Deep Edge Detection Methods for the Automatic Detection of the Breast Contour

Nuno Freitas[1]
nuno.p.silva@inesctec.pt
Daniel Silva[1]
daniel.j.barros@inesctec.pt
Carlos Mavioso[2]
carlos.mavioso@fundacaochampalimaud.pt
Maria J. Cardoso[2]
maria.joao.cardoso@fundacaochampalimaud.pt
Jaime S. Cardoso[1]
jaime.cardoso@inesctec.pt

[1] CINDERELLA Team,
INESC TEC,
4200-465, Porto, Portugal

[2] Breast Unit,
Champalimaud Foundation,
1400-038, Lisbon, Portugal

Abstract

Breast cancer conservative treatment (BCCT) is a form of Breast Cancer treatment used to treat early-stage breast cancer patients as an alternative to mastectomy. This procedure consists of removing the cancerous tissue and maintaining the remaining healthy tissue intact, thus, improving aesthetic results. Currently, there is still no gold standard for evaluating the aesthetic outcome of BCCT objectively.

Recent approaches, such as the BCCT.core, automatically classify the results based on key features extracted from digital photographs of the breast. For this automatic approach to be applicable on a large scale it is necessary to automatically extract breast features from digital photographs. Our approach improves upon previous work that used the shortest path for the detection of breast contour by using a Deep Learning model for edge detection. This method achieved state-of-the-art results and surpassed the conventional method on 2 out of 3 datasets.

1 Introduction

Breast cancer is the most frequently diagnosed cancer in women worldwide. According to recent data [6], the mortality rate of breast cancer has been steadily decreasing in the past years, which created an interest in the scientific and medical community on the patient's Quality of Life (QoL) after treatment. BCCT has become a frequent alternative to mastectomy as it achieves a superior cosmetic outcome with a similar survival rate. Despite that, there is still no gold standard for objectively evaluating the cosmetic results of the operation. Common practice includes a subjective appreciation of the aesthetic outcome.

The aesthetic classification of BCCT is commonly done according to the Harvard scale introduced by Jay Harris [5]. This scale separates outcomes into 4 categories: Excellent, Good, Fair, and Poor. Considering the subjectivity of human evaluation, recent approaches have developed objective methods for the classification of the aesthetic outcome of BCCT using digital photographs of the patient.

Fitzal *et al*. [3] and Cardoso and Cardoso [1] have proposed semi-automatic methods for the objective evaluation of BCCT aesthetic outcomes based on breast features identifiable on digital images of the patient. Both methods need human annotation of keypoints in the photographs. In that way, it is important to improve the automatic extraction of features from digital photographs. The main contribution of this work is the introduction of Deep Edge detection methods with the shortest path method introduced by Cardoso and Cardoso [2] for the semi-automatic detection of the breast contour. A more comprehensive version of this work can be found at [4].

1.1 Previous Work

In 2008 Cardoso and Cardoso proposed an automatic method for breast contour detection in BCCT patients based on 2D digital torso images [2]. This method requires previous knowledge of breast endpoints. It calculates the shortest path between endpoints using the Dijkstra algorithm to find the breast contour.

For this, it is necessary to model the image as a graph-like object, where pixels representing edges have lower values and, thus, are preferred in path selection. For this, Cardoso and Cardoso used the Sobel operator for edge detection and then converted it to a weighted graph where each node represents a pixel and the weight of each arc can be calculated by the pixels connecting them. Finally, the Dijkstra algorithm is used to calculate the shortest path between the breast endpoints. The cost of any path in a graph is defined by the sum of all arcs connecting its nodes.

In 2019 Silva *et al*. [7] proposed a new Deep Neural Network (DNN) model for automatic keypoint detection. This model used two modules: The first module used the U-NET to generate 2 consecutive heatmaps obtained from Gaussian filtering the ground truth keypoints. The second module used keypoint regression to detect the breast keypoints from the generated heatmaps.

2 Our Method

The method proposed follows a hybrid approach that joins conventional and Deep methods. It consists of two modules: Deep Edge Detection and Shortest Path Estimation. This approach is similar to the method developed by Cardoso and Cardoso [2] but replaces the Sobel Edge detector with a Deep Model trained for Edge Detection. The rationale behind this method is that the Deep Edge Detection can be trained to enhance skin edges and, thus, improve the result of the shortest path approach.

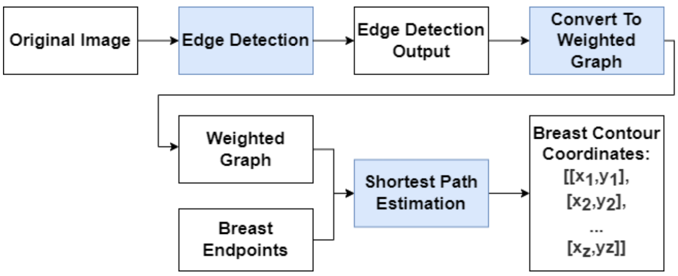

Figure 1: Diagram of the method pipeline.

2.1 Model Optimization

Like in the conventional approach, the Edge Detection output is used to model a graph for shortest path estimation. Let I be an image in the dataset and gt(I) be the annotated groundtruth path between a starting pixel $\mathbf{x}_s$ and an ending pixel $\mathbf{x}_e$. In addition, let $\mathbf{w}$ be the set of all parameters of our neural network (NN) and $f(I;\mathbf{w})$ be the (edge) map outputted by the NN. The cost of the groundtruth path in the current edge map can be represented as $c_{gt}(f(I;\mathbf{w}), gt(I))$. For the current edge map, we also compute the predicted shortest path between endpoints $\mathbf{x}_s$ and $\mathbf{x}_e$, pp(f(I;$\mathbf{w}$); $\mathbf{x}_s$, $\mathbf{x}_e$) using the Dijkstra algorithm. The goal is for the NN to learn edge representations that favor the breast contour and, thus, make the predicted path the same as the ground truth.

$$\mathcal{L}(I;\mathbf{w},\mathbf{x}_s,\mathbf{x}_e) = ReLU\left(cost(gt;f(I;\mathbf{w})) - cost(pp;f(I;\mathbf{w}))\right) \quad (1)$$

Our loss function penalizes cases where the cost of the true path is higher than the cost of the predicted path (Equation 1).

2.2 Deep Edge Detection

As discussed before, the new method uses a Deep model for Edge detection. Our model, SobelU-Net, (as seen in Figure 2), incorporates the Sobel filter in the UNet traditional architecture. The pipeline follows the basic U-Net model and includes an accompanying encoding path that starts with the Sobel operation result of the original image. The encoder pathway uses four sets of convolutional blocks, composed of two 3x3 convolutional operations followed by max pooling. After the convolutional operations, it reaches the bottleneck stage with 256 features. The decoding pathway takes the bottleneck representations and performs four iterations of convolutional blocks. In each iteration it concatenates and crops the decoded rendering with an encoded block from the Sobel pathway.

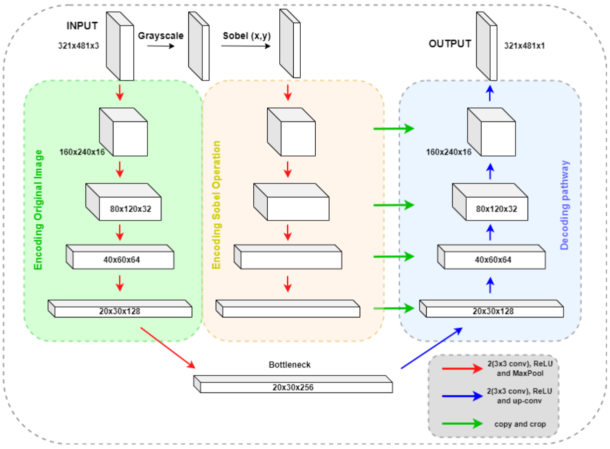

Figure 2: Diagram of the SobelU-Net model.

3 Results

The proposed models were trained and tested on datasets consisting of photographs of the torso of the patient and corresponding 17 keypoints for each breast contour. The models were first trained on a dataset of 221 images that consisted of three smaller datasets. The second dataset was used for validation and contained images from a single Breast Care Unit from the Champalimaud Foundation. The last dataset was used for testing and came from the CINDERELLA project and the photographs were taken using an automatic photo robot. In this section, we compare the results of our Sobel U-Net model on all datasets against the conventional model using the Sobel operator proposed by Cardoso and Cardoso [2] and the Deep Learning model proposed by Silva *et al*. [7] (DNN model). Table 1, 2 and 3 show the percentage of the mean, standard deviation and maximum error distance measured in pixels and standardized by the image diagonal.

Model	Mean(%)	Std Dev(%)	Max(%)
Sobel	0.36	0.71	7.08
SobelU-NET	**0.31**	0.39	2.83
DNN model	0.76	**0.29**	**2.61**

Table 1: Results for 5-fold-cross-validation on the mix dataset.

Model	Mean(%)	Std Dev(%)	Max(%)
Sobel	0.42	0.99	8.80
SobelU-NET	**0.36**	**0.56**	**4.88**
DNN model	10.97	3.78	23.94

Table 2: Results are for testing on the Breast Unit dataset.

Table 1 shows the error results over 5 fold cross validation in the training dataset. Table 2 shows the error results when the model was trained on the 221 image dataset and validated on the Breast Unit dataset. In this experiment, the model was not trained on the Breast Unit dataset images. However, the model chosen during training was the one that presented the best results on the validation dataset. Table 3 shows the error results for testing the model on the Cinderella dataset when it was trained on the 221 image dataset and validated on the Breast Unit dataset. It is visible that the SobelU-NET model achieved superior results to the conventional method on the training and validation datasets while the conventional model achieved superior results on the testing dataset. The DNN model achieved good results on the training dataset but presented poor performance when faced with the Validation and Testing datasets.

Model	Mean(%)	Std Dev(%)	Max(%)
Sobel	**0.28**	**0.61**	**4.56**
SobelU-NET	0.37	0.73	5.72
DNN model	9.07	3.21	20.33

Table 3: Results are for testing on the CINDERELLA dataset.

4 Conclusion

This work proposed a new method for the automatic detection of breast contours that improves the conventional shortest-path approach devised by Cardoso and Cardoso [2] by replacing the conventional Sobel operator with a deep-learning U-NET model. Previous Deep Learning models showed positive results on training data but failed to generalize well to new data. On the other hand, the conventional shortest path model presented poor performance under specific data points where the breast contour edges are not as pronounced. In that sense, our model combines both approaches to create a more robust Deep Learning model.

Our method presented better results than the conventional shortest-path approach in the Training and Validation datasets but the conventional method presented the best results in the Testing dataset. These results show that the method can perform better than the conventional approach but it needs to be trained on a bigger and more diverse dataset to make a more robust model that performs well on new data.

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