Breast Contour Detection for the Aesthetic Evaluation of Breast Cancer Conservative Treatment

Jaime S. Cardoso[1] and Maria J. Cardoso[2]

[1] INESC Porto, Faculdade de Engenharia, Universidade do Porto, Portugal
jaime.cardoso@inescporto.pt
[2] Faculdade de Medicina, Universidade do Porto, Portugal
mjcard@med.up.pt

Summary. Cosmetic assessment of breast cancer conservative treatment (BCCT) plays a major role in the evaluation of this form of treatment. Objective assessment methods are being preferred to overcome the drawbacks of subjective evaluation. A recent computer-aided medical system was developed to objectively and automatically perform the aesthetic evaluation of the result of BCCT. In order to extract relevant features from the image, the detection of the breast contour is necessary. In this paper an algorithm based on the shortest path on a graph is proposed to detect the breast contour. The proposed method was applied to 300 breast images with an accuracy of 98%.

1 Introduction

Breast cancer conservative treatment (BCCT) has been increasingly used over the last few years as a consequence of its more acceptable cosmetic outcome when compared with mastectomy, but with identical oncological results. Although considerable research has been put into BCCT techniques, diverse aesthetic results are common, highlighting the importance of this evaluation in institutions performing breast cancer treatment, so as to improve working practices.

Traditionally, aesthetic evaluation has been performed subjectively by one or more observers [1].The categorization of the aesthetical result relies on the complex interplay of various factors, subjectively estimated and combined by observers through visual inspection. Taking into account the inherent subjectivity of any human decision, the final evaluation of aesthetic result performed by observers is questionable. In fact, this form of assessment has been shown to be poorly reproducible [2], which creates uncertainty when comparing results between studies. It has also been demonstrated that observers with different backgrounds evaluate cases in different ways [3].

Objective methods of evaluation have emerged as a way to overcome the poor reproducibility of subjective assessment. Initially they consisted only of measurements between identifiable points on patient photographs [2]. The correlation of objective measurements with subjective overall evaluation has been reported by several authors [2]. Latter, the overall cosmetic outcome was simply the sum of the individual scores of subjective and objective individual indices [4]. Recently, a computer-aided medical system was developed to objectively and automatically perform the aesthetic evaluation of the result of the intervention [5]. The development of this system entailed the automatic extraction of several features from the photographs (Fig. 1), capturing the main factors with impact on the overall cosmetic result: breast asymmetry, skin colour change due to the treatment and surgical scar visibility. In a second phase, a support vector machine classifier was trained to predict the overall cosmetic result from the recorded features [5].

(a) Facing, arms down. (b) Facing, arms up.

Fig. 1. Positions used in the photographs.

In order to extract the identified relevant features from the image, the detection of the breast contour is necessary. In this work, an algorithm for the automatic detection of the breast contour is described. The proposed approach is formulated as the solution to the shortest path between the end points of the breast contour, after conveniently modelling the image as a weighted graph. The algorithm has been implemented in a semi-automatic software, where the user just has to identify some key points on the image: breast contour end points and nipples position. The software automatically finds the contours, extracts relevant features and outputs a predicted overall cosmetic assessment (*excellent*, *good*, *fair*, *poor*).

Previous work

Although several studies have addressed breast contour detection, they all concern the detection on digital mammograms, on a side view of the breast — see [6] and references within. Our preliminary research was based on the polynomial modelling of the breast contour. After a pre-processing step to extract image edges (using e.g. a canny detector), a 2D polynomial $P_n(x, y)$ was then fitted by a regression method to the contour pixels. Suitable degrees of the polynomial were evaluated. Nevertheless, results were unsatisfactory as the regression was biased by the high number of contour pixels not belonging to the breast and/or the polynomial had not enough flexibility to adjust to the breast contour. Note that the breast contour may be severely deformed, departing from the typical round or tear drop shape.

A second line of experiments was conducted with active contours. Active contours have also been successfully applied to breast contour detection on mammograms [7]. However, results were still behind the expected. Moreover, the computation time was excessive. The minimization of the user involvement and the total user's time required for contour detection is obviously paramount.

2 A shortest path approach to contour detection

Knowing the two endpoints of the breast contour (inputted by the user), we are left with the problem of finding the path between both endpoints that goes through the breast contour. As the interior of the breast itself is essentially free of edges, the path we are looking for is the shortest path between the two endpoints, **if** paths (almost) entirely through edge pixels are favoured.

2.1 Definitions and notation

A *graph* $G = (V, A)$ is composed of two sets V and A. V is the set of nodes, and A the set of arcs (p, q), $p, q \in V$. The graph is *weighted* if a weight $w(p, q)$ is associated to each arc, and it is called a *digraph* if the arcs are directed, i.e., $(p, q) \neq (q, p)$. A path from p_1 to p_n is a list of unique nodes $p_1, p_2, \ldots, p_n$, $(p_i, p_{i+1}) \in A$. The *path cost* is the sum of each arc weight in the path.

In graph theory, the shortest-path problem seeks the shortest path connecting two nodes; efficient algorithms are available to solve this problem, such as the well-known Dijkstra algorithm [8].

2.2 Proposed algorithm

To detect the breast contour we propose a two step approach:

1. Apply an edge detector to the original image. The resulting binary image enhances the points of interest.
2. Detect the breast contour on the edge image, by finding the shortest path between the two endpoints defined by the user.

We now detail this second step.

Starting by modelling the edge image as a graph, match a node to each pixel. Connect two nodes with an arc on the graph iff the corresponding pixels are neighbours (8-connected neighbourhoods) on the image. The weight of each arc is a function of pixels values and pixels relative positions — see Fig. 2:

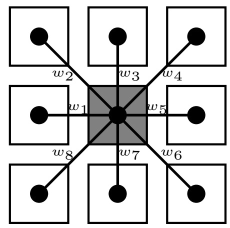


Fig. 2. Arc weight between two pixels.

$$w_i = \begin{cases} f(p, q_i) \text{ if } q_i \in \text{ 4-connected neighbourhood of } p \\ h(p, q_i) \text{ if } q_i \notin \text{ 4-connected neighbourhood of } p \end{cases}$$

In this work we set $h(.,.) = \sqrt{(}2)f(.,.)$.

Now, because we want to favour paths through edge pixels, we set

$$f(p, q) = \begin{cases} c_1 \text{ if both p and q are edge pixels} \\ c_2 \text{ otherwise} \end{cases}$$

with $c_2 > c_1$. In this work c_1 and c_2 were experimentally determined as 2 and 32, respectively. Note that c_1 must be set greater than zero in order to also favour the smallest path, when more than one exists through edge pixels only. Finally, the solution to the shortest path problem will yield the intended breast contour.

2.3 Algorithm generalization

The proposed paradigm can be conveniently generalized. The application of an edge detector in the first step can miss to detect segments of the breast contour. This is especially true for women with small breasts (leading to weak contours) or when the breast is severely deformed with the excision of a large sample of tissue. A natural improvement is to replace the binary image outputted by the edge detector with a richer gradient image. Now, the shortest path algorithm should try to follow pixels with high gradient values. The $f(.,.)$ and $h(.,.)$ functions have to be properly generalized. A simple strategy is to set $f(p, q) = \hat{f}(255 - \min(p, q))$, where $\hat{f}(.)$ is a monotonically increasing function. Note that this more general setting has the binary case as a particular instantiation. To summarize, the proposed general framework to find the contour between two endpoints encompasses:

- A gradient computation of the original image. In a broader view, this can be replaced by any feature extraction process that emphasizes the pixels we are seeking for.
- Model the gradient image with a weighted graph, assigning to the weight between two neighbour pixels the cost $w(p,q) = f(p,q)$ or $w(p,q) = h(p,q)$, as described before.

3 Results

The proposed methodology was applied to a set of images from 150 patients. For each patient two positions were assessed: facing, arms down and facing, arms up (see Fig. 1). Before applying the breast contour detection, each image was downsized to a constant width of 768, keeping the aspect ratio. Only the luminance information was used in the analysis.

The binary model makes use of the Canny edge detector [9] on the first step, as implemented in the Open CV library [10]. The low and high thresholds were experimentally tuned to 32 and 128, respectively. In the graph derived from the binary image, costs were assigned as previously stated: 2 when both incident pixels are edge pixels, 32 otherwise. The gradient model is based on the Sobel operator. The Sobel operator is applied on the x and y directions; from the computed values, S_x and S_y, the magnitude of the gradient is estimated as $z = \sqrt{S_x^2 + S_y^2}$. Costs were assigned based on an exponential law:

$$\hat{f}(z) = \alpha \exp(\beta z) + \delta, \quad \alpha, \beta, \delta \in \Re$$

The parameters α, β, δ were chosen to yield $\hat{f}(0) = 2$ and $\hat{f}(255) = 32$, leading to the same range of costs as the binary model. The third degree of freedom was experimentally tuned. The adopted transformation was (see also Fig. 3) $\hat{f}(z) = 0.15 \exp(0.0208z) + 1.85$.

Fig. 4 shows three breast contour detection results obtained with the binary model. The end points specified by the user are shown as small circles. The method successfully completed the gaps between detected edge pixels and ignored spurious edge pixels.

Problems with the binary model are noticeable when the edge detector misses to detect significant portions of the breast contour. The shortest path algorithm is misled to follow non-breast pixels — see Fig. 4(f) and Fig. 4(i). The gradient model presents a more robust behaviour, correctly following the breast contour, even in the presence of contours not well defined — see Fig. 5. While in the right breast of Fig. 4(f) the binary model followed a straight path to fill the gap corresponding to a soft edge, the gradient model correctly

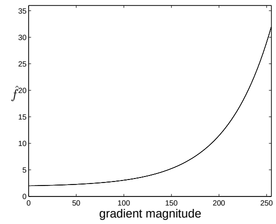
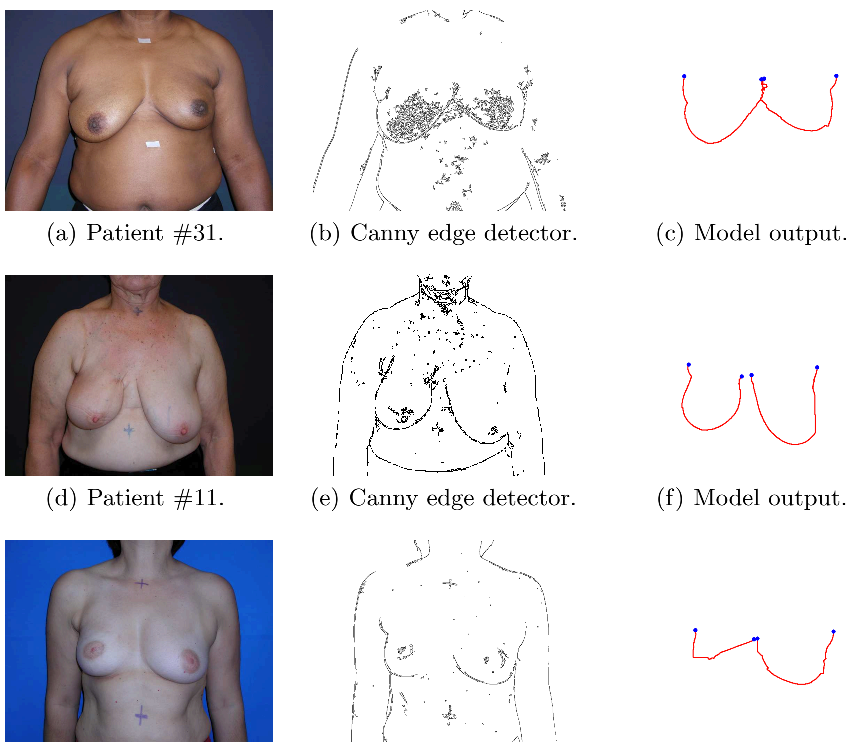


Fig. 3. Transformation $\hat{f}(.)$.



(a) Patient #31. (b) Canny edge detector. (c) Model output.

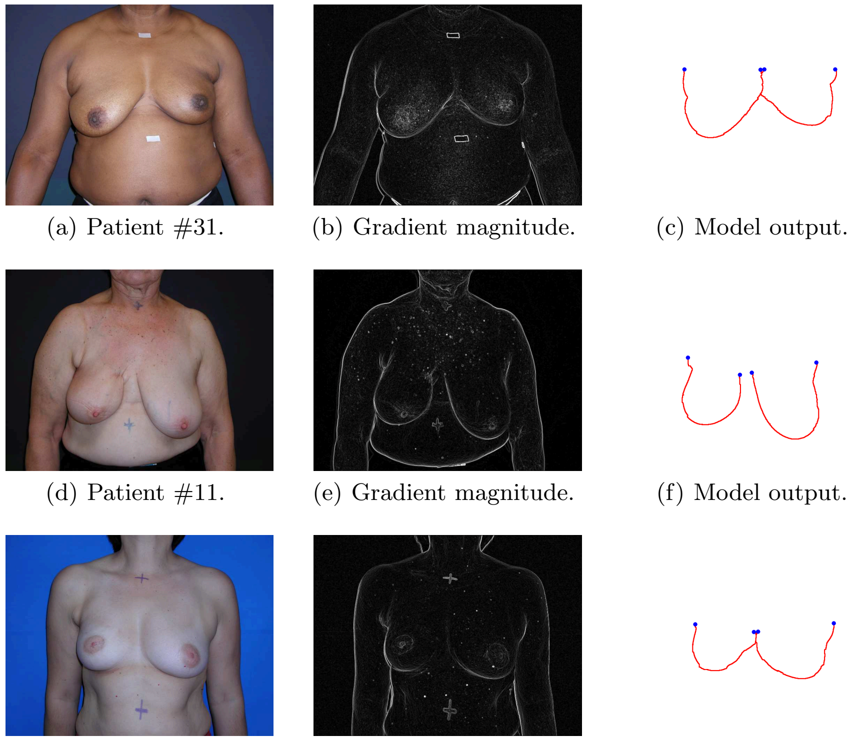
(d) Patient #11. (e) Canny edge detector. (f) Model output.

(g) Patient #27. (h) Canny edge detector. (i) Model output.

Fig. 4. Results for the binary model.

followed the contour. Similarly, in Fig. 4(i) the binary model was completely deceived by the presence of edges around the nipple and their absence along the breast contour; the gradient model properly identified the contour.

Finally, the evaluation of the breast contour detected in the photographs was performed by an observer, in the photograph dataset. The accuracy of



(a) Patient #31. (b) Gradient magnitude. (c) Model output.

(d) Patient #11. (e) Gradient magnitude. (f) Model output.

(g) Patient #27. (h) Gradient magnitude. (i) Model output.

Fig. 5. Results for the gradient model.

contour detection is presented in Table 1, discriminated by arms down/ arms up and treated/untreated breast.

Table 1. Performance of the proposed method.

	arms down		arms up		average
	treated	untreated	treated	untreated	performance
binary	0.94	0.97	0.91	0.94	0.94
gradient	0.98	1.00	0.96	0.98	0.98

Results bring to light the superiority of the gradient model over the binary model. Moreover, both models behave worse on the treated breasts than on the untreated breasts, most likely due the deformations resulting from the treatment. It is also visible a better performance in the arms down position, this time due to the better definition of the breast contours.

4 Conclusions

We have described how the breast contour can be found as the solution to the shortest-path problem is the graph theory framework, after conveniently modelling the image as a weighted graph. The proposed approach is computationally efficient, taking only a few milliseconds to detect a breast contour, in a standard PC. This is an important aspect in user interactive applications. Preliminary results also indicate an excellent performance. The proposed framework can potentially be applied on similar edge tracking problems.

Acknowledgments

This work was partially funded by Fundação para a Ciência e Tecnologia (FCT) - Portugal through project PTDC/EIA/64914/2006.

References

1. J. R. Harris, M. B. Levene, G. Svensson, and S. Hellman, "Analysis of cosmetic results following primary radiation therapy for stages i and ii carcinoma of the breast," *International Journal of Radiation Oncology Biology Physics*, vol. 5, pp. 257–261, 1979.
2. D. R. H. Christie, M-Y. O'Brien, J. A. Christie, T. Kron, S. A. Ferguson, C. S. Hamilton, and J. W. Denham, "A comparison of methods of cosmetic assessment in breast conservation treatment," *Breast*, vol. 5, pp. 358–367, 1996.
3. M. J. Cardoso, A. C. Santos, Jaime S. Cardoso, H. Barros, and M. C. Oliveira, "Choosing observers for evaluation of aesthetic results in breast cancer conservative treatment," *International Journal of Radiation Oncology, Biology and Physics*, vol. 61, pp. 879–881, 2005.
4. S. K. Al-Ghazal, R. W. Blamey, J. Stewart, and A. L. Morgan, "The cosmetic outcome in early breast cancer treated with breast conservation," *European journal of surgical oncology*, vol. 25, pp. 566–570, 1999.
5. Jaime S. Cardoso and Maria J. Cardoso, "Towards an intelligent medical system for the aesthetic evaluation of breast cancer conservative treatment," *Artificial Intelligence in Medicine*, vol. 40, pp. 115–126, 2007.
6. H. Mirzaalian, M. R. Ahmadzadeh, and F. Kolahdoozan, "Breast contour detection on digital mammogram," in *Proceedings of IEEE International Conference on Information and Communication Technologies (ICTTA'06)*, 2006, vol. 1, pp. 1804–1808.
7. Michael A. Wirth and Alexei Stapinski, "Segmentation of the breast region in mammograms using snakes," in *Proceedings of the First Canadian Conference on Computer and Robot Vision (CRV04)*, 2004, pp. 385–392.
8. E. W. Dijkstra, "A note on two problems in connexion with graphs," *Numerische Mathematik*, vol. 1, pp. 269–271, 1959.
9. J. Canny, "A computational approach to edge detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 8, pp. 679–698, 1986.
10. "Intel corporation, open source computer vision library," http://www.intel.com/technology/computing/opencv/index.htm.