Breast Cancer Detection

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Contributor: Jesus A. Basurto-Hurtado , Irving A. Cruz-Albarran , Manuel Toledano-Ayala , Mario Alberto Ibarra-Manzano , Luis A. Morales-Hernandez , Carlos A. Perez-Ramirez

Breast cancer is one the main death causes for women worldwide, as 16% of the diagnosed malignant lesions worldwide are its consequence. In this sense, it is of paramount importance to diagnose these lesions in the earliest stage possible, in order to have the highest chances of survival. While there are several works that present selected topics in this area, none of them present a complete panorama, that is, from the image generation to its interpretation.

breast cancer

mammography

magnetic resonance

1. Introduction

According to the World Health Organization, Breast Cancer (BC) represents around 16% of the malignant tumors diagnosed worldwide ^[1]. In Mexico, BC is the leading death cause for cancer in the female population ^[2]. BC develops when any lump begins an angiogenesis process, that is, the process that causes the development of new blood vessels and capillaries from the existent vasculature ^[3]. Unfortunately, BC has a mortality rate of 69% in emergent countries, which is greater than the one in developed countries ^[1]. This increase is explained as the cancer is detected in a later stage, making the treatment a financial obstacle as its price increases, especially if the disease is detected in an advanced stage ^[4]. Hence, the development of strategies that can perform an early detection of BC is a priority topic for governments, as an early detection increases the survival chances and lowers the financial burden the disease imposes to families and health systems ^[4].

A methodology for the BC detection can be composed of 4 steps: (1) image acquisition, (2) Segmentation and preprocessing, (3) feature extraction, and (4) classification. An illustration of the abovementioned concepts is described in **Figure 1**.



Figure 1. BC detection using image processing strategies.

From this figure, it can be seen that the first step uses the different technologies available to acquire the internal tissue dynamics of the breast, so they can be expressed in an image; the second step is used to execute algorithms that perform basic tasks on the images (for instance, correcting the color scale), so the segmentation, which is the detection of Region-of-interest (ROI), can be done; then, the third step quantifies the differences between images that have abnormalities from the ones that do not have; finally, once the differences are quantified, it is necessary to classify them to provide a diagnosis. With the rapid development of novel technologies that can capture more accurately the dynamics of the breast tissues, numerous advances have been done in all the aforementioned fields; in this sense, the goal of detecting all the abnormalities without generating false alarms is still a highly desirable feature for all the proposals ^{[5][6]}.

2. Technologies Used to Obtain Breast Tissue Images

One of the steps require to develop a diagnose system is the representation of the breast tissue dynamics. In this sense, there are several technologies that are commonly used to represent the tissue by means of images. This section presents the most used ones.

2.1. Mammography

Mammography is a study used to screen the breast tissue in order to detect abnormalities that could indicate the prescience of cancer or other breast diseases ^[7]. This technique has a sensibility of up to 85% in the recommended population. Essentially, mammography uses low doses of X-ray to form a picture of the breast internal tissues ^[8]. To form the picture, the breasts are compressed by two plates with the aim of mitigating the dispersion of the rays, allowing to obtain a better picture without using an X-ray high-dose ^[8], where the tissue changes might appear as white zones on a grey contrast ^[8]. On average, the total radiation dose for a typical mammogram with 2 views for each breast is about 0.4 ^[8]. **Figure 2** illustrates the mammography procedure.



Figure 2. Mammography procedure.

Several works have focused on the processing of the digital mammographies to detect the most common symptoms that could indicate the presence of cancer: calcifications or masses ^[9]. Traditionally, the specialist looks for zones that have a different appearance (size, shape, contrast, edges, or bright spots) than the normal tissue. With the employment of segmentation algorithms ^{[10][11][12]}, the automatization of this task has been proposed, where some attempts using neural networks have done ^{[9][13][14]}, delivering encouraging results.

Recently, the utilization of the Breast tomosynthesis (BT) and the Contrast-Enhanced Mammography (CEM) ^[Z] have been proposed as improvements to the traditional digital mammography. The former is a 3D breast reconstruction that allows to further improve the image resolution whereas the latter improves the image resolution injecting a contrast agent; in this way, the anatomic and vascularity definition of the abnormalities is exposed. In this sense, some improvements when dealing with breast-dense tissue patients are obtained; yet, the detection of clustered micro calcifications is still an issue ^[Z]; on the other hand, additional screening tests are required to determine if the abnormality detected by CEM is cancer or not, besides of requiring more expensive equipment.

2.2. Ultrasound

Ultrasound is a non-invasive and non-irradiating technique that uses sound waves to create images from organs, in this case the breasts, to detect changes in their form. To create the images, a transducer sends high-frequency sound waves (>20 kHz) and measures the reflected ones ^[7]. The image is formed using the wave sound reflected from the internal tissues. This procedure is depicted in **Figure 3**.



Figure 3. Ultrasound procedure.

Ultrasound is used for three purposes: (1) assessing and determining the abnormality condition, that is, to help doctors if the abnormal mass is solid, which might require further examination, is fluid-filled, or has both features; (2) as an auxiliary screen tool, which is used when the patient has dense breasts and the mammography is not the reliable enough, (3) or as a guide to develop a biopsy in the suspected abnormality ^[7]. Several computer-aided

diagnose (CAD) systems that analyze ultrasound images have been proposed ^[15]. One of the points they note it is necessary to improve is the resolution of the images ^[16] using specific-designed filters. Another modification proposed is the utilization of micro-bubbles that are injected into the abnormalities detected at first sight ^[17].

It should be noticed that the mass tends to stay in its position when compressed, i.e., they do not displace. Elastography is the technique that is employed to measure the tumor displacement when compressed using a special transducer ^[18]. These developments have led to discover masses that usually require performing a biopsy to determine the mass nature, which delay the diagnosis confirmation ^{[7][18]}; moreover, the image interpretation requires a well-trained specialist, which is not always available to perform all the studies.

2.3. Magnetic Resonance Imagining (MRI)

Breast MRI (BMRI) uses a magnetic field and radio waves to create a detailed image from the breast. Usually, a 1.5 T magnet is used along with a contrast, usually gadolinium, to generate the images of both breasts ^[19]. To acquire the images, the patient is located in a prone position, in order to minimize the respiration movement and to allow the expansion of the breast tissue ^{[7][19]}. When the magnet is turned on, the magnetic field temporary realigns the water molecules; thus, when radio waves are applied, the emitted radiation is captured using specific-designed coils, located at the breast positions, which transforms the captured radiation in electrical signals. The coils position must ensure an appropriate field-of-vision from the clavicle to the infra-mammary fold, including axilla ^[7]. An illustration of the patient position is depicted in **Figure 4**.





The main objective of getting the images is to assess for the breast symmetry and the possible changes in the parenchymal tissue, since those changes might indicate the presence of lesions that can be malignant. In general, malignant lesions have irregular margins (or asymmetry), whereas the benign ones usually have a round or oval geometrical shape with well-defined margins (symmetry). To deliver the best possible result, it is necessary to remove the homogenous fat around the breast and parenchyma since fat can render images that can be uninterpretable, specially to detect subtle lesions [7][19].

On the other hand, one of the problems that BMRI has is the false-positive (specificity) rate, as the technique can detect low-size masses (lesions whose size is less than 5 mm) that are benign $^{[7][19]}$. To mitigate the aforementioned issue, nanomaterials have been developed, so they stick to the cancer masses but not to the benign ones $^{[20]}$ as well as contrast agents $^{[21]}$. Recently, it has been proposed that a multiparametric approach has been suggested as a strategy to improve the specificity rate $^{[7]}$.

2.4. Other Approaches

Recently, microwave radiation has been employed as an alternative to obtain information about the breast tissue. The microwaves, whose frequency range varies from 1 to 20 GHz, are applied to the breast and the reflected

waves are measured using specific-designed antennas. To have the best possible results, some works propose that the tissue must be immersed in a liquid ^[22]. In this sense, some works have proposed acquisition systems that deal with this issue ^{[23][24][25][26]}.

When it is necessary to perform a biopsy to confirm, images from the cells that form the abnormalities are obtained using among other techniques, the fine needle aspiration citology (FNAC), core or excisional biopsy. Once the cell images are captured, an image processing technique is applied in order to detect the differences between normal and malignant cells, which are classified using modern strategies ^{[27][28][29]} such as neural networks, probabilistic-based algorithms and association rules coupled with neural networks.

It should be pointed out that other alternatives for imaging are employed such as Computed Tomography (CT) or Positron Emission Tomography (PET). The former employ X-rays to form images from the chest using different angles; using image processing and reconstruction algorithms, a 3D image of the chest (including the breasts) is obtained ^{[30][31]}; on the other hand, the latter uses a small amount of tracer, that is a specific-designed sugar with radioactive properties known as fluorodeoxyglucose-18. The main idea of using this type of sugar is that cancer cells have an increased consume of glucose compared with the normal cells; in this sense, the tracer sticks in the zones where there is an increased glucose consume ^{[32][33]}. It is worth noticing that these techniques are recommended to determine the cancer stage rather than first-line diagnosis scheme ^{[7][34]}. In this way, they complement the three main techniques to provide more information from the tissues surrounding the breasts ^[34]. **Table 1** presents a table that summarizes the abovementioned methods.

Imagining Technique	Advantages	Disadvantages	Recommended Population	Some Types of Cancer Detected	Sensitivity and/or Specificity
Mammography	 Equipment is widely available worldwide. Methods, such as tomosynthesis, can improve the specificity and sensibility of the technique with patients that have dense breasts ^[7] 	 The rate of both false positive and false negatives increases since there is no possibility to determine if the masses are benign The procedure used to obtain the images could be bothersome. Dense breasts or young patients are not indicated to use this 	Women whose age is greater than 40 years, have low-dense breast and an average risk of contracting the disease.	1. Ductal Carcinoma in Situ 2. Invasive Breast Cancer.	Sensitivity up to 85%.

Table 1. Summary of the used breast image generation technologies.

Imagining Technique	Advantages	Disadvantages	Recommended Population	Some Types of Cancer Detected	Sensitivity and/or Specificity
		imaging technique.			
Ultrasound	 Can be used in young patients or have dense breast. The equipment used is available in most of the hospitals 	 Calcifications could not be detected. Sensitivity depends on the operator ability to interpret the images False-positivity rate is an issue. 	Women with heterogeneously or extremely dense breast tissue ^{[35][36]} . Women that are pregnant or lactating ^[37] .	 Ductal Carcinoma in Situ. Invasive ductal carcinoma 	Sensitivity ranging between 40–75% in younger high-risk women ^[37] .
Magnetic Resonance Imaging	 Effective for detecting suspicious masses in high- risk population ^[7]. The breast tissue density is no longer an issue ^{[35][36][37]}. Multifocal lesions can be detected ^{[7][38]} 	 Equipment is only available in specialized hospitals. Expensive False positive findings are an important concern ^[38] 	 Women that may carry mutation in ATM, BRCA1, BRCA2, CHEK2, PALB2, PTEN, TP53 genes. Women that had radiation therapy in the chest zone during the childhood. 	 Ductal in situ carcinomas Invasive ductal carcinomas. Invasive lobular carcinomas Invasive mammary carcinomas with mixed ductal and lobular features ^[21] 	Sensitivity ranging from 83 to 100% ^[39] ^{[40][41]} .

higher risk for developing the disease, allowing to achieve the cancer detection in the earliest possible stage. On the other hand, these novel imagining techniques should be able to operate without requiring additional requirements, such as specific electrical or mechanical conditions, so they can be easily adopted in hospitals, or in an ambulatory area.

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