Smartphone Mammography for Breast Cancer Screening

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Abstract. In 2020 alone approximately 2.3 million women were diagnosed with breast cancer which caused over 685,000 deaths worldwide. Breast cancer affects women in developing countries more severely than in developed country such that over 60% of deaths due to breast cancer occur in developing countries. Deaths due to breast cancer can be reduced significantly if it is diagnosed at an early stage. However, in developing countries cancer is often diagnosed when it is in the advanced stage due to limited medical resources available to women, lack of awareness, financial constraints as well as cultural stigma associated with traditional screening methods. Our paper aims to provide an alternative to women that is easily available to them, affordable, safe, non-invasive and can be self-administered. We propose the use of a smartphone's inbuilt camera and flashlight for breast cancer screening before any signs or symptoms begin to appear. This is a novel approach as there is presently no device that can be used by women themselves without any supervision from a medical professional and uses a smartphone without any additional external devices for breast cancer screening. The smartphone mammography brings the screening facility to the user such that it can be used at the comfort and privacy of their homes without the need to travel long distances to hospitals or diagnostic centers. The theory of the system is that when visible light penetrates through the skin into the breast tissue, it reflects back differently in normal breast tissue as compared to tissue with anomalies. A phantom breast model, which mimics real human breast tissue, is used to develop the modality. We make use of computer vision and image processing techniques to analyze the difference between an image taken of a normal breast and that of one with irregularities in order to detect lumps in the breast tissue and also make some diagnosis on its size, density and the location.

Keywords: Smartphone · Breast cancer screening · Early detection · Mammography

1 Introduction

Breast cancer is the most common cancer diagnosed in woman worldwide. It is also the second most common cancer overall [1]. Nearly one in nine women will develop breast

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cancer at some point in their lives, among which 30% are terminal [2]. Early detection is vital in any cancer. However, in case of breast cancer more treatment options are available if detected early and it also increases the chances of survival by 40%.

In the United States (US) the mortality rates due to breast cancer reduced by 40% from 1989 to 2017. This decline is attributed to increased mammography screening rates starting from mid-1980's [3]. In contrast, breast cancer in LMIC (Low- and Middle-Income Countries) represents one-half of all cancer cases and 62% of the deaths globally [4]. Breast cancer disproportionately affects young women in LMICs, such that 23% of new breast cancer cases occur among women aged 15 to 49 years in LMICs versus 10% in high-income countries [5].

In India, the latest statistics suggest that in the near future breast cancer will surpass cervical cancer, which is currently the most common gynecological cancer among women in India [6]. This increase in incidence rate comes with an increased mortality rate which can be attributed to non-existent screening facilities, especially among the underserved population. Studies have shown that not only women coming from low-income rural backgrounds but also metropolitan cities, despite understanding the importance of early detection and having access to medical facilities, did not seek medical help when required [7]. Women, especially from rural background, have cited embarrassment, which can be due to the presence of male health workers or doctors, and cost as factors that dissuade them from screening. They are also often discouraged from screening by family members and community due to prevailing cultural norms, conservative mindset and social stigma associated with traditional screening methods [8].

One of the most commonly used breast cancer screening technique is mammography, which utilizes low dosage X-ray. However, it has a significant false positive rate of approximately 22% in women under 50 and is also not recommended for women under 30 years of age due to radiation exposure [9]. Magnetic resonance imaging (MRI) and Ultrasound are screening techniques that are sometimes used in addition to mammography for more accurate results, but they too have limitations such as limited specificity for MRI and low sensitivity for ultrasound. One of the major drawbacks of the above-mentioned techniques is that they are available only at diagnostic centers in cities. Some of these equipment's are available in mobile clinics and rarely available for the rural and the disadvantaged population. They are also expensive screening methods which discourages women from low-income background to use them.

Handful of research studies suggest the non-viability of mammography in India, considering the cost benefit analysis [10]. Alternatives are recommended for screening. Therefore, it is imperative that we develop an imaging system for early detection of breast cancer that can be used by women, especially the underserved and vulnerable group who do not have access to medical facilities. A system that can be used by the women themselves so the stigma and embarrassment associated with being in contact with male doctors or health workers can be avoided. It must be affordable, easy to use, accessible, safe and can be used privately.

Keeping all these in mind we have developed a novel smartphone mammogram system that uses only the camera and flashlight that are inbuilt in all smartphones. While there are a few papers which have also proposed the use of smartphone for cancer detection, they require an additional external device which makes the system expensive, bulky and difficult to use for general public by themselves. Our system is non-invasive and fully functional without any external attachments which makes it easy to use for women by themselves privately without any assistance from a medical professional. It is safe as it uses visible light from the flashlight, to do screening, which we are exposed to in our everyday life. Furthermore, the system is affordable and easily accessible as the average cost of a smartphone in India is $150 while the average cost of a single mammography is $106 [11]. Due to its affordability, smartphone penetration in rural India is over 59% as of February 2021 and in the next 3 years the number of smartphone users in rural areas will be higher than that of urban areas [12]. The smartphone mammography system is especially useful for the underserved and disadvantaged population who cannot afford and do not have easy access to medical facilities by bringing the medical facility at the doorstep of the beneficiary thereby eliminating the need to travel long distances to hospitals or diagnostic centers. Using the camera and flashlights in smartphones we detect anomalies in the breast tissue using visible spectrum of light that is portable, compact, and economically viable. The idea we worked on is that the absorption and reflection of visible lights will be different for normal tissues and lumps in the breast. For the purpose of experiment, we used Blue Phantom's breast model [13]. Image processing and computer vision techniques are used for analysis and detecting presence of lumps in the breast.

2 Related Work

The use of light as a way to take images of the breast is quickly emerging as a non-invasive approach for breast cancer screening. Several authors have proposed methods that use visible and near-infrared spectral window of light for non-invasive imaging. One paper presents Diffuse Optical Tomography (DOT) for breast imaging which uses near-infrared light to examine tissue optical properties [14]. In DOT the near-infrared light sequentially excites the breast tissue at several locations and then the scattered light is measured at several locations at the surface of the breast which is used to compute parameters such as the concentration of water, lipid, oxy-hemoglobin and deoxy-hemoglobin [15]. These parameters are used to calculate total oxygen saturation and hemoglobin concentration which is linked to angiogenesis, which in turn is critical for autonomous growth and the spread of breast cancer. Although it is being increasingly used as a breast cancer detection technique, DOT is bulky, has high cost and requires complete darkness [16].

Another study discusses Hyperspectral Imaging (HSI) for detection of breast cancer which uses a broad range of light which covers the ultraviolet, visible, and near-infrared regions of the electromagnetic spectrum. This technique captures hundreds of images in contiguous, narrow, and adjacent spectral bands to create a 3D hypercube that contains spatial as well as spectral data of the imaged scene. It measures diffusely reflected light after it has experienced several scattering and absorption events inside the tissue, creating an optical fingerprint of the tissue which displays the composition and morphology of the tissue, that can be utilized for tissue analysis [17]. HSI is however costly and complex which makes it difficult to use. Although DOT and HSI are non-invasive techniques, they are either expensive which makes it unaffordable for people with low incomes or they are bulky and complex which makes it difficult for people to use on themselves for self-test.

In one of the pioneering works, Peters et al. measured the scattering coefficients of optical absorption for specimens of normal and diseased human breast tissues. They measured the total attenuation coefficients for thin slices of tissue cut on a microtome using standard integrating sphere techniques [18]. Very recently Taroni did a pilot study on an optical mammograph that operates at 7 red-near infrared wavelengths, in the same geometry as x-ray mammography, but with milder breast compression. The instrument is mounted on wheels and is portable [19].

Several papers have proposed the use of a smartphone along with an external device for cancer screening. Joh et al. developed a chip, along with EpiView — a smartphone-based imaging platform. They developed an external handheld imaging device that could rapidly switch between brightfield and fluorescence modes without extensive re-assembly or recalibration. The switchable imaging units are attached to a common base unit that is mounted on a smartphone [20]. Another paper proposes the use of smart-phone with an infrared camera for breast cancer detection using infrared thermography. The infrared camera takes thermal infrared images of the breast which are then sent to the smartphone for analysis [21]. Papers [22] and [23] discuss the use of AI and Machine Learning for disease prediction and classification. They used the Breast Cancer Wisconsin (Diagnostic) dataset for breast cancer prediction and detection.

3 System Description

Light reflects, scatters, and absorbs differently in healthy normal tissue and tissue with anomalies [18]. When light penetrates human tissue, it goes through multiple scattering and absorption events. The depth of light penetration into human tissue depends on how strongly the tissue absorbs light. Absorption spectra shows the oxygen saturation and concentration of hemoglobin which reveals angiogenesis which is critical for cancer growth. The vital chromophores-tissue components absorbing light for visible light are blood and melanin whose absorption coefficient decreases with increase in wavelength of light. When light falls on human tissue surface it is either reflected directly or scattered due to spatial variations in tissue density and then reemitted to the surface. Due to multiple scattering, the reemitted light is random in direction which is known as diffuse reflectance.

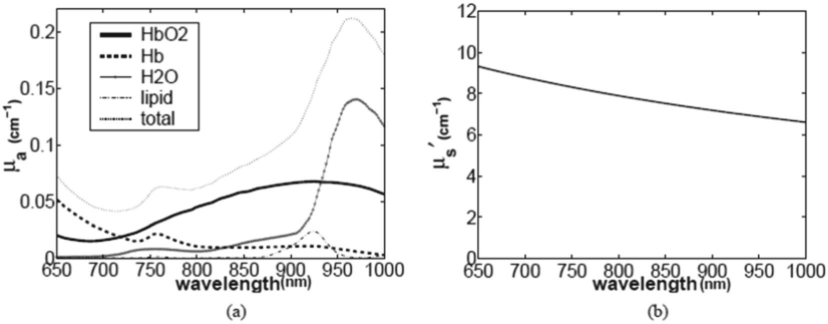

Fig. 1. (a) Spectra of major chromophores with adjusted concentrations found in typical breast tissue (b) Scattering spectra

The diffuse reflectance signal can be used to probe the microenvironment of the tissue non-invasively as it contains information about scattering and absorbing components deep within the tissue. Alterations in tissue morphology due to disease (breast cancer) progression can affect scattering signals which should lead to corresponding changes in the pattern of light reflected from the tissue [24]. We have conducted experiments to determine relation between light reflected and change in size of anomaly, light reflected and change in density of anomaly. Figure 1 (a) shows the spectrum of absorption and scattering in the near-infrared range of major chromophores found in breast tissue such as oxygenated hemoglobin, deoxygenated hemoglobin (Hb), water and lipid [8].

In order to perform experiments, we made use of a Blue Phantom tissue model [13]. The Blue Phantom simulated human tissue model is generally used for training clinicians in the psychomotor skills associated with breast ultrasound guided fine needle biopsy procedures. The model has been created with a highly realistic synthetic human tissues that is able to mimic the physicochemical, mechanical as well as the optical and thermal properties of live tissue. For the mammogram we used the mobile smartphone camera with the inbuilt flashlight.

To simulate the breast cancer tumor, we used lumps of different sizes and densities as shown in Fig. 2. The density of the Blue Phantom breast model is comparable to that of a normal human breast tissue and the lumps are of higher density than the phantom breast model. The breast model includes components such as skin, subcutaneous fat, bulk fat, a natural wear layer of dead skin at the surface and three discrete layers of epidermis, dermis and hypodermis which are present in an actual breast [10]. We used a total of 6 lumps which are categorized as small low-density lump (diameter = 1.2 cm), small high-density lump (diameter = 1 cm), medium low-density lump (diameter = 2.2 cm), medium high-density lump (diameter = 1.9 cm), large low-density lump (diameter = 2.8 cm) and large high-density lump (diameter = 3 cm). All lumps are assumed to be spherical in shape. The actual density of all the lumps is unknow.

To begin with, we choose two 3 cm by 3 cm cross sectional areas on the phantom breast model as shown in Fig. 3. We chose Area 1 for placing the small lumps and Area 2 for placing the medium and the large lumps. At both the areas the lumps are placed at the center of the cross-sectional area which is row 2 column 2 at a depth of 2 cm. First, images of the Area 1 and Area 2 are taken without any lumps and then we place the lumps one by one in their respective areas and take images of the phantom breast model with lumps (Fig. 4). For all the images, the camera was making physical contact with the surface of the phantom breast model and the camera flashlight was on. Since phone camera was touching the surface of the phantom breast model a single image could not cover the entire area, therefore 9 images, each covering 1 cm $\times$ 1 cm area, had to be taken to cover the entire 3 $\times$ 3 cross section. The 9 images are then stitched together, using the image processing toolbox in MATLAB, to form a single image. Once we have the two stitched images of the cross-sectional areas without lumps and six stitched images of the cross-sectional areas with the 6 different lumps, image processing techniques are used to derive results.

Fig. 2. Phantom breast model with 6 lumps

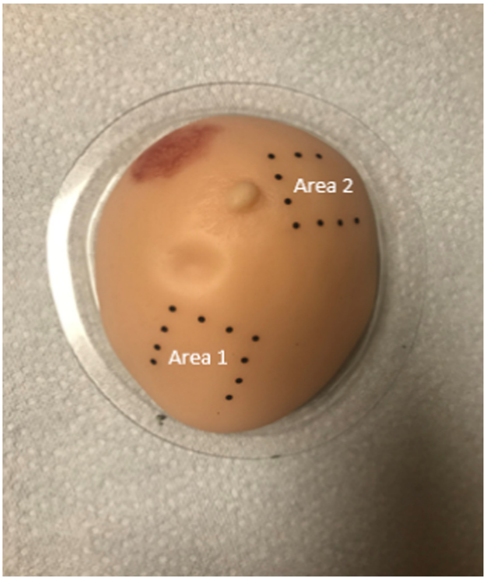

Fig. 3. Phantom breast model with marked 3 cm × 3 cm areas

This experiment is to determine the relationship between the density of the lump and the intensity of the light received by the smartphone camera, as well as the relationship between the size of lump and the intensity of light. This experiment had many variables such as the overlapping or exclusion of some parts in the 3 cm × 3 cm cross-section when taking the 9 images and a change in angle of image being taken.

Second set of experiments were also performed to eliminate the variables in the previous experiment where instead of the camera touching the surface of the phantom breast model, we captured a single image of the 3 × 3 cross-sectional area by placing the camera at a distance of approximately 2 cm with flashlight on. All other parameters such as depth, size, density and position of lumps being the same as the previous experiment. Here also images are captured of cross-sectional areas without lumps and then with the six types of lumps. This experiment is to determine the relationship between the density of the lump and intensity of light received as well as the relationship between the size of lump and intensity of light. Once again image processing techniques are used to derive some results which will be explained in the Simulations section of the paper.

4 Simulation

We performed all the experiments using iPhone 7s. All images were captured using the iPhone 7s camera with flashlight. All image processing techniques was carried out on MATLAB. For the experiment with lumps of different sizes and densities, background subtraction was performed. Each of the six images with lumps were background subtracted with the two images without lumps based on which lump was placed in which area. This was done for the images from experiment with the camera touching the surface of the phantom breast as well as the images from experiment where the camera was approximately 2 cm away from the surface of the breast. Background subtraction allows us to see how the light has reflected differently due to scattering when there is a lump present.

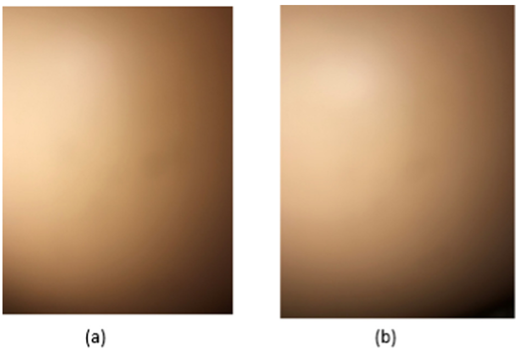

Fig. 4. Original images taken on iPhone 7s camera(a) Image of Area 2 with large high-density lump (b) Image of Area 2 without lump

The MATLAB function '`imsubtract`' is used to perform background subtraction. This function subtracts each element in one image with the corresponding element in the other image and when the subtraction goes into negative the function normalizes it to zero. In cases where the subtraction results in negative value, the '`double`' function in MATLAB is used. The 'double' function is used to first convert both images to double and then subtract them without using 'imsubtract'. This way the corresponding pixels of the two images are subtracted which gives a normalized RGB scale image that is easier to understand and visualize. The normalized images are then analyzed to see the relation between size and density of lump with light intensity. In order to do this, we first find the average RGB values of the image by adding the square of RGB values of each pixel and dividing by the total number of pixels and take the square root of the result. If $(n \times m)$ is the pixel dimension of the image then the below equations are used to calculate the average of RGB values.

$$R_{avg} = \sqrt{\frac{(R_{1\times1})^2 + (R_{1\times2})^2 + (R_{2\times1})^2 + (R_{1\times1})^2 + \cdots + (R_{n\times m})^2}{(n \times m)}}$$

$$G_{avg} = \sqrt{\frac{(G_{1\times1})^2 + (G_{1\times2})^2 + (G_{2\times1})^2 + (G_{1\times1})^2 + \cdots + (G_{n\times m})^2}{(n \times m)}}$$

$$B_{avg} = \sqrt{\frac{(B_{1\times1})^2 + (B_{1\times2})^2 + (B_{2\times1})^2 + (B_{1\times1})^2 + \cdots + (B_{n\times m})^2}{(n \times m)}}$$

Then the intensity is found by adding the RGB values and dividing it by three. The size of lump is then plotted against intensity values to get an insight on the relation between them. The below equation shows the intensity of an image.

$$Image\ Intensity = \frac{R_{avg} + G_{avg} + B_{avg}}{3}$$

5 Results

Figure 5 shows the result of subtracting large high-density image from no lump image for the experiment where the camera touches the phantom surface. The parts of the image that is black means that there is no difference in the light intensity between the images with and without lump.

When there is no difference in light intensity it means that light reflected and refracted from a surface of the same density. The part of the image which has the most color is where the light has scattered most when reflecting. As mentioned before, light reflects differently when there are anomalies in the tissue which results in change in light intensity. Therefore, according to Fig. 5 the lump is located in the middle cell of the right most row.

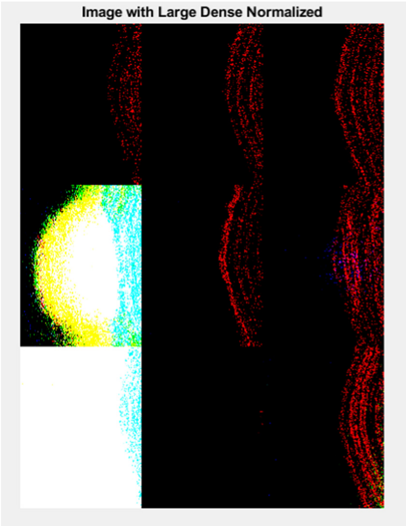

Fig. 5. Large high-density lump when camera in contact with phantom surface

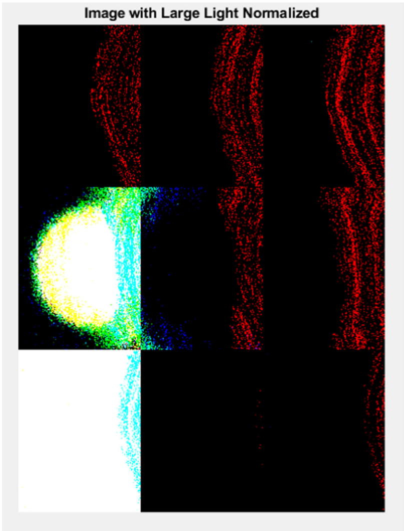

Fig. 6. Large low-density lump when camera in contact with phantom surface

Figure 6 shows the result of subtracting large low-density image from no lump image for the experiment where the camera touches the phantom surface. Similar to Fig. 5 we can see the lump at the middle cell of the rightmost row. When Figs. 5 and 6 are compared we see that large high-density lump image has lower intensity than the large low-density lump. This is because when the density is higher there is more scattering of light which reduces the intensity of light reflected.

Figures 7 and 8 show the result of subtracting medium high-density and medium-low density image from no lump image for the experiment where the camera is touching the phantom surface respectively. Similar to Figs. 5 and 6 we can see that most of the image is black except for the middle cell in rightmost row where the lump is located.

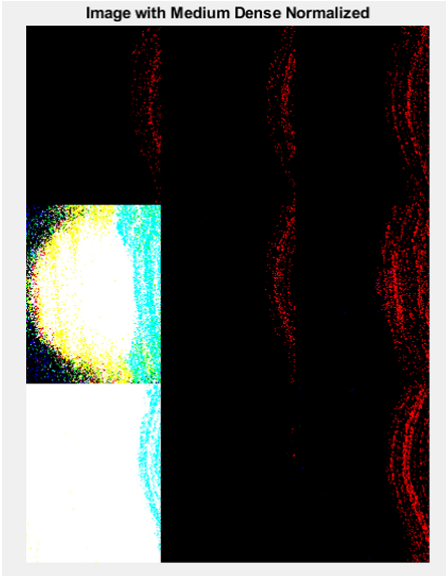

Fig. 7. Medium high-density lump when camera in contact with phantom surface

Figure 9 shows the result of subtracting large high-density lump from no lump image wherein both images are taken where the camera is 2 cm above the phantom surface. Here also we see that most of the image is black which means the breast tissue is normal and the areas that have color is where the lump is located.

In all of the images where the camera is in contact with the breast surface there is some scattered red color outside of the area that has been identified as where the lump is located. This is due to camera position and angle being different between the images taken without lump and with lump due to which the light has reflected with different intensity. However, in Fig. 9 where the camera was placed 2 cm above the phantom surface the red scattering is far lesser since only a single image has been taken here which eliminates the problem of changes in camera position and angles. In all of the above images the lumps have been detected in the same area which demonstrates that the position of the lump has been identified accurately regardless of lump size and density.

Figures 10 and 11 show graphs of diameter of lumps vs their intensity value when the camera is in contact with the phantom breast model surface. It can be inferred from the graph that the lumps with low density have a higher intensity value than the lumps with high density for all sizes. This is because high density lumps cause more scattering of light which reduces its intensity. We can deduce from the graph that larger the size of the lump, lower the intensity value. This is because when the size is large, light is

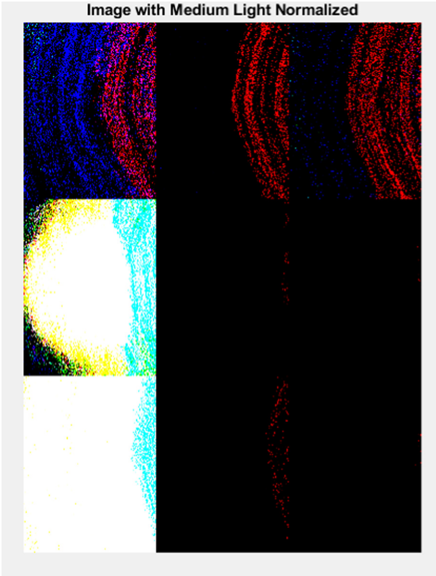

Fig. 8. Medium low-density lump when camera in contact with phantom surface

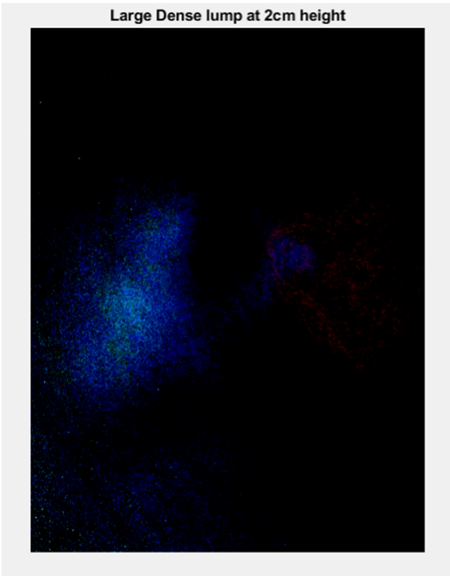

Fig. 9. Normalized large high-density lump when camera is 2 cm above phantom surface

reflected differently and scattered over a greater surface area which reduces the intensity of light.

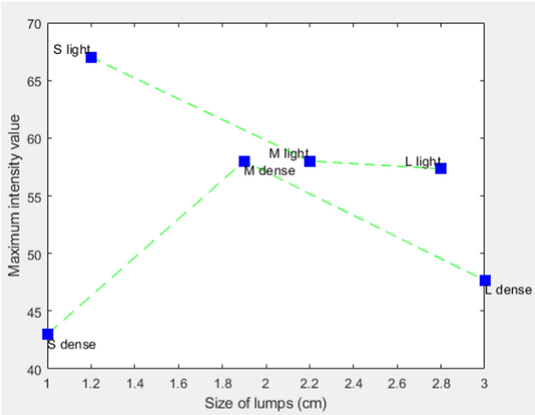

Fig. 10. Diameter of lumps vs intensity value based on density of lump

In Fig. 10 we can spot some irregularities in the light intensity values such as the small high-density lump with lower value than medium and large high-density lumps. The medium and large low-density lumps have almost the same value. These irregularities are due to changes in the angle or positioning of the camera or some parts of the image may be missing or overlapping when the 9 1 cm by 1 cm images taken are stitched as mentioned in Sect. 4. These irregularities can be reduced when the camera does not touch the surface of the phantom model. Table 1 shows the diameter of lumps versus intensity value when the camera is not in contact with the breast model. Here we can see that as the size of the lump increases the light intensity decreases and it also eliminates some irregularities seen when camera touches the surface of the phantom model.

Table 1. Size of lumps and its associated light intensity in no-contact case

Lump description	Lump size (cm)	Light intensity
Small low-density lump	1.2	73
Small high-density lump	1.0	68
Medium low-density lump	2.2	59
Medium high-density lump	1.9	57
Large low-density lump	2.8	53
Large high-density lump	3.0	48

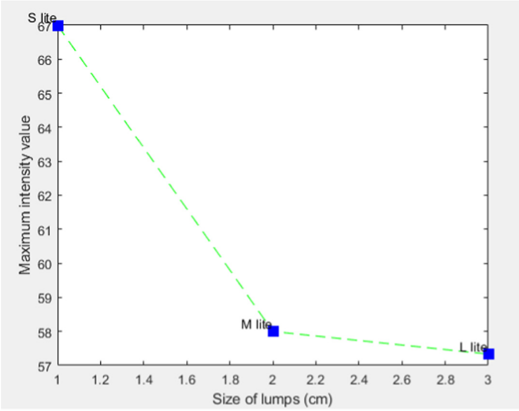

Fig. 11. Diameter of lumps vs Intensity Value based on size of lump

Therefore, we can not only detect the presence of anomaly in the breast tissue by performing image processing techniques we can also make some assumptions on the size and the density of the anomaly present in the breast tissue by analyzing the intensity values. This system has now been implemented using Flutter where the images are taken on an android smartphone and the image processing carried out at the backend in Python.

6 Conclusion and the Future Work

The basic goal of this work is to propose a technology that is easily accessible, affordable, and widely available for breast cancer screening. Inbuilt camera and flashlight of a smartphone serves that very well. We propose optical tomography to validate the viability of smartphone mammography. This is a unique method as it is the first time that only a smartphone, without any additional external device, is being used for breast cancer screening. Moreover, it also has the potential to overcome the socio-cultural barrier as a woman can herself use the smartphone without the help of a trained medical professional.

Our work identifies the anomaly in the tissue if any and provide an approximation of the size and position of this lump or anomaly based on the intensity of the reflected light. One of the many challenges we faced when performing the experiments is the precise positioning of the camera to enable decent background subtraction. This is important if we aim to deduce the position or the size of the lump. It is possible that only a portion of the lump is captured owing to camera positioning errors. Future experiments would aim to stabilize the light source and detector (camera) and only move the breast model around to accommodate for the positioning errors. As the flashlight on the camera is not very strong as a light source, it would be prudent to decouple the light source and detector system which in turn will also eliminate lighting and shadow issues due to ambient light.

Currently, we are working with a single source/detector system but we plan to leverage the use of multiple source/detector pairs placed alternatively and excited one after the other to achieve precise reconstruction of the tissue and for error correction. We also hope to do human trials on women with and without breast cancer to validate our system. Moreover, we are porting the MATLAB algorithms presented in this paper into Python3 and use the smartphone mammograph as an AIoT device. The AIoT smartphone mammograph will be connected to the oncologists in remote towns through the telemedicine system [25].

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