAM on the breast border are also plotted. All mammograms are taken from the MIAS database

gradient of this line is denoted by m_i. The gradient of the normal at $(B(y_i), y_i)$ is estimated as $-1/m_i$, defined with concerns to the search area described above. Associated with this normal is the angle Θ_i, which it forms with the positive x-direction. Pixels intersecting the normal at various distances j, $(j = 1, \ldots, k)$, from the test point $(B(y_i), y_i)$ are identified. The depth in the normal direction, described in Sect. 3.2, k needs to be 30 mm to be certain to include the nipple. As put in pixels 30/R, where resolution R is 400 μm gives us 75 pixels in the normal direction. The intensity gradient along the normal direction, for each of these, $I(x_{ji}, y_{ji})$, is computed as (Fig. 3): $G_{ji} = \frac{I(x_{ji},y_{ji})-I(x_i,y_i)}{j}, \forall j \in (1, \cdots, k)$ and $\forall i \in (1, \cdots, n)$. The average of the k intensity gradients is defined to be the average intensity gradient along the normal, $G_i = \frac{1}{k}\sum_{j=1}^{k} G_{ji}, \forall i \in (1, \cdots, n)$.

The sequences G_i and Θ_i are smoothed and normalized to yield zero mean, and unit variance, and denoted g_i and θ_i, respectively. These two sequences are passed through a differentiator to yield g'_i and θ'_i. The maximum value of g_i is found, g_{max} and its index $i_{g_{max}}$. The minimum value of θ'_i is also found, θ'_{min} and its position, $i_{\theta'\_min}$, see Fig. 4. If θ'_{min} is less then a predefined threshold t_θ, the nipple is inferred to be in profile otherwise it is not. However, there might exist θ'_{min} which is less then t_θ, but not in profile. This is handle with a distance measure between i_{gmax} and $i_{\theta' min}$ [1].

3.4 Problems Related to Using Experts for Validation of the Method

Since our main objective is to develop a system for assessing accuracy of the breast positioning we need to investigate how to quantitatively describe quality criteria expressed in imprecise terms such as *the glandular tissue should be*

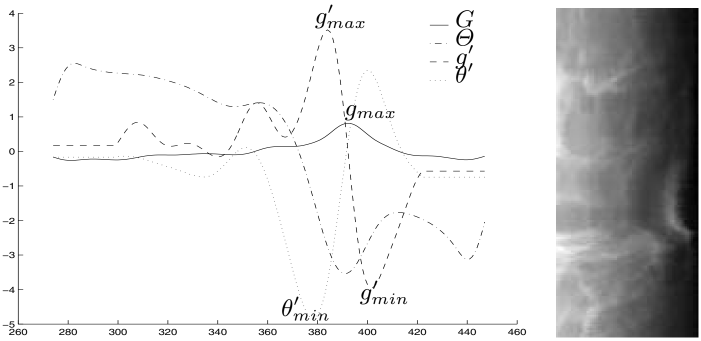

Fig. 4. Mammogram No. 101 from MIAS database. Graphs of normal intensity gradient g, its derivative g', the angle θ and its derivative θ' plotted against y coordinate of the skin-air interface. To the right, the intensity profile along the normal direction to the breast border is visualized in a grey-level intensity image

well spread. In reality, it is difficult (if not impossible) to define rules that determine the exact meaning of such a term in each possible case. Humans tend to base their decision on which is being known to them due to earlier experience in similar situations and can handle the flexibility in the definition of the notions that constitute the rules, in connection with the flexibility of human logic.

To gather data about the way in which human experts assess the quality of mammograms, we performed a questionnaire. It forms the basis for a study in which we are asking radiologists and radiographs, from several countries in Europe, to evaluate 200 randomly selected mammograms from two different standard databases common used during development of computer aided mammography methods. They are asked to mark anatomical features as well as answer questions concerning their decision making. Based on these markings we have seen that there is a large variance between the experts asked and since many medical methods use expert panels as ground truth we wanted to evaluated the accuracy of such comparison.

3.5 Definition of the Ground Truth Used for Evaluation of the Method

The accuracy of the implemented automatic nipple location algorithm is evaluated based on the 121 out of the images, described in Sect. 3. The performance measure of the automatic algorithm was evaluated by calculating the vertical distance between the extracted locations of the nipple and to locations defined as the ground truth. The ground truth was defined as follows: For each of the images in MIAS database, the images were enhance by histogram-equalizing the images so that the nipple could be easily identified and marked by one of the authors. This was carefully performed in a dark room, on a screen with high resolution three times in order to be absolutely sure that the nipple marked is

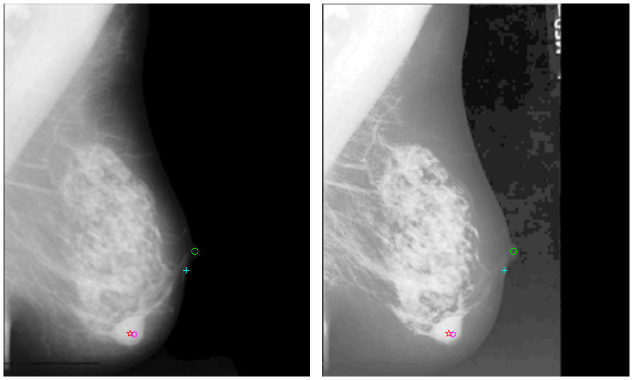

Fig. 5. A mammogram is selected for visualizing that the nipple actually can be seen on the histogram-equalize version of the mammograms. Mammogram no. 21 belongs to the subset of the most difficult mammograms to mark by a layperson. Even though this belong to the most difficult subset, we can see by carefully inspecting the image to the right that we can detect and mark the location of the nipple in this image (the circle). The marks of the three experts are the; plus sign, hexagram and pentagram

the true position of the nipple. Even in the most difficult images we can see the nipple in the enhanced images, as shown in Fig. 5.

4 Result

A fully automatic method is presented for automatically finding the location and determining whether or not the nipple is in profile. To reduce the complexity

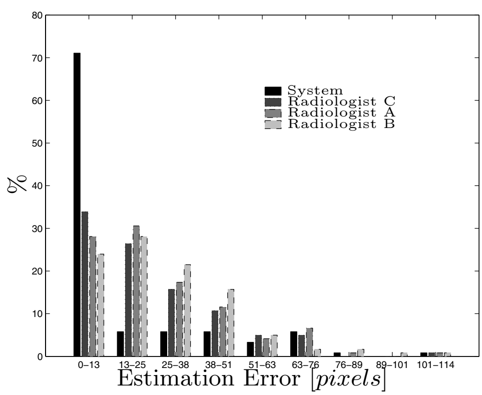

Fig. 6. The distance between the ground truth and the proposed location of the nipple by the System (leftmost column in each group), Radiologist C, Radiologist A, and finally Radiologist B (rightmost column). The errors are grouped in intervals of half the diameter of the average nipple (diameter: 23.5 pixels). Thus the first group corresponds to markings of the nipple that are placed within the nipple

of finding the locations and if the nipple was in profile, a successful method for extracting the ROI was developed. Based on this region, the proposed method is tested on 121 randomly selected mammograms from the MIAS database and produces correct result in 71% of the mammograms compared to the ground truth. Our expert panel (consisting of three mammographic experts) produced results like: 34%, 28% and 24% see Fig. 6, compared to the defined ground truth. The results given by our expert panel is only evaluated considering the location of the nipple, not the determination of the quality criteria *in profile or not*.

5 Discussion

The method for extracting the location of the nipple is based on the fact that at the nipple the glandular-like tissue extents all the way to the breast border. The evaluation of the nipple detection is more thorough (based on more images) than the ones presented in relation to comparable methods. The method has similar performance to the established technique for locating the nipple but with a higher degree of automatization and robustness. The work on detecting the nipple differs in the following points [1]: We make use of geometrical assumptions verified against the MIAS database regarding the location of the nipple along the breast border and we make use of a geometrical model for deciding how far into the breast region that the nipple can occur. These two models allow us to restrict the search for the nipple to an area smaller than the ones proposed by others, but still knowing that we can be very certain that the nipple will occur within the area. Furthermore, the modelling, reduces the need for fixed numbers to determining the search area and thus making the method more general.

The 71% correctly classified nipple features is a lower performance measure than the performance measure reported by Chandrasekhar and Attikiouzel [1]. However, one reason that might reduce the performance measure of our implementation compared to Chandrasekhar and Attikiouzels' [1] implementation is the difficulty of based on an algorithm described in a paper implement and test the same method. Most likely something is either missed to explain by the authors or misinterpreted during our implementation. However, the most interesting is the performance measure difference between our method and the experts compared to the ground truth.

One critical point in our evaluation of the performance measure might be that we actually compare our method to ground truth that we have defined. However, if we observe the image on which we adjusted the contrast during marking, we can see that it is quite obvious on these enhanced images even for laypersons where the locations of the nipple are (Fig. 5).

According to the radiologists' marking compared to the ground truth it appears, knowing that the ground truth is quite true, that many of their markings do not correspond to the location of the nipple. This give rise to the question "what feature do the experts consider the location of the nipple?" One answer might be that our expert panel is asked to mark the anatomical features on mammogram with lower resolution than they are used to in their clinical practice. Another might be that they are not necessary in their clinical environment while marking these anatomical features. On the other hand, one reference radiologist was, prior to the quality questionnaire study, sent both paper copies and copies printed on copier film of the mammographic database, which could be put on the light box commonly used in their clinical environment considered the mammogram printed on paper to give the highest contrast and was considered suitable for the specific task.

One important thing to remember is that the performance measure of many algorithms in medical imaging is compared to an expert panel, consisting of one to several experts, where the experts often are physician (like our expert panel) working daily with the particular task the algorithm is developed to solve.

Finally, automatic extraction of features in medical images is a well known difficult task. Several pre-processing step might quite often ease the task significantly. Not only considering pre-processing image processing methods but also considering methods to reduce the problem by selecting region of interests (ROI) are useful. However, if this should be useful for the automatic method, these ROI methods needs to not only be dynamic related to some features of the object in focus for extraction (i.e. in our case, related to features of the breast object) but also fully automatic.

6 Conclusion

The automatic development of the region of interest and then the evaluation by implementing a known nipple location method show good results based on comparison to the ground truth. This indicates that for future work a more robust and comprehensive location detection algorithm of the nipple might has performance measures with even higher accuracy. Unfortunately since the question "how are we going to evaluate our method since there is, for many medical applications, no objective ground truth available" is still unanswered, we also need to develop objective methods for assessing ground truth, which most be used for evaluating the developed method.

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