A Machine Learning Based Algorithm to Determine Unloaded Geometry of the Breast Using MRI Image Data

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Abstract— **Biomechanical modelling has many medical applications in computer assisted diagnosis and intervention related to the breast. Examples include accurate breast cancer diagnosis, biopsies and surgeries, and breast post-surgery reconstruction. This approach also has industrial applications such as bra design. Breast mechanical models can be developed using Finite Element Method (FEM). Fundamental to reliable such breast models is the breast reference geometry under no loading. Most breast models use the breast Magnetic Resonance Image (MRI) to develop patient-specific FE models. However, the breast MRI scan is acquired under a prone body position which is associated with large breast tissue deformation resulting from gravity loading. As such, the breast MRI scans can only provide an approximate breast reference geometry, hence compromising the model's expected accuracy. Such compromised accuracy can impact the accuracy of vital medical procedures such as breast biopsies that require needle targeting within few millimeters. In this study, an inverse algorithm is developed which aims at accurate determination of the breast reference geometry. In the proposed framework we generated two breast shape spaces, one filled with points representing a breast undeformed shape while the other containing points representing corresponding breasts deformed due to gravity loading under prone body position obtained using each breast's FE model. To obtain a compact representation of the two spaces before fitting a function between them, principal component analysis was applied to each shape point set. A neural network was trained to find a mapping relationship between the two spaces. For validating the accuracy of reconstructed stress-free breast geometry, we applied gravity-loading to assumed unloaded breast geometry using accurate FE simulation and used it as input geometry. To validate output stress-free breast shape, Intersection of Union (IoU) score and Hausdorff distance to compare it to the input breast geometry. Results indicated that the proposed inversion algorithm is accurate in capturing the breast's stress-free configuration as well as in predicting its mechanical behavior.**

Keywords— **Computer assisted medical procedures, Breast mechanical modeling, Reference geometry, Finite Element, Neural Networks**

I. INTRODUCTION

Breast surgeries, as well as tumor tracking, prosthesis implantation, and bra design, are critical applications that require precise understanding of breast tissue mechanics. The mechanical behavior of breast tissue is known to be nonlinear which is best captured using hyperelastic models. As such, accurate modeling of the breast requires precise representation of both its reference stress-free geometry and its tissue mechanical characteristics. Once this essential data is provided, determining the breast configuration and tissue distribution under loading conditions pertaining to medical procedures is relatively straight forward using finite element (FE) modeling. While Magnetic Resonance Imaging (MRI) can capture the 3D breast geometry and its tissue distribution with desirable accuracy, it can only provide the breast configuration under gravity loading while the patient is in prone position. Such deformed geometry cannot be used to develop accurate FE models of the breast due to the breast tissue substantial nonlinearity. This tissue nonlinearity adds another complexity which pertains to the validity of the tissue hyperelastic model used to describe its mechanical behavior. It necessitates availability of such models obtained without gravity effects, otherwise, accuracy of the breast model and its fidelity is reduced. It is noteworthy that algorithms developed to estimate the breast stress-free geometry require hyperelastic model of the breast tissue. Most breast FE models have been developed using hyperelastic models derived from experimental data obtained with breast tissue samples loaded by gravity before they are mechanically stimulated. This approach has led to development of algorithms of the breast stress-free geometry prediction where inaccurate hyperelastic models derived from tests with gravity loading conditions are utilized [1] [2], hence reduced reliability of the estimated breast unloaded geometry.

Some studies have addressed the critical issue of the breast stress-free shape through designing algorithms that employ a generalized FE displacement/pressure (u/p)-formulation where they assumed that the tissue exhibits quasi-incompressible behavior under conditions of finite deformation [3]. However, the material properties utilized in these studies are often derived from transform matrix, neglecting the complexities introduced by the non-homogeneous distribution of breast tissue in practical simulation models. Another study proposed an iterative inverse FE algorithm aimed at identifying the unloaded configuration of the breast [4]. Other researchers employed different approaches to determine the stress-free configuration of the breast. For example, Rajagopal et al. [5]used water immersion and hyperelastic models, Lee et al. [6]inverted gravitational forces, Pathmanathan et al. [7] solved finite elasticity problems, Carter et al. [8] utilized iterative finite element methods, and Eiben [9]and Eder [10]also employed iterative techniques. The computational burden associated with these methods renders such developed methods both too complex and time-consuming.

To address these challenges and mitigate the above limitations, we introduce an easily implementable technique that utilizes MRI images as input for modeling. For accounting for the heterogeneous characteristics inherent to breast tissue, we introduce a space-filling strategy to generate numerous conceivable configurations, hence mimicking the tissue properties of a large hypothetical population. To tackle the issue of breast tissue hyperelastic models under stress-free conditions, we employed an machine learning based algorithm we previously developed on our laboratory to calculate tissue hyperelastic parameters under zero-gravity conditions from corresponding parameters obtained using conventional mechanical testing techniques. The integrated approach presented here allows for a more accurate and comprehensive representation of breast tissue, enhancing the reliability of the model for various clinical and research applications.

II. METHODS

The proposed algorithm was engineered to create two separate breast geometry spaces that represent the unloaded and loaded shapes of the breast. Compact representation of these two spaces are obtained using PCA before a mapping model between them is obtained using a Neural Network (NN) function. This algorithm is illustrated in Figure 1 which shows a detailed block diagram. As seen in this diagram, the algorithm is divided into three fundamental parts. First, we built a breast shape space filled with stress-free configurations generated using a combination of FE modeling and non-isotropic scaling. In the second part, we generated corresponding shape space of the breasts generated in the first space by applying gravity loading through FE simulation. In the third part of the algorithm, we employed PCA to obtain compact representations of the two spaces before training a NN to find a robust mapping between the unloaded and loaded breast geometry spaces. After training, the NN can be used effectively to determine the corresponding stress-free breast configuration for any input breast geometry acquired under gravity loading conditions.

To generate a shape space pertaining to a population of stress-free breasts, we initiated the process with a deformed breast geometry obtained from MRI scans acquired in prone position. Each image was then segmented and converted into a FE mesh. Subsequently, we identified two sets of hyperelastic parameters: one derived from existing literature [11] (denoted by $C_{loaded,i}$) and the other obtained from our previous work [12] for unloaded hyperelastic parameters (denoted by $C_{unloaded,i}$). These parameters were then paired to form loaded and unloaded hyperparameter sets. To fill the first space with stress-free shapes using FE simulation, each breast model was subjected to varying levels of anti-gravity loading, starting from 0.65G and incrementing by 0.05 up to 1.0G. For each level of anti-gravity loading, we assigned corresponding hyperelastic parameters to the breast tissue using the following linear interpolation equation, thereby obtaining a set of geometries corresponding to each simulation.

$$C_{0.x,unloaded,i} = C_{unloaded,i} + 0.x \times (C_{loaded,i} - C_{unloaded,i}) \quad (1)$$

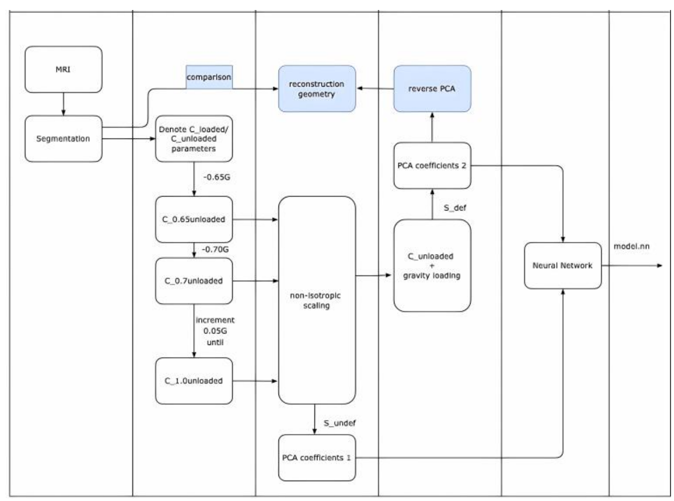

Fig. 1: Block diagram outlining the proposed inversion algorithm developed for constructing the breast stress-free geometry

To enrich the population of the undeformed breast shape space, for each geometry obtained from the FE simulations, we applied non-isotropic scaling to the node coordinates in a cylindrical coordinate system. Two scaling factors were employed: ar for the radial direction and aL for the longitudinal direction, with ar = 0.5aL. The value of aL varied from 0.85 to 1.3 in increments of 0.05 after multiple experimental trials. In addition to enriching the population, the scaling factors aims at compensation for inaccuracies in the FE model pertaining to the tissue stress induced anisotropy.

Upon the construction of the two shape spaces, we extracted the surface nodes from the FE mesh models derived from each space to represent each shape point in the space. Due to using tetrahedral second-order finite elements for meshing for accurate modeling of the breast tissue, the total number of nodes of each model surface were averaged at more than 1000 nodes. Based on the large amount of data included in these points and their coordinates, PCA was performed on the surface node sets in each shape space to obtain a compact representation of the sets denoted by S_{undef} and S_{def} . The two sets of coefficients obtained from PCA served as the input and output for training a NN to find a computationally effective mapping function between the two shape spaces. As for the selection of the optimal number of principal components considering the computation time, we conducted experiments ranging from 7 to 11 to strike a balance between retaining at least 95% of the information content and compressing the data vector as much as possible. This multi-faceted evaluation ensured that the chosen PCA dimensionality captures the essential features of the data while rendering it computationally efficient for the subsequent NN training (total 8 layers containing fully connection and dropout layers, 1600 neurons applying rectified linear unit ReLU as activation). Following a thorough cross-validation, we opted for RMSprop as our optimization algorithm. Its adaptive learning rate and fewer hyperpaameters made it particularly apt for dimensionality-reduced datasets, thereby miti-gating the risk of overfitting.

For validation, we employed a reversed simulation approach, wherein we applied gravity to reconstructed state-free geometry of the breast using FE simulation before computing a synthetic MRI image using the FE displacement field and MR image intensity values. This image was compared with the original MRI model. To assess the differences between the two point cloud models, we compare their Intersection over Union (IoU) to identify areas of the greatest discrepancy, which correspond to specific locations within the breast tissue. The accuracy of reconstructed the stress-free breast geometry was then evaluated using the Hausdorff distance between the two point clouds, providing a quantitative measure of the model's accuracy and reliability.

III. RESULTS

The evaluation metrics are shown in Table 1. Based on varying selections of the number of PCA terms (PCs), we evaluated Mean Squared Error (MSE) for prediction accuracy, Intersection over Union (IoU) for object overlap, and Hausdorff Distance in millimeters to measure shape discrepancies. Additional metrics include Mean HDu (mm) for aver -aged shape differences under specific conditions and Recon -struction Time in minutes is included to assess computational efficiency.

Table 1: Evaluation Metrics

PCs	7	8	9	10	11
MSE	0.142	0.018	0.0064	0.0062	0.0063
IoU	0.799	0.853	0.898	0.903	0.9041
HD (mm)	2.613	2.285	1.218	1.109	1.097
Mean HDu (mm)	0.25	0.22	0.212	0.209	0.21
Time (mins)	4.8	5.4	7.1	13.3	18.5

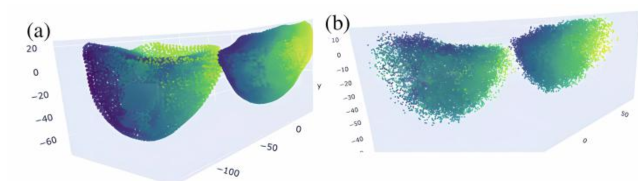

Fig. 2: Comparison between two point clouds of (a) the ground truth breast model extracted from MRI and (b) reconstructed breast model generated by loading the state-free geometry with gravity loading.

IV. CONCLUSION

In this study, we introduced a novel method for determining the reference geometry of the breast under no gravity conditions. This method is founded on integrating machine learning with finite element simulation. It builds upon and validates our prior work on estimating hyperelastic parameters of unloaded breast tissue, offering a more nuanced understanding of breast tissue mechanics. Utilizing an exhaustive exploration of the breast shape space, our approach accounts for the often-neglected heterogeneous and stress induced anisotropy characteristics of breast tissue. We employed multiple sets of parameters to validate the robustness of our model, showing that it is not sensitive to the choice of parameters as long as they are within a reasonable range. For quantitative assessment, we evaluated the model's performance based on specific criteria, demonstrating a significant reduction in error rates and an improvement in the reliability of the estimated reference geometry.

The depth of our model's application suggests potential suitability for various medical and engineering tasks, enhancing both safety and efficacy. Future work may include further validation using experimental set ups pertaining to clinical applications and extension to other organs that undergo substantial deformation under gravity such as the liver. Particularly, the model's performance under larger external force loading conditions warrants further investigation. Overall, our study marks a substantial advancement in breast tissue mechanics and modeling, paving the way for enhanced diagnostic and surgical techniques as well as material design innovations.

V. Compliance with Ethical Standards

This study involving human participants was conducted in strict adherence to ethical principles. Written informed con- sent was obtained from all individual participants involved in the study. Furthermore, the research protocol was rigorously reviewed and approved by the Institutional Ethics and Review Board at each participating institution, ensuring compliance with ethical standards and participant safety.

Clinical Relevance

The algorithm can be used as an effective tool in developing breast models with high fidelity, paving the way for developing reliable systems of image and computer assisted medical diagnosis and intervention of the breast. Input of the algorithmis preloaded breast geometry which can be extracted from conventional breast MRI data. The output is the breast's stress-free reference geometry which can be used to develop highly accurate nonlinear mechanical model of the breast.

Conflict of Interest

The authors declare that they have no conflict of interest.

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