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Research Article

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New Approaches to the Design of Automatic Diagnostic Systems and Math Algorithms of Breast Cancer

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Abstract

The present study aimed to investigate the design of a computer-assisted pathology system for diagnosis and clustering of cancerous lesions in magnetic resonance imaging of breast, using computer code in MATLAB software. In the analysis of breast segmentation by Atlas method, mass tumors 4 and non-mass tumors 5 are identified and segmented. Characteristics of the morphology, kinetics and matrix of the gray level co- occurrence of the tumors are extracted. In this study, a new feature called "dual-tree complex wavelet transform (DTCWT" was extracted and five characteristics associated with this type of property were extracted. After extracting these properties, the feature vectors were assigned to the clustering with different kernels and the combined clustering, which combine the linear discriminate analysis method and the nearest neighbor, and clustering of the tumors was performed into two benign and malignant categories. Using the new feature introduced in this study and applying it to the SVM cluster, AZ values for mass tumors, non-mass tumors and their combination were 0.71, 0.77 and 0.70, respectively, and by applying it to the combined cluster s LDA and NN-k were 0.70, 0.44 and 0.69, respectively.

Also, in the Atlas-based segmentation, the FCM cluster was used for them first time. The use of this cluster caused that there is no empty cluster and the accuracy of the results would increase. In the feature extraction section, the feature of dual-tree complex wavelet transform (CWT-DT) was applied for the first time in magnetic resonance images of the breast and on mass and non-mass tumors and a combination of them was applied. Detection and extraction of non-mass tumors is the main challenge of this study, and applying the proposed feature group of non-mass tumors created an acceptable result, and the value of AZ increased compared to previous studies.

Keywords: Computer-Aided Diagnosis, Magnetic Resonance Imaging, Breast Magnetic Resonance Images, SVM Clustering, and a Combination of LDA and K-NN

Introduction

Breast cancer is one of the most common cancers among women worldwide. The cause of this type of cancer is still unknown, so it is impossible to prevent it. Therefore, performing imaging to detect it as soon as possible is important to reduce its mortality rate [1].

Usually breast screening is performed using x-ray mammography. This type of imaging is low cost and the time required to produce the resulting images is low, which leads to an increase in its operational capacity. Although X-ray mammography has a high negative error rate (i.e., low sensitivity), it needs to squeeze the breast, which is not effective for dense tissue breasts [2]. Because of the disadvantages of X-ray mammography, alternative imaging techniques such as CT, ultrasound, PET, and magnetic resonance imaging (MRI) can be used. Among these methods, MRI has a higher reliability [3]. Specifically, magnetic resonance imaging improved dynamic contrast detection has a high reliability in detecting breast cancer because of high sensitivity [4]. The magnetic resonance imaging method also has disadvantages; the time required to produce DCE-MRI images is greater than the corresponding time for the preparation of X-ray images of mammography (30-45 minutes for DCE-MRI images, 5-10 minutes for mammography). Magnetic resonance imaging is much more expensive than mammography because it requires the injection of contrasting material (Gadolinium is used as a standard contrast agent).

By performing magnetic resonance imaging, the number of images obtained for each patient reaches 700 to 2000 images. It will take a lot of time to check the number of images; therefore, computer diagnostic systems are designed to help the radiologist to diagnose more accurately and as soon as possible. One of the most important parts of the CAD system is the separation of the breast to reduce the wrong positive results.

In several studies by local and foreign researchers automated CAD systems are presented. Tachowaet al., using regional and cluster descriptor of the neural network, the clustering of lesions was done in two benign and malignant groups [5]. They used four benign tumors and 10 malignant tumors to test their algorithm. They initially considered regions with high signal intensity as suspect areas. Then, using two features of curvature classifier and eccentricity as well as the cluster of the neural network, the lesions were divided into benign and malignant clusters. The accuracy of the clustering algorithm presented by them was 92.3%.

Chen et al. applied 3-D volumetric growth algorithm to separate lesions in the breast region [6]. They extracted three sets of features from separated 3-D regions: morphological characteristics, kinetic characteristics, and characteristics related to improvement modifications. They tested their proposed algorithm on 77 malignant tumors and 44 benign tumors. ROC curve of the proposed algorithm was 0.86.

Tulmen et al. by using gray-level thresholding algorithms were able to separate the breast area [7]. They initially used Utsothresholding method to make the images binary and then considered a close region as breast. They tested their proposed method on 12 patients. To cluster lesions into benign and malignant, they applied neural network. ROC of their algorithm was 0.99.

Kale et al., applied the co-occurrence matrix of grey level and 3-D observation window to separate the suspect lesions in MRI images [8, 9]. They achieved 21 different features by grey level co-occurrence matrix and applied these features on neural network clustering. They applied the images of 14 patients to test their algorithm.

Dustin Newelet al., applied characterization of the morphology and enhancement kinetic parameters of breast lesions to differentiate among four groups of lesions: 88 malignant (43 mass, 45 non-masses) and 28 benign (19 mass, 9 non-masses) [10, 11]. For each mass eight shape/margin parameters and 10 enhancement texture features were obtained. For the lesions presenting as nonmass-like enhancement, only the texture parameters GLCM were obtained. Finally, by artificial neural network (ANN), lesions were separated from each other. For lesions presenting as mass, the four morphological features were selected and AZ value to evaluate separation of benign and malignant lesions was 0.87. The kinetic parameter analyzed, AZ was 0.88. The combined morphological and kinetic features improved the AUC to 0.93, with a sensitivity of 0.97 and a specificity of 0.80. For lesions presenting as non-mass-like enhancement, four texture features GLCM were selected by the ANN and achieved an AZ of 0.76. The kinetic parameter achieved AZ of 0.59.They found that the given CAD had high efficiency only for mass like enhancement and there was no high efficiency for non-mass lesions. Alfaris et al. applied Seeded Region Growing (SRG) based on Particle Swarm Optimization (PSO) image to separate the lesions in MRI images [12]. They tested their algorithm on the images of 5 patients. To reduce the noise of salt and pepper, they used middle filter. The signal intensity region of skin and tumor was similar and they should delete the skin. To do this, they applied Level Set Active Contour and Morphological Thinning. ROC of the given algorithm was 0.95.

Ton et a., applied binarization operation on MRI images of breasts of 3 patients and each one had 100 2-D images, they separated breast area [13, 14]. They computed the average images of each patient and obtained the average volume of breast of each patient. Then, they applied Otsu thresholding on the obtained volumes. Finally, the biggest connected region was considered as breast region.

Sebastian Hoffman et al. used the images of 84 patients and focused more on non-mass lesions. They evaluated morphological, kinetic and Zernike moment separately [15-17]. By correction of non-rigid motion, increased the efficiency of clustering. To do clustering process, support vector machine with different types of kernels was applied. They achieved AZ value by extracting Zernike moment, morphological and kinetic features as 0.81, 0.61 a d0.78, respectively.

Felix Retteret al. applied the images of 63 patients. They extracted kinetic and morphological features from non-mass lesions [18]. Then, introduced a new feature called 5-Radius Krawtchoukmoment as non-varied with rotation. For clustering, support vector machine with three different kernels was applied. By motion correction, the efficiency of presented method was increased. They obtained AZ by extracting the new introduced feature and support vector machine as 0.84.

Methods

In this study, Breast segmentation was performed automatically. One of the purposes of CAD design for magnetic resonance imaging is helping the physician to interpret a lot of data and meeting the doctor's need to check all the images. Therefore, automating the process of finding areas of suspicion in these images is important. In a breast magnetic resonance image, in addition to the breast tissue, there are other additional areas, such as the heart. The heart is one of the organs of the human body with a high accumulation of veins, and its contrast is enhanced by injecting contrast agent, with the similar intensity of the signal to the tumor. Therefore, by automatic segmentation of the breast, the wrong positive results that can be due to the presence of the heart are reduced. On the other hand, these algorithms are applied to the whole area of the image. Magnetic resonance imaging of the breast, in addition to the breast tissue, includes the surrounding area of the patient, the area within the chest, lungs, heart and muscle of the pectoral; therefore, by segmenting the breast and looking for the suspect lesions in this region, the calculation load and algorithm implementation time will be significantly reduced. After segmenting the breast from the rest of the image, using the vessel filter, the veins in the breast are removed. Then the false positive results are reduced and the lesions in the breast are detached. After the removal of the lesions in the breast, a dual-tree complex wavelet transform (DT-CWT) was applied to them and the size of the coefficients of this wavelet as a separating feature, as well as other features such as shape, kinetics, and gray level co-occurrence matrix was applied to separate benign and malignant tumors clustering. In this research, clustering of support vector machines, a combination of linear discriminant analysis method and nearest neighbor was used.

Results

In this study, we have 60 mass tumors. The features of DT-CWT, GLCM, a combination of shape, kinetics and DT-CWT, as well as a combination of shape, kinetics and GLCM were extracted from tumors. Thus, four groups of features were obtained. These features were applied to SVM clusters with different kernels and evaluation parameters were estimated. ROC chart of these features is plotted in Fig 1. Also, the resulting AZ value is indicated in (Table 1) and the values of sensitivity, reliability, accuracy, FN error and FP error are given in (Table 2).

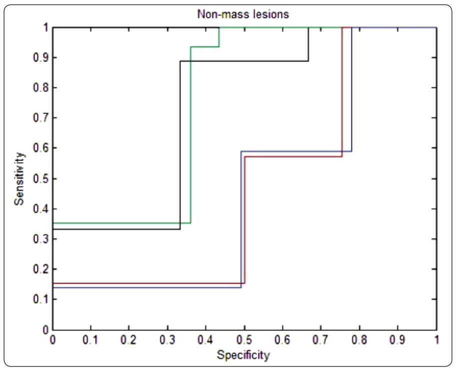

Figure 1: ROC charts of the Features of Mass Tumors applied to SVM. The black, green, red and blue colors are respectively CWT-DT, GLCM, -CWT-DT- Figure kinetics and -GLCM Figure -kinetics. In these charts, the Gaussian kernel is used, which produces a higher AZ value than other kernels.

Table 1: Examination of AZ values of extracted features from mass tumors applied to SVM

Radial Gaussian	Polynomial	Gaussian	Linear	Kernel / Feature
60/0	65/0	71/0	53/0	CWT-DT
69/0	74/0	77/0	65/0	GLCM
56/0	59/0	64/0	50/0	Shape, Kinetics CWT-DT
59/0	61/0	69/0	55/0	Shape, Kinetics GLCM

Using different kernels in SVM clustering, the highest AZ value is 0.77 as achieved by Gaussian kernel and extracting GLCM features from mass-lesions.

Table 2: The evaluation of SVM assessment parameters using Gaussian kernel to cluster mass tumors

FP error	FN error	Accuracy	Reliability	Sensitivity	Kernel / Feature
32	28	64	31	55	CWT-DT
38	30	71	37	64	GLCM
26	46	60	25	51	Shape, Kinetics CWT-DT
291	45	62	28	53	Shape, Kinetics GLCM

The Gaussian kernel, which produces more AZ than other kernels. Accuracy, sensitivity and reliability of SVM clustering have been obtained by extracting the GLCM feature group from mass tumors with the highest value. The DT-CWT feature group will produce the lowest FN error value and the shape-kinetics; DT-CWT feature group had the lowest FP error value.

The polynomial kernel with larger amount of AZ than the rest of the SVM kernels is used. Accuracy and sensitivity of SVM clustering by extraction of GLCM features from a combination of mass and non-mass tumors had the highest value, the DT-CWT feature group, with the highest reliability value, the GLCM feature group had the lowest FN error value and kinetic feature group, the DT-CWT had the lowest FP error.

Comparison of different clustering used in this research

In this section, the cluster performance used in this study is compared and shown in Tables (3), (4) and (5). These tables use the proposed DT-CWT feature, and are used in the SVM cluster section of the Gaussian kernel and the polynomial produces relatively better results than other kernels.

Table 3: Comparison of LDA and combined NN-k and SVM clustering with extraction of CWT-DT features from mass tumors

FP error	FN error	Accuracy	Reliability	Sensitivity	AZ	Clustering / criterion
37	40	66/66	36	65	0/74	LDA+k-NN
41	35	68	40	65	0/77	SVM

Table 4: The comparison of LDA, NN-K combined clustering and SVM clustering by extracting CWT-DT feature from non-mass lesions

FP error	FN error	Accuracy	Reliability	Sensitivity	AZ	Clustering / criterion
37	40	66/66	36	65	0/74	LDA+k-NN
41	35	68	40	65	0/77	SVM

Table 5: The comparison of LDA, NN-K combined clustering and SVM clustering by extracting CWT-DT feature from a combination of mass and non-mass tumors

FP error	FN error	Accuracy	Reliability	Sensitivity	AZ	Clustering / criterion
38	35	65	37	70	0/69	LDA+k-NN
46	30	64	45	63	0/70	SVM

According to the results and comparisons done, it can be concluded that:

1. Using the proposed DT-CWT feature and applying it to the SVM clustering and the combination of LDA and k-NN combination clusters, the SVM cluster produced a slightly higher AZ value.
2. By applying the four features introduced into the SVM cluster, the GLCM feature group generated the highest AZ value.
3. By applying each of the four groups to the cluster combination of LDA and k-NN, the DT-CWT attribute group resulted in a higher AZ value.

Comparison of proposed method with previous methods

Since the study of non-mass tumors is the main challenge of this research, this section examines the methods presented by other researchers to extract the characteristics of non-mass tumors and cluster them by using SVM and AZ estimates.

Felix Retteret al. presented 63 non-mast tumors (30 malignant and 36 benign tumors), showing Radial Krawtchouk as a new feature [16, 17]. Sebastian Hoffman et al., by extracting Zernike moments as new feature, 84 non-mastitis (61 malignant and 23 benign cases). Dustin Newel and colleagues introduced four features of texture as a new feature [10, 18-44]. The database contained 54 non-mass tumors (45 malignant and 9 benign). In order to compare the methodology of other researchers with the proposed method and emphasize on the efficiency of the proposed method, the AZ value estimated by these researchers and the amount of AZ obtained from the proposed method are presented in Table (6).

AZ	Year	Method
66/0	2013	Felix Retter
66/0	2013	Sebastain et al.
76/0	2010	Dustin Newel
77/0	2018	Proposed method

As it is seen, the proposed method produces more AZ as compared to other methods

Conclusion

In this research, various features and different classifications have been used to enhance the reliability and performance of CAD systems.

The first extracted extraction group is a morphology feature group that is extracted only from mass tumors. This feature group consists of 6 attributes, namely: volume, c1, c2 (which shows both the compression properties of the interconnected areas), the radius, the speculation (which both measures how the boundary mass is measured) and Cant oxalis also measured.

The second group of extracted attributes, the kinetic feature group, is extracted from mass, non-mass and a combination of tumors. This feature group consists of 20 features that are: mean and standard deviation of maximum kinetic feature of contrast enhancement, peak time, absorption rate, loss rates, and ROA of the extracted kinetic curve from a total of tumors and again from points are extracted with maximum contrast enhancement.

The third group is the extracted feature, the group of grey level co-occurrence matrix feature extracted from mass, non-mass and combinational tumors.

This feature group which has 11 features energy, inertia, correlation, entropy, inverse differential moment, differential mean, differential variance, differential entropy, total sum, total variance and total entropy.

The fourth extracted group is the characteristics of a complex-wave mixed wavelet (DT-CWT). This feature group is extracted from mass, non-mass tumors and a combination of them. The study of non-mass tumors is a major challenge for this study, and the application of this feature group to these tumors is a satisfactory result compared to previous studies.

The size of the DT-CWT coefficients can be considered as an effective feature for non-mass tumors, because this wavelet can be characterized in different directions in extraction and provides more details of the image texture. Each image has 6 inter-pass coefficients representing the image details and 2 low-pass coefficients that represent the overall picture.

Finally, 8 factors are extracted from each image. We have empirically found that the first factor yields a better result. Therefore, in this research, only the first coefficient, which represents the general picture, is extracted and the statistical calculations of mean, standard deviation, entropy, skewness and peak ratio to the vector derived from the first coefficient can be considered. Finally, for each image, 5 features will be obtained.

Using SVM clustering, Gaussian kernel and polynomials that produce relatively better results than other kernels, and applying DT-CWT to the masse, non-mass tumors, and the combination of these, AZ values were 0.71, 77 0 and 0.70, by applying the GLCM feature group to mass and non- mass tumors and their combination, AZ values were 0.77, 0.84 and 0.76, respectively, by applying the shape feature group, kinetics and DT-CWT to the mass tumors, AZ 0.64, with the application of the kinetic feature and DT-CWT to non-mass tumors and a combination of mass and non-mass tumor, AZ were 0.65 and 0.60, respectively, by applying, shape kinetics and GLCM to mass tumors, AZ 0.69, with the application of the kinetic feature of the group and GLCM to non-mass tumors, and the combination of these, resulted in AZ values of 0.69 and 0.62, respectively. Using the combined cluster of LAD and NN-k, and applying the DT-CWT feature group to mass tumors, non-mass, and a combination of these, the amounts of AZ were 0.70, 0.74 and 0.69, respectively, by applying the GLCM feature group to mass tumors, non-mass and a combination of them , the value of AZ was 0.66, 0.70 and 0.66, respectively, by applying the shape feature group, kinetics and DT-CWT to mass tumors of AZ 60, / with e kinetic and DT-CWT features of non-mass tumors and a combination of mass and non-mass tumors, AZ values were 0.65 and 0.59, respectively, by applying the shape, kinetics and GLCM features to mass tumors of AZ 0.64, with the kinetic feature group and GLC M for non-mass tumors and a combination of mass and non-mass tumors of AZ were 0.68 and 0.62, respectively.

Innovation

In this research, we have innovations in the Atlas-based segmentation sections and the extraction of tumor-specific features.

These innovations are as follows:

1. In the Atlas-Based segmentation section, the FCM Clustering is first used in the process of creating a possible Atlas. Using this clustering cause that no empty cluster exists and the accuracy of results is increased.
2. The dura complex wavelet transform feature (CWT-DT) was first applied to magnetic resonance imaging of the breast and on mass and non-mass tumors and a combination of them. Detection and extraction of non-mass tumors is the main challenge of this research, and the proposed feature group applied on non-mass tumors yields a satisfactory result and the amount of AZ was higher than in previous studies.

Suggestions

1. In this study, the segmentation method was based on Atlas and FCM. To increase the accuracy of segmentation, we can use other segmentation methods with high accuracy.
2. Extraction and detection of non-mass tumors is challenging as it has no definite boundary and morphology features for their expression are not effective and kinetic features cannot describe these tumors well. To extract the feature of these tumors, we can introduce new features to increase the evaluation parameters values.
3. In the conducted research, SVM clustering with different kernels and LAD, NN-K combined cluster are used for clustering. We can use other clustering as neural networks and compare the results with the proposed method results and in case of its superiority to the proposed system, the clustering is used.

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