



## Retraction Notice

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**History**

Expression of Concern:

yes, date: yyyy-mm-dd

no

Correction:

yes, date: yyyy-mm-dd

no

**Comment:**

The Editorial Board would like to extend its sincere apology for any inconvenience the paper withdrawal may have caused.



# A Model to Predict Cosmetic Outcome after Breast Conservation Surgery

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## Abstract

Breast conservation surgery (BCS) is a preferred choice for most females. However, BCS can still result in disfiguring and non-aesthetically pleasing results. It is important that patients and surgeons have a tool that can produce an accurate visual projection of the breast post-BCS. This will help patients make a decision for BCS versus mastectomy. In our paper, we describe a technique to enable the prediction and projection of 3D breasts models post-BCS. The accuracy of the model compared to actual post surgical outcomes is a match of 87%.

## Subject Areas

Public Health

## Keywords

Breast, Conservation, Model, Cosmetic, Aesthetic Outcomes, Predict

## 1. Introduction

Traditionally, mastectomy was the standard operation for breast cancer patients. However, this surgical option has a profound impact on the aesthetic appearance and self-confidence of women [1] [2] [3].

With widespread use of screening mammography, the average sizes of detected tumors have decreased. With smaller tumours, breast conservation surgery (BCS) is an increasingly feasible option [4]. However, in Southeast Asia, women tend to be more petite, with smaller breast sizes. Therefore, despite resecting less breast tissue with BCS, the amount of deformation can be rather significant.

Patients are now routinely offered between mastectomy and BCS; and after a period of counselling, are expected to choose between the two surgical options. However, without adequate visual tools to truly demonstrate to pa-

tients what the expected outcome of BCS might be, this decision is incredibly difficult for most patients.

However, the creation of such models is a challenging task due to the complex nature of the deformations imposed by surgery. The final aesthetic outcome can be affected by so many different variables, from different surgical practices and expertise, to breast characteristics, such as volume and density, tumor size and location.

There are described strategies to model breast deformations. However, each technique is usually designed for specialized applications: estimate pose transformation [5]-[10], model breast deformation [11] [12] [13] [14], predict the healing process of the breast after tumor removal [15] [16], among others. Vavourakis *et al.* [16], proposed a 3D surgical simulator to predict a patient-specific outcome after BCS. This simulator relies on a coupled multiscale Finite Element (FE) numerical procedure to solve two mathematical models: a biochemical model for wound healing and angiogenesis, and a biomechanical model for soft tissues and pose estimation.

In this paper, we build on Vavourakis' [16] techniques to develop an algorithm that predicts BCS outcomes. This algorithm was tested on 135 women, and the results from the 3D prediction are compared against actual clinical outcomes at 3 and 12 months.

## 2. Methods and Methodology

This study was conducted from January to December 2016. We recruited 135 female patients with histologically proven invasive breast cancer, who were undergoing breast conservation surgery. All gave informed consent and the study was conducted according to the principles of Helsinki. These women would have MRI breasts pre-operatively and also agree to have their data analyzed by our protocol and algorithm as will be discussed below.

The patients would subsequently undergo breast conservation surgery with or without axillary clearance, in accordance to their local surgeons' protocols and techniques. Post-operatively, they would be followed up and have their photographs taken at 3 and 12 months' post-surgery. All surgeons observed the same guidelines of surgery: to excise a core of breast tissue with 1 cm margins around the foci of cancer, down to the chest wall. The surgeons then applied level I oncoplastic techniques, with local tissue mobilisation to surgically repair the defect.

The patients' pre-operative MRI was used to plan and predict the surgical aesthetic outcomes post-operatively. The 3D rendered models would be compared against the actual patients' photographs at 3 and 12 months' respectively. The models and photographs would be overlaid and the distance between the two calculated to estimate fit.

### 2.1. Algorithm Methodology

#### 2.1.1. Constructing the Basic Breast Model

The first step was to create a Finite Element Model (FEM) of the breast, using the method described by Vavourakis *et al.* [16]. Vavourakis' BCS simulator models the 3D post-surgical shape of the breast by coupling a physiological model of tissue recovery with a Mooney-Rivlin biomechanical model of pose estimation. Upon the segmentation of the structures of interest, a 2D surface mesh of FEM that represents skin and a 3D mesh representing the interior of the breast are generated.

### 2.1.2. Simulating the Tumor and Surgical Volume Excised

Vavourakis' model [16] simulates the wound healing process, by taking the volume excised during surgery as input data. This volume depends on the tumor position and size, and therefore, a virtual surgery has to occur in which all FE inside the volume to excise are re-labelled as damaged. This virtual surgery is simulated in the supine position: the surgeon identifies the tumor position, defines the incision lines and outlines the incision path inside the breast. The excision volume is then approximated by a cylinder that contains the lesion and whose axis is perpendicular to the chest-wall, extending from the skin to the pectoral muscle. All FE contained inside this cylinder are assigned with damaged tissue properties.

### 2.1.3. Dataset Building

T1-weighted MRI images were used, containing approximately 60 axial slices each. 3D point clouds of patient's torsos were created using the breast contour, Latissimus Dorsi and the pectoral muscle. The torso point cloud (PCL) was vertically divided with a plane defined along the sternum, thus giving individual breasts PCLs. Each resulting breast PCL was converted to a 3D triangulated surface mesh to model the skin, using the Ball-Pivoting algorithm [17], in MeshLab [18].

The breast volume was next meshed in Gmsh [19], by inserting uniformly distributed points inside the object, subsequently connecting them with tetrahedron elements. To complete the creation of the FEM, distinct boundary conditions and material properties were assigned to the surface mesh [16]. The Breast Imaging Reporting and Data System (BI-RADS) [20] was used for weighting the material property values.

The center of the tumor position is defined with 3 spatial coordinates ( $x$ ,  $y$  and  $z$ ) and the excision volume is computed. The line between the nearest point of the pectoral muscle and the tumor position sets the normal vector to the muscle, and a predefined cylinder (with a known radius, height and, consequently, volume) is aligned through this direction. Different tumor volumes can then be modeled by varying the ratio between cylinder and breast volumes. Once the cylinder is defined, the FE inside it are set as damaged, and assigned the correspondent biomechanical and biochemical properties used by Vavourakis *et al.* [16].

## 3. Regression Models

A machine learning regression model was adopted. Using PCL as continuous variables and subject to the following Equation [21]:

$$\begin{bmatrix} P^{pre} & F \\ \vdots & \vdots \end{bmatrix} \xrightarrow{f} \begin{bmatrix} disp^{pre \rightarrow post} \\ \vdots \end{bmatrix}$$

where  $P^{pre}$  is pre-surgery PCL,  $F$  is the feature list per instances (pre-surgery points),  $f$  is the demanded regression model, and finally  $disp^{pre \rightarrow post}$  expresses the required displacements to convert pre-surgery PCL to post-surgery. Having predicted the displacement, predicted breast shape ( $P^{pred}$ ) is attainable via Equation [1]:

$$P^{pre} + disp^{pre \rightarrow post} = P^{pred}$$

#### 4. Results

Of the 135 patients who enrolled into this study. All 135 had unilateral invasive ductal carcinoma. 84 patients had right breast cancer, 51 patients had left breast cancer. When the actual photographs and 3D models were overlapped, an analysis was performed to evaluate similarity. The Euclidean point-wise distance method was used, since it measures the amount of displacement of each pair of points. This was also used to measure the global measurement of the distances: from the source to target PCL and from the target PCL to the source.

Post-processing, there was an average similarity of about 87% (range 78 to 96%), with an average mean point distance of 1.3 cm at 3 months and 2.2 cm at 12 months. This meant that in general, the 3D model estimation was 1.3 cm larger on average than the actual image. However, besides the actual quantification of distance difference, the overall overlap and similarity was an average match of 87%.

This analysis was further described in **Table 1** and **Table 2**. When analyzing the Upper Outer Quadrant of the breast, the 3D model measured about 2.1 cm larger than the actual photograph. This difference was much less when predicting for the Upper Inner and Lower Outer Quadrants. The most likely reasons

**Table 1.** Data at 3 months.

Location of Cancer in Right Breast	No of Patients	Mean Point Distance of 3d Model to Actual Photographs
Upper Outer Quadrant	32	2.1 cm
Upper Inner Quadrant	14	0.8 cm
Lower Inner Quadrant	8	-0.3 cm
Lower Outer Quadrant	30	1.8 cm
Location of Cancer in Left Breast		
Upper Outer Quadrant	18	2.1 cm

Upper Inner Quadrant	7	0.8 cm
Lower Inner Quadrant	8	-0.3 cm
Lower Outer Quadrant	18	1.8 cm

**Table 2.** Data at 12 months.

Location of Cancer in Right Breast	No of Patients	Mean Point Distance of 3d Model to Actual Photographs
Upper Outer Quadrant	32	3.6 cm
Upper Inner Quadrant	14	1.8 cm
Lower Inner Quadrant	8	-0.0 cm
Lower Outer Quadrant	30	1.8 cm
Location of Cancer in Left Breast		
Upper Outer Quadrant	18	2.1 cm
Upper Inner Quadrant	7	0.8 cm
Lower Inner Quadrant	8	-0.3 cm
Lower Outer Quadrant	18	1.8 cm

due to pose transformation. The MRI breasts were captured with the patient in the prone position. The model was transposed to a gravity free state and directional forces artificially factored in, to allow pose transformation to a supine position for surgical planning. Conversely the actual patients' photographs were captured in the erect posture. The breasts will naturally weigh down due to gravity. The tissue found in the Upper Outer Quadrant would be displaced by the farthest distance from the supine to the erect posture. The model was not able to fully account for the gravitational effect and thus over-estimated the volume in the UOQ of the breast.

The converse was also true. The model's fidelity underestimated the size of the Lower Inner Quadrant; where the 3D model was 0.3 cm smaller than the actual clinical photograph. It is in the LIQ, where most of the breast mass will be displaced towards when changing from a supine to erect position.

The location of the cancer did not make a difference in the fidelity and performance of this model's post-surgical volume projection. This was because Vavourakis's [16] cylinder of resection enabled this to be compensated for.

In general, the 3D model over-estimated the post-surgical size; and this was more pronounced at 12 months compared to 3 months. This difference was most likely due to seroma and scar remodeling. At 12 months, any seroma would have been resorbed; and scar tissue remodeling due to gravity and stress as vectoral forces, would have been more pronounced than when at 3 months.

## 5. Discussion

In this study, we aim to develop a technique to reliably predict the aesthetic outcome of breast conservation surgery. This technique would help

patients to better visualize and appreciate a customized 3D model of their breast post-surgical resection; and thus make an informed choice on BCS vs. mastectomy.

We built on work put in place by Vavourakis *et al.* [16]. There are many models that attempt to predict the surgical outcomes of BCS. Vavourakis's [16] model however was a biomechanical model that factored in the process of wound healing simulation. In our study, our results were satisfactory. However, we acknowledge that this was a small study, and the fidelity and performance of this model need to be tested out on greater number of patients.

Our model's main weakness was in the reliance of MRI, which was performed in the prone position. The pose transformation formula which converts data, by projecting gravitational stresses is not yet complete. In the future, there is a need to incorporate other machine learning techniques such as convolution neural network regression, and deep geometric learning. These deep learning techniques would continue to improve on the program's performance and likewise overcome factors such as pose transformation.

### Conflict of Interest

This author declares that there are no conflicts of interests.

### Funding

No funding received.

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