Learning based estimation of the unloaded state for biomechanical models of the breast

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ABSTRACT

Breast deformation simulations typically require estimating a stress-free (unloaded) state, often using iterative FEM-based methods on gravity-loaded MRI data—an approach that is computationally intensive. This work aims to accelerate that process using a machine learning (ML) model. Building on our previous work in this field, we adapt and extended the approach to the given problem and furthermore treat tissue stiffness as a free parameter. After normalizing the data and extracting features from the biomechanical model, we used XGBoost to predict the unloaded node positions from those of the gravity-loaded state. The model was trained on 418 datasets from 23 patients, each simulated with 10 different Young's moduli. In 10-fold cross-validation, the average prediction error was $2.7, mm$ compared to FEM ground truth. This ML approach reduces unloaded state estimation time from 20 minutes to just 0.06 seconds, enabling real-time deformation.

Keywords: Biomechanical Model, Machine Learning, Unloaded state, Breast Imaging, Multimodal diagnosis and intervention

1. INTRODUCTION

The early and accurate detection of breast cancer increasingly depends on multimodal imaging, including X-ray mammography, magnetic resonance imaging (MRI), and sonography, to harness complementary diagnostic information. Nevertheless, these modalities exhibit substantial differences in patient positioning and breast compression, resulting in pronounced non-linear tissue deformations that complicate image interpretation and computer-aided diagnostic processes. Notably, mammography can induce breast compression of up to 70%, introducing significant morphological alterations that pose considerable challenges for lesion co-localization.

Biomechanical breast simulations are widely used for multimodal image registration.[1] The aim of those methods is estimate the deformation field which relates points of interest in one modality to the corresponding ones in the other modality. Finite Element Methods (FEM) are commonly employed to model tissue response under loading. Due to anatomical variability, these models are typically patient-specific, constructed from medical images, most often 3D MRI scans.[2] In our previous work[3,4] we have developed an automated pipeline to generate patient-specific biomechanical models of the breast including tissue segmentation and tetrahedral meshing, enabling simulation of various deformation states, such as breast compression during mammography.

One drawback of using an MRI as input for the generation of a biomechanical model is the stress which acts on the breast during image acquisition in prone position due to gravity. This poses a pre-deformation of the breast in the biomechanical model which is not present in the actual imaging scenario of the target modality it should be registered to. Hence, as a basis for modeling realistic deformations, an estimation of the unloaded state from the gravity loaded MRI is required as an intermediate, stress-free and undeformed state. This poses an inverse problem, which can be solved in different ways, see e.g. Eiben et al.[5] We have chosen to use an iterative estimation of the unloaded state, since it provides superior accuracy to a one-step inversion of the gravitational force vector.[5] This approach involves repeatedly simulating gravity on an estimation of the unloaded state until the simulated shape matches the MRI. It requires many FEM simulations, resulting in long run times of minutes to hours.

The aim of this work is to accelerate the iterative estimation of the unloaded state by a machine learning (ML) method, similar to our previously published work on the estimation of the compressed state of the breast.[6] Unlike earlier models with fixed material properties, our ML model treats tissue stiffness as a free input parameter, enabling predictions of the deformation field across varying material conditions.

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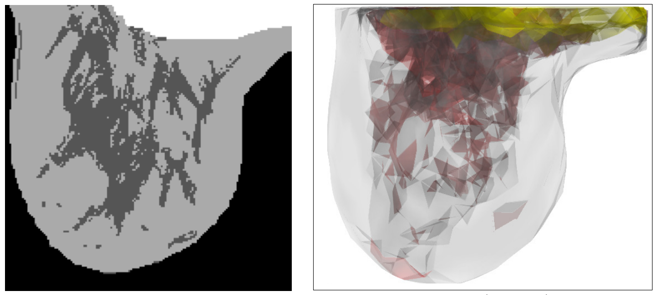

Figure 1: Left: Slice of a right breast in an MRI segmented into background(black), fatty tissue (light gray), fibroglandular tissue (dark gray) and muscle (white). Right: Semi-transparent volume rendering of the corresponding biomechanical model with yellow elements showing muscle tissue, red elements showing fibroglandular tissue and light gray showing surface of fatty tissue.

2. METHODS

2.1 Biomechanical model

Our biomechanical breast model builds on the one used for registration of MRI and X-ray mammography.[3] The patient-specific breast geometry is extracted by segmenting T2-weighted MR images using an unsupervised neural network.[7] The tissue is classified to fatty, glandular, and muscular tissue. A tetrahedral mesh with approximately 2500 4-node tetrahedral elements is generated using iso2mesh[8] by defining iso-surfaces between the segmented regions (Figure 1).

An isotropic, nearly incompressible neo-Hookean model was used to represent the nonlinear mechanical behavior of breast tissue. Each finite element was assigned a material parameter based on its segmented region. A constant Poisson's ratio ($\nu = 0.495$) was applied across all tissues. The Young's modulus for fatty and glandular tissue was varied due to the wide range of values reported in the literature and its strong influence on force-driven deformation (see Section 2.2).[9] Lower moduli result in greater deformation under the same applied force. In practice, the Young's modulus is optimized per patient during image registration,[10] so the proposed ML model treats it also as a free parameter (feature input) in order to predict stiffness and patient-specific deformation output. To reduce the computational effort for data generation with FEM simulations, a fixed ratio of 3.6 between glandular and fatty tissue stiffness was applied based on Wellman's findings,[11] i.e. glandular tissue was for all simulations modeled 3.6 times stiffer than fatty tissue. Fatty tissue moduli ranged from 1100 Pa to 5676 Pa. Muscle tissue was modeled with a constant Young's modulus of 6000 Pa and treated as a rigid body, with constrained motion at the muscle–tissue interface. A 2 mm thick skin layer was included using triangular membrane elements on top of the outer tetrahedral elements with a Young's modulus of 1000 Pa.

2.2 Data generation: iterative estimation of unloaded state

To estimate the unloaded state from the gravity-loaded MRI we apply an iterative method, which sequentially performs a forward simulation applying a gravitational force in posterior-anterior direction to a current guess of the unloaded state. The gravitational force is simulated by applying a body load to the biomechanical model with an acceleration of 9.81 m/s^2. ABAQUS[12] is used to solve the FEM simulation. The initial guess is calculated by simply inverting the force direction, i.e. simulating an antero-posterior directed gravitational force to the biomechanical model derived from the gravity loaded MRI. After each iteration, the resulting mesh of the forward simulation is compared to the mesh generated from the MRI. For each node, the displacement between both models is calculated by the Euclidean distance and the displacement direction. A given step width into the displacement direction is used to update the estimate of the unloaded state for the next forward simulation. Iterations will be stopped if either the change of the estimate of the unloaded state is small (empirically a threshold of 10% of the initial error is chosen) or a maximum number of iterations is reached (empirically a maximum number of 20 iterations is defined in this work). The computation of the unloaded state with this method took approximately 20 minutes per breast.

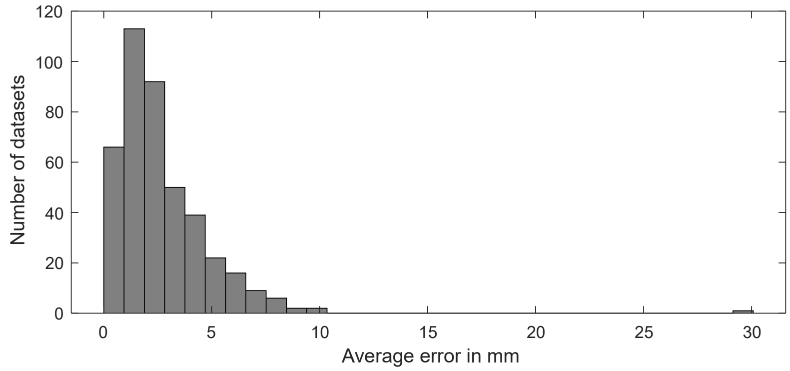

Figure 2: Histogram of errors for all considered 418 datasets.

2.3 Machine learning approach

Our machine learning approach is based on our previous work.[6] The basic idea is to predict the unloaded state directly from the biomechanical model, which was created from the gravity loaded MRI. For this purpose we propose a supervised training, in which the unloaded state simulated according to the method described in subsection 2.2 serves as ground truth.

As the datasets typically differ in the field of view due to manual selection in the acquisition process, all biomechanical models are first brought into a common coordinate system by applying a Min-Max-Normalization to the node positions. Subsequently we extract a total of 12 features from the biomechanical model, which serve as a basis for the machine learning model thereafter. Features include the initial Cartesian node positions, the percentage of fat, glandular and muscle tissue in the breast, the breast volume, the number of elements representing fatty, glandular and muscle tissue, the Young's modulus for fatty and glandular tissue. One instance used in the training/testing therefor corresponds to a row vector representing one node of one dataset with the respective 12 columns representing the features. For supervised training, the resulting node position of the estimated unloaded state is used as label. The machine learning approach aims to directly predict the unloaded state from the gravity loaded MRI in one evaluation step for each node.

Similar to our previous work we applied XGBoost as machine learning model.[13] XGBoost is an optimized, distributed implementation of gradient boosting algorithms designed for high-performance predictive modeling. It employs additive tree-based models trained via gradient descent on differentiable loss functions, incorporating regularization to mitigate overfitting. Hyperparameters like learning rate, maximum depth of the trees, minimum child weight and the number of trees in the model have been optimized by a grid search.

2.4 Evaluation methods

A total of 418 datasets from 23 patients, including in most cases both breasts and simulations of 10 Young's moduli each, have been generated with the methods described in 2.2. For analysis we performed a ten-fold cross-validation. To assess the accuracy of the predicted unloaded state, the Euclidean distance between the predicted nodal position and the ground truth was calculated. Each dataset consisted in average of 2263 nodes (standard deviation: 1516 nodes). The error metric used in the following result section was computed by the averaged Euclidean distances over all nodes for each simulated dataset.

3. RESULTS

Training for the 10-folds took approximately 30 s in total on a NVidia RTX 3090 GPU with 24 GB VRAM. The time for prediction was approximately 15 s during the 10-fold cross-validation, which equals approx. 0.06 s per breast. The optimized hyper parameters included a learning rate of 0.08, a maximum depth of the trees of 8, a minimum child weight of 50 and 100 trees per model.

The average error across all predicted datasets was 2.7 mm (median: 2.2 mm, std: 2.4 mm). Figure 2 shows a histogram of the errors. The majority of datasets are predicted with an error below 3 mm.

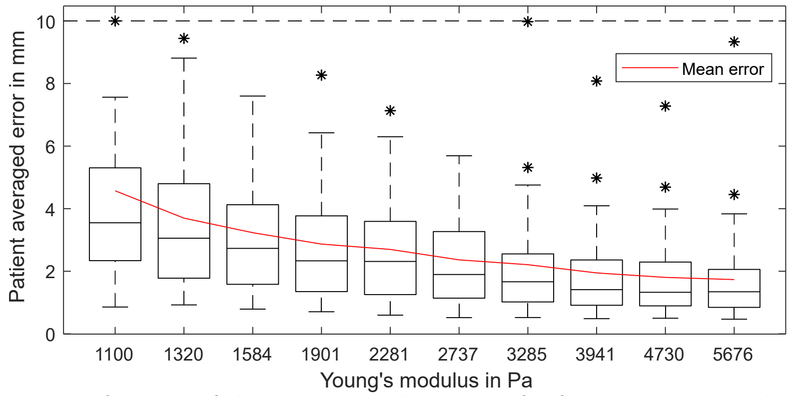

Figure 3: Boxplot of errors as a function of the Young's modulus used for fatty tissue. Note that outliers are clipped to $10\,mm$ for better visualization as indicated by the dotted line. The red line indicates the mean errors for each Young's modulus.

Further analysis showed that the average error is lower for higher Young's moduli, see Figure 3. This is likely due to the fact that the tissue displacement is generally lower with higher Young's modulus, see section 2.1. The mean error across all predicted datasets with a Young's modulus of $1100\,Pa$ was $4.6\,mm$ and at a Young's modulus of $5676\,Pa$ it was $1.7\,mm$.

Since the current approach predicts the nodal positions independent of each other, i.e. neither with knowledge about their connectivity nor with physical constraints, we assessed the volume change of resulting mesh, reconsidering that the biomechanical simulation is modeled nearly incompressible. The mean volume loss of the ML predicted unloaded state compared to the original biomechanical model was 2.5%, while in comparison the volume loss of the FEM simulated unloaded state against the original biomechanical model was 0.4%. While the volume loss is still relatively low, we are currently exploring the use of graph-based and/or physics informed neural networks to encoded the incompressibility.

An exemplary result of the predicted unloaded state compared to the ground truth and the gravity loaded biomechanical model is shown in Figure 4.

4. DISCUSSION AND CONCLUSION

We presented a machine learning algorithm to simulate the mechanical response of breast tissue when estimating the unloaded state. In contrary to our previous work,[6] the estimation is based on the more accurate iterative estimation approach which leads to a more complex deformation of the biomechanical model than by simple inversion of the gravity force vector. To our best knowledge this is also the first approach to predict the outcome of an FEM based deformation simulation of the breast with the Young's modulus as free input parameter. The results are encouraging with a mean error of $2.7\,mm$ across more than 400 datasets.

The application of the ML approach presented in this work would reduce the computation time of the iterative estimation of the unloaded state from approx. $20\,min$ to $0.06\,s$, allowing for interactive real time deformation, which could be well integrated into clinical workflows, e.g. for interactive prediction of corresponding locations in modalities viewed side-by-side. The prediction of the unloaded state is a precondition for subsequent biomechanical deformation simulations such as mammographic compression. It remains to be researched in future if the additional error from the machine learning model - though low - has an impact on the registration results if e.g. combined with a compression simulation for aligning MRI to X-ray mammography.

Our approach is based on traditional machine learning techniques included hand-crafted feature extraction from the biomechanical model. While a basic set of features was applied in this work, more descriptive features may be added in future to further improve the results. Furthermore the current method does not respect continuity of the meshes or physically based restrictions. While the results with this relatively simple approach are already encouraging and the volume-loss is low, we are exploring graph-based and physics informed neural networks for future improvement.

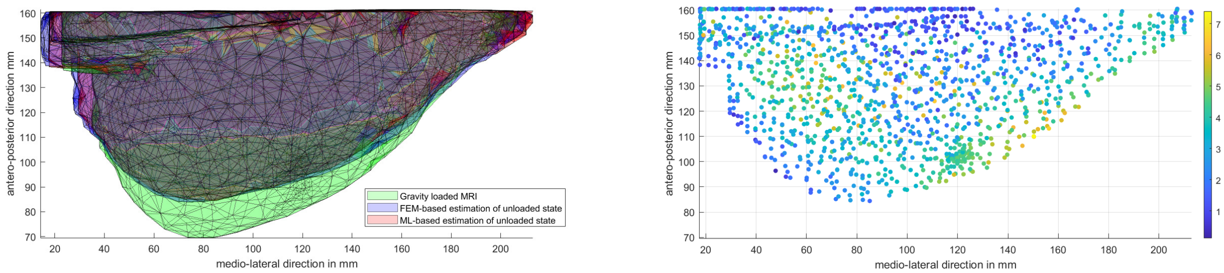

Figure 4: Left: rendering of the biomechanical model in gravity loaded state (green), in the unloaded state estimated by the FEM simulation (blue) and the unloaded state estimated by the ML approach. The average error for this dataset was 3.0 mm. Right: Nodal position with color-coding of the local error per node.

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