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Review Article

Simplification of breast deformation modelling to support breast cancer treatment planning

Marta Danch-Wierzchowska [a,*], *Damian Borys* [a], *Barbara Bobek-Billewicz* [b], *Michal Jarzab* [c], *Andrzej Swierniak* [a]

[a] *Institute of Automatic Control, Silesian University of Technology, Gliwice, Poland*

[b] *Dept. of Radiology, Maria Skodowska-Curie Memorial Cancer Center and Institute of Oncology, Gliwice Branch, Gliwice, Poland*

[c] *IIIrd Dept. of Radiotherapy and Chemotherapy, Breast Cancer Unit, Maria Skodowska-Curie Memorial Cancer Center and Institute of Oncology, Gliwice Branch, Gliwice, Poland*

ARTICLE INFO

Article history:
Received 27 December 2015
Received in revised form
26 May 2016
Accepted 7 June 2016
Available online 17 June 2016

Keywords:
Breast deformation
Modelling
Treatment planning
MRI

ABSTRACT

The exact delineation of tumour boundaries is of utmost importance in the planning of cancer therapy, either surgery or pre- or post-operative radiation treatment. In the case of breast cancer one of the most advanced modalities is magnetic resonance imaging (MRI). Although MRI scans provide wealth of information about the structure of a tumour and the surrounding tissues, the data obtained represent the patient in a prone position, with breast, in a coil while surgery is performed in a supine position, on lying breast. There is no doubt that a patient's breast in both positions has a different shape and that this influences the intra-breast relations. Our present preliminary study introduces a simple breast model developed from prone images. The model should be built rapidly and by a simple procedure, based only on essential structures, and the goal is to prove its usefulness in treatment planning.

1. Introduction

Recent studies show that breast cancer is the most frequent women's cancer around the world. According to WHO's report GLOBOCAN 2012 [1]a constantly growing incidence is observed since 1975 across all woman's age groups (20–80). Consequently, diagnosis needs to be precise and fast, whereas treatment needs to be as much personalised as possible.

The most precise examination, in which tissue images are obtained with high resolution, is magnetic resonance imaging (MRI). Images from MRI examinations contain information about breast tissue structures, both shape and physical properties. MRI data offers information about tissue conditions that can not be obtained by other popular imaging techniques, such as mammography, ultrasound or computed tomography [2]. The most precise examination, in which tissue images are obtained with high resolution, is magnetic resonance imaging (MRI). Images from MRI examinations contain information about breast tissue structures, both shape and physical properties. MRI data offers information about tissue conditions that can not be obtained by other popular imaging techniques,

* *Corresponding author at*: Institute of Automatic Control, Silesian University of Technology, Akademicka 16, 44-100 Gliwice, Poland.
E-mail address: marta.danch-wierzchowska@polsl.pl (M. Danch-Wierzchowska).

http://dx.doi.org/10.1016/j.bbe.2016.06.001
0208-5216/

such as mammography, ultrasound or computed tomography. The bigger the breast, the more its shape differs in each position [2]. Consequently, sometimes the lack of proper tumour delineation leads to mastectomy and causes significant functional deterioration of patient status. An alternative is a partial, breast preserving wide tumour excision, sometimes supported by oncoplastic procedures of tissue displacement. In this case only the tumour and the surrounding tissues are removed. However, in this case, the region of interest must be precisely determined. Consequently, the need arises to easily convert MRI data to the position of the patient during surgery/radiation therapy which would facilitate the safe and efficient flow of these procedures. This cannot be obtained by placing the patient in a supine position for MRI nor in a prone position during surgery, and therefore the only way to achieve this goal is by computer image processing. A similar problem was addressed in [3], where mammogram compression was simulated based on a simple breast model. MRI image deformation was discussed in [4], but the model presented was very complex regarding breast tissues. In recent studies [5,6] models that consist of four structures: fat, glandular, cancerous and skin tissues are considered. Building a model for each patient with such complex structure, extend significantly computation time and the same, time of diagnosis.

One way to simplify models could be reached by taking into account that the parameters of fat tissues have a much greater influence on deformation than those of fibroglandular tissues [7]. Moreover, experimental data suggested that tumour stiffness has a minimal effect on breast deformation [7]. It is also observed, that with age, fibroglandular tissue volume shrinks compared to fat tissue [8]. Another simplification [9], is to model skin and fat as one material with the same properties. To our knowledge, the above simplifications were never applied in one model.

In this work we present a basic concept for a model of a breast and its deformation, paying special attention to its further use in clinical practice. Our study consists of creating a breast model which transforms prone MRI images as fast as possible into a supine plane and its comparing the results with supine images, to prove the feasibility of this technique for surgical planning support.

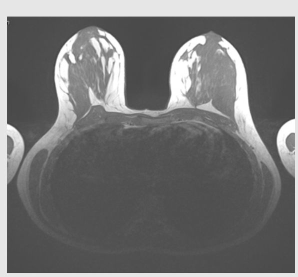
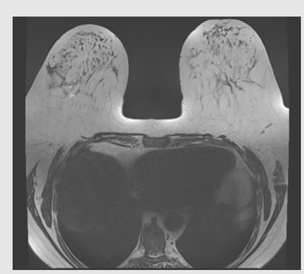
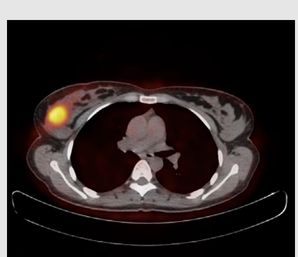
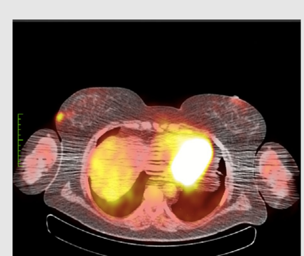
2. Material and methods

2.1. Data acquisition

Breast MRI data. MRI is widely used in medical diagnosis, in particular in breast imaging [10]. T1 and T2-weighted MRI scans were acquired at the Center of Oncology – Maria Sklodowska-Curie Memorial Institute, Branch in Gliwice, Poland on a Siemens scanner MAGNETOM Aera 1.5T. The data covered approximately 0.7 mm $\times$ 0.7 mm $\times$ 3 mm real volume per voxel. Examples of images are shown in Table 1.

Breast PET-CT data. Positron Emission Tomography with Computer Tomography (PET-CT) is a fusion of 3D X-ray structural examination (CT) with metabolic examination (PET) performed using fluorodeoxyglucose (FDG), an analogue of glucose, to indicate tissue metabolic activity. PET-CT scans were acquired at the Center of Oncology – Maria Sklodowska-Curie Memorial Institute, Branch in Gliwice, Poland on a Philips GeminiGXL 16 scanner. The data consisted of ca. 280 axial slices of patients in a supine position covering almost the whole body. The data covered approximately 1.17 mm $\times$ 1.17 mm $\times$ 3 mm real volume per voxel. PET-CT scans were obtained in a supine position and were used as a reference to validate the computed deformation. Examples of images are shown in Table 1.

Table 1 – Patient datasets.

	Patient 1	Patient 2
Age	29	64
Tumour diameter	1 cm	0.4 cm
MRI image		
PET-CT image		

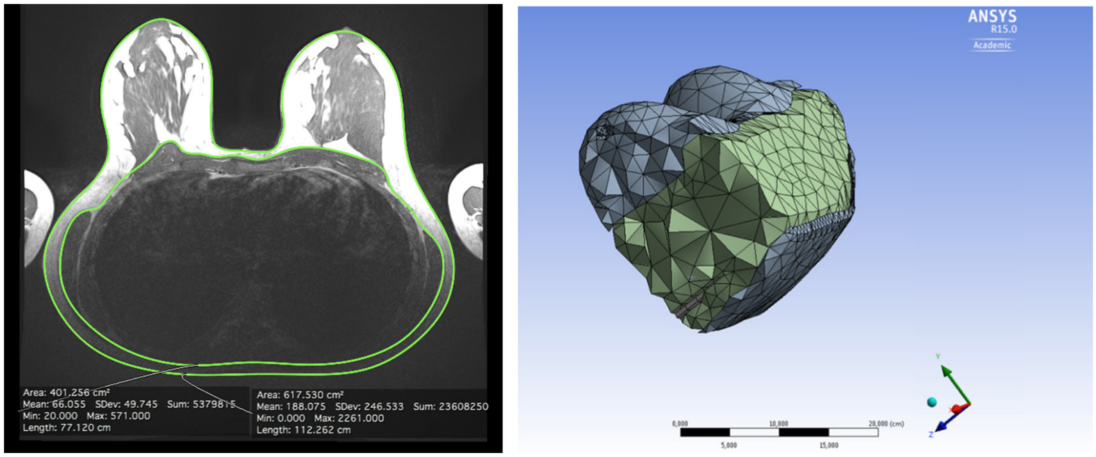


Fig. 1 – Visualisation of steps in creating a model; (a) Example of an MRI image with internal and external model green contours; (b) The final model mesh – intersection through tumour sphere.

Patient data. Our method was tested on patient's datasets, i.e. MRI and PET-CT examinations. Table 1 shows examples of patient images with the tumour diameter. Among many patients, two with extremely divergent cases were chosen to represent different types of issue. Patient 1 is a young women (age 29) with a tumour (1 cm diameter) in relatively low total breast volume. Patient 2 is an older women (age 64) with a relatively small tumour (0.4 cm diameter) in relation to breast volume. The fibroglandular to fat ratio also differs in both cases.

2.2. Breast modelling

Our approach consisted of several steps which are based on ANSYS modelling best practices:

Tissue segmentation. Based on the data two classes of tissue were segmented, muscles with the thorax wall and internal organs defined as the internal region, and breast volume with fat and skin surrounding the body as a second, external region (see Fig. 1a). Segmentation was achieved using Osirix software tools [11]. Since some parts of images were not segmented properly, manual correction was needed.

Model building. A volume was created from each segmented region using Osirix tools and exported as.stl files into ANSYS software [12]. The internal body region (thorax wall and muscles) was cut out from the external region (skin with breast volume) with shearing boundary nodes between each volume. The volumes created were unruffled to create smoother layers and simplify mesh creation. Previously published results [13] showed that tumour shape does not influence significantly breast displacement. Thus, including a real segmented tumour is not critical for our line of reasoning. In the external body region a sphere was created corresponding to the tumour's location, setting the sphere diameter according to the real tumour size. As proposed in [5,9,14,15] we used a T4 tetrahedron mesh, which is the most precise to mimic a natural body deformation. The final mesh is shown in Fig. 1b.

Setting of boundary conditions. To set our model in space we defined the back side of the internal body region (thorax wall with muscles) as a fixed support. MRI images represent the body region from the clavicles to the lower end of the ribcage. To prevent the external body region (skin with breast tissues) from sliding out of the region covered by MRI images, a pressure was introduced at both ends of the model. The pressure values were introduced by trial and error experiments. The external body region was free to slide on the internal region.

Setting of material parameters. Based on the simplifications mentioned in Section 1, we used only three types of tissues in our model. To simulate the properties of internal body tissues, a linear model was used, whereas a Neo-Hookean model was used for the external body regions and the tumour sphere. The values of the model parameters were set according to [9] (see Table 2).

Deformation forces setting. The main force considered in the model is the gravitational force. When a patient is prone this force acts in a dorsoventral direction, and in order to simulate the supine position a gravitational force in the opposite direction needs to be applied. Another force present in the model simulates arm and ribcage movements which can be naturally observed during changes of positions.

Deformation analysis. To evaluate deformation results, two features were taken into account, the tumour sphere displacement and the total deformation of the body surface.

Image comparison. To validate the results we compared the deformed model with the reference PET-CT images. This comparison was performed slice by slice, but only slices in which tumour tissue was visible were taken into account.

Table 2 – Parameters used for modelling tissue regions.

Tissue	Model	Young modulus	Poisson ratio	Density
External part	Neo-Hookean	10 kPa	0.47	980 g/cm^3
Internal part	Linear	100 kPa	0.45	1100 g/cm^3
Nodule	Neo-Hookean	10 kPa	0.45	1000 g/cm^3

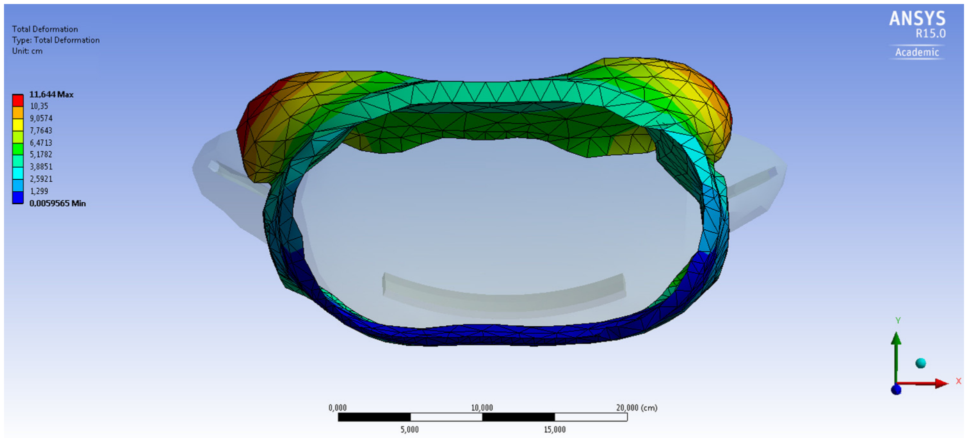


Fig. 2 – External region deformation model result in transverse plane (anterior term).

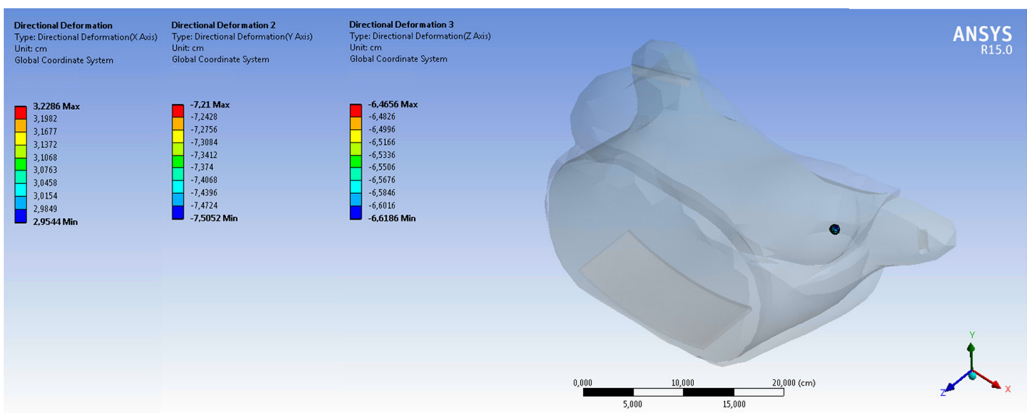
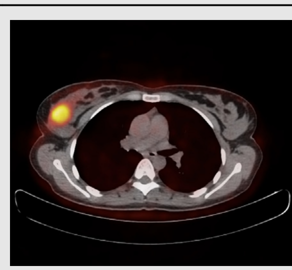
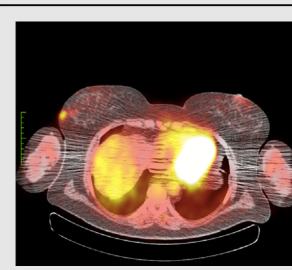
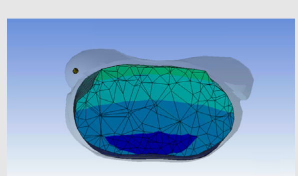
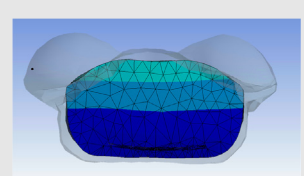


Fig. 3 – Tumour displacement results along the X (mediolateral), Y (dorsoventral) and Z (anteroposterior) axes. Deformation results represent translation of the tumour sphere.

Table 3 – Comparison of patient data with calculated deformation.

	Patient 1	Patient 2
PET-CT image		
ANSYS deformation		
Directional differences	X: 1.1 cm Y: 1.4 cm Z: 1.9 cm	X: 0.4 cm Y: 0.3 cm Z: 1.8 cm

3. Results

3.1. Deformation results

An example of deformation results from skin surface are shown in a transverse plane in Fig. 2. The tumour displacement is shown as the result of an ANSYS Directional Deformation, along the X (mediolateral), Y (dorsoventral) and Z (anteroposterior) axes. Examples of tumour directional displacements are shown in Fig. 3. According to the previously mentioned assumptions, the tumour is a sphere, and the medium values of displacement along the axes represent the translation of the tumour centre.

3.2. Model validation

Table 3 shows the results obtained for the two examples of patient data, a PET-CT slice and the final calculated model intersection with tumour diameter in all images for both patients. The difference between the location of the centre of the reference tumour and the calculated centre of the displaced sphere was ca. 2 cm. Distance differences along the axes are also shown in Table 3.

4. Conclusions

This work is focused on simplification of breast modelling and increasing the efficiency of one of the most time-consuming steps, geometry creation. The simplifications proposed in [7,9,13] were found attractive and useful when implemented in single model. Among many patients, two were chosen with extremely divergent cases to represent different types of issue. Despite some differences, our method gives acceptable and comparable results in both cases.

Different modalities of breast imaging are carried out in different patient positions. Especially, MRI imaging, the most powerful method nowadays, is acquired in patients lying in prone body position, with the breast handing down into the coil. However, majority of therapeutic procedures, like surgery or radiation therapy are carried out in supine body position, with significant displacement of breast tissue. Thus, the simple method of breast deformation modelling will be of clinical use, even if it is expected that the error of this modelling will not allow for ideal transposition of image. However, even rough transformation gives the better estimation of tissue relationships than the routinely carried out visual assessment, regularly used in the clinic.

Modelling of breast deformation is mainly focused on the impact of gravitational force on the breast shape. One of the main challenges is a compromise between model accuracy and efficient and rapid calculations, and tissue models which are too complex could never be used in clinical practice since adapting them to each patient would be too time-consuming. Developing an automated tool for creating a simplified shell model from medical images could speed up deformation analysis significantly. Analysis using available commercial software (i.e. ANSYS) gives acceptable results, but implementing a model inside it is still highly time-consuming. The best solution seems to be to build a model based directly on medical images, without using any third-party software. An interesting challenge would be to implement such a deformation method within the software used by physicians to create medical images.

Another important issue in model building is proper tissue segmentation. Segmentation of breast MRI images is still a difficult job because of complex structures, field non-homogeneity, and image noise, which need to be overcome to create automatic finite element models of the breast [7]. Sufficiently efficient, automatic chestwall segmentation methods were already presented in [16–18]. Since segmentation of the breast shape from the background is simple enough [19–21] and the only problem is segmentation of the back side of the chestwall, which is weakly distinguishable on MRI images due to field non-homogeneity caused by signal enhancement coils. Models which bypass the back side of the chestwall while simultaneously preserving other model properties are the subject of our present studies.

Although our results are preliminary, they show that it is possible to create a simple model and in a few steps to deform it in a way useful for treatment planning. Our main goal was to mimic body displacement in the smallest possible number of steps, and it is clear that the results obtained have a limited precision. At the moment the methodology allows to estimate the procedure error to be approx. 2 cm when distance between the calculated, hypothetical tumour volume and the peak metabolic activity is estimated. In future we will seek the methods to narrow this error to below 1 cm, to allow adequate application in treatment planning purposes. In PET-CT image, falls into the tissue region that needs to be removed during surgery anyway. Even during less invasive surgery (lumpectomy), the breast has to be cut and the tumour is removed with surrounding tissue. The method which we propose here for fast calculation of deformation may be helpful in minimizing damage to healthy tissue. In conclusion, our approach provides one of the first examples of use modelling simplification to support breast cancer treatment planning.

Acknowledgments

Grants: This work was supported by The Polish National Center of Research and Development grant No. STRATEGMED2/267398/4/NCBR/2015 (MILESTONE – Molecular diagnostics and imaging in individualized therapy for breast, thyroid and prostate cancer) (DB, BBB, MJ)

This work was supported by the Polish National Science Centre (NCN) under Grant No. 2011/03/B/ST6/04384 (AS).

This work was supported by the Institute of Automatic Control under Grant No. BKM-514/RAU1/2015/t.12 (MDW).

This work was supported by the Scholarship Program "Doktoris" – Program stypendialny na rzecz innowacyjnego Slaska.

Calculations were performed using a ANSYS licence purchased in the GeCONiI, POIG.02.03.01-24-099/13 project, on the Ziemowit computer cluster in the Laboratory of Bioinformatics and Computational Biology, created in the EU Innovative Economy Programme POIG.02.01.00-00-166/08 and expanded in the POIG.02.03.01-00-040/13 project.

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