Gradient Flow Based Detection of Prominent Points on BCCT Depth-Map Images

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Abstract

Breast Cancer Conservative Treatment (BCCT) is established as the most used procedure for breast cancer treatment. The use of this technique made essential the aesthetic outcome evaluation. Surgical outcome depends on several factors, leading to significantly heterogeneous results, due to the difficult to assess them. The limited reproducibility of subjective evaluation, led to the development of different techniques based on objective methodologies, such as Breast Cancer Conservative Treatment.cosmetic results (BCCT.core) software tool. Recently, several studies proved that the introduction of simple three-dimension (3D) approaches could improve the performance of BCCT.core, maintaining the simplicity and concept behind the tool. The introduction of this new type of data, led to new challenges on the detection of important characteristics.

The objective of this work is to develop a simultaneous detection of breast contour and breast peak point, in images acquired using a depth-based low-cost system. Experimental results show the suitability of our depth-map based approach. The proposed algorithm has proven accurate and robust for a wide number of patients. Additionally, in comparison with previous research, the procedure for detecting prominent points was automated.

1 Introduction

Breast conservative therapeutic methodologies aim to obtain, local tumour control and survival rates equivalent to mastectomy, with better aesthetic results. However, the cosmetic outcome does not yet have an evaluation standard [2].

Until recently, the aesthetic evaluation was performed subjectively by one or more observers either by directly observing the patient or photographs, using scales which compares the treated with non-treated breasts. The most widespread scale is the Harvard scale, introduced by Jay Harris in 1979, which classifies the overall cosmetic results in four classes from excellent, good, fair to poor. Soon became clear that this kind of subjective evaluation had significant disadvantages. For example, exemption is not guaranteed, reproducibility is difficult to attain and the level of agreement between observers is low or moderate.

Objective methods were introduced in an attempt to overcome the lack of objectivity and reproducibility. These methods compare the two breasts with simple measurements marked directly on the patients or on photographs of them. BCCT.core [1] is a recent computer-aided tool, which predicts the overall cosmetic result using features semi-automatically extracted from frontal photographs of patients. These features captures some of the factors which are considered to have an impact on the overall cosmetic results: breast asymmetry, skin colour changes caused by radiotherapy and surgical scar [1]. Although it is innovative and reproducible, this tool has important setbacks that are related to the complete automation of the software – which is fundamental for high reproducibility – and the ability to extract volumetric information to improve the overall cosmetic evaluation.

Several research groups have recently made efforts with 3D technology [3, 4]. However, current 3D technologies are very costly and difficult to operate, thus requiring specialized staff and are not a feasible choice for daily clinical practice, therefore, its widespread use in the near future is not predictable.

Recently, we introduced Microsoft Kinect [5] as a promising low-cost and easy to use tool to evaluate the aesthetic result of BCCT, because it can not only simplify automation, but also provide volumetric data.

The goal of this paper is to model the mutual context of *breast contour* and *breast peak* (the area in the breast closer to the camera or further away from the chest wall, not necessarily the nipple) so that each can facilitate the recognition of the other.

2 Detection of Breast Contour and Breast Peak Points

Using context to aid visual recognition is recently receiving more and more attention. Context plays an important role in recognition in the human visual system, with many important visual recognition tasks critically relying on it.

When performed independently (breast contour and breast peak points detection), both tasks are non-trivial since many other parts of the image may be falsely detected. However, the two tasks can benefit greatly from serving as context for each other [6]. The algorithm was implemented with the following operations: 1) background segmentation; 2) breast peak candidates detection; 3) contour detection; 4) peak and breast contour decision. The simultaneously detection of the peak and breast contour will be addressed first by over-detecting peak candidates, followed by a contour detection near them.

Although the background should preferably be uniform for the acquisition process, sometimes it is cluttered. The presence of different objects at different depths, possibly at depths similar to the patient's, dismisses the application of simple thresholding methods, such as Otsu's (see Fig. 1(c)). To solve this problem we admit that the patient is in a somewhat central position in the image and it is likely the 'object' closer to the camera. A density image was defined by transforming the depth information on the XY plane to the XZ plane, where the value at position (x,z) represents the histogram of the column x, by counting along the Y direction (see Fig. 1(a)). Then for each (x,z) position we computed the variance above and below. Each column x presents 3 different patterns: (1) background; (2) 'object' and background; (3) 'object'. The XZ image is then replaced by the following rule: (1) cumulative value of the minimum of the variance from 1 to $Nbins$; (2) average of the two variances; (3) cumulative value of the minimum of the variance from $Nbins$ to 1 (see Fig. 1(b)) A global thresholding method of the original XY image corresponds to defining a horizontal line in the XZ image, discriminating background from foreground (see Fig. 1(a) and Fig. 1(c)). An adaptive thresholding method can be defined as a curve in the XZ image from left to right margins. This results in a threshold that varies from column to column in the original XY image. Since it is necessary for the curve in the XZ image to avoid the parts of the image with high values (high countings), the threshold curve was computed as the shortest path from left to right margin, where the cost of each pixel is its 'intensity' value (see Fig. 1(b) and Fig. 1(d)).

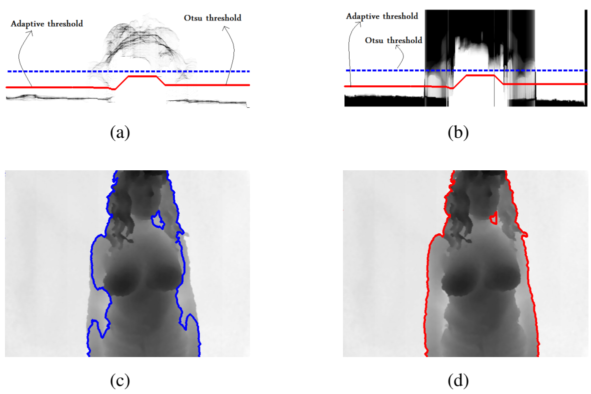
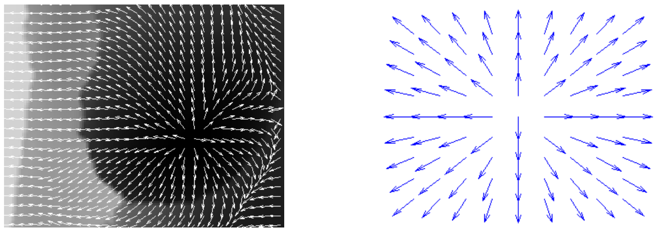


Figure 1: a) XZ plane depth information; b) XY variance plane; c) Otsu's segmentation; d) Adaptive segmentation.

To model the breast peak point, a filter is used which evaluates the degree of divergence of the gradient vectors within its region of support from a pixel of interest (see Fig. 2). The peak point of the breast corresponds to the point in the breast where disparity attains the lowest value. The typically round or tear drop shape of a breast, leads to a distinctive pattern in the gradient vector field where the gradient diverge in all directions (see Fig. 2(a)). Breast peak candidates were detected based on all local maximum positions, assessing the similarity between the template (see Fig. 2(b)) and the image using two different measures: cross-correlation ($(f*g)[n] \stackrel{def}{=} \sum f^*[m]g[n+m]$), where f^* denotes the complex conjugate of f; and circular correlation introduced by Nicholas Fisher in 1983.

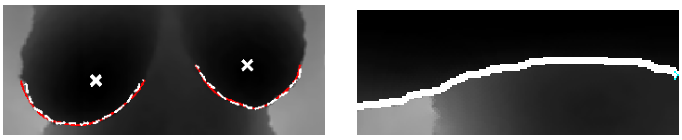


(a) (b)

Figure 2: (a) Breast gradient vector field (5-pixel spacing); (b) Template vector field.

Breast contour detection was performed using a shortest path approach. Intuitively, breast boundary manifests itself as a change in the grey-level values of the pixels, thus originating an edge in the resulting image. Therefore, interpreting the image as a graph with each pixel as a node and edges connecting adjacent pixels, the breast contour corresponds to a low-cost path through pixels, with the appropriate weight function. Since the breast contour is approximately circular and centered on the breast peak candidates, the computation is more naturally performed by adopting polar coordinates, with the origin of the coordinates in the peak candidate. Each column in the polar image corresponds to the gradient along each radial line in the original space, computed using a 3-point numerical differentiation: $G_\theta(r) = \frac{f(r+h)-f(r-h)}{2h}$, where $h = 1$ and r is the radius. Then, the gradient image is considered as a weighted graph with pixels as nodes and edges connecting neighbouring pixels. Each 4-neighbour pixel arc corresponds to a weight determined by the gradient value of the two incident pixels, expressed as an exponential law: $f(g) = f_l + (f_h - f_l)\frac{\exp(\beta(255-g))-1}{\exp(\beta 255)-1}$, with $f_l, f_h, \beta \in \Re$ and g is the minimum of the gradient computed on the two incident pixels. For 8-neighbour pixels the weight was set to $\sqrt{2}$ times that value. The parameters f_l, f_h, and β were fixed at $f_l = 2$, $f_h = 128$, $\beta = 0.0208$.

In this work, we are mainly interested in obtained the localization of the breast contour, not so much in its complete delineation. Therefore, the angle θ was varied only between π and 2π (see Fig. 3(a)). The candidate contour was then the output of the shortest path algorithm in the polar image (see Fig. 3(b)). The shortest path was computed between the whole external margin and a single point (point of highest gradient) in the internal margin.



(a) (b)

Figure 3: (a) Breast contour - ground truth (solid red line), detected (dashed white line); (b) Polar image and detected contour (white line).

The quality or probability of the join model ($Q(Cp) = \mu(\Delta C)\cdot\rho_p$) for the co-occurrence of breast peak and breast contour will be proportional to the individual qualities of the two parts, where $\mu(\Delta C)$ is the mean gradient alongside the contour and ρ_p is the cross-correlation of the centre candidate. Therefore, the final decision consists in selecting the pair (peak, contour) that maximizes the quality measure.

3 Results

The database now consists of 144 cases (depth images with 640×480 px). Manual ground truth annotation was performed both to breast peaks position and breast contour definition. The breast peak points detection accuracy was measure using Euclidean metric distance (see Table 1).

Table 1: Breast peak points detection error (in pixels).

Metric	Breast	Standalone		Simultaneous detection	
		μ (σ)	# Miss	μ (σ)	# Miss
Circ. corr.	Right	18.02 (46.86)	16	8.23 (14.34)	8
	Left	13.61 (39.02)		10.32 (27.51)	
Cross-corr.	Right	8.65 (17.65)	4	5.81 (3.44)	0
	Left	6.68 (3.60)		6.68 (3.60)	

First column (standalone) shows the detection error that would be obtained by grounding the decision on the maximization of the output of the convergence filter. The second column (simultaneous detection) depicted the performance for the proposed scheme. Miss detection means that breast peak point was detected outside from breast area. It is clear the advantage of the proposed method. Moreover the cross-correlation attains better results both in the mean error and in the miss detection.

Breast contour detection error was evaluated based on the Hausdorff and the average distances (Table 2). The Hausdorff distance is defined as $h(A,B) = \max_{a\in A}\min_{b\in B}\|a-b\|$, where B represents the set of pixels of the ground truth and A the segmented breast contour; $\|.\|$ is the Euclidean distance. The motivation for using this metric is that it represents the worst case scenario.

Table 2: Breast contour detection error (in pixels).

	Right breast		Left breast	
	Mean	Hausdorff	Mean	Hausdorff
Average	1.80	4.88	1.83	5.21
Stdev	0.90	2.27	1.11	2.80

4 Conclusions

In this paper part we presented the simultaneous detection of prominent points on the breast using depth-map data acquired with a Microsoft Kinect sensor. Breast peak points were found based on gradient vector field information associated with the convergence filter theory. Breast contour was found as the solution to the shortest path problem is the graph theory framework, after conveniently modelling the image as a weighted graph. It was shown that depth-map images facilitate the automation of BCCT.core, keeping this software low-cost and easy to perform. The results obtained also indicate an excellent performance and robustness for a wide variety of patients. Since the Kinect resolution is 1.3mm/px, the average error corresponds to 2.36mm. Future work will focus on the detection of the complete breast contour, including start and end points, conversion of prominent points to colour images, automatic nipples detection and extraction of volumetric information.

Acknowledgments

This work is financed by the ERDF - European Regional Development Fund through the COMPETE Programme (operational programme for competitiveness) and by National Funds through the FCT - Fundação para a Ciência e a Tecnologia (Portuguese Foundation for Science and Technology) within project FCOMP - 01-0124-FEDER-022701 PhD grant with reference SFRH/BD/43772/2008 and project PTDC/SAU-ENB/114951/2009.

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