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Computer Vision-Based Breast Self-Examination Stroke Position and Palpation Pressure Level Classification Using Artificial Neural Networks and Wavelet Transforms

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***Abstract*— This paper focuses on breast self-examination (BSE) stroke position and palpation level classification for the development of a computer vision-based BSE training and guidance system. In this study, image frames are extracted from a BSE video and processed considering the color information, shape, and texture by wavelet transform and first order color moment. The new approach using artificial neural network and wavelet transform can identify BSE stroke positions and palpation levels, i.e. light, medium, and deep, at 97.8 % and 87.5 % accuracy respectively.**

I. Introduction

Breast cancer is a global problem and North America continues to have the highest incidence rate of 1 in 8 followed by Western Europe and Australasia with 1 in 10 according to a recent study among 187 countries [1]. Breast cancer in its advanced stage is not curable, thus the key to survival is early detection and treatment. Women who practice regular breast self examination (BSE) are the ones most likely to detect early abnormalities in their breast, i.e. lumps, change in size or shape, nipple changes or discharges, etc. However, past studies have shown that most women performing BSE do not carry out the procedure efficiently due to lack of training and/or proper guidance [2].

Early stage of breast cancer typically produces no symptoms when the tumor is small and most treatable. When breast cancer has grown to a size when it can be felt, the most important sign of breast cancer is a painless mass [3]. Breast cancer screening is commonly performed through BSE, clinical breast examination (CBE), and mammography. BSE is the procedure where a woman examines her own breast for lumps and other abnormalities. It is simple, inexpensive, non-invasive, and non-hazardous. CBE is similar to BSE, the breast and armpit area are examined, but in this case by a certified medical practitioner. This method is also simple and non-hazardous but can be invasive and expensive. Finally, mammography is the application of a light dose of x-ray radiation to the compressed part of the breast. Although this method has become a standard in breast cancer screening, it has plenty of inherent deterrents. It requires an expensive machine, a trained x-ray technologist, and a radiologist to interpret the results. This method is invasive and requires breast compression which causes discomfort to the patient. The process also exposes the breast to x-ray radiation which may induce carcinogens in the body [4]. In addition, mammography is less accurate in women under 40 years old since breast tissue in younger women is generally denser compared to older women.

This paper introduces a new computer vision-based BSE guidance system. It is organized as follows: Section II contains the review related studies and Section III explains the computer vision-based BSE system. The experimental results are explained in Section IV and the paper is concluded in Section V.

II. Related Work

The common sources of information regarding BSE are found in pamphlets, magazines, books, instructional videos, and one-to-one discussions with a medical practitioner. These can be integrated into a single BSE multimedia system as proposed by BIOCORE of Coventry University [5-6]. The development of a multimedia authoring methodology could provide an effective solution to BSE training insufficiency and the prototype multimedia material has proven to be more effective in BSE training than traditional methods alone [7]. Another development in BSE training is the training instrument developed by Leight et al. [8]. Their system is composed of a silicon breast model with attached linear voltage displacement transducers (LVDTs) to various areas to detect the stroke position and determine the three levels of palpation pressure, light, medium, and deep. A light palpation disturbs only the portion just beneath the skin surface. A medium palpation examines the middle breast tissue. A deep palpation requires enough pressure to reach the breast tissue along the rib cage. These three palpation levels are necessary as lumps can be located at any level in the breast tissue. Finally, the performance of a novice BSE user is compared to that of an expert where the entire breast area is covered while incorporating three levels of palpation pressure at each portion.

The latest development is the BIOCORE's computer vision-based BSE multimedia system which can guide an actual examination in real time using image processing techniques [9-10]. Basically, the system is composed of a webcam to monitor the breast examination, speaker for real-time feedback to the user, and video processing unit to

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interpret the image data and evaluate whether BSE has been performed properly (Fig. 1). However, the determination of BSE palpation level remains an open research area.

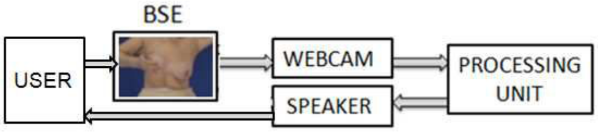

Figure 1. BSE Multimedia System

III. Artificial Neural Network based BSE Image Classification System

Artificial neural networks (ANNs) are attractive for pattern recognition problems such as image classification. A neural network with enough neurons can classify any data with arbitrary accuracy. ANNs have been widely used in content based image classification in conjunction with wavelet transform [11-13]. However, simply inputting the pixels of an image generally requires large networks, thus, more computing power. A particular algorithm of interest is the one described in [14] where the original image is down-sampled then decomposed into three RGB bands of a color image to extract the describing features. Each color band of the original image is divided into parts and wavelet transform is performed on each partition. This procedure significantly decreases the number of inputs to the neural network while preserving the color and texture information. However, the RGB scheme is problematic in cases with shadows and specular reflections, thus, we will adopt a different scheme in our system.

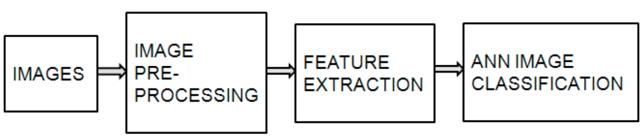

Figure 2. BSE Image Classification Block Diagram

A. Image Pre-processing and Feature Extraction

In the proposed BSE guidance system, the image frames which are mainly taken from BIOCORE's actual BSE video [7] are extracted, down sampled into 256*256 pixels and then, decomposed into Hue, Saturation, and Value (HSV). The HSV color space is better suited to handle shadows and specular reflections [15-16]. These frames are then divided into six parts as shown in Fig. 3. The input to the neural network will consist of the wavelet transform data, first order color moments, and corresponding wave energies of the main frames, i.e. HSV.

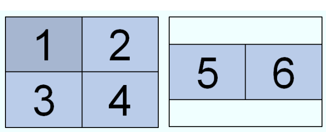

Figure 3. Image division into 6 regions. Notice that regions 5 and 6 overlap with other regions.

In the feature extraction, wavelet transform is used to decompose the image into four frequency sub-bands, (LL_n, LH_n, HL_n, HH_n), where L denotes the low frequency and H denotes the high frequency and n is the decomposition level of the wavelet transform. LL_n is the residual low resolution image (cA_n), HL_n is the vertical detail of image (cV_n), LH_n represents the horizontal details (cH_n) and HH_n presents the diagonal information of image (cD_n). The algorithm for the computation of order n Daubechies (db_n) scaling filter is discussed in [17]. In this paper, we are using db4 wavelet transform with sixth level of decomposition to six partitions of three basic frames of original image (HSV) to get the horizontal, vertical and diagonal detail with a down-sampled size of 2*2 (cH6, cV6,cD6). Note that Hue is invariant to shadows and specularities but since it involves the ratio of color channels differences, it also discards most information. While saturation on the other hand withstands at least the shadows, the value is not invariant [16]. Thus to further limit the number of inputs to our ANN without compromising the variation of the inputs, we utilize the horizontal information of six parts of the H frame (cH6-Hue), the vertical information of six parts of S frame (cV6-Saturation) and the diagonal information of six parts of Value frame (cD6-Value). This produces 72 inputs for the ANN. In addition, the first order color moments for each six parts (Fig. 3) for HSV frames were computed by simply getting the mean value adding 18 more inputs. Finally, the next 9 inputs to the ANN are obtained from the wavelet decomposition energies Eh, Ev and Ed, which contain the percentages of energy corresponding to the horizontal, vertical, and diagonal details of the HSV frames, completing a total of 99 inputs to our ANN (Fig. 4).

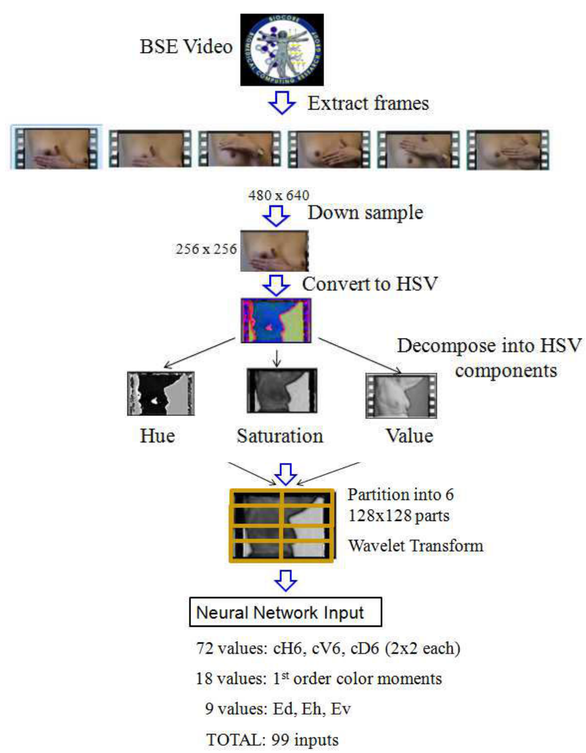

Figure 4. Artificial Neural Network Inputs

B. *Artificial Neural Network Classifier*

A back-propagation neural network (BPNN) with one hidden layer is used for the BSE classification. It has 99 input units, 64 hidden units (after exhaustive trials, this number provides the best performance), and 6 output classes corresponding to the breast stroke positions. The ANN architecture and the corresponding stroke positions are shown in Figs. 5 and 6.

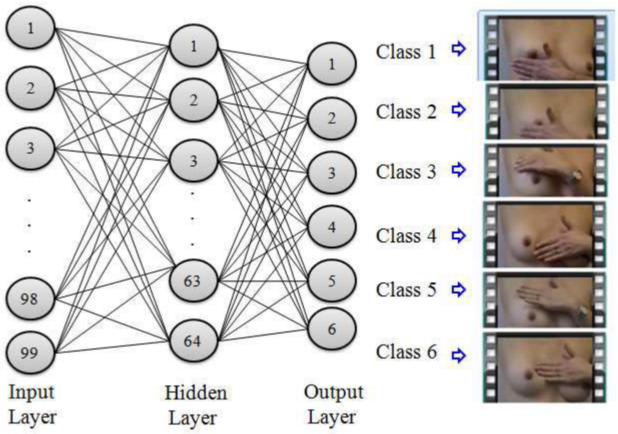

Figure 5. BSE Stroke Position ANN Architecture with six target classes

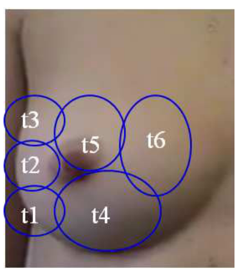

Figure 6. BSE ANN target stroke positions

The ANN used for breast palpation pressure level detection is similar to the one previously used in stroke position classification, except that there are 3 output classes representing the palpation levels: light (class 1), medium (class 2), and deep (class 3) as shown in Figure 7.

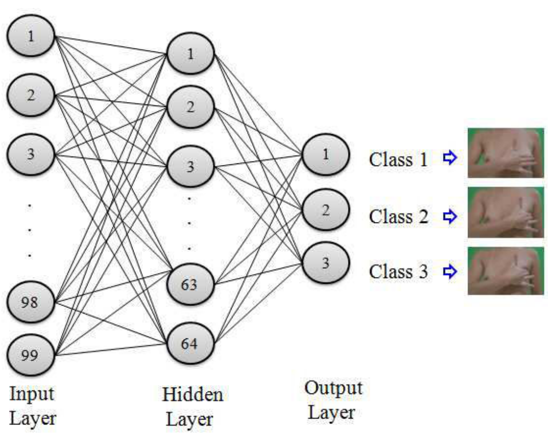

Figure 7. BSE Palpation Level ANN Architecture with three target classes

IV. Experimental Results

To verify the results, 300 image frames were extracted from an actual BSE procedure video. 70% of the data was used for training, 15% of the data for test and the remaining 15% for validation. Training continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy. Since the ANN starts with random initial weights, the results differ slightly every time the ANN is run. The best performance as measured in terms of mean squared error is 0.0000116 after 26 epochs (Fig. 8) with a 97.8 % correct classification accuracy. Note that an epoch of training is defined as a single presentation of all input vectors to the neural network and validation error no longer improves after epoch 26. The confusion matrix (Fig. 9) shows the percentages of correct (diagonal) and incorrect classifications. The confusion matrix for all data includes training, validation, and test.

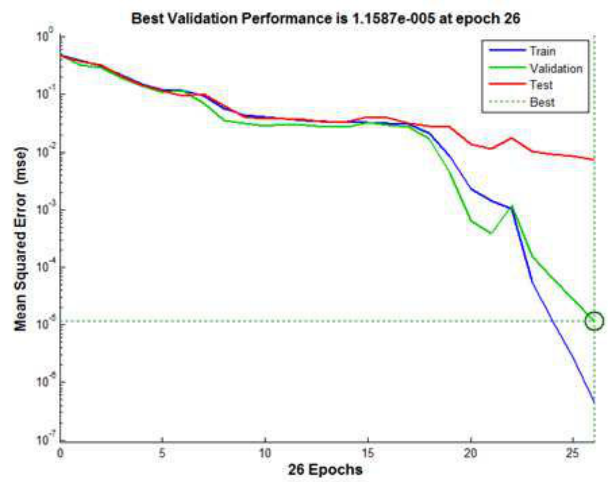

Figure 8. BSE Stroke Position ANN Error Performance

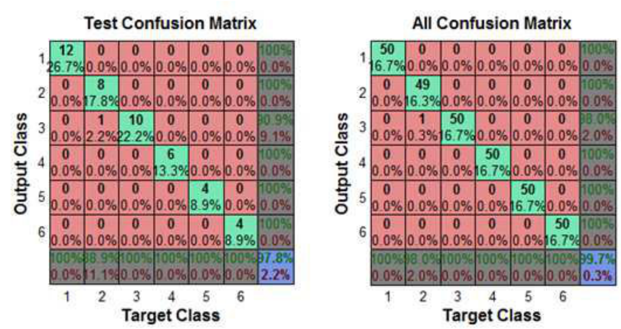

Figure 9. BSE Stroke Position ANN Confusion Matrices

For the ANN breast palpation pressure level detection, a more focused dataset of image frames representing one BSE stroke position are utilized. As with the breast stroke position ANN, 70% of the data were used for training, 15 % for testing and the remaining 15% for validation. The best performance as measured in terms of mean squared error is 0.05631 after 14 epochs (Fig. 10) with an 87.5% correct classification accuracy as shown in the corresponding test confusion matrix (Fig. 11). Notice that the error on the test set is considerably higher than on the validation set due to the very slight distinction between images of different palpation levels.

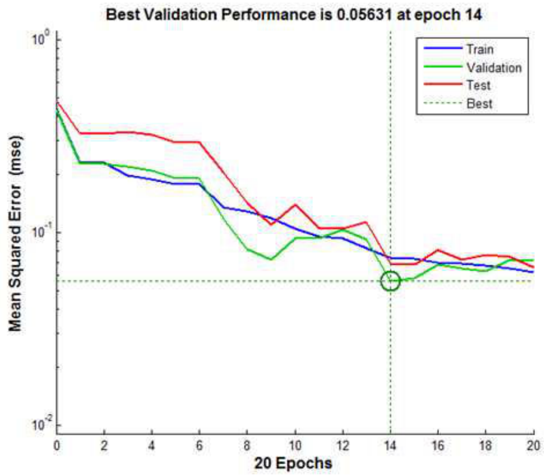

Figure 10. BSE Palpation Level ANN Error Performance

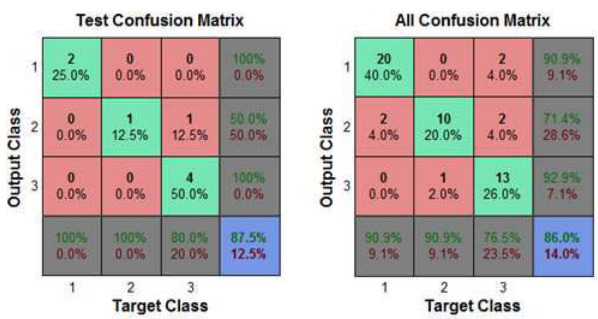

Figure 11. BSE Palpation Level ANN Confusion Matrices

V. CONCLUSION

In this paper, we introduced a new method in breast stroke position and breast palpation level classification for a computer vision-based BSE system using artificial neural network and wavelet transform. Both the BSE stroke position and BSE palpation level ANNs obtained high accuracies of 97.8% and 87.5%. These findings could lead the way towards the integration of ANNs to a computer vision-based BSE training and guidance system for assisting with the early detection of breast abnormalities. However, more complicated situations, such as body movements and variations in breast sizes, and forms should be considered further in future research.

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