MULTI-MATERIAL, APPROACH-GUIDED, CONTROLLED-RESOLUTION BREAST MESHING FOR FE-BASED INTERACTIVE SURGERY SIMULATION

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ABSTRACT

This paper proposes a guided, controlled resolution framework for 3D multi-material meshing. Using data from magnetic resonance (MR) images, we efficiently focused on demonstrating our framework for patient-specific breast cases. As a result, we can preserve the shared boundaries and enhance the resolution without negating the aspect of simulation computing time needed for finite element analysis (FEA). Our output is a high-quality volumetric mesh comprising 21K cells representing the three main parts for breast surgery simulation and planning, fat, fibroglandular (FGT), and tumor mass. Our approach combines three steps, surface meshing, surface mesh decimation, and generating a volumetric mesh. We showed experimental results for every stage and compared our final output to other literature, proving our method's efficiency in an accurate, simple, and high-quality presentation of a patient-specific breast meshing.

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Keywords: multi-material breast mesh, shared boundaries, simulation, breast surgery, surgery planning.

1 INTRODUCTION

Patient-specific representations of anatomical structures are crucial for surgical interventions like breast cancer surgery; inaccurate structures can lead to possible complications such as repeatable surgery and total mastectomy. Thus, we choose the breast model as a case study of our work since breast cancer is the most common cancer among women, after skin cancer (Torre 2015). In 2022, new cases of 287,850 invasive breast cancer and 51,400 new cases of non-invasive breast cancer were anticipated in the U.S. (Giaquinto et al. 2022). Lumpectomy and mastectomy are invasive treatments to remove tumor masses, preoperative, operative, and postoperative visualizations are required and are achieved mainly through ultrasound (U.S.) and MR imaging (Gittleman 2003). However, the images of the patient's position noticeably vary between the preoperative and operative imaging, leading to a misalign between the images. Hence, it is vital to create a way to enhance breast tissue localization accuracy in real-time applications. Nonlinear and linear finite elements analysis (FEA) techniques are proposed to simulate tissue deformation precisely, and since the breast is hyper-elastic anatomy, nonlinear FEA is preferred over linear FEA.

Consequently, Multi-material meshing plays a vital role in the resolution of FEA and localization accuracy. The main challenge with breast imaging is the irregular anatomy, posing difficulty in constructing a high-quality mesh model for FEA. (Bro-Nielsen and Cotin 1996) simplified the FEA problem where the breast mesh only contains the surface, resulting in fast simulation but lower accuracy. On the other hand, (Mendizabal et al. 2020) created a hexahedral grid for the whole breast structure, neglecting the different tissue properties such as fat and FGT. (Wang and Kesavadas 2022) created one mesh set and then identified the parts of the corresponding tissue from the generated mesh which failed to preserve the shared boundaries

To overcome these challenges, we present a multi-material patient-specific breast phantom mesh that is first initialized using MR data from (Alqaoud et al. 2022) in Section 2.1. Then, in Section 2.2, we preserve the shared tissue boundaries by surface meshing. Thirdly, as in Section 2.3, we apply decimation to enhance the resolution of tissue surface meshing. Finally, we apply volumetric meshing for every tissue individually, then merge them in one mesh, as detailed in Section 2.4. Hence, this pipeline we create allows us to preserve the boundaries and the resolution without increasing the computing time for the simulation process. Our final output can be used for intraoperative surgery planning and anatomical modeling for breast surgery simulation.

2 DATA AND METHODS

It is critical to recognize the structure of breast anatomy to create multi-material patient-specific breast mesh for FEA. The breast anatomy consists of skin, fat, FGT, nipple, and sometimes tumors. The breast can be simplified to fat, FGT, and tumor masses if located in the breast (Zolfagharnasab et al. 2018). The pipeline of our manual methodology consists of 3 steps, preserving the shared tissue boundaries, tissue surface meshing decimation, and 3D mesh generation, as shown in Figure 1.

2.1 Datasets

Our breast phantom is constructed based on data and the methodology from our previous work (Alqaoud et al. 2022), as shown in Figure 2. They used breast MR images from 10 patients with both left and right breasts to train a deep neural network using the nnUNet model for an automatic method. We segmented the MR images into fat, FGT, and tumors using the nnUNet model (Alqaoud et al. 2022). Therefore, we choose to construct a breast phantom to advance future experiments on breast surgery research.

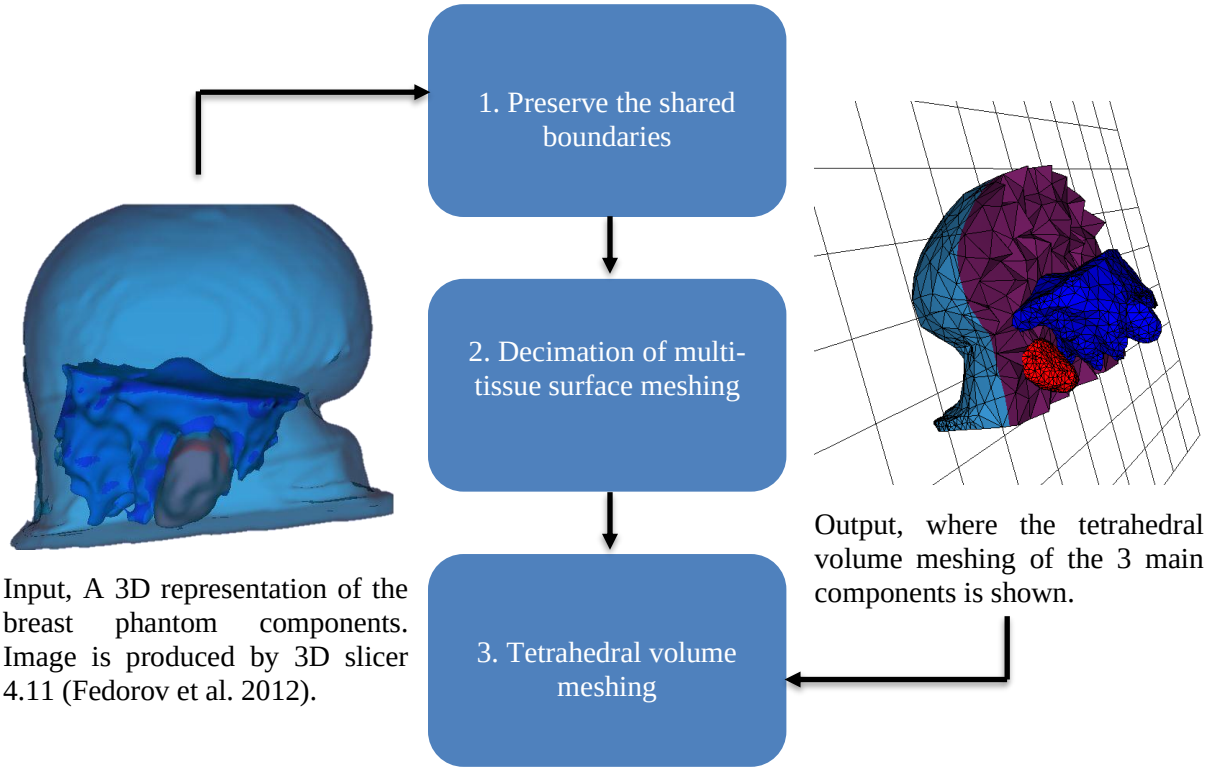


Figure 1: A flowchart of the 3 main steps of our methodology fat, FGT, and tumor, represented in cyan, blue, and red, respectively.

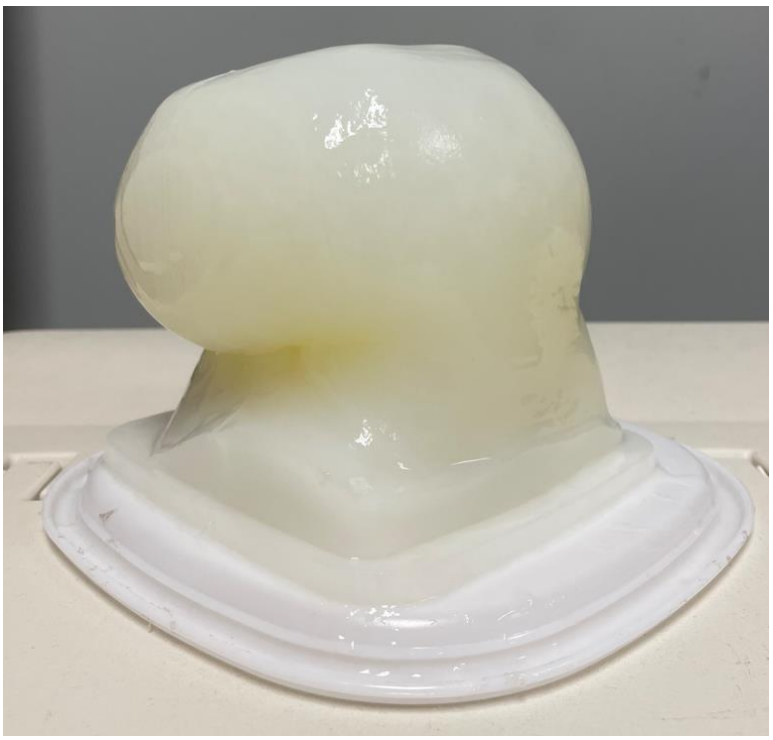


Figure 2: The constructed breast phantom where we follow the methodology from our previous work (Alqaoud et al. 2022).

2.2 Preserve the shared boundaries

We use the surface meshing algorithm introduced by (Rashid et al. 2017). Thus, it is a multi-material version of the deformable 2-simplex mesh framework. A 2-simplex model is a 2-manifold discrete mesh; every vertex is linked to its three adjacent vertices. It experiences deformations based on image-based external forces and geometry-based internal forces, following the Newtonian law of motion (Delingette 1999):

$$m_i \frac{d^2 P_i}{dt^2} = -\gamma \frac{dP_i}{dt} + F_{int} + F_{ext} \tag{1}$$

Where m_i, P_i represent the mass and the vertex position of the mesh. $F_{int}$and F_{ext}represents all internal forces and all the image-based, gradient-attracted external forces acting on P_i, while γ represents a damping coefficient.

2-simplex meshes are topologically dual to triangular meshes; this geometric duality can be utilized to generate 2-simplex meshes from triangular surface meshes. The centroids of triangles in the triangular mesh match the vertices of the simplex mesh. Edges of the simplex mesh are then generated by linking these simplex vertices. Thus, the mesh's material information is preserved. Multi-material 2-simplex (MM2S) mesh can be defined as a set of S^m where V represents the set of n vertices, M is the set of positive integers relating to the material, and p and q are the pairwise material assigned to each vertex. E represents the set of m edges (Rashid et al. 2017).

$$S^m = \{V, E\} \tag{2}$$

$$\{V_i^{p,q}\}, \{i = 0, \dots \dots, n\}, v_i \in R^3, \{p, q \in M\}, \{p \neq q, M\}, p \neq q, M \in N^+$$

$$\{\{v_i, v_j\}_m\}, \forall v_i \in V, \forall v_j \in V, i \neq j \tag{3}$$

2.3 Decimation to enhance the resolution of multi-tissue surface meshing.

We use an algorithm provided by (Valette and Chassery 2004) for surface meshing decimation and mesh coarsening, which creates uniform triangulations. Hence, the algorithm is open-source and publicly available at (https://github.com/valette/ACVD). Thus, the first step of the algorithm is clustering the mesh cells (triangles) into an approximation of a Centroidal Voronoi Diagram (CVD), which is the primary part of the algorithm. The clustering is established on validity checking and energy minimization. The second step comprises substituting each cluster with a single vertex and then creating the triangulation based on the cluster's contiguity relations. Thus, this step simultaneously simplifies the mesh geometry and topology while preserving mesh information. We option in this step for two cases: 21K vertices and 2.1K vertices, to compare the surface meshing resolution and its information presentation. Our choice was based on the lowest resolutions possible as 2.1K vertices compared to its 10 times in magnitude to 21K vertices

2.4 Tetrahedral volume meshing

We create a tetrahedral mesh with CGAL 5.5.1 using the mesh generation package that generates isotropic simplicial meshes (Alliez 2022). The meshing engine of this package is based on Delaunay refinement (Chew 1993; Ruppert 1995; Shewchuk 1998). It uses the concept of restricted Delaunay triangulation to ensure a fair representation of mesh features. A mesh optimization stage follows this to provide a good quality mesh and remove any noise. The output mesh is a 3-dimensional triangulation. This step is critical for a fast and accurate FEA simulation (Wang and Kesavadas, 2022). The generated tetrahedral mesh

quality and tetrahedron numbers impact FEA simulation results, given that a good mesh quality would have a high number of tetrahedrons is an indicator of the accuracy of an FEA simulation. Still, on the other hand, it would negatively impact the computing time.

3 RESULTS

After surface meshing is performed, the phantom mesh has the number of vertices and cells 37414 and 74812, respectively. This process took around 34 seconds (s). Figure 3 shows the output result of the surface meshing step. Therefore, we were able to preserve the boundaries in this step. In the decimation step, we have two cases: 21K vertices and 2.1K, as shown in Figure 4. This process took around 1 s and 15 s, respectively. The evaluation mesh geometry quality for the surface meshing and the decimation steps are presented in Table 1. The mesh quality results are based on the resulting triangle angles: the average minimal angle, the minimal angle, and the percentage of angles that are less than 30 degrees $P30^o$. (Valette and Chassery 2004). Likewise, we validate the mesh geometry quality based on the shape of the triangles: average quality Qav, minimal quality Qmin, the values range between 0 and 1, as stated in (Frey and Borouchaki 1997).

Lastly, we generated a tetrahedral 3d volumetric mesh, as shown in Figure 5, for; fat, FGT, and tumor mass individually. This process took around 40 s for 2.1K case and about 300 s for 21K case. Thus, the total time for the mesh creation is 75 s and 349 s for 21K and 2.1K, respectively. The number of vertices and cells after each step is shown in Table 2, and a comparison between our results and two related studies is presented in Table 3.

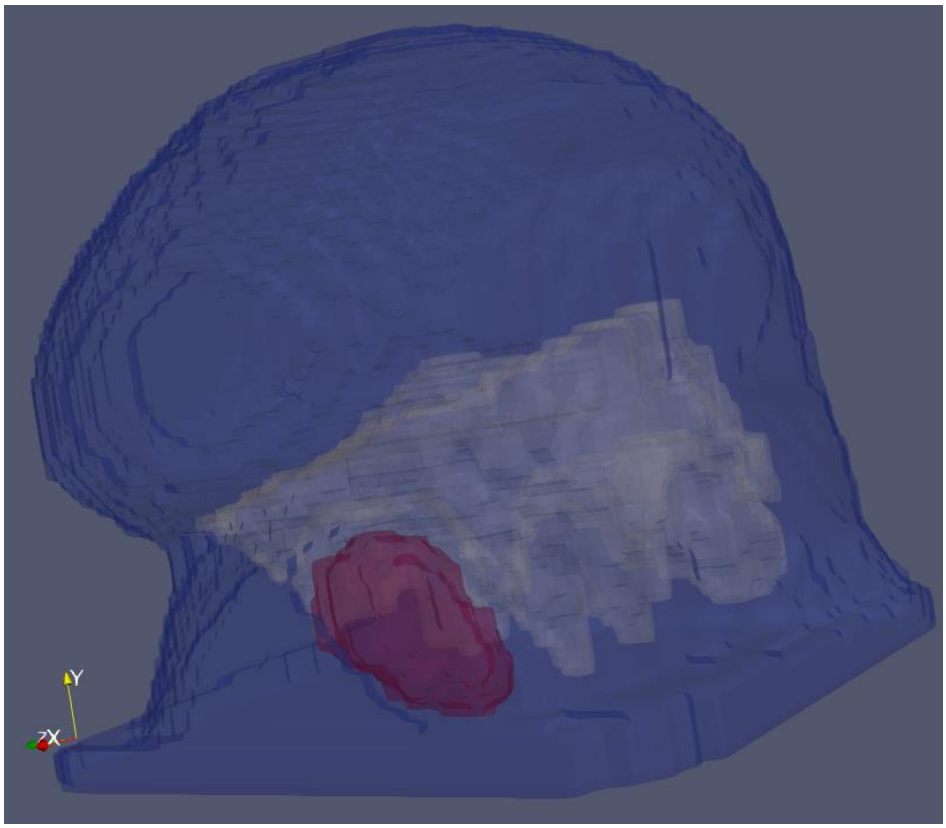
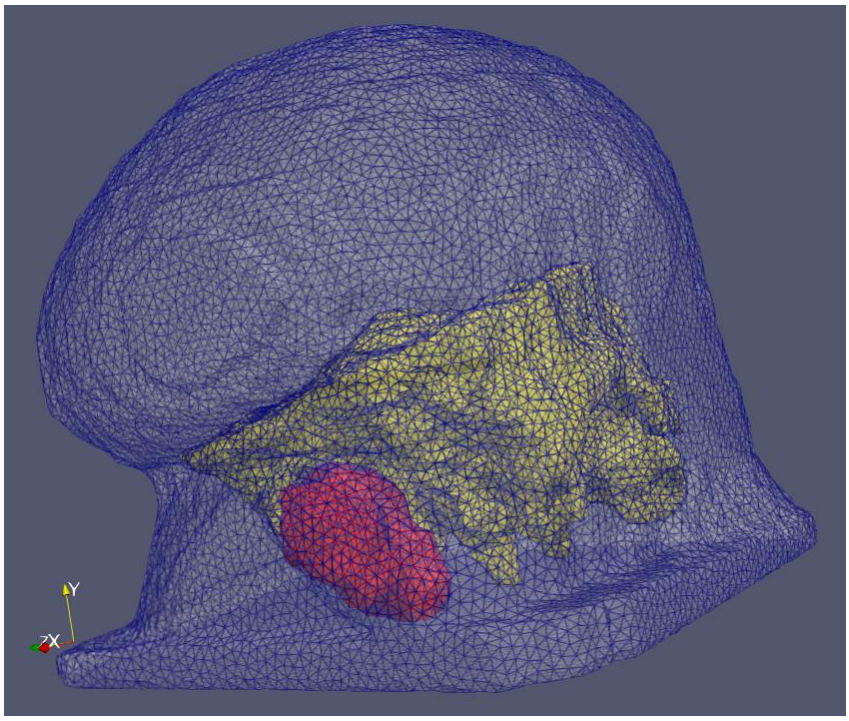
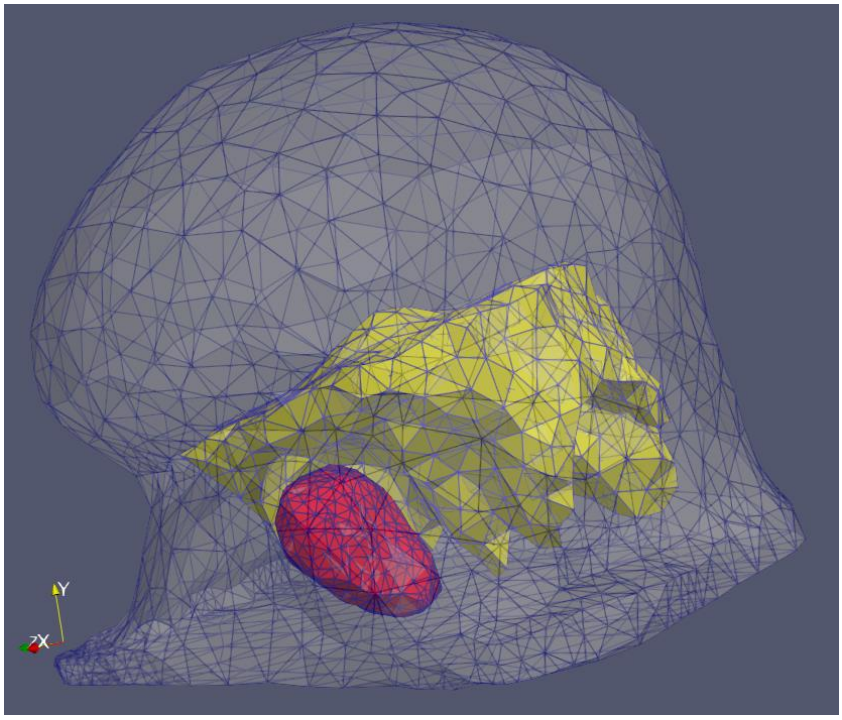


Figure 3: The output result of the surface meshing algorithm where the shared boundaries are preserved. Fat, FGT, and tumor are represented in blue, light yellow, and red, respectively.



(a)



(b)

Figure 4: (a). The output result of the 21K vertices case of mesh decimation algorithm, where the surface meshing resolution is improved. Fat, FGT, and tumor are represented in ivory blue, yellow, and red, respectively. (b) The output result of the mesh decimation algorithm of 2.1K vertices case. Fat, FGT, and tumor are represented in ivory blue, yellow, and red, respectively.

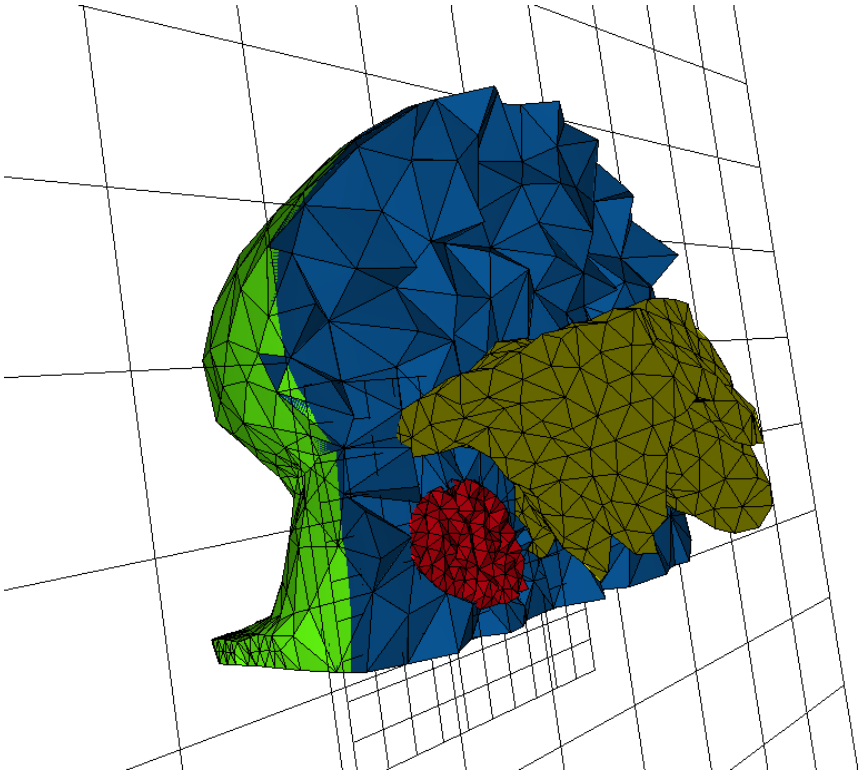


Figure 5: Intersection view of the 3D tetrahedral mesh step. Dark blue presents the volumetric tetrahedral mesh of the fat tissue, the FGT mesh surface is shown in dark yellow, and the volumetric tetrahedral mesh of the tumor mass is shown in red.

Table 1. The quality of mesh geometry for the surface meshing and the decimation steps.

	Average Min. Angle	**Min. Angle**	**P30**	**Qav**	**Qmin**
1st step: surface meshing	41.317	13.7691	1.23777	0.706846	0.232047
2nd step: mesh decimation	1st Case: 21K: 49.0487	26.5	0.00555714	0.860981	0.412079
	2nd Case: 2.1K: 48.0243	28.5458	0.0397962	0.848394	0.486425

4 DISCUSSION AND FUTURE WORK

We Compare our results to two literature (Mendizabal et al. 2020) and (Wang and Kesavadas 2022), as shown in Figure 6. Table.2 shows that we did not sacrifice the quality elements of the mesh when we reduced the model size. Thus, our output mesh is proper for FEA. Furthermore, we present a less complicated but more accurate shape of each part as we carefully preserve the shared boundaries. The

pipeline we developed and propose to generate a high-accuracy patient-specific breast for breast deformation simulation has three main steps detailed in section 2.

Table 2. The number of vertices and cells after each step.

	1st step	**2nd step**			**3rd step**	
		1st Case: 21K		**2nd Case: 2.1K**	**1st Case: 21K**	**2nd Case: 2.1K**
Number of vertices	37414	Fat	15143	1519	2714	1653
		FGT	5148	511	3288	1255
		Tumor	709	70	1072	853
Number of cells	74812	Fat	30282	3034	16089	9563
		FGT	10292	1527	20434	7651
		Tumor	1414	136	6152	4707

Table 3. Comparison between the number of mesh cells of our method and other literature.

Author	**number of total cells**	**Notes**
Mendizabal et al. (2020)	2174 hexahedral	Neglecting the breast's different tissue properties
Wang and Kesavadas (2022)	Total of 900K-1M Tetrahedrons	Neglecting to preserve the tissue-shared boundaries
Ours	Total of ≈ 21 K	Presenting an accurate method to multi-material patient-specific mesh without neglecting the computing time aspect

Our study has some limitations. First, we only test our method on one object, but we plan to increase it in future work. Another limitation is that our work is ongoing, and we could not perform an FEA simulation yet. Still, we expect our simulation to be less time-consuming and yield accurate results. However, despite these limitations, our pipeline allowed us to represent outstanding results and exhibit the potential capabilities of accurate meshing methodology. This mesh will then be used for FEA simulation, and then use the output data in a state-of-the-art graph neural network (GNN) to synthesize tissue-aware FE. We are working on using a physics–driven graph neural network (PhysGNN) based model to predict breast tissue deformation (Salehi and Giannacopoulos 2021). PhysGNN will be utilized to be used on our data, and thus, will then solve the elastic transformation between preoperative MR imaging and intraoperative 3D ultrasound (U.S.) to estimate deformation due to a change in patient orientation from prone to supine, intraoperative deformations due to compression by the U.S. transducer, and due to surgical intervention.

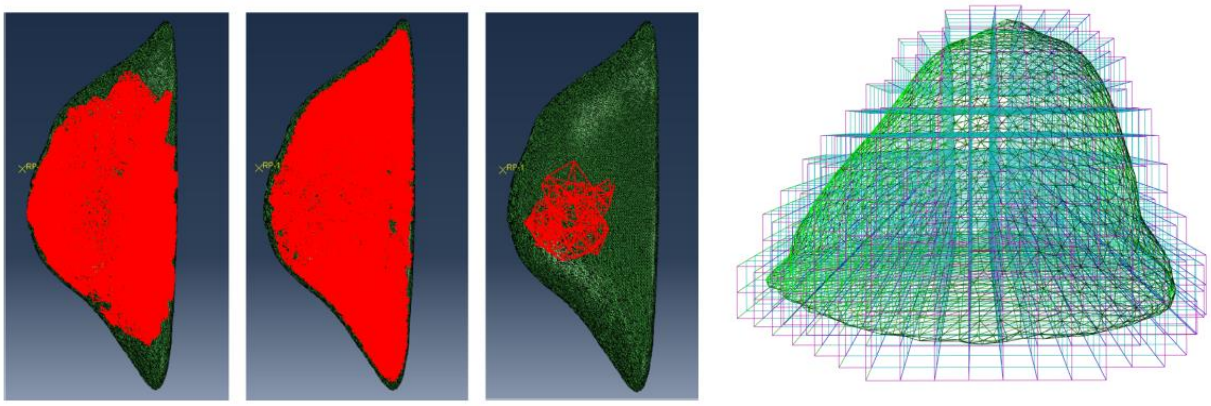


Figure 6: Two methods for representing the breast mesh from two literature. The left part is from (Wang and Kesavadas 2022), and the red area is, from left to right, FGT, fat, and tumor, respectively, assigned individually for multi-material presentation. The right is from (Mendizabal et al. 2020), representing the hexahedral mesh for one mesh set.

5 CONCLUSION

In this paper, we proposed a methodology using patient-specific breast data phantom to generate an accurate 3D multi-material breast mesh for future FEA simulation. Furthermore, we were able to preserve the shared boundaries without neglecting the computing time factor. Finally, our method would allow us to further our research into visualizing a real-time deformation and give an accurate prediction for tumor location during breast surgery through FEA simulation and graph neural network.

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