Trends in Biomechanical Finite Element Breast Deformation Modelling

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Abstract. Breast tissue deformation has recently gained interest in various medical application. The recovery of large deformation caused by gravity or compression loads and image registration is non-trivial task. The need arise to estimate large breast deformation, which can mimic natural body movement caused by examinations or surgery. Finite element methods (FEM) have been widely applied in this field. In this work we present the current breast deformation modelling trend. The meaningful applications and essentials examinations are described. The modelling software and basic techniques are presented.

Keywords: Breast deformation · FEM · Breast modelling

1 Introduction

Breast cancer is the most frequent women's cancer around the world and is the second most frequent among all human cancers. Consequently, diagnosis needs to be precise and fast, whereas treatment needs to be as personalised as possible. Considering specific anatomy of the female breast any examination or intervention results in breast deformation. Due to that, on every resulting image set the tumour in question is placed in different area. There are several methods, which were created to allow fusion of images obtained in different modalities. One can discriminate three types of deformation models: geometric transformation based on physical models, geometric transformation derived from interpolation theory and knowledge-based geometric transformation [32]. In case of breast deformation modelling both types of geometric transformation are mainly used for rigid and small non-rigid deformation (i.e. respiratory movements) [27]. To model big non-rigid deformation (i.e. mammography compression or prone to supine movement) knowledge-based transformation inspired by biomechanical models is used. The main motivation of biomechanical models usage is that more information enables reliable estimation of complex deformation [21]. Usually Finite Element

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Method (FEM) is used to model biomechanical properties of tissue [32]. FEM is a numerical technique, which allows approximate solving of partial differential equations (PDE). Solving PDE for complex structures is reached by decomposing object domain into smaller elements which limits degrees of freedom of the object and simplified computations.

This paper presents briefly main ideas and techniques in FEM breast deformation modelling.

2 Finite Element Modelling of Breast Deformation

2.1 Model Simplification

Breast modelling relates strictly to its anatomical structure. Female breast consist of glandular lobules, adipose, milk ducts, connective tissues and skin. It is impossible to model glandular lobules and milk ducts as separate layers, since it is almost impossible to differentiate them on the MRI. Due to that, these are both usually treated as one fibroglandular tissue. Between breast tissue and chest wall, there is pectoralis muscle, which also determines the breast shape and movement.

2.2 Modelling Applications

There are several applications of biomechanical breast modelling. Almost all of them are related to breast cancer diagnostics and treatment. The oldest praxis is a mammography simulation which presents the breast deformation caused by the plates compression [14,24]. Another, more recent, application is breast deformation caused by the gravitational force. Such simulation is commonly used when different breasts shapes comparison is needed [15]. Breast shape simulation in different patient positions is used while treatment planning and to locate tumour during medical procedures, e.g. a biopsy procedure [2].

The breast cancer related simulations are used to predict the breast deformation in order to predict tumour location [3]. Examination performed in different patient position using equipment causing deformation needs to be converted into one space. Known practice is comparison between breast MRI and mammograms [35]. The modelling task is to get mammograms into MRI space. Fusion of different examinations helps with more accurate diagnosis [1]. There are also visualizations performed to simulate breast reconstruction after mastectomy [36]. The same praxis is used during a standard plastic surgery, which may not be related with the breast cancer [10]. FEM deformation modelling is also used to test movement of breast implant materials [11].

2.3 Model Input Data

The model usually is created using data from *in-vivo* acquisitions with modalities as described in following subsections [12,19]. However, in some cases it is more optimal to use known geometry and data conditions. A phantom measurements are very useful to obtain that aim [22].

2.3.1 Mammography

Mammography technique uses low-energy X-rays to contrast very low differences in electron densities between breast tissues. It has very high resolution in comparison to others modalities, but it requires high doses of radiation. High sensitivity and low risk on inducing cancer in women population after age of 50 makes it a perfect tool for screening [4]. The mammograms are taken while the breast is compressed for stabilization and better image quality. In most cases craniocaudal (CC) view and mediolateral oblique (MLO) images of the breast are taken. Any suspected regions of higher density are localised for biopsy and tissue identification.

2.3.2 Magnetic Resonance Imaging

The Magnetic Resonance Imaging (MRI) uses differences in proton's magnetization relaxation times to create contrast in images. MRI can create anatomical images of proton (water) concentrations and relaxation times. Additionally, MRI can create functional images like metabolite imaging, diffusion imaging and blood oxidation imaging. It can also measure flows of blood. During the examination a patient is in prone position with breasts placed in signal receiving coils. Breasts are not fixated. It is very safe technique because the MRI do not use the ionizing radiation. The possibility of multiple contrasts acquisitions, both anatomical and functional, plays a key role of MRI breast cancer detection.

2.3.3 Positron Emission Tomography and Computer Tomography

Positron emission tomography with computed tomography (PET) is a functional imaging modality. A radio-tracer is injected to patient and it binds according to its metabolic path. In breast cancer a Flurodeoxyglucose is administered. This radio-traces accumulates in all cells that use energy and the uptake is proportional to energy consumption. This method is very sensitive due to selective uptake, but it lacks of specificity. Higher uptake of glucose may localize, beside the cancer, inflammations, mechanical injuries and all other physiological processes that temporally elevate the glucose consumption. In breast cancer, the PET is used for metastasis localisation and for therapy effectiveness evaluation. Since the breast cancer is localised, the PET examinations during the chemotherapy can monitor the effects on-line and allows for treatment adjustments [33]. The patient is scanned in supine position with arms above the head and the breasts are not fixated.

2.3.4 3D Scanning

3D Scanning is a 3D, non-invasive surface imaging method. 3D scanning allows to acquire spatial coordinates of surface points with relative high resolution. 3D scanning provides useful information about shape [30]. It is commonly used to pre- and postoperatively evaluate breast shape [7]. Recent work presents also 3D scanning as a tool used for breast surface deformation simulation and correspondence finding. However, commercially available system do not take into account the biomechanical behavior of the tissue [10].

2.4 Modelling Software

To create breast model and deform it, several programs can be used. All of them are based on similar modelling techniques mentioned in further sections. The software used can be divided into two types. The first group consists of general purpose modeling software, like ANSYS [12,35], Abacus [40], MSC.Marc [31], which in particular case allow to create a breast deformation model. The second group consists of dedicated algorithms created in research facilities, specifically for breast modelling [3,16]. There are also papers which present solutions based on both own algorithms and commercial software [19,28].

2.5 Modelling Techniques

In breast deformation problem, one can specify a few issues that need to be addressed. According to breast deformation modelling medical images obtained during mammography, MRI or PET-CT examinations constitute basis for the domain creation.

2.5.1 Types of Mesh

To approximate breast shape created from medical images two mesh types are chosen. The most common is tetrahedral mesh [10,12,24,31], i.e. each element is a polygon composed from four triangular faces. Tetrahedron could be 4-nodes or 10-nodes. Another, less often used, is hexahedral mesh, i.e. each element is a polygon composed from six faces [3]. Similar to tetrahedrons there are more than one type of hexahedrons. One can discriminate between 8-nodes, 20-nodes and 27-nodes hexahedrons. Mesh element type determines it's shape function, which characterizes nodes dependencies and some of the material properties. Depending on the shape function one can obtain different computation precision. The more complex shape function of the element, the more precise the result, but also longer computational time. In practice, the simplest 4-nodes tetrahedron and 8-nodes hexahedrons meshes are used.

2.5.2 Types of Tissues Considered in Modelling

Whole model, also called object or geometry consist of layers, which represent individual tissue types. In general, breast models consist of fat, muscle and glandular tissues, tumour and skin. However, there are set of models, which do not consider separate part for skin. Fat tissue with modified parameters is treated as external model boundary [14,19]. There are also models, in which fat and fibroglandular tissues are one part with averaged parameters [9,16].

2.5.3 Types of Boundary Conditions

Boundary conditions describe models boundary behaviour. When concerning mammography simulation, the reaction between breast and compression plates needs to be described. The contact is modelled as frictionless [14], rough - no sliding [19] or as frictional, with estimated friction coefficient [22] e.g. set on values 0.2 [31] or 0.5 % [35]. In every type of model, back side of the breast needs to be considered. Created model ends on thorax wall [12,24,35], which movement can be also simulate [9]. Representation of the tissues boundaries are modelled as rigid - shared nodes between fat and glandular [19], surface based motion constrained for chest wall movement [8], frictionless - free sliding between chest wall and muscles [15] or constrained to zero-displacement - fixed chest wall [31] with Dirichlet boundary conditions [17].

2.5.4 Types of Tissue Constitutive Models

The simplest way to model breast deformations is to treat the whole object as isotropic, linear elastic, homogeneous, incompressible body - Poisson ratio close to 0.5 (eg. 0.4995) [35]. However to represent specific breast movement, there are several types of models, which represent the tissue behaviour in more reliable way. Most popular way to describe stress-strain relationship for fat and glandular tissues is the hyperelastic neo-Hokean constitutive model [14,18], isotropic with right Cauchy-Green deformation tensor [10,22]. There are also anisotropic [24], quasi-incompresible [13] and polynomial quadratic hyperelastic [35] models.

2.5.5 Model Parameters

In breast deformation modelling three main parameters are taken into account: Young modulus, which defines the relationship between stress and strain in a material, Poisson ratio, which is the negative ratio of transverse to axial strain and material density. The first two material parameters are usually set as constant [24] or optimised during simulations [12], with constant initial value, upper and lower limits [14]. Material density differs from real measured values, to water density for every model part.

Fat material parameters have more influence on deformation results than fibroglandular material parameters. 10 % fat parameter change results in 10 % change in deformation. 10 % fibroglandular parameters change results in 1 % change in deformation [24]. According to deformation modelling small tumour parameters has negligible impact on breast deformation. Its stiffness should be 10 times greater, than surrounding tissue, to imply deformation change ca. 5 %. Such difference do not occur in nature [24]. However, there are significant stiffness differences measured for malignant and benign tumours, which influences breast deformation [23]. Moreover spiculated tumour generate stress increase at a local level [39].

One of the reliability testing method is verification of calculated von-Mises stress values [17]. Another method is comparing resulting model with real MRI or mammograms [15,35] or with landmarks applied on patient skin [25].

2.6 Modelling Difficulties

Despite different models development there appear some limitations that cause inaccuracies of the created models. The main issue is accurate tissue parameter estimation. Biomechanical properties of breast tissues have been measured *ex vivo* [29,38]. However living tissues have different properties that those, extracted from body, void of blood circulation. Moreover existing *in vivo* measuring methods (i.e. elastography) do not provide information precise enough to estimate big deformation [20]. Another issue is accurate mesh selection. Different types of mesh elements and different mesh node density gives different results [28] and in some cases the FE mesh requires manual intervention [14] as well as image segmentation [15,24]. Further difficulty provides boundary conditions setting, especially on chest wall side, where the model ends but the real body consistency needs to be preserved [34]. Still unsolved modelling issue remains patient-specific fully-automation, which is essential in clinical practice.

3 Conclusions

This paper provides an overview of FEM practices applicable to breast deformation modelling. Common breast deformation practices have been outlined. The most popular models and techniques have been described and key difficulties for future development have been specified. Authors are currently working on own deformation model, which would enable patient-specific fusion of PET-CT and MR images in supine position. Our preliminary results and conclusions were presented in [5,6].

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