Interactive 3D Breast Model: Empowering Women's Health

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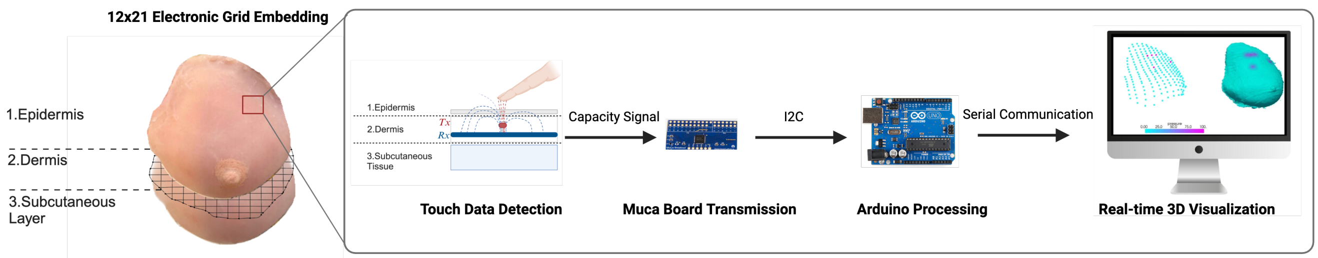

Figure 1: Overview of the sensor-integrated breast model.

Abstract

Early detection of breast cancer significantly improves survival rates, yet many individuals lack proper training in breast self-examination (BSE). A major challenge lies in the absence of realistic models with real-time instruction on palpation technique. To address this, we developed a low-cost, interactive 3D breast model that detects and visualizes touch location and pressure in real time using a stretchable mutual capacitance sensor grid integrated into a biofidelic silicone structure. The physical model was digitized using 3D scanning, and touch data were spatially mapped onto the surface of the digital mesh using an inverse-distance weighted interpolation algorithm. The system processes 252 intersection signals at 60 Hz via the Muca sensing board and Arduino, enabling dynamic visualization of interaction data. Sensor accuracy was validated through calibration, and touch data was recorded for offline analysis. The model accurately replicates human breast texture and enables sensitive touch detection. Real-time feedback guides users to perform systematic palpation, enhancing BSE technique and awareness. A pilot with public participants is being conducting to compare their palpation completeness and technique in palpation after receiving system guidance. By promoting systematic examination and awareness, it holds strong potential for public health applications.

CCS Concepts

• **Human-centered computing** → **Haptic devices**; **Scenario-based design**.

Keywords

Breast Cancer Awareness, 3D Interactive Model, Healthcare Education, Biofidelic Manikin

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1 Introduction

Breast cancer (BC) is one of the most common malignant tumors worldwide, posing a significant threat to women's health. In 2022, an estimated 2.3 million women were diagnosed with breast cancer, and approximately 670,000 died from the disease, making it the leading cause of cancer-related deaths among women and accounting for one-quarter of all [14] female cancer cases globally [4]. The incidence and mortality rates are rising, particularly in transitioning countries [2].

Breast cancer typically originates in the lobules or ducts of the breast(Figure 2). While early-stage, non-invasive (in situ) cancer is not life-threatening, invasive cancer can spread to surrounding tissues and form tumors [18]. However, early-stage breast cancer often presents no symptoms [6], making regular monitoring crucial. This is especially important in resource-limited settings, where access to routine mammographic screening is limited, and individuals often bear a significant share of healthcare costs.

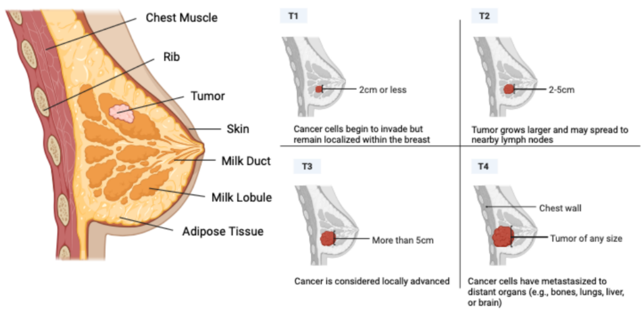

Figure 2: Anatomical and Histologic Origins of Breast Cancer.

Breast self-examination (BSE) has been widely recommended as a cost-effective method for early detection of breast cancer [13]. Regular self-examinations help identify abnormalities, such as lumps or changes in tissue texture, which can significantly improve outcomes [17]. Despite its potential benefits, awareness and practice of BSE remain low in many regions. For example, a study in China revealed that only 3.0% of female college students performed monthly self-examinations, highlighting the need for better educational tools and professional guidance [1, 9].

Current tools for BSE training, such as educational apps, instructional videos, and silicone breast models, have notable limitations [7]. Although these tools aim to improve self-examination skills, many lack tactile realism and fail to provide interactive feedback to guide users in systematically examining all areas of the breast with appropriate pressure [3, 11]. Consequently, users may not develop the necessary skills to perform effective self-examinations, reducing the overall efficacy of these methods.

To address these limitations, this project proposes the development of an interactive 3D breast model that simulates the tactile properties of real breast. The model integrates capacitive multi-touch electrodes to track the position and pressure of user interactions in real-time. This data is processed and visualized on a computer, providing immediate feedback to guide users in performing comprehensive and accurate breast self-examinations. Designed with input from medical professionals, this model aims to enhance the educational and clinical relevance of BSE, particularly in resource-constrained environments.

2 Methodology

2.1 System Overview

The interactive 3D breast model integrates both hardware and software components to provide an effective training platform for breast palpation. The model consists of a realistic silicone breast replica embedded with a capacitive electrode grid to detect touch pressure and position. The collected data is processed in real time and visualized on a digital interface, providing users with interactive feedback to improve their palpation skills.

2.2 Hardware Components

2.2.1 Muca Board. [1] A multi-touch capacitive sensing platform that serves as the core data acquisition unit. It is an open-source mutual capacitance sensing development board, which supports 21 transmit electrodes and 12 receive electrodes, enabling a high-resolution capacitive sensing grid. It operates on an I2C interface, providing efficient two-wire serial communication with a host processor [15].

2.2.2 Conductive Stretchable Yarn. Used to create the electrode grid on the breast model's surface and detect the capacitive change while touching. This material *(Datastretch)* [16]conforms to the model's curved shape while maintaining stable electrical properties, with elasticity of 30%, weight of 0.15g/m, diameter of 0.20mm, resistivity of 4.2 Ω/m.

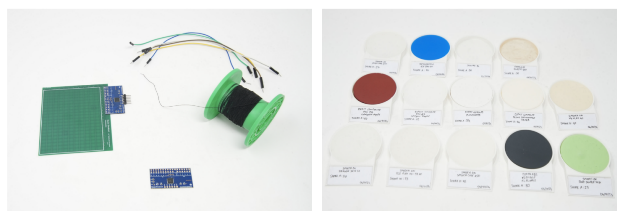

Figure 3: Main hardware and silicone materials.

2.2.3 Silicone Materials. Various silicone types were selected to simulate the different tissue layers of the breast:

- Ecoflex 00-33AF: Shore 00-33 hardness, used for the outer skin layer to mimic human skin softness and elasticity.
- RTV SKIN FX 00-20: Shore 00-20, used for the subcutaneous fat layer to replicate soft tissue resistance.
- Body Double SILK: A skin-safe molding rubber capturing fine skin details.
- RTV EC33 HT: Shore A 33, used to create simulated tumor masses.

2.3 Breast Casting Process

2.3.1 Overview. To accurately replicate breast shape, size, and texture, a volunteer-based casting process was employed. This involved using alginate and silicone to create detailed negative molds, supported by a plaster shell. All materials used were skin-safe and biocompatible.

2.3.2 Step-by-Step Procedure.

(1) **Negative Mold Creation**: 200 g of alginate was mixed with an equal amount of water to achieve a smooth consistency, then evenly applied to the breast. This quickly solidified, capturing fine details such as skin texture and contours. A secondary mold using 200 g of two-part silicone rubber (A/B

[1] https://muca.cc

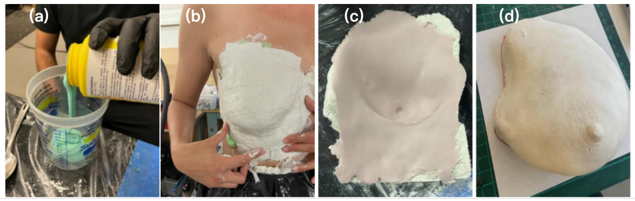

Figure 4: Breast Modeling and Fabrication.(a)silicone mixing (b)breast casting (c)negative mold (d)positive mold

components mixed equally) was also prepared for durability and reuse.

(2) **Plaster Shell Support**: Plaster bandages were layered over the alginate to form a rigid outer shell, ensuring mold stability during curing.
(3) **Mold Removal**: Once fully set, the plaster shell and alginate mold were carefully removed, forming the negative mold for subsequent breast casting.
(4) **Positive Mold Creation**: 250 g of plaster powder was mixed with an equal amount of water and poured into the negative mold. After 2-3 days of curing, the hardened plaster formed a positive mold for further fabrication.

2.4 Skin Interface Construction

2.4.1 Epidermal Layer. The outermost layer of the breast model was created using silicone to replicate human skin [8] . Various formulations were tested at the beginning, including gelatin and silicone. Then a thin 0.6 mm layer of pigmented silicone was poured into the mold, forming a soft and flexible epidermis.

2.4.2 Dermal Layer and Electrode Placement. Firstly an electrode grid was placed on the curved surface of breast model. A 12x21 electrode array was precisely marked and embedded within the dermal layer. During fabrication, 10 g each of Ecoflex A and B components were mixed with 0.8 g of red flocking agent. Conductive yarn electrodes were aligned and bonded to the silicone surface, ensuring a secure connection for touch sensing.

2.5 Subcutaneous Tissue and Tumor Simulation

2.5.1 Fat Layer. RTV SKIN FX 00-20 was used to replicate the subcutaneous fat layer, providing soft resistance during palpation.

2.5.2 Tumor Simulation. To simulate tumor detection: The 3D tumor model used in this study was obtained from the open-source medical imaging repository embodi3D[2]. A 3D-printed negative mold was used to cast 2-3 cm tumor pieces. The tumor piece was embedded within the breast model, creating a palpable abnormality detectable during self-examinations.

2.6 Signal Processing and Visualization

The capacitive data collected by the Muca board was processed and mapped onto a 3D digital breast model for real-time feedback and visualization.The capacitive signals were visualized on the digital model using PyVista in Python.

[2]https://www.embodi3d.com/files/file/6368-stl-files-for-3d-printable-model-of-breast-cancer/

2.6.1 Data Processing. To efficiently associate touch data from the physical breast model with its digital counterpart, a KD-Tree algorithm was implemented [10]. Given an electrode position $p_i = (x_i, y_i, z_i)$ on the physical model and a query point $q_j = (x_j, y_j, z_j)$ on the digital surface, the nearest-neighbor search minimizes the Euclidean distance:

$$d(p_i, q_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \tag{1}$$

This ensures each capacitive touch interaction on the physical model is accurately mapped to its corresponding point on the digital model.

2.6.2 Real-Time Visualization. Interpolation was performed based on weighted contributions from neighboring electrodes, where the influence of an electrode p_i at query point q_j was computed as [12]:

$$w_{ij} = \frac{1}{d(p_i, q_j)^k} \tag{2}$$

where k is a weighting exponent. The normalized weights for interpolating touch data were then calculated as:

$$\hat{w}_{ij} = \frac{w_{ij}}{\sum w_{ij}} \tag{3}$$

The final interpolated pressure P_q at query point q_j was computed as:

$$P_q = \sum \hat{w}_{ij} P_j \tag{4}$$

where P_j represents the pressure value at each neighboring electrode.

This approach ensures that visual indicators effectively highlight under-examined regions during self-examination training.

3 Results

3.1 The Breast Model Replicates Anatomical Structure and Tactile Properties, Ensuring Realistic Palpation Training

The 3D breast cancer model is successfully developed that replicates the anatomical and biomechanical properties of human skin and thebreast, ensuring an effective training platform for palpation-based examination. With different types of materials, the model contains specific layers that closely mimic the elasticity and softness of human skin. It can provide a realistic tactile experience [5]. The tumor mass was embedded at the subcutaneous layer and provides a distinct contrast in tactile perception, aiding in the identification of abnormalities. The capacitive electrode grid (12×21 array) within the dermal layer, maintained structural integrity and functionality under deformation, ensuring consistent and reliable data acquisition.

3.2 The Capacitive Sensing System Enables Accurate Touch Detection and Real-Time Visualization with Open-Access Framework

The capacitive sensing system, utilizing the Muca board and Arduino Uno with I2C communication, enables seamless data transmission and real-time visualization at a stable 60 FPS. This allows for high-fidelity mapping of 2D pressure data onto a 3D digital

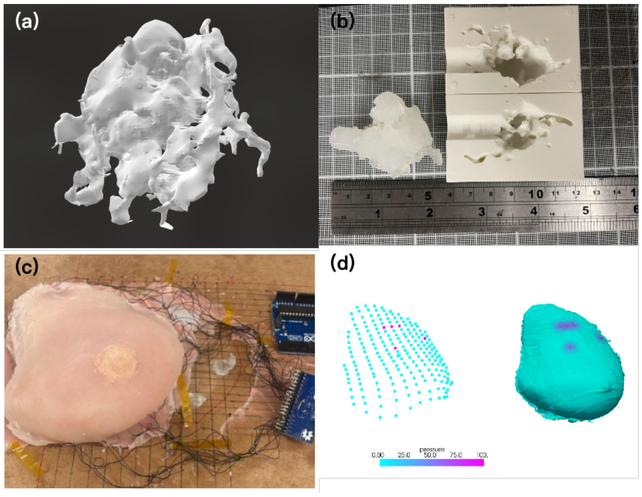

Figure 5: Establishment of Sensor-based 3D Breast Cancer Model.(a)tumor mass 3D digital model (b)tumor mass negative mold (c)sensor-embedded breast model (d)3D breast cancer model visualization

breast model, where pressure intensity is visually represented using a gradient scale (e.g., blue for light touch, red for firm pressure), providing immediate feedback to users.

Given the system's 60 FPS refresh rate, each frame is processed within:

$$T_{\text{frame}} = \frac{1}{60} \approx 16.67\text{ms} \tag{5}$$

This integration of real-time pressure mapping and interactive visualization enhances systematic training, enabling precise alignment between physical and digital touchpoints. The system serves as an educational tool for public health, improving palpation skills for breast self-examinations and medical diagnostics.

To facilitate further research and development, the **open-source implementation** of the capacitive sensing and visualization pipeline is available at Github [3].

Further structured user studies is being conducted to quantitatively assess the model's efficacy in improving palpation skills and breast health awareness.

4 Conclusion

This study presents the first high-fidelity 3D breast model with integrated capacitive sensing technology, designed to enhance breast palpation training through interactive feedback. By combining anatomical realism with real-time touch sensing and visualization, the model addresses a critical gap in breast health education: the lack of tactile, instructive tools for systematic palpation. It supports both medical trainees and the general public in developing essential palpation skills. Furthermore, the open-source release of the capacitive sensing and visualization pipeline lays the groundwork for future research in human-computer interaction and medical training technologies.

[3] https://github.com/severinferard/breasts-pressure-modelisation/blob/main/live.py

5 Future Work

The next step will focus on comprehensive user evaluations to assess training effectiveness, usability, and knowledge transfer. Planned studies include clinical trials with medical students to evaluate learning outcomes, palpation completeness, and technique improvement; and community-based pilots with non-expert participants to assess accessibility and engagement. Evaluation criteria will include quantitative metrics such as touch coverage and pressure accuracy, as well as qualitative feedback on user experience and perceived confidence. Additionally, improvements in signal processing algorithms and the incorporation of multi-layer sensing are planned to enhance the model's responsiveness and fidelity.

This study presents the first high-fidelity 3D breast model with integrated capacitive sensing technology, designed to enhance breast palpation training through interactive feedback. By combining anatomical realism with real-time touch sensing, this model represents a significant advancement in the field of medical training and self-examination tools. The release of an open-source capacitive sensing and visualization pipeline, enabling further research and development in human-computer interaction for medical applications.

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