ELSEVIER

Journal of Clinical Imaging 29 (2005) 179–184

CLINICAL IMAGING

Support vector machines in sonography
Application to decision making in the diagnosis of breast cancer

Yu-Len Huang[a], Dar-Ren Chen[b,*]

[a]Department of Computer Science and Information Engineering, Tunghai University, Taichung 407, Taiwan
[b]Department of General Surgery, Changhua Christian Hospital, Changhua 500, Taiwan

Received 10 May 2004; received in revised form 20 July 2004

Abstract

We evaluated a series of pathologically proven breast tumors using the support vector machine (SVM) in the differential diagnosis of solid breast tumors. This study evaluated two ultrasonic image databases, i.e., DB1 and DB2. The DB1 contained 140 ultrasonic images of solid breast nodules (52 malignant and 88 benign). The DB2 contained 250 ultrasonic images of solid breast nodules (35 malignant and 215 benign). The physician-located regions of interest (ROI) of sonography and textual features were utilized to classify breast tumors. An SVM classifier using interpixel textual features classified the tumor as benign or malignant. The receiver operating characteristic (ROC) area index for the proposed system on the DB1 and the DB2 are 0.9695$\pm$0.0150 and 0.9552$\pm$0.0161, respectively. The proposed system differentiates solid breast nodules with a relatively high accuracy and helps inexperienced operators avoid misdiagnosis. The main advantage in the proposed system is that the training procedure of SVM was very fast and stable. The training and diagnosis procedure of the proposed system is almost 700 times faster than that of multilayer perception neural networks (MLPs). With the growth of the database, new ultrasonic images can be collected and used as reference cases while performing diagnoses. This study reduces the training and diagnosis time dramatically.

Keywords: Breast cancer; Computer diagnosis; Support vector machines; Textural analysis; Ultrasonography

1. Introduction

Breast cancer is one of the leading causes of deaths from cancer for the female population in both developed and developing countries. The most useful way to reduce deaths due to breast cancer is to treat the disease at an earlier stage. Earlier treatment requires early diagnosis, and early diagnosis requires an accurate and reliable diagnostic procedure that allows physicians to differentiate benign breast tumors from malignant ones. The most frequently adopted medical imaging studies for the early detection and diagnosis of breast cancers include mammography and ultrasonography. Mammography gained publicity, whereas breast sonography does its job quietly behind the scenes [1]. Usually, breast sonography was used as an adjunct to mammography. Although mammography can visualize nonpalpable and minimal tumors, and sonography is suitable for palpable tumors, sonography is more convenient and is safer tool than mammography is in the evaluation of a breast mass in daily clinical practice. However, sonography is an operator-dependent examination technique, there is a considerable overlap of benignancy and malignancy in breast sonography, and interpretation is subjective. The sonographic examination is much more extensive than the usual examinations performed at most breast imaging centers. Stavros et al. [2] found that the sensitivity of breast ultrasound for malignancy is 98.4%, the specificity is 67.8%, the overall accuracy is 72.9%, the positive predictive value (PPV) is 38%, and the negative predictive value (NPV) is 99.5%. We noticed that the above diagnostic results are achieved by experienced

* Corresponding author. Department of General Surgery, Changhua Christian Hospital, 135 Nanhsiao Street, Chunghua, Taiwan, 500. Tel.: +886 4 7238595; fax: +886 4 7267167.

E-mail addresses: ylhuang@mail.thu.edu.tw (Y.-L. Huang), dlchen88@ms13.hinet.net (D.-R. Chen).

0899-7071/05/$ – see front matter © 2005 Elsevier Inc. All rights reserved.
doi:10.1016/j.clinimag.2004.08.002

radiologists. In practice, many invasive diagnostic procedures are still required in most cases. Most of these procedures could be avoided if a more specific diagnostic test was available, because the rate of positive findings at biopsy for cancer is low, between 10% and 31% [3–5]. The biopsy is expensive because of a great quantity of indeterminate lesions, which need to be differentiated.

Recent technical advances in ultrasound image have expanded the potential utility of this modality for the evaluation of breast lesions [6–10]. In these approaches, Chen et al. used 2-D auto-covariance coefficients and the neural network (NN) classifier to determine whether the breast tumors are benign or malignant in breast sonography. The computer-aided diagnostic system (CAD) utilizes a multilayer perception neural network (MLP) to perform a good diagnostic result. However, the learning procedure of MLP is very time consuming and initial parameter dependent; that is, the number of neurons, learning rate, and moment values are hard to decide. Unfortunately, the selections of initial parameters will affect the results drastically. Whereas, the support vector machine (SVM) reveals the feasibility and superiority to extract higher order statistics and has become extremely popular in terms of classification and prediction. This study employs this SVM model as a classifier instead of MLP to determine whether the breast tumors are benign or malignant. The diagnosis system proposed herein can classify the ultrasonic images of a breast more accurately and efficiently. The SVM is a reliable choice for the new proposed system because it is fast and excellent in ultrasonic image classification.

2. System description

In this paper, we supposed that the physician has already identified the tumor. The proposed system can use the intensity variation and interpixel texture information from the sonography to diagnose the tumor. The physician first extracted the rectangular subimage of the region of interest (ROI), and then the computer analyzed the ROI to make a differential diagnosis.

2.1. Ultrasonic image databases

This study evaluated two sonographic image databases of solid breast nodules. All images in these databases contained only one image from each patient. The ultrasonic images were captured at the largest diameter of the tumor. Sonography was performed using an ALOKA SSD 1200 (Tokyo, Japan) scanner and with freeze-frame capability and a 7.5-MHz linear transducer. No acoustic standoff pad was used in any of the cases. The databases were supplied by the coauthor, an experienced physician, Dr. Chen, from the Department of General Surgery, Changhua Christian Hospital, Changhua, Taiwan. The sonographic gain setting remained unchanged throughout the entire period of study, except for changes made to obtain the best view.

2.1.1. Ultrasonic image database 1 (DB1)

To compare the performance with the CAD that was proposed by Chen et al. [9], the identical sonography

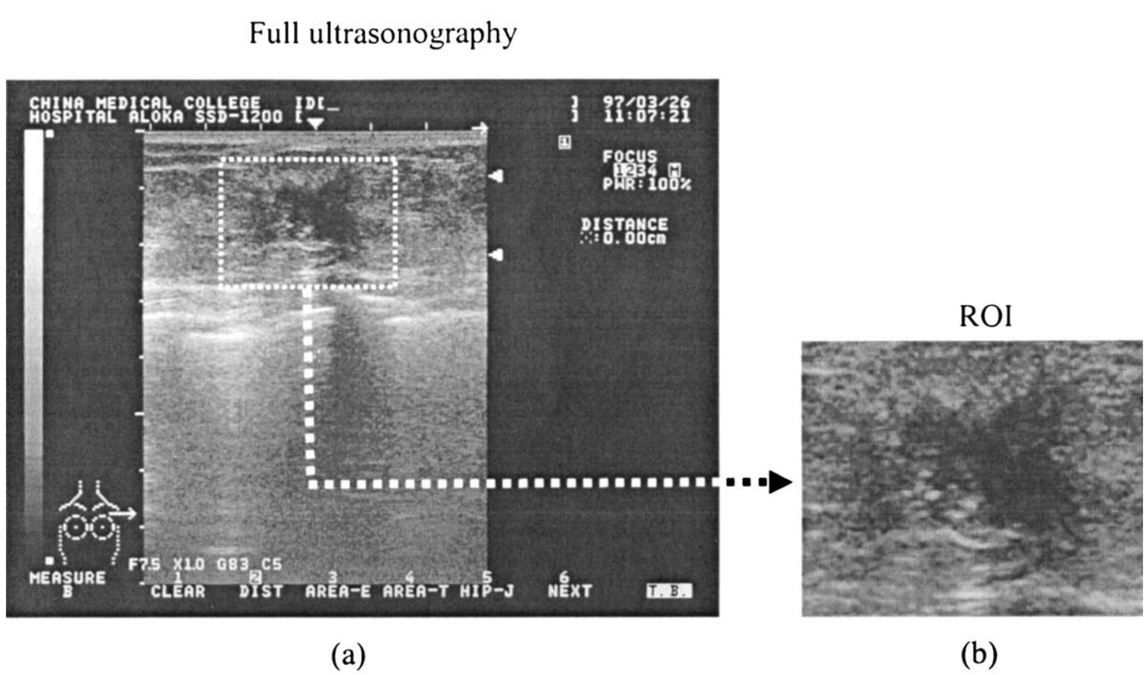

Fig. 1. Full ultrasonography. (a) A 736×556 full breast sonography. (b) The ROI rectangle is approximately 2.91×2.33 cm in size, captured with a resolution of 169×135 pixels (a 1×1 cm rectangle contains 58×58 pixels).

database is used in DB1. The DB1 consists of 140 images of pathologically proven benign breast tumors from 88 patients and of carcinomas from 52 patients (tumor size: >1 cm in all cases). The images were collected from January 1, 1997, to May 31, 1998; the patients' ages ranged from 18 to 62 years.

2.1.2. Ultrasonic image database 2 (DB2)

A total of 250 sonograms from patients, including 35 cancers, 56 fibrocystic nodules, 115 fibroadenomas, 1 intraductal papilloma, 3 lipomas, 38 cysts, and 2 galactoceles, was used as DB2 samples (tumor size: >0.8 cm in all cases). The images were collected from March 1, 1998, to April 30, 1999; the patients' ages ranged from 18 to 68 years. The ultrasonic appearances were then correlated either with the fine-needle aspiration, core biopsy, or surgical excision. Most of the cases are tissue proved and some were followed up at least 2 years.

The monochrome sonographic images in the databases are quantized into 256 gray levels, i.e., 8 bits/pixel. The ROI is manually selected by Dr. Chen, using the ProImage package. That is, the hardware-bundled software package was used to capture the full image of the ultrasonic scanner and to select the ROI manually. The ROI was then saved as a digital form for later analysis by the SVM program. Fig. 1(a) illustrates a real-time digitized monochrome ultrasonic image. Fig. 1(b) presents an ROI for the tumor.

2.2. Textural analysis

Observably, different tissues always have significantly different textures in an ultrasonic image. The textural information extracted from sonography has been found to be an efficient feature to classify breast tumors. The proposed CAD system used the correlation between neighboring pixels within the images as features to classify breast tumor. The modified auto-covariance coefficients

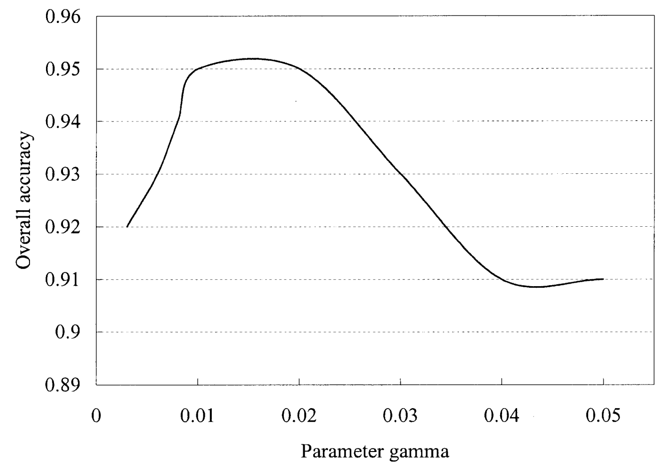

Fig. 3. Performance of the proposed SVM system with different parameter γ (gamma) values.

between pixels (i,j) and $(i+\Delta m, j+\Delta n)$, in an image with size $M \times N$, is defined as

$$\gamma(\Delta m,\Delta n) = 1 - \frac{A(\Delta m,\Delta n)}{A(0,0)}, \qquad (1)$$

where

$$A(\Delta m,\Delta n) = \frac{1}{(M-\Delta m)(N-\Delta n)} \times \sum_{x=0}^{M-1-\Delta m} \sum_{y=0}^{N-1-\Delta n} |\left(f(x,y)-\bar{f}\right) \times \left(f(x+\Delta m, y+\Delta n)-\bar{f}\right)|, \qquad (2)$$

where $\bar{f}$ is the mean value $f(x,y)$. This study utilized the coefficients for each breast tumor ultrasonic image as the

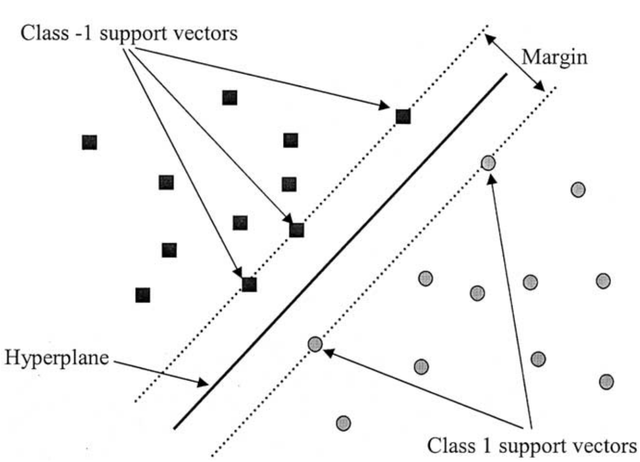

Fig. 2. SVM optimal hyperplane.

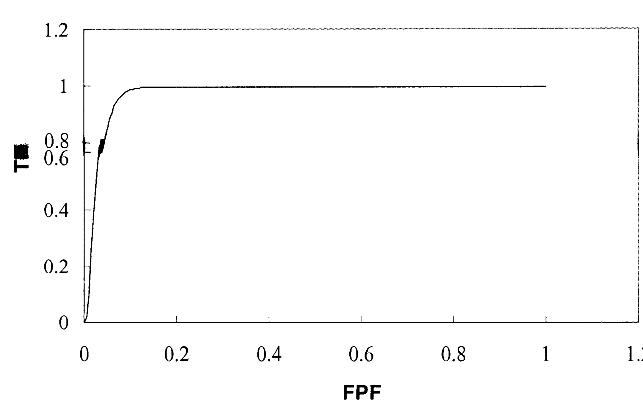

Fig. 4. Diagram of the ROC curve for the DB1 in the classification of malignant and benign tumors. The A_Z value for the ROC curve is 0.9695 ± 0.0150.

interpixel features to distinguish the differences between benign and malignant tumors.

2.3. Support vector classification

The aim of SVM is to devise a computationally efficient way of learning separating hyperplanes in a high-dimensional feature space [11,12]. The SVMs have been shown to be an efficient method for many real-world problems because of its high generalization performance without the need to add a priori knowledge. Recently, SVMs have attention much as a useful tool for image recognition, hand-written digit recognition, and bioinformatics [13–18]. The SVM can map the input vectors into a high-dimensional feature space through some nonlinear mapping, chosen a priori. In this 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 upper bound on the generalization error. Given a set of training vectors (l in total) belonging to separate classes, (x_1,y_1), (x_2,y_2), (x_3,y_3),. . ., (x_1,y_1), where $x_i \in R^n$ denotes the ith input vector and $y_1 \in \{+1,-1\}$ is the corresponding desired output. The maximal margin classifier aims to find a hyperplane w: $wx+b=0$ to separate the training data. In the possible hyperplanes, only one maximizes the margin (distance between the hyperplane) and the nearest data point of each class. Fig. 2 shows 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 decision function

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{N_{SV}} \alpha_i y_i k(s_i,x) + b\right), \quad (3)$$

where α_i is the positive Lagrange multiplier, s_i is the support vectors (N_{SV} in total), and $k(s_i,x)$ is the function for convolution of the kernel of the decision function. The radial kernels performs best in our experimental comparison, hence, is chosen in the proposed diagnosis system. The Radial kernels is defined as

$$k(x,y) = \exp\left(-\gamma(x-y)^2\right), \quad (4)$$

where $\gamma \in R$ is a nonzero parameter.

The modified normalized auto-covariance matrix is used as the feature vector for the input of the SVM classifier. In this work, both Δm and Δn are 5; thus, processing an ultrasonic image produces a 5×5 auto-covariance matrix (25 auto-covariance coefficients). Because the value of $\gamma(0,0)$ is always 1, thus, except for the element $\gamma(0,0)$, other coefficients are formed as a 24-D textural feature vector. Take note that the output value of the SVM is either −1 or 1. When the output value of a sonographic breast image is larger than 0, the system will classify the tumor in the image as malignant. Conversely, when the output value is smaller than 0, the tumor will be diagnosed as benign.

Table 1
The number of misdiagnosed cases of the MLPCAD and the proposed SVMCAD for each test in the DB1

	MLPCAD (threshold = 0.2)		SVMCAD	
Test set	Malignant cases	Benign cases	Malignant cases	Benign cases
1	0/5	0/9	0/5	0/9
2	1/5	0/9	0/5	0/9
3	0/5	1/9	0/5	1/9
4	0/5	0/9	0/5	1/9
5	0/5	1/9	0/5	1/9
6	0/5	3/9	0/5	3/9
7	0/5	0/9	0/5	0/9
8	0/5	0/9	0/5	0/9
9	0/6	0/8	0/6	0/8
10	0/6	1/8	0/6	1/8

Table 2
Classification of breast nodules in the DB1 by the proposed SVM system with γ=0.01

	Benign	Malignant
SVM output < 0	TN 81	FN 0
SVM output ≥ 0	FP 7	TP 52
Total	88	52

TN = true-negative; FN = false-negative; FP = false-positive; TP = true-positive.

3. Results

The k-fold cross-validation method and the receiver operating characteristic (ROC) curves (software package LABROC1 by Professor C. E. Metz, University of Chicago) are used to estimate the performance of the proposed SVM system (denoted by SVMCAD) and the MLP system proposed by Chen et al. (denoted by MLPCAD) [9]. Usually, the overall performance of a diagnostic system can be evaluated by examining the ROC area index, A_Z, over the testing output values. Moreover, because the radial kernels perform best in the experimental results, the kernels are chosen in the proposed SVM diagnosis system. Fig. 3

Table 3
The performance of the proposed SVM system on the DB1 with γ = 0.01

Item	Proposed SVM system
Accuracy (%)	95.00
Sensitivity (%)	100.0
Specificity (%)	92.05
PPV (%)	88.14
NPV (%)	100.00

Accuracy = (TP+TN)/(TP+TN+FP+FN); Sensitivity = TP/(TP+FN); Specificity = TN/(TN+FP); PPV = TP/(TP+FP); NPV = TN/(TN+FN).

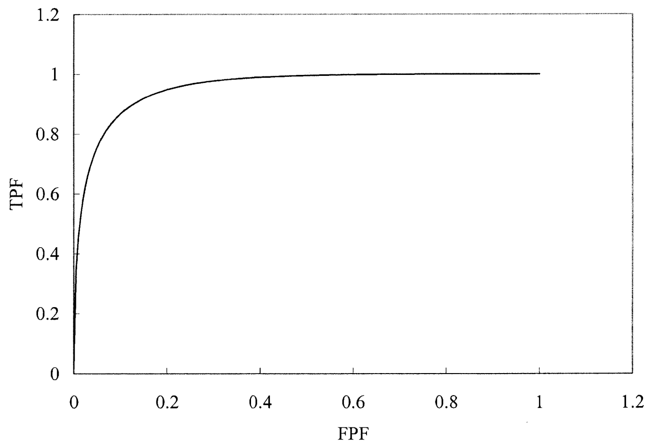

Fig. 5. Diagram of the ROC curve for the DB2 in the classification of malignant and benign tumors. The A_Z value for the ROC curve is 0.9552±0.0161.

shows the diagnosis performance for the SVM system with different γ values. With the γ ranging from 0.01 to 0.02, the SVMCAD obtained a stable and the highest accuracy.

3.1. Simulation results of the DB1

In the simulations, k is 10, and each group has 14 ultrasonic images. The training data and the test data are equivalent to that of the study by Chen et al. [9]. Fig. 4 illustrates the diagram of the ROC curve for the SVMCAD in the classification of malignant and benign tumors. The SVMCAD and MLPCAD achieve A_Z=0.9695±0.0150 (SD) and 0.9560±0.0183 (SD), respectively. The system correctly identifies all of the malignant tumors and 81 of the 88 benign tumors. Table 1 lists the number of misdiagnosed cases of the MLPCAD (threshold=0.2) and the SVMCAD for each test set. The accuracy of the proposed SVMCAD for malignancy is 95.0% (133/140), the sensitivity is 98.1% (51/52), the specificity is 93.2% (82/88), the positive predictive value (PPV) is 89.5% (51/57), and the negative predictive value (NPV) is 98.8% (82/83), as illustrated in Tables 2 and 3. On the other hand, the MLPCAD performs that the overall accuracy is 95.0%, the sensitivity is 98.1%, the specificity is 93.2%, the PPV is 89.5%, and the NPV is 98.8.

Table 4
The performance of the proposed SVM system on the DB2 with γ=0.01

Item	Proposed SVM system
Accuracy (%)	93.20
Sensitivity (%)	91.43
Specificity (%)	93.49
PPV (%)	69.57
NPV (%)	98.53

Accuracy=(TP+TN)/(TP+TN+FP+FN); Sensitivity=TP/(TP+FN); Specificity=TN/(TN+FP); PPV=TP/(TP+FP); NPV=TN/(TN+FN).

Table 5
The computation time by using the proposed SVMCAD and the MLPCAD

	Training time (in s)	Diagnose time (in ms)
MLPCAD	140.71	357.12
SVMCAD	0.20	0.15

The training time is evaluated by using the sonography database that contains 140 images. The diagnose time is the average computation time for an ultrasonic image.

3.2. Simulation results of the DB2

In the simulations, k is also 10, and each group has 25 ultrasonic images. Fig. 5 illustrates the diagram of the ROC curve for the SVMCAD in the classification of malignant and benign tumors. The SVMCAD achieves A_Z=0.9552±0.0161 (SD). The accuracy of the proposed SVMCAD for malignancy is 93.2% (233/250), the sensitivity is 91.4% (32/35), the specificity is 93.5% (201/215), the PPV is 69.6% (32/46), and the NPV is 98.5% (201/204), as illustrated in Table 4.

3.3. Training time and diagnosis time

We also compared the computation time for the SVMCAD and the MLPCAD. All simulations are made on a single-CPU Intel Pentium III, 1-GHz personal computer with the Windows XP operating system. Table 5 shows the training for the ultrasonic image database and the average diagnosis time for each tumor sonography. The training and average diagnosis times of the MLPCAD are 700 and 2380 times longer than that of the proposed SVMCAD, respectively. In all simulation results, the results from the proposed SVMCAD obtain the better classification performance and the speedy computation than those obtained with the MLPCAD.

4. Discussion

Many lesions found by breast sonography are not clinically apparent by palpation. Improved imaging techniques permit the management of sonographically detected breast lesions to become less invasive. Hence, this investigation proposes an efficient diagnosis system using SVM to differentiate between benign and malignant tumors. The proposed system diagnoses breast tumors using interpixel texture within the ultrasonography. The MLP classifier (A_Z=0.956) proposed by Chen et al. [9] is replaced by the SVM (A_Z=0.970) to obtain a better result. The proposed system adopts the SVM to distinguish between benign and malignant cases more efficiently. The proposed SVM diagnostic model performs differential diagnosis very well. From the highly satisfactory specificity and sensitivity of the results, the proposed system is expected to be a helpful tool for classifying benign and malignant tumors in sonograms and can provide a second reading to help reduce misdiagnosis. With the growth of the database, more and more cases will be collected and used as training set. The MLP system suffered from the time-consuming and initial-condition-dependent problems. Hence, the proposed SVM approach for differencing benign and malignant tumors is the best choice. Experimental results demonstrate the feasibility and excellent performance of the proposed system in ultrasonography classification.

Acknowledgments

This work was supported by the National Science Council, Taiwan, Republic of China, under Grant NSC 91-2213-E-029-021.

References

[1] Raymond HW. Letter from the editor. Semin Ultrasound CT MR 2000;21(4):285.
[2] Stavros AT, Thickman D, Rapp CL, Dennis MA, Parker SH, Sisney GA. Solid breast nodules: use of sonography to distinguish between benign and malignant lesions. Radiology 1995;196(1): 123–34.
[3] Bassett LW, Liu TH, Giuliano AE, Gold RH. The prevalence of carcinoma in palpable vs impalpable, mammographically detected lesions. AJR Am J Roentgenol 1991;157(1):21–4.
[4] Rosenberg AL, Schwartz GF, Feig SA, Patchefsky AS. Clinically occult breast lesions: localization and significance. Radiology 1987; 162(1 Pt 1):167–70.
[5] Gisvold JJ, Martin JK. Prebiopsy localization of nonpalpable breast lesions. AJR Am J Roentgenol 1984;143(3):477–81.
[6] Chen D, Chang RF, Huang YL. Breast cancer diagnosis using self-organizing map for sonography. Ultrasound Med Biol 2000;26(3): 405–11.
[7] Chen DR, Chang RF, Huang YL, Chou YH, Tiu CM, Tsai PP. Texture analysis of breast tumors on sonograms. Semin Ultrasound CT MR 2000;21(4):308–16.
[8] Chen DR, Chang RF, Kuo WJ, Chen MC, Huang YL. Diagnosis of breast tumors with sonographic texture analysis using wavelet transform and neural networks. Ultrasound Med Biol 2002;28(10): 1301–10.
[9] Chen DR, Chang RF, Huang YL. Computer-aided diagnosis applied to US of solid breast nodules by using neural networks. Radiology 1999;213(2):407–12.
[10] Kuo WJ, Chang RF, Chen DR, Lee CC. Data mining with decision trees for diagnosis of breast tumor in medical ultrasonic images. Breast Cancer Res Treat 2001;66(1):51–7.
[11] Vapnik V. Statistical learning theory. New York: Wiley; 1998.
[12] Christianini N, Shawe-Taylor J. An introduction to support vector machines and other kernel-based learning methods. United Kingdom: Cambridge Univ. Press; 2000.
[13] El Naqa I, Yang YY, Wernick MN, Galatsanos NP, Nishikawa RM. A support vector machine approach for detection of microcalcifications. IEEE Trans Med Imaging 2002;21(12):1552–63.
[14] Yang MH, Roth D, Ahuja N. A tale of two classifiers: SNoW vs. SVM in visual recognition. Comput Vis—Eccv 2002 Pt Iv 2002;2353: 685–99.
[15] Kim KI, Jung K, Park SH, Kim HJ. Support vector machines for texture classification. IEEE Trans Pattern Anal Mach Intell 2002; 24(11):1542–50.
[16] Sun YF, Fan XD, Li YD. Identifying splicing sites in eukaryotic RNA: support vector machine approach. Comput Biol Med 2003; 33(1):17–29.
[17] Song MH, Breneman CM, Bi JB, Sukumar N, Bennett KP, Cramer S, Tugcu N. Prediction of protein retention times in anion-exchange chromatography systems using support vector regression. J Chem Inf Comput Sci 2002;42(6):1347–57.
[18] Song Q, Hu WJ, Xie WF. Robust support vector machine with bullet hole image classification. IEEE Trans Syst Man Cybern, Part C Appl Rev 2002;32(4):440–8.