REVIEW ARTICLE

Computer-aided Diagnosis Using Neural Networks and Support Vector Machines for Breast Ultrasonography

*Yu-Len Huang**

Modern medical ultrasound equipment performs real-time high-resolution imaging without the use of ionizing radiation. The cost-effectiveness and portability of this facility are particularly important in small-scale hospitals, in which the equipment is useful in conducting complex medical imaging in a timely manner. The use of ultrasonic images to analyze the homogeneity of an internal echo is important to physicians in making diagnostic decisions. However, medical ultrasound images contain significant speckles, noises and ultrasound examination is operator dependent owing to experiences of the interpreter. A computer-aided diagnosis (CAD) system will provide a second beneficial opinion and avoid inter-observer variation. Hence CAD has become a major research topic in medical ultrasound imaging and diagnosis. The artificial neural networks and support vector machines (SVMs) models are extensively used in classification for its ability to model the complex system. Various breast ultrasound CAD systems using the neural network and SVM algorithms have been proposed and the results demonstrated that the classification models have theirs potential effectiveness. This article will review the applications of neural network and SVM in the current breast CAD systems of ultrasound.

KEY WORDS — artificial neural network, breast ultrasound, computer-aided diagnosis, sonography, support vector machine

■ *J Med Ultrasound* 2009;17(1):17–24 ■

Introduction

Sonography is a convenient and safe tool for the human body. Modern medical ultrasound equipment provides real-time high-resolution imaging without the use of ionizing radiation, and it is relatively inexpensive and portable. The cost-effectiveness and portability of this modality are particularly important in small-sized hospitals, in which the equipment is useful in conducting complex medical imaging in a timely manner. High resolution probes, computer enhanced imaging, and portable machinery have led to the widespread adoption of real-time ultrasound by physicians. Therefore ultrasound has become an increasingly integral part of the evaluation, diagnosis, and treatment of various diseases. The use of ultrasonic images to analyze the homogeneity of an internal echo is important to physicians in making diagnostic

Received: January 31, 2008 Accepted: February 3, 2008
Department of Computer Science, Tunghai University, Taichung, Taiwan.
**Address correspondence to:* Associate Professor Yu-Len Huang PhD, Department of Computer Science, Tunghai University, Taichung 407, Taiwan. *E-mail: ylhuang@thu.edu.tw*

decisions. Thus physicians have a much greater clinical correlation than radiologists by performing ultrasound studies. However, medical ultrasound images contain significant speckles, noises and ultrasound examination is operator dependent owing to experiences of the interpreter. Due to the rapid development of sonography it seems advisable to reconsider the clinical value, especially in high resolution, of real time ultrasound and computer aids in diagnosis.

In this decade, computer-aided diagnosis (CAD) has become a major research topic in medical imaging and diagnosis [1–4]. A CAD system will provide a computer output which may act to serve as providing a second opinion to assist physicians in image readings and avoid inter-observer variation [5,6]. In fact, CAD is a concept established by considering equally the roles of physicians and computers [7,8]. Established CAD systems, for the most part, consist of four stages (1) preprocessing, a significant issue before the segmentation due to the considerable noise of the ultrasound images that make segmentation difficult; (2) segmentation, the object in sonography is segmented from the background tissue; (3) feature extraction, features relevant to the classification are extracted; and (4) decision making, the classifier presents the diagnostic results based on the extracted features. Figure 1 illustrates the flowchart of a conventional CAD system for ultrasound imaging. Up to now, a large number of CAD systems have been employed for assisting physicians in the early detection and/or characterization of various lesions (e.g. breast, thyroid, lung, and liver) in medical ultrasound imaging.

The artificial neural networks and support vector machines (SVMs) models are extensively used in classification for their ability to model the complex system. Neural network and SVM were widely used artificial intelligence models in image classification. Therefore various breast ultrasound CAD systems using the neural network and SVM algorithms have been proposed and the results demonstrated that the classification models have their potential effectiveness. This article will review the applications of the neural network and SVM in current breast CAD systems on sonogram.

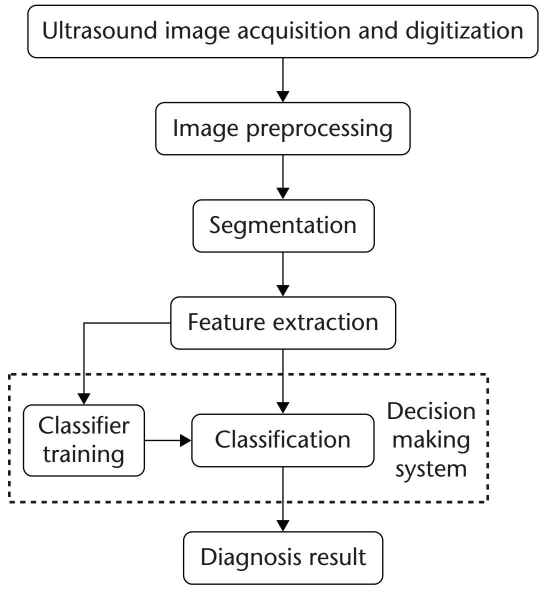

Fig. 1. *Block diagram of a general computer-aided diagnosis (CAD) system for ultrasound imaging.*

Neural Networks and SVMs

In early 1989, the Joint Conference on Neural Networks encouraged the rapid growth in the field of artificial neural network. The neural network is extensively used in classification for its ability to model the non-linear system by using hidden units in a compact range. Due to the fact that the neural network learns by example and deals with ambiguous data, it can provide an educated guess; something conventional classification algorithms could not do well, or at all. Furthermore, SVM reveals the feasibility and superiority to extract higher-order statistics. Therefore the SVM is widely used in classification and regression for its high generalization performance, using pattern recognition. Both the neural network and SVM model are reliable choices as classifiers for CAD systems because they train well and compute efficiently. Concise reviews of an important class of neural networks and SVM were presented below.

Multilayer perceptron neural network

The multilayer perceptrons (MLPs), i.e. multilayer feedforward neural networks, are an important and prevalent type of neural network. The MLPs have been applied successfully to solve some difficult and

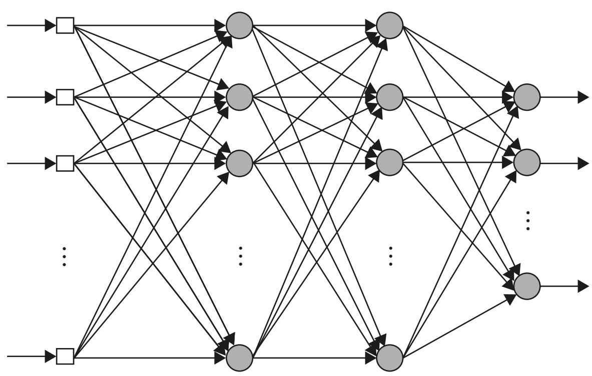

Fig. 2. *Structural graph of multilayer perceptron (MLP) neural network model.*

diverse problems. There are one or more hidden layers in an MLP model and the function of the hidden layer neurons is to arbitrate between the input and the output of the neural network [9]. Figure 2 shows the structural graph of the MLP neural network. At first the input vector is fed into the source nodes in the input layer. The neurons of the input layer then constitute the input signals and applied the results to the neurons of the hidden layer. The output signals of the hidden layer are used as inputs to the next hidden layer. Finally, the output layer obtains the output results and terminates the MLP computing process.

Among the algorithm used to design the MLPs, the back-propagation algorithm is the most popular due to the fact that the algorithm is extremely efficient for neural network learning [10,11]. The back-propagation algorithm consists of two different phases, i.e. the forward phase and the backward phase. In the forward phase, the input signals are computed and passed through the neural network layer by layer. Afterward the neurons in the output layer generate the output signals the error signals will be generated by comparing the output response with the desired response. In the backward phase, some free parameters are able to adjust to minimize the distortion of the MLP neural network by referring the error signals.

The on-line implementation of the back-propagation learning algorithm is executed iteratively based on training samples and then produces the synaptic weight vectors for the MLP neural network. The back-propagation learning algorithm was described in following steps.

Step 1 Initialization

Set all initial synaptic weight vectors and the learning rate parameter for the MLP, and select a terminating error threshold value which is used to stop the back-propagation learning process. This step also prepares the training samples and the corresponding desired outputs for the following steps.

Step 2 Forward computation

Compute the output values of the MLP layer by layer. The error signals are generated using the differences between the output values of the current MLP and desired output.

Step 3 Backward computation

Compute the vectors of local gradient of the MLP layer by layer in the backwards direction. The local gradient vectors can point to the required changes in synaptic weights. The connection synaptic weights of the neural network are then modified according to the changes of local gradient vectors and the predefined learning rate parameter.

Step 4 Iteration of learning procedure

The learning algorithm will execute iteratively until the stopping criterion is satisfied. The back-propagation learning algorithm is terminated when the value of the average distortion function is smaller than the predefined threshold.

Eventually, the learning procedure generates the final synaptic weight vectors. By adding the final synaptic weight vectors into an MLP neural network, this model is able to be used as classifier in CAD system.

Support vector machines

The aim of the SVM is to devise a computationally efficient way of learning to separate hyperplanes in high dimensional feature space [12,13]. The SVM has been shown to be an efficient method for many real-world problems because it can map the

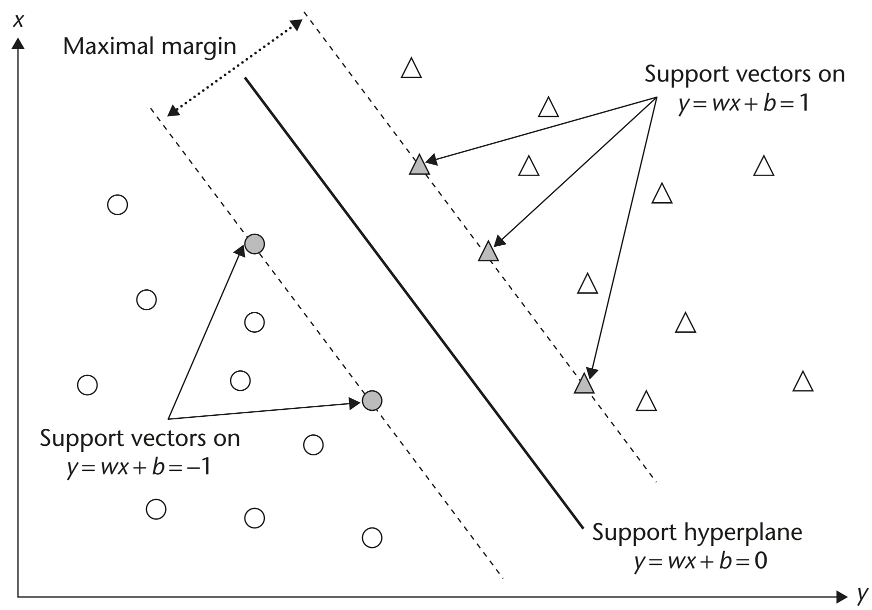

Fig. 3. *An example of the optimal separating hyperplane of support vector machine (SVM) with the maximal margin between two parallel hyperplanes.*

input vectors into a high dimensional feature space through some nonlinear mapping, chosen a priori. In the feature space, an optimal separating hyperplane is constructed. Generally, the SVM is an implementation of the structural risk minimization principle whose object is to minimize the generalization error of the classifier. Given a set of training vectors (m in total) belonging to separate classes, (x_1, y_1), (x_2, y_2), (x_3, y_3), …, (x_m, y_m), where $x_i \in R^n$ denotes the i^{th} input vector and $y_i \in \{-1,-1\}$ is the corresponding desired output. The maximal margin classifier aims to find a hyperplane w: $wx + b = 0$ to separate the training samples. In the possible hyperplanes, only one maximizes the margin (the distance between the hyperplane) and the nearest data point of each class. Figure 3 illustrates an example of the optimal separating hyperplane with the largest margin. The support vectors denote the points lying on the margin border. The solution to the classification is given by the function for convolution of the kernel of the decision function and the support vectors. The polynomial, radial, anova kernels are now often seen choices in SVM-based CAD applications. Take note that the output value of the SVM is either –1 or 1. When the output value of a test sample is larger than 0, the system will classify the lesion in the image as malignant. Conversely, when the output value is smaller than 0, the lesion will be diagnosed as benign.

Ultrasound CAD Systems

Ultrasound CAD systems have been developed and achieved good results in the diagnosis of solid breast nodules. With the computerized features extracted by computer, the extracted information is fed into a classifier, which is employed as a tool to distinguish benign from malignant lesions on breast ultrasound images. In this article, the development of breast ultrasound CAD systems using the MLP neural network and SVM are presented.

Texture-based CAD systems

In breast ultrasonography, a number of CAD systems have been developed [14] especially for texture-based CAD. Chen et al [15] have proposed an efficient CAD using neural networks to differentiate between benign and malignant tumors. The authors employed textural information (normalized autocovariance coefficients) that was extracted from the digitized ultrasound image and then fed the features into an MLP neural network to distinguish benign from malignant solid breast nodules. The performance of the CAD was estimated using a receiver operating characteristic (ROC) curve and the k-fold cross-validation method. The proposed CAD showed the area under the ROC curve (AUC) was 0.96. Moreover, they introduced a multi-view breast ultrasound CAD system [16] with MLP neural networks. Each tumor case contains four different rectangular sub-images from longitudinal and transverse imaging planes. The normalized auto-covariance coefficients of the four sub-images were extracted to represent the textural information. A hierarchical MLP model with four diagnostic subsystems (Fig. 4) was then employed to classify the breast tumor. In their study, the multi-view CAD had a high AUC of 0.98.

In 2002, a proposed CAD system with wavelet-based textural features (variance contrast, autocorrelation contrast, and distribution distortion of wavelet coefficients) on sonogram and an MLP classifier was presented [17]. An AUC of 0.94 for all 242 lesions was demonstrated in this study. Chang et al [18] further tested the SVM-based CAD and compared its performance with that of the MLP. The authors concluded that the classification ability of the SVM (AUC = 0.94) is nearly equal to that of the neural network model (AUC = 0.94) and the proposed SVM CAD has a much shorter training time that is up to 189 times faster than the MLP CAD. They also utilized an SVM model [19] to classify breast tumors according to their texture information surrounding speckle pixels. By combining speckle information with auto-covariance coefficients as features, the authors claimed that the proposed CAD improved the diagnostic performance AUC to 0.95 for all 250 cases.

Morphology-based CAD systems

The appearance of information about shape, provided by a tumor contour, was almost independent of the sonographic gain setting and could tolerate reasonable variations in boundary delineation associated with the different ultrasound machines used. Thus morphology-based diagnosis of solid breast tumors takes advantage of nearly independent settings on different ultrasound systems or distinct

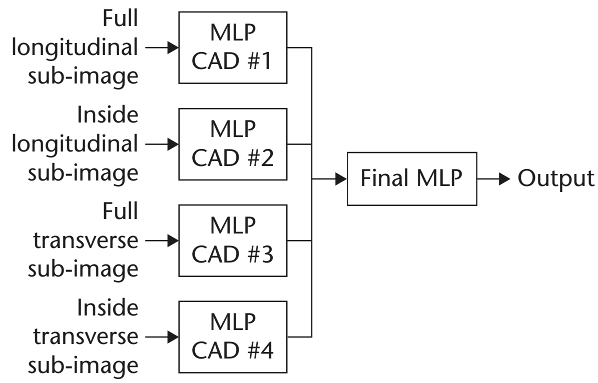

Fig. 4. *Block diagram of a proposed multi-view diagnostic system. With permission from reference 17.*

ultrasound machines. Chen et al [20] developed a CAD with five valuable morphological features (number of substantial protuberances and depressions, lobulation index, elliptic-normalized circumference, elliptic-normalized skeleton, and long axis to short axis ratio) and the MLP neural networks to differentiate benign from malignant breast lesions. According to this study, the AUC value was 0.95 for all 271 lesions. Another study about breast CAD using morphological features was proposed by Joo et al [21]. The authors developed an MLP-based CAD with features representing the shape, edge characteristics, and darkness of a nodule. The diagnostic performance of an AUC value of 0.95 for 584 histologically confirmed cases was shown in the study. In addition, Chang et al [22] developed an automatic segmentation method to obtain contours of breast tumors and six pieces of uncomplicated shape information were then used as input features. The SVM was used to classify the tumors and the AUC achieved 0.95 (210 ultrasonic images). In a recent study, Huang et al [23] proposed a CAD system based on level-set contouring for breast tumors in sonography. The automatic segmentation methods [24,25] save much of the time required to sketch a precise contour with high stability. The results showed that the diagnostic performance of such a classification using an SVM model is satisfactory.

3-Dimensional CAD systems

A study [26] dealt with the MLP CAD with textural features for use within the 3-dimensional (3D) ultrasound images of the breast and compared its performance with 2-dimensional (2D) versions. The authors reported that the 3D and 2D ultrasound CAD systems yielded an AUC of 0.97 and 0.85, respectively. Their study suggested that using 3D over 2D ultrasound images for CAD can represent a potentially significant advantage. Another texture classification of 3D ultrasound breast diagnosis using run difference matrix (RDM) with MLP neural networks was developed by Chen et al [27]. The authors declared that the AUC of the proposal 3-D RDM method can achieve 0.97 for all 215 patients. Besides, 3D power Doppler ultrasound (PDUS) offers a beneficial tool for investigators to inspect the signals of blood flow and vascular structures in breast cancer. Huang et al [28] proposed a CAD system for quantifying PDUS images based on an MLP neural network. This study utilized nine vascularity features including vessel-to-volume ratio, number of vascular trees, length of vessels, number of branchings, mean of radius, number of cycles, and three tortuosity measures in the classification of benign and malignant breast tumors. The results showed the AUC value is 0.94 for all 221 lesions. An investigation evaluated the use of 3D PDUS in the differential diagnosis of solid breast tumors [29]. This study computed three indices (vascularization index, flow index, and vascularization flow index) for the tumor itself and for the tumor plus a 3-mm shell surrounding it and then applied the features to the MLP classifier. The AUC was 0.89 for all 195 lesions in their study.

CAD systems using hybrid features

By using the age of patients, margin sharpness, margin echogenicity, and angular variation in margin as inputs, Song et al [30] compared two classifiers logistic regression (LR) and MLP neural network for CAD on breast sonograms. The results showed that no difference in performance between LR (AUC = 0.85) and the MLP (AUC = 0.86) as measured by the ROC curve. The authors also reported that the MLP had a higher specificity compared with LR value at a fixed 95% sensitivity. Moreover, Jesneck et al [31] developed and evaluated CAD systems that include both mammographic and sonographic descriptors. The Breast Imaging Reporting and Data System (BI-RADS) was developed by the American College of Radiology to standardize the interpretation of mammograms [32] and sonograms [33]. Totally 39 features including mammographic BI-RADS features, sonographic BI-RADS features, morphological features, and patient history features were used as input features for linear discriminant analysis (LDA) and the MLP models. In their study, mammographic and sonographic examinations were performed in 737 patients, which yielded 803 breast mass lesions. The authors demonstrated that both the LDA and MLP CAD systems achieve high diagnostic performance with cross validation (AUC = 0.92 for both the LDA and MLP). Wu et al [34] improved the interpretation of sonogram abnormalities by combining the texture and morphologic features of ultrasound breast tumor imaging. The SVM was used as classifier to identify the tumor as benign or malignant. The results revealed the diagnostic performance AUC of 0.95 for all 210 lesions.

Conclusion

The architectures of the MLP neural networks and SVM models are simple and they are appropriate for hardware design. With the expansion of the database, the features extracted from new cases can easily be trained and used as references. When the performance of the classifier is not good enough for some ultrasonic images, the off-line learning algorithm can be reused to obtain a new set of weighting factors by adjusting the free parameters or by adding some distinct training samples to the training set. Notably, the classification modules are able to redress weighting factors without modifying the other functions. Compared with other classification models (e.g. LDA, LR, and decision tree models) the flexibility and the capability of solving problems are certainly advantages.

Ultrasound has become one of the major imaging modalities for the diagnosis of many different types of lesions. Excluding breast CAD, the MLP and SVM have been utilized in various ultrasound

CAD systems including the diagnosis of the kidney, prostate, and liver diseases amongst others and achieved good results recently. Several ultrasound CAD systems using MLP neural networks have been proposed in the detection and staging of prostate carcinoma [35], in identification of kidney categories [36,37], in identification of carotid atherosclerosis [38], in differentiation of malignant from benign thyroid nodules [39], and for classifying focal liver lesions [40]. Similarly, the SVM-based CAD systems were applied in the analysis of carotid plaque morphology for the assessment of a stroke [41], in the selection and pattern classification of cervical lymph nodes [42,43], in identification of fatty liver [44], and in assessing the predictability of urodynamic stress incontinence [45].

Improved ultrasound imaging techniques permit the management of detection of many human diseases to become less invasive. Moreover, CAD systems have the potential to assist radiologists in their interpretations and improve diagnostic accuracy by providing a "second opinion" in the management diagnostic decisions. It is also believed that several developed CAD systems with machine learning classifiers may assist the physician to predict the future possibility of a normal subject becoming abnormal based on extracted features. Such CAD systems help the physician to study extensively the tissue property on sonograms more reliably. In the future, ultrasound CAD is expected to be a useful tool for diagnostic examinations in daily clinical practice.

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