

A Virtual Instrument to Detect Masses In Breast Cancer using CAD tools

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ABSTRACT

Breast cancer is the second-most driving and normal explanation behind death in view of tumor among one in every ten women. It has become a major health problem in the world over the past 50 years, and it has increased in recent years. Early detection is an effective way to diagnose and manage breast cancer. Mammography is the best and most suitable imaging technique for treatment of cancer at the early stage. The problems in mammography images such as high brightness value, dense tissues, noise and inefficient contrast level make analysis of these images a hard task for physicians for mass identification. This paper presents a CAD tool which are combination of image processing techniques to remove noise and enhancement of mammography images for identification & classification of masses. Efficient methods includes wavelet transformation and adaptive histogram equalization techniques, in addition with fusion techniques are used. Algorithms for identification of signs are tested on five patients, the associated abnormalities are clearly identified. The images for experimentation are taken from radiopedia. Experimental results show that a detection rate of 94.44% or higher can be achieved using this method, hence improved accuracy in breast cancer lesion detection. The proposed system achieves 100% sensitivity and 2.56 false positive for every image.

Keywords: PSO, Digital Mammograms, Image Processing, CAD.

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I. INTRODUCTION

Nowadays, cancer is the leading cause of world's population death which cancer mortality statistics is increasing especially the cancer usually occurring in women. However, the higher rate of cancer-related death in women is caused by breast cancer, which the causes of this kind of cancer are still unclear. There is a set of external risk factors for developing breast cancer, which the most significant factors are age and a family history of breast cancer. The middle-aged and elderly women should have a physical examination of the breast which early detection of cancer is key element of treatment planning.

According to the worldwide cancer statistics breast cancer is the third most common cancer in the world (796,000 cases in 1990) in terms of number of new cases. The fifth cause of death from cancer is ranked by breast cancer and it is the leading cause of cancer mortality in women (the 314,000 annual deaths represent 14.1 % of cancer deaths in females). One-third (nearly 400,000 lives) of these cancer deaths could be decreased by early diagnosis and treatment. The world health organization (WHO) has suggested the mortality rate due to breast cancer can be reduce in great extent by the early detection. As indicated by estimation by National Cancer Institute one among eight women in the United States are victims of breast cancer. Early detection is the key to Improve breast cancer prognosis and chances of complete recovery. There are several imaging techniques for examination of breast including Magnetic Resonance Imaging (MRI), Ultrasound imaging and X-ray imaging. X-ray mammography is the most common imaging technique that uses a low-dose x-ray systems to examine the breast and is the most effective method in screening and diagnosis of breast cancer. Cancer is detected by identifying either of four signatures of breast cancer:

1. Micro calcifications
2. Masses
3. Bilateral asymmetry
4. Architectural distortion.

The American College of Radiology (ACR) and Breast Imaging Reporting and Data System (BI-RADS) provides a standardized database for breast cancer images. Currently, early detection strategies, such as self-assessment and mammography have proven to be effective. An increasing number of women have saved their own lives by receiving cancer treatment after detecting stage-zero or stage-one tumors.

II. LITERATURE REVIEW

Much work has been done in mass detection in the mammography images and different methods are adapted for this purpose. Some of them are explained in this section in summery. Sampaio et al. (2011) has applied geostatistical functions as texture signatures, Cellular Neural Networks (CNNs) and Support Vector Machine (SVM) for classification images. They have achieved True Positive = 80% and False Positive = 84% clusters/image. Kom et al. (2007) they have used local adaptive thresholding filter for image classification and this algorithm has been tested on 61 images and they have achieved True Positive = 95.61% and False Positive = 2 clusters per image. Sun et al. (2004) they have used adaptive Fuzzy CMeans (FCM) algorithm for segmentation, directional wavelet transform and tree structured wavelet transform. They have achieved True Positive = 90% and False Positive = 3clusters/image. Cheng and Muiyi (2004) implemented FNN and co-occurrence matrix for feature extraction. They have achieved True Positive = 92% and False Positive = 1.33 clusters/image. Zheng and Andrew (2001) they have used Discrete Wavelet Transform (DWT), multi resolution markow random field, dogs and rabbits algorithm and other algorithm to segmentation. They have achieved True Positive = 97.3% and False Positive = 3.92 clusters/image.

The mass detection mechanism proposed by Kai Hu et al. [3] involves, cancer masses segmentation, using the histogram based and window-based adaptive thresholding method. This mechanism was simple and fast, and was effective in segmenting masses in a mammogram. A true-positive identification rate of 91.3% was achieved after testing 89 mammograms. However, this method had a poor identification rate of 78.9% for spiculated masses (SPIC). Cascio el al. [4] brought forward the supervised neural network algorithm to segment mass lesions from a mammogram by searching for the mass's contours based on predefined threshold values. The true-positive detection rate for this method was 82%. The mammogram screening algorithm proposed by Jinshan Tang et al. [5] was based on image contract enhancement in the wavelet domain. This algorithm first applied wavelet transform on the image, and then the direct contrast enhancement algorithm was used to identify images of relevant malignant masses and calcified tissues. The careful selection of appropriate enhancement coefficients was essential to achieve a satisfactory detection rate with this algorithm.

III. METHODOLOGY

A. Image Enhancement

In order to better accommodate human's visual system and to aid radiologists in interpreting the images, the images undergo wavelet transformation such that the mass contrast can be processed to become sharper in frequency domain, creating a higher contrast for mass lesions in a mammogram, thereby making the masses more discernible to the human eye. Finally, PSO is applied to the image to mark the suspicious regions for further assessment by the radiologists. Mammogram images are read by software as input and then after optimizing the image and extracting breast tissue from image, the Chebyshev moments are estimated to the breast tissue after applying log transform. Applying Chebyshev moments in whole image extracts some special properties of image like mass asymmetry and edge sharpness, which in turn is important for specialists and then after using an appropriate threshold, suspicious regions are determined. This process will help increase the rate of accurate diagnosis, and reduce the risk of breast cancer.

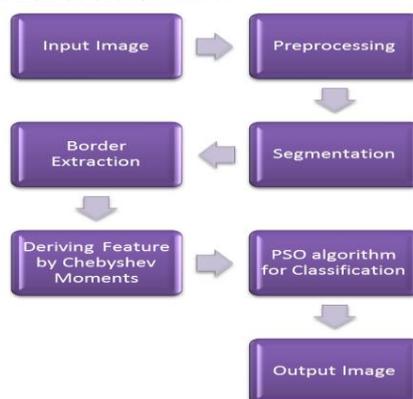


Fig 2: Flowchart of designed system

B. PSO Technique

The mammogram image undergoes wavelet transformation and enhances the mass signals before being inverse-transformed back to an image; an image with enhanced processes would make masses easier to discern. Then, possible masses are identified and positioned using particle swarm optimization, PSO technique. In PSO, the entire swarm of particles is initialized with random numbers; whether a particle moves to the individual's or the swarm's optimal location depends on the value of the weight parameter. In addition, particles move about with certain randomness, allowing a particle to escape from its current situation, hence the local optimum. Among artificial intelligence based algorithms, PSO has the fastest search speed and its particles have memories. These characteristics are non-comparable by many other algorithms. And because mathematical computation involved with PSO is simple and can be easily achieved in microcomputer systems with little cost, PSO is adopted in many practical applications. Mammogram images, after wavelet transform, reveal the highest grayscale values for areas of the tumor mass and relatively low values for breast tissue and the background. We can take advantage of these characteristics by applying PSO on the image to find the locations of the highest grayscale values, which are, essentially, the locations for the tumor masses. Experimental results reveal the recognition rate of 94.44% or higher can be accomplished utilizing this method, thus improved accuracy.

C. Chebyshev Moments

Chebyshev moments can be calculated after optimizing the image and by applying log-polar transformation in all areas of breast tissue. The abnormal malignant masses can be determined after extracting features by applying appropriate threshold, these masses are important for the specialists and physician. The outcomes of this method allowed us to draw a FROC curves. When linked the FROC curve with similar methods experts, the high ability of our system was confirmed. In this process, images undergo a sensitivity analysis having different thresholds like 450, 445, 455. This procedure accomplishes great results 100%, 92% and 84%, and a false positive rate for each image is 0.86, 2.56, 0.26, respectively have been calculated. Comparing other automatic mass detection systems, the proposed technique has a few advantages over earlier systems: Our method allows us to determine the amount of false positives and sensitivity parameters within the system. And it can be controlled by the significance of the recognition work being done. The proposed methodology reaches 100% sensitivity and false positive of 2.56 for every image.

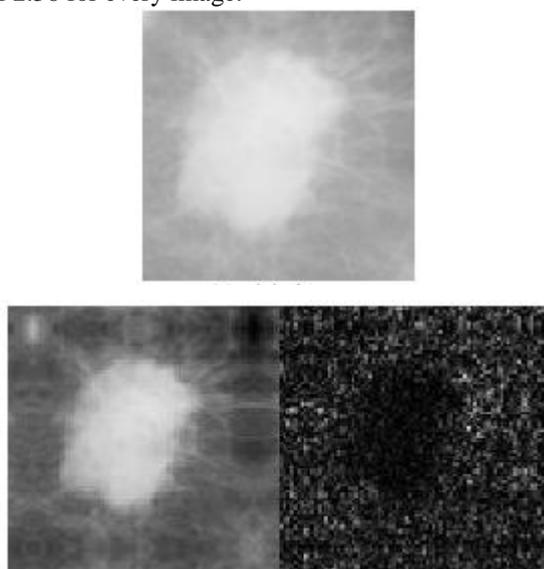


Fig 1: Original mass & low-High frequency wavelets

IV. RESULTS

Each image had the dimensions 1024x1024, and 90 of them contained tumor masses and were processed using the PSO algorithm. On each image, the tumor mass was marked based on the location (X, Y) and radius provided. Once marked, PSO was applied to the image to search for and mark the suspicious masses with three 15x15 squares. Radiologists were to verify the efficiency of PSO screening based on the rate of true-positive identifications. The results illustrates that the screening method proposed by this study is both reliable and reason- able.

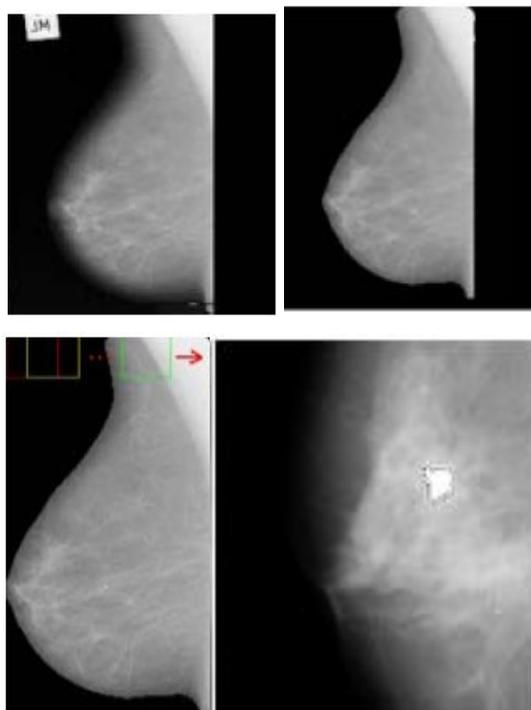


Fig 3: Main image, Border Extraction & Restricting image to reduce calculations.

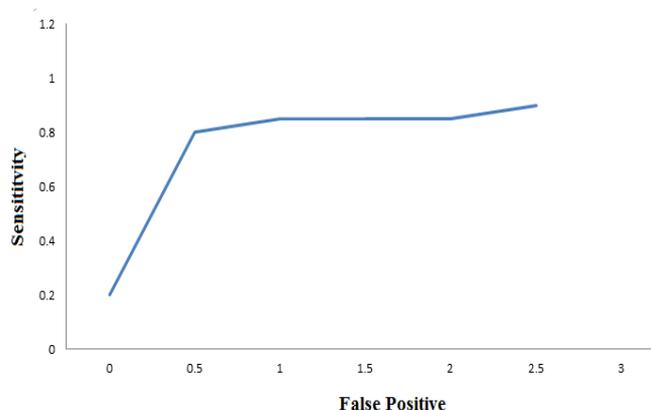


Fig 4: Free Response Receiver Operating Characteristic (FROC) Curve.

V. CONCLUSIONS

We suggest a breast cancer screening process based on the PSO algorithm. With this method, the test subject's information and other body parts are cropped from a mammogram, leaving only an area of interest. The remaining image undergoes wavelet transform followed by direct enhancement technology to increase contrast of the lesion-containing region by enhancing the grayscale values in that area. Then Chebyshev moments and thresholding are applied. The system is simple and can be easily realized; doctors are able to obtain results immediately after the mammogram is analyzed. This proposed screening method is fast and highly accurate, allowing abnormalities to be found and treated promptly. It also enables doctors to make right decisions for diagnosis, helping women eliminate threats posed by breast cancer. Other cancers are also of great concern; future studies will look into all types of mass abnormalities.

REFERENCES

- [1] J. Griffin, GF. Joseph, C. Lee, et al. ACOG statement: begin annual mammograms at age 40 years. *Obstet Gynecol*, pp. 372–382, 2011.
- [2] G. Kom, A. Tiedeu, and M. Kom, "Automated detection of masses in mammograms by local adaptive thresholding," *Computers in Biology and Medicine*, vol. 37, pp. 37–48, 2007.

- [3] K. Hu, X. Gao and F. Li, "Detection of Suspicious Lesions by Adaptive Thresholding Based on Multiresolution Analysis in Mammograms," *IEEE Transactions on Instrumentation and Measurement*, vol. 60, pp. 462–472, Feb. 2011.
- [4] D. Cascio, F. Fauci, R. Magro, G. Raso, R. Bellotti, F. De Carlo, S. Tangaro, G. De Nunzio, M. Quarta, G. Forni, A. Lauria, M. E. Fantacci, A. Retico, G. L. Masala, P. Oliva, S. Bagnasco, S. C. Cheran, and E. L. Torres, "Mammogram Segmentation by Contour Searching and Mass Lesions Classification With Neural Network," *IEEE Transactions on Nuclear Science*, vol. 53, pp. 2827–2833, 2006.
- [5] J. Tang, X. Liu, Q. Sun, "A Direct Image Contrast Enhancement Algorithm in the Wavelet Domain for Screening Mammograms," *IEEE Journal of Selected Topics in Signal Processing*, vol. 3, pp. 74– 80, 2009.
- [6] J. Suckling, J. Parker, D.R. Dancce, et al, "The Mammographic Image Analysis Society Digital Mammogram Database," Elsevier Science, pp. 375–378, 1994.
- [7] R. Kronland-Martinet, J. Morlet, A. Grossmann, "Analysis of sound patterns through wavelet transforms," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 1, pp. 273–302, 1987.
- [8] Y. Meyer, "Principe d'incertitude, bases Hilbertiennes et algèbres d'opérateurs", *Séminaire Bourbaki*, vol. 662, pp.1985 -1986.
- [9] I. Daubechies, "The wavelet transform, time-frequency localization and signal analysis," *IEEE Trans. Inform. Theory*, vol. 39, pp. 961–1005, 1990.
- [10] R.N. Strickland, H.I. Hahn, "Wavelet Transforms for Detection Microcalcifications in Mammograms," *IEEE Transactions on Medical Imaging*, vol. 15, pp. 218–229, 1996.
- [11] T.A. Docusse, A.S. Pereira, and N. Marranghello, "Microcalcification Border Characterization," *IEEE Engineering in Medicine and Biology Magazine*, vol. 28, pp. 41–43, 2009.
- [12] P. Liu, "An Enhancement Technology for X-Ray Images Based on Wavelet Transform," *Journal of North University of China (Natural Science Edition)*, vol. 28, 2007.
- [13] J. Feng, N. Xiong and Bi Shuoben, "X-ray Image Enhancement Based on Wavelet Transform," *IEEE Asia-Pacific Services Computing Conference*, 2008, paper 10.1109, p. 1568–1573.
- [14] J. Kennedy and R.C. Eberhart, "Particle swarm optimization," in *Proc. IEEE Int. Conf. on Neural Networks*, Perth, Australia, 1995, p.1942–1948