Classification of Kidney Medical Ultrasound Images by DMKL and LDA Using Weiner Filter

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Abstract:

Ultrasound imaging techniques is considered to be safest technique and it plays a crucial role in emergency investigative method. Ultrasound images are prone to speckle noise and other limitations, so it is a challenging task to establish a suitable classification technique. This paper aims at classification of medical ultrasound images of kidney as bacterial infection, cystic and polycystic images. For this research work the kidney images are manually cropped to find the region of interest (ROI) of kidney. The cropped images are preprocessed using Weiner filter to remove speckle noise. The despeckled images are used for extraction of features that provide tissue characteristics of kidney region in ultrasound images after performing segmentation by Markov random field. Two classifiers have been incorporated with LBP features identified to classify the kidney ultrasound image as bacterial infection, cystic and polycystic image. The proposed method has the vision of implementing a computer-aided diagnosis system for ultrasound kidney images. The overall detection rate of detected kidney diseases using DMKL classifier is 89%. The experimental results demonstrate the efficacy of the method.

Keywords –Kidney Ultrasound Imaging, Weiner Filter, LBP, LDA, DMKL.

I. Introduction

Kidney diseases are widespread throughout the world, and many people do not feel the symptoms as it damages the organ slowly. With increasing patients with kidney disorders, it is necessary to design new methods for early detection and prevention of kidney diseases.

Kidney diseases can initiate serious health hazards namely diabetes, blood pressure, pulmonary hypertension, and other cardiovascular diseases. It is more necessary to diagnose the kidney diseases at early stages which can prevent us from the several serious diseases. Ultrasound modality is one of the best imaging diagnostic techniques when compared to other imaging modalities such as Magnetic resonance imaging (MRI), Computed tomography (CT) and X-ray, because of it is available at less expense with no harmful radiation exposure and its smart portability. It has several virtues like noninvasive, non-radioactive and inexpensive. This paper concentrates on the most significant chronic kidney diseases such as Bacterial kidney disease, cystic and Polycystic kidney diseases. Each malformation is diagnosed through US images having distinct echogenic properties. The kidney cyst is characterized as by bag of fluid which causes the echo properties. The US image may contain speckle noise due to loss of proper contact or air gap between transducer and body part. The speckle noise can also be formed during beam forming process or signal processing. The speckle may cause the image to be blurred. Hence despeckling is performed prior to the texture feature extraction. Classification is being performed on extracted features using DMKL and SVM.

In order to find a methodology to diagnose and detect kidney disease and other diffused and focal kidney diseases, some authors recently proposed methods and tools based on computer-aided diagnosis (CAD) to help the clinicians and experts to detect and categorize kidney ultrasound images [1].

Akkasaligar et al. [2] investigated the method for the classification of ultrasound kidney images into normal kidney image and other Kidney Diseases. The Ultrasound Despeckled image was tested using different filters, Gaussian Low-pass Filter and Median Filter. It has been found that the Gaussian Low-pass filter is best. Textures are the main features that are used to determine objects or images. Therefore, the text characteristics of the texture and characteristics of the texture extracted from GLCM, which were used for the classification.

Royal et al. Features of the extracted image of the ultrasound kidney image is based on the features described plurality of content [3] the geometric characteristics of the points [4] and the regional distribution of gray levels. [5]. The results show that it is possible to pick up signs of kidney ultrasound, based on these signals, and they are very effective in the classification of disease, and kidney disease.

Karthikeyini et al. used methods for the analysis of the main components (PCA) and their analysis suggests that there are important measures of relevance for the vector of the weights in the classification of the kidneys [4,6].

The rest of the paper is organized as follows. Section II explains the main methodology applied for classification of kidney ultrasound image as Bacterial kidney disease, cystic and Polycystic kidney diseases. Different classification techniques are described in Section III. The results of experiment are explained in section IV. Section V draws the conclusion and of experiment done.

II. Methodology

Ultrasound images are prone to speckle noise, so to remove the speckle noise the acquired kidney ultrasound image is preprocessed using weiner filter first. Markov Random Field Segmentation method is applied on preprocessed image to segment the region of interest. The features are extracted from segmented kidney image by Local Binary Pattern(LBP). Based upon the extracted features classification is done by LDA and DMKL classifiers. The kidney images were categorized as bacterial infection, cystic and polycystic. Comparative study of classification by these two classifiers is being shown further. Flow diagram of the proposed method is being shown in Figure 1.

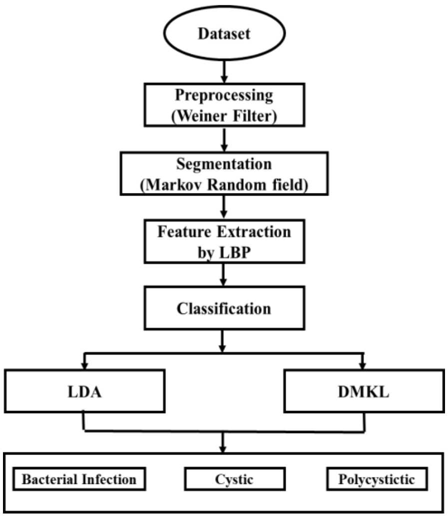

Figure 1: Flow Diagram of Kidney Ultrasound Image

Classification

A. Weiner Filter

The Wiener filter is a popular technique that has been used in many image and signal enhancement methods. The Wiener filtering is a linear type of filter. It helps in inverting the blur. The basic principle of the Wiener filter is to obtain an estimate of the clean signal from that corrupted by additive noise.

It optimally minimizes the overall mean square error in the process of inverse filtering and noise smoothing. This rating is obtained by modifying the square average error (MSE) between the desired signal s(n) and the estimated signal ˆs(n).

B. Markov Random Field Segmentation

The MRF is a stochastic process that specifies the local characteristics of an image and is combined with the given data to reconstruct the true image. The MRF of prior contextual information is a powerful method for modeling spatial continuity and other features, and even simple modeling of this type can provide useful information for the segmentation process. The MRF itself is a conditional probability model, where the probability of a voxel depends on its neighborhood. It is equivalent to a Gibbs joint probability distribution [14] determined by an energy function. This energy function is a more convenient and natural mechanism for modeling contextual information than the local conditional probabilities of the MRF. The MRF, on the other hand, is the appropriate method to sample the probability distribution.

The MR segmentation algorithm includes nonparametric statistics, neighborhood correlations, and signal inhomogeneity's. A MRF a priori probability p(x) for the segmented image is used to model the spatial correlations within the image. A smooth inhomogeneity field is provided by a restrictive a priori MRF distribution p(y) . Given the a priori probabilities for the tissue x_i and the inhomogeneity y_i at a voxel i , the conditional probability of the observed echo intensity z_i is calculated by a Parzen- window distribution $p(z_i \mid x_i , y_i)$.

C. Feature Extraction

The local binary pattern operator is an image operator which transforms an image into an array or image of integer labels describing small-scale appearance of the image. These labels or their statistics, most commonly the histogram, are then used for further image analysis. The LBP feature extraction method is a theoretically and computationally simple, and efficient methodology for texture analysis.

III. Classification Techniques

A. Linear Discriminant Analysis(LDA)

In LDA labelled data is optimally separated to find a projection for a supervised algorithm. The covariance of the data of each class is described and for achieving it optimization is done by LDA within-class measure, which shows the relation of the class means (Eq. 1, 2) [7], [8], [9]:

$$S_w = \sum n \in c_1 \left(\vec{x}_n - \vec{\mu}_1 \right)\left(\vec{x}_n - \vec{\mu}_1 \right)^T + \sum n \in c_2 \left(\vec{x}_n - \vec{\mu}_2 \right)\left(\vec{x}_n - \vec{\mu}_2 \right)^T \quad (1)$$

$$S_B = (\mu_1 - \mu_2)(\mu_1 - \mu_2)^T \quad (2)$$

where S_w is the within-class scatter matrix and S_B is the between-class scatter matrix.

The optimal projection matrix W^* can be found by solving the generalized eigenvalue problem of Eq. 3 [10]:

$$S_w^{-1} S_B W^* = \lambda W^* \quad (3)$$

Many object recognition tasks suffer from the small sample size problem in which the training data set is significantly smaller than the dimensionality of the sample space. In case of LDA this results in a within-class scatter matrix S_w that is singular, thus its invers cannot be calculated. To tackle this problem, several alternatives are applicable, one of which is adding a regularizing term to S_w making the within-class scatter matrix non-singular (see Eq. 4) [11]:

$$S_w^{/} = S_w + \in I \quad (4)$$

Where is a small constant and I is the identity matrix.

B. Discriminative Multiple Kernel Level Method

The purpose of this classification is to predict the possible class labels as much as possible. The mapped spaces will be constituted by class labels themselves, if a mapping function exists between the data samples and the corresponding labels. The sample is linearly divided in this space due to different labels for different classes. The kernel equivalent to this mapping is called an ideal kernel and can be calculated by an inner product among the labels [12]. The values of an ideal kernel are calculated as follows:

$$k(x_i, x_j) = \begin{cases} 0, & y_i \neq y_j \\ 1, & y_i = y_j \end{cases} \quad (5)$$

Discriminative Multiple Kernel Level Method is based on this instinctive idea, which is the groundwork of the linear. A series of M basic kernels. M kernel matrices are obtained from applicant basic kernels $\mathbf{K}_0 = \{ \mathbf{K}_m,\ m = 1, 2, \ldots, M,\ \mathbf{K}_m \in \mathrm{R}^{N\mathrm{x}N} \}$ [13]. These kernels can stem from diverse feature sets, from the same sets, but with diverse parameters, or both. A 3-D data cube of size $(N \times N \times M)$ is generated by the series of kernel matrices. In order to facilitate the subsequent operations, the3-D data cube is transformed to a 2-D matrix by using a vectorization operator $\mathbf{k}_m = \mathrm{vec}(\mathbf{K}_m)$, $m = 1, 2, .$

$. ., M$, where vec(·) is the vectorization operator which converts a matrix into a vector

[eq no. 6]. The vectored set of kernels is $\mathbf{P} = [\mathrm{vec}(\mathbf{k}_1), \mathrm{vec}(\mathbf{k}_2), \ldots, \mathrm{vec}(\mathbf{k}_M)]^T = [\mathbf{p}_1, \mathbf{p}_2, \ldots, \mathbf{p}_{N^2}] \in \mathrm{R}^{M \times N^2}$. Once $\mathbf{P}$ has been produced, two classes are extracted, denoted as c_1 and c_2. The elements of c_1 were denoted as

$$k^{c_1} \in R^{M \times \left(\sum_{i=1}^{c} n_i^2 \right)} \qquad (6)$$

which is established by the diagonal elements of the basic kernels. Those training samples belonging to the same class these elements correspond to. The residual elements of the basic kernels constitute c_2, and its elements are denoted as

$$k^{c_2} \in R^{M \times \left(N^2 - \left(\sum_{i=1}^{c} n_i^2 \right) \right)} \qquad (7)$$

where n_i is the number of training samples of class i and C is the number of classes. They resemble to the kernel values between points of different classes. Two scalars (nc_1 and nc_2) are defined as the sum of elements of classes c_1 and c_2, formulated as $nc_1 = \sum_{i=1}^{C} n_i^2$, $nc_2 = N^2 - \sum_{i=1}^{C} n_i^2$, respectively. Then, calculate the mean vectors of each class as follows:

$$m^{c_1} = \frac{1}{nc_1} \sum_{j=1}^{nc_1} k_j^{c_1} \in R^{M \times 1} \qquad (8) \qquad m^{c_2} = \frac{1}{nc_2} \sum_{j=1}^{nc_2} k_j^{c_2} \in R^{M \times 1} \qquad (9)$$

IV. Experimental Results and Discussions

Classification of kidney Ultrasound image is described in this section. The input dataset consists of 2-D kidney ultrasound images. The input set of 100 kidney ultrasound images has been taken in which 36 are of normal kidney images, 27 of bacterial infections ,37 are of cystic and polycystic kidney images. Due to the presence of speckle noise and other constraints, establishing the general segmentation and classification scheme for different classes of kidney in ultrasound image is a challenging task. Figure 2 shows the kidney Ultrasound image.

Figure 2: Kidney Ultrasound Image

Feature Extraction is having very significant role for classification of any image and it gives us the relevant information required for classifying the image. Local Binary pattern have been used in this experiment to extract the features required for classification. Based upon the extracted features the image is classified bacterial infection, cystic or polycystic kidney image by LDA and DMKL classifiers.

A performance indicator confusion matrix has been computed for the information about the number of correctly and incorrectly classified instances for each classifier. In Table I, 41record of kidney ultrasound image data are used to find confusion matrix of each technique. For two possible outcomes i.e positive and negative, each classifier generates a *2x2* confusion matrix. The four possible values of a confusion matrix are:

• **True Positive (TP):** TP is the total number of positive predictive instances which are classified correctly and truly positive.

• **True Negative (TN):** TP is the total number of negative predictive instances which are classified correctly and truly negative.

• **False Positive (FP):** FP is the total number of positive predictive instances which are classified incorrectly and truly negative.

• **False Negative (FN):** FN is the total number of negative predictive instances which are classified incorrectly and truly positive.

Table I: Confusion Matrix of Classifiers

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Classifier	Confusion matrix for kidney ultrasound image	
LDA	**TP(53)**	**FN(16)**
	FP(9)	**TN(22)**
DMKL	**TP(67)**	**FN(2)**
	FP(9)	**TN(22)**

To analyze the confusion matrix we consider the following performance parameters: Specificity = TN/(TN + FP)

Accuracy = (TN + TP)/(TN+TP+FN+FP)

The classified process performance is shown in Table II.

Table II: Performance measures of classifiers

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Technique	Specificity(%)	Accuracy(%)
LDA Classifier	71	75
DMKL Classifier	71	89

V. Conclusion

This paper addresses the prediction of kidney disease according to some input attributes. It cannot be easily predicted as it is a difficult task that demands expertise and higher knowledge for prediction. Classification techniques with feature selection extracts hidden information that plays a major role in making prediction and decision. An experiment has been performed using two different classifiers techniques to find out a more accurate technique for the kidney disease prediction. Result shows that for kidney ultrasound image classification, DMKL classifier gives the optimum result for qualitative & innovative approach among the investigated two classifiers: LDA and DMKL. The classification results and statistical measures were used for evaluating the two classifiers.

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