

# Automatic Landmarks Detection in Breast Reconstruction Aesthetic Assessment

Francisco J. NÚÑEZ-BENJUMEA<sup>a,1</sup>, Carmen SERRANO<sup>b</sup> and Begoña ACHA<sup>b</sup>

<sup>a</sup>*Technological Innovation Group, Virgen Macarena – Virgen del Rocío Univ. Hospitals. Sevilla.*

<sup>b</sup>*Signal Theory and Communications Dept. Univ. of Sevilla. Sevilla.*

**Abstract.** This paper addresses a fully automatic landmarks detection method for breast reconstruction aesthetic assessment. The set of landmarks detected are the supraesternal notch (SSN), armpits, nipples, and inframammary fold (IMF). These landmarks are commonly used in order to perform anthropometric measurements for aesthetic assessment. The methodological approach is based on both illumination and morphological analysis. The proposed method has been tested with 21 images. A good overall performance is observed, although several improvements must be achieved in order to refine the detection of nipples and SSNs.

**Keywords.** Anatomic Landmarks, Breast Reconstruction, Outcome Assessment, Computer-Assisted Image Processing

## Introduction

Breast cancer is the most common cancer in women in both the developed and less developed world. It is estimated that worldwide over 508.000 women died in 2011 due to breast cancer. Breast cancer survival rates vary greatly worldwide, ranging from 80% or over in North America, Sweden and Japan to around 60% in middle-income countries and below 40% in low-income countries [1]. The low survival rates in less developed countries can be explained mainly by the lack of early detection programmes, resulting in a high proportion of women presenting with late-stage disease, as well as by the lack of adequate diagnosis and treatment facilities.

In order to overcome this disease, several surgical procedures could be performed depending on the tumour extension and location. Most commons are mastectomy and lumpectomy [2].

Changes in appearance as a result of the breast cancer treatment have a considerable impact in survivors' quality of life, while current approaches for mammary aesthetic outcomes assessment are quite limited, remaining a challenge to define the optimum parameters in order to facilitate its quantification [3].

Nowadays, surgeons, physicians and patients often assess symmetry and proportionality of reconstructed breasts in a subjective and qualitative way [4]. However, these methods are highly dependent of inter- and intra-observer variability, and its qualitative nature limits further analysis. Current quantitative approaches for

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<sup>1</sup> Corresponding Author.

breast aesthetic assessment include anthropometric measurements [5], two-dimensional measurements [6] or three-dimensional measurements [7]. In this work, a set of landmarks defining commonly used anthropometric measurements has been automatically detected. These landmarks are: supraesternal notch (SSN), armpits, nipples, and inframammary folds (IMFs).

## 1. Methods

In order to carry out an objective assessment of the aesthetic outcomes after breast reconstruction surgery, an optical image of the patient is acquired and is then processed with a fully automatic algorithm made up of four steps: silhouette segmentation, global references detection, image parcellation and landmarks detection.

### 1.1. Automatic silhouette segmentation

In order to segment patient's silhouette, the Otsu binarization [8] algorithm is performed over the red channel of the image. To refine the result, morphological closing and opening are also performed with a disk-shaped structuring element which radius was automatically calculated as follows:

$$r = \sqrt{(f^2 + c^2)/k} \quad (1)$$

where  $f$  is the number of rows and  $c$  is the number of columns of the image.  $k$  is a constant which value has been empirically calculated in order to optimize segmentation result. In our case,  $k = 50$ .

### 1.2. Global references detection

Once the silhouette has been segmented, we calculate the centroid and the vertical symmetry axis. The centroid is calculated as the discrete mass center of the pixels defining the silhouette, considering the mass of each pixel equal to 1.

The vertical axis is directly calculated as the middle point, for each row, between the first and the last point belonging to the silhouette.

### 1.3. Automatic image parcellation

In order to define a region of interest (ROI) for each landmark, an anthropometric approach is applied. This approach has been tailored according to an image acquisition protocol developed for this work. Five ROIs have been automatically segmented for each image: 1 neck ROI, 2 armpit ROIs, and 2 breast ROIs.

First, we find the row with the closest points of each side of the silhouette. This is considered as the initial row of the neck ROI. The distance between these points is the ROI's width. The ROI's length is the 20% of the total number of rows.

The left armpit ROI's first row (the right one is calculated symmetrically) is the following row of the neck ROI's last row. The pixel's column belonging to the silhouette at that row, plus the 4% of the total number of columns, is the left armpit

ROI's first column. The width and the length of this ROI is the 15% of the total number of columns and rows, respectively.

Finally, the breast ROIs' first row is the upper armpit's row. This is feasible given that the armpit is detected before the breast ROI. The pixel's column belonging to the silhouette at that row is the left breast ROI's first column. The centroid's column minus one is the last column. The right breast ROI is calculated symmetrically. The length of these ROIs is the 50% of the total number of rows.

#### 1.4. Automatic landmarks detection

##### 1.4.1. Supraesternal notch (SSN) detection

In order to automatically detect the SSN, an approach based on illumination analysis is proposed. Changes in illumination in the neck ROI are mainly due to muscular and bone structures. The SSN is usually located at the most shaded area in the neck ROI. Therefore, we correct the global illumination bias in the neck ROI's red channel by modeling the average of both rows and columns with a second order polynomial, and the SSN coordinates are the global minima for averaged and corrected rows and columns after discarding initial and final minima in order to avoid dispersion.

##### 1.4.2. Armpit detection

The automatic armpit detection is based on an illumination and morphological analysis approach. The armpit ROI's red channel is segmented making use of a multi-threshold algorithm based on the Otsu method. Three thresholds are applied to the image, discarding the regions belonging to the three brighter levels. Afterwards, a morphological closing with a disk-shaped structural element which radius is equal to the 5% of the ROI's height is performed in order to remove spurious regions. Besides, regions having pixels in the first row and/or in the first and last column are removed. The armpit is then considered as the highest point of the remaining regions.

##### 1.4.3. Nipple detection

The automatic nipple detection is carried out by a two steps algorithm: find candidates in both ROIs and then classify them. First, the nipple ROI's green channel is segmented making use of a multi-threshold algorithm based on the Otsu method. Five thresholds are applied to the image, discarding the regions belonging to the three brighter levels. Afterwards, a morphological closing and opening with a disk-shaped structural element is performed in order to smooth the boundaries of the remaining regions. Its radius is calculated as follows:

$$r = \sqrt{(f_{ROI}^2 + c_{ROI}^2)} / \alpha \quad (2)$$

where  $f_{ROI}$  and  $c_{ROI}$  are the number of nipple ROI's rows and columns, respectively.  $\alpha$  is a constant which value has been empirically calculated in order to optimize segmentation result. In this work  $\alpha = 250$ .

The following morphological features are excluding criteria for the remaining regions: regions having at least one pixel in the ROI's frame, region's major axis is three (or more) times greater than minor axis, regions with at least one hole, region's

size is less than structural element's size. Finally, our candidates in each nipple ROI are the convex polygons of the three greater regions.

In order to classify the candidates, a set of features are calculated for each couple of regions belonging to different ROIs. These features express the differences between regions' sizes, distances to the symmetry axis, to the first row, and mean intensities. The couple which has the least overall difference is considered to be the nipples.

### 1.5. Inframammary fold (IMF) detection

In order to automatically detect the IMF, a gradient-based approach combined with the shortest path algorithm of Dijkstra [9] is proposed. This approach is a modification of the Cardoso's one [10]. First, we calculate the gradient of the breast ROI's green channel, normalize its values between 0 and 1, and a non-linear transformation  $h(\bar{\mathbf{D}})$  is then carried out with the equation 3:

$$h(\bar{\mathbf{D}}) = \begin{cases} 1 - \bar{d}_{ij}^\gamma & \text{if } \bar{d}_{ij} \geq t_h \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where  $\bar{\mathbf{D}}$  is the normalized gradient matrix,  $t_h$  is a threshold calculated as the mean value of  $\bar{\mathbf{D}}$ , and  $\gamma$  is a constant which value has been empirically calculated in order to optimize segmentation result. In this work  $\gamma = 0.5$ .

Afterwards, the resulting image is segmented and quantized making use of a multi-threshold algorithm based on the Otsu method with three thresholds, and discrete values [2, 16, 2048] are assigned to regions belonging to each level (2 is assigned to darker regions, while 2048 is assigned to brighter ones). Finally, we apply the Dijkstra's shortest path algorithm to the quantized image being the armpit the initial point and a point at the same height in the opposite side of the ROI the final point. The result is then refined by removing ending points in case they do not belong to the IMF. This method is applied when their cost is greater than the average cost of the path.

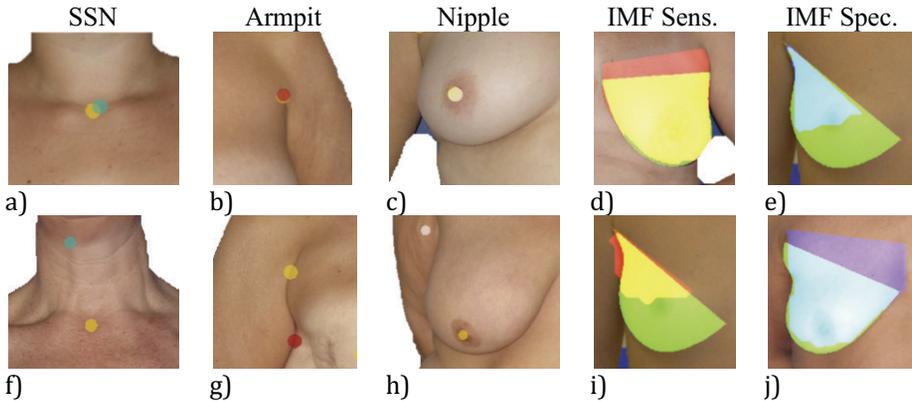
## 2. Results

The proposed method has been applied to 21 images provided by the Plastic Surgery Clinical Unit of the Virgen del Rocío Univ. Hospital from patients suffering from any breast related disease (all patients gave their consent to make use of them for research purposes). These images have also been manually processed by an expert in order to obtain the ground truth. The error detection rates are displayed in the table 1 in terms of error distance for SSN, armpit, and nipple. For the IMF detection, sensitivity and specificity rates are shown.

**Table 1.** Error detection distribution. Q1 refers to 1<sup>st</sup> quartile, Q2 to 2<sup>nd</sup> quartile, and Q3 to 3<sup>rd</sup> quartile.

Error	SSN [cm]	Armpit [cm]	Nipple [cm]	IMF Sens. [%]	IMF Spec. [%]
Min	1.04	0.19	0.12	42.25	86.91
Q1	1.91	1.04	0.56	89.26	93.26
Q2	2.19	1.68	6.78	93.18	96.56
Q3	4.21	2.59	11.39	94.06	98.32
Max	11.02	8.46	18.58	98.45	99.85

The figure 1 shows best and worst detection cases for each landmark.



**Figure 1.** First row are best detection cases after testing the proposed method. Second row are worst detection cases. Yellow spots and green areas are the ground truth. Green, red and white spots and red and dark blue areas correspond to the automatic detection method outcome. Yellow and light blue areas correspond to the overlapping between the ground truth and the method outcome.

## Discussion

A fully automatic method for landmarks detection in breast reconstruction aesthetic assessment has been developed and tested. A good overall performance is observed, although several improvements must be achieved in order to refine the detection of nipples and SSNs. Inter and intra-observer variability analysis must be performed in order to yield a strong assessment of the proposed method performance. In any case, it could be used as an objective aesthetic assessment tool in screening programs.

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