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Classification of Fetal Heart Abnormalities based on AKFCM Clustering and SVM Techniques

Shobana Nageswari and K. Helen Prabha
Department of Electronics and Communication Engineering, RMD Engineering College,
Anna University, Chennai, Tamil Nadu, India

Abstract: Image segmentation plays vital role in image understanding and practical vision systems. The main objective of medical image segmentation is to extract and characterize anatomical structures with respect to some input features or expert knowledge. Fetal heart abnormalities are the leading cause of infant mortality related to birth defects. As a non invasive and low cost imaging modality, the ultrasound imaging has become an important tool for medical diagnosis especially in the prenatal care. Soft computing algorithms are developed for the segmentation of fetal heart image and to identify the abnormalities. The proposed method of fetal heart image classification comprises of three steps namely, preprocessing, segmentation and classification. The preprocessing technique should be possible by shearlets which shows better continuum theory and low computational complexity. Adaptive K-means Fuzzy C-Means (AKFCM) clustering algorithm is utilized to segment an image into k-clusters which is computationally faster, finally Support Vector Machine (SVM) algorithm classifies the segmented image which is identified and contains components of non-parametric applied statistics Neural Networks (NNs) and machine learning. The experimental results demonstrate that the proposed method which combines the shearlet, K-Means Fuzzy clustering algorithm and Support Vector Machine (SVM) techniques are better than the other conventional techniques in the preprocessing, segmentation and classification techniques, respectively.

Key words: Ultrasound fetal heart image, shearlet transform, Adaptive K-means Fuzzy C-Means (AKFCM), Support Vector Machine (SVM), classification techniques, complexity

INTRODUCTION

The International Society of Ultrasound in Obstetrics and Gynecology ISUOG recommends the outflow tract view and the four-chamber view of fetal heart be added to routine screening (1-3). CHD is a major cause of infant mortality with an approximated incidence of about 4-13/1000 live births of all (Ferencz *et al*., 1985). Cardiac Structural anomalies are often missed by prenatal ultrasonography (Harb *et al*., 1994). Continuous feedback-based training of medical professionals and low threshold ultrasound images and careful access to fetal heart specialists are important factors to improve the effectiveness of a screening (Carvalho *et al*., 2002). The maximum heart anomalies can be detected during the second-trimester (Lee, 1998). Suspected heart anomalies needs more comprehensive evaluation using prenatal ultrasonography (Lee *et al*., 2008). Thus, the segmentation and classification of four chamber fetal heart is performed using soft computing methods.

Thurner *et al*. (1998) utilized a comparable methodology and concentrated on the estimations of the wavelet coefficients variance as opposed to on the scaling exponent of the WT. Though, WTs will not get the smoothness along the contours. Curvelet have been redesigned with another scientific numerical architecture which is easier and simple to be executed, more basic, processed speedier and less repetitive than the WT techniques. Thurner *et al*., (1998) utilized Curvelet for image denoising for the upgraded segmented ultrasound echocardiography images enhanced the diagnosis of ultrasound fetal echocardiography for intrinsic anomalies. The essential drawbacks of Curvelet technique are firstly, this system is not independently produced and its development incorporates rotations and these authorities don't ensure the digital lattice which dodges a direct transition from the continuum theory to the digital setting. The contourlet transform (GadAllah and Badawy, 2013) separated into 2 essential steps: Laplacian Pyramid (LP) decomposition and

Corresponding Author: C. Shobana Nageswari, Department of Electronics and Communication Engineering, RMD Engineering College, Anna University, Chennai, Tamil Nadu, India

Directional Filter Bank (DFB) decomposition. Wavelets do not hold directionality and anisotropy which are the advantages to contourlet and wavelets are smashed in various image processing applications by contourlet. Be that as it may, the computational complexity of contourlet transform is too high and appropriate continuum theory is lost in this methodology. Shearlets (Po and Do, 2006; Kutyniok and Labate, 2012; Easley *et al*., 2008; Kutyniok *et al*., 2012) were derived inside a greater class of relative like systems-the charged composite wavelets as a multivariate extension of wavelet framework. One of the distinctive characteristics of shearlets is the usage of shearing to control directional selectivity, instead of rotation used by curvelets. This is a fundamentally distinctive idea, since it permits shearlet systems to be induced from a single or restricted set of generators and it also guarantees a unified treatment of continuum and digital world as a result of way that the shear matrix saves the integer lattice.

Ma and Plonka (2010) segmented ultrasound images by Artificial Neural Network (ANN) technique. Be that as it may, the ANN performs on sample images only which is worse characteristic appealing. In the digital image processing, the application of clustering algorithms has been applied as segmentation techniques such as biomedical image analysis. Because of simple and less complex, Fuzzy C-Means (FCM) (Sa *et al*., 1994; Ravindraiah and Tejaswini, 2013) Clustering algorithm was utilized to recognize the ultrasound fetal heart image. However, to segment the heart image the FCM clustering algorithm was corrupted due to noise. To beat this disadvantage for segmentation, Kernel based FCM (KFCM) algorithm have been proposed. The KFCM is map the input data into a characteristic space with high dimension by a nonlinear transform then executes the FCM in characteristic space and directs genuine and synthetic images and deciphers the problems of noise and inhomogeneity. Although, it has a few weaknesses such as dependent on initialization, sensitive to outliers, skewed distributions, may converge to a local minimum and may miss a small cluster. To conquer this, this study proposes Adaptive K-means Fuzzy C-means (AKFCM) clustering algorithm.

K Nearest Neighbors (KNN) (Cai *et al*., 2007) is a straightforward algorithm that stores every available cases and classifies new cases in light of a similarity measure. One major disadvantage is that it measures distance straightly from the training set where variables have unusual measurement scales or there is a combination of numerical and definite variables. SVMs (Lu *et al*., 2008; Leonarduzzi1 *et al*., 2015) are another new technique suitable for paired binary classification tasks which is identified with and contains components of non-parametric applied statistics, neural networks and machine learning. SVM gives a good out-of-sample generalization can be powerful.

MATERIALS AND METHODS

Ultrasound image classification comprises of three steps namely preprocessing, segmentation and classification (Fig. 1) illustrates the process flow diagramof the proposed method. As a matter of first importance, the input of the fetal heart image is preprocessed by using shearlet transform. The shearlet transform decomposes the fetal heart image to suppress the unwanted distortions and enhances the important features of the image. The preprocessed image is segmented by using AKFCM clustering algorithm which segments the preprocessed image into multiple segments and gives more information to analyze effectively and the classification is done by SVM algorithm.

Shearlet transform for preprocessing: Essentially, shearlets are composite wavelengths $L^2(\mathbb{R}^2)$ which are all around localized, ideally sparse and satisfy parabolic scaling. Each element $\hat{\psi}_{j,l,k}^{(d)}$ supportsa pair of trapezoids. Also, every element is contained $2^j \times 2^{2j}$ size shown in Fig. 2.

The shearlet transform is most helpful to depict the accumulation of shearlets introduced above properties. Its numerical implementation can be characterized as follows. For $D_0 = \{(\xi_1, \xi_2) \in \hat{\mathbb{R}}^2, |\xi_1| \geq 1/8, |\xi_2/\xi_1| \leq 1, j \neq 0\}$ and $l = -2^j, ..., 2^j-1$, let $\hat{\Psi}^{(0)}$ is defined as:

$$\hat{\Psi}^{(0)}(\xi) = \hat{\Psi}^{(0)}(\xi_1, \xi_2) = \hat{\Psi}_1(\xi_1)\hat{\Psi}_2\left(\frac{\xi_2}{\xi_1}\right) \quad (1)$$

$$W_{j,l}^{(0)}(\xi) = \begin{cases} \hat{\psi}_2\left(2^j \frac{\xi_2}{\xi_1} - l\right)\chi D_0(\xi) + \hat{\psi}_2\left(2^j \frac{\xi_1}{\xi_2} - l + 1\right)\chi D_1(\xi) & \text{if } l = -2^j \\ \hat{\psi}_2\left(2^j \frac{\xi_2}{\xi_1} - l\right)\chi D_0(\xi) + \hat{\psi}_2\left(2^j \frac{\xi_1}{\xi_2} - l - 1\right)\chi D_1(\xi) & \text{if } l = 2^j - 1 \\ \hat{\psi}_2\left(2^j \frac{\xi_2}{\xi_1} - l\right) & \text{otherwise} \end{cases} \quad (2)$$

and $D_1 = \{(\xi_1, \xi_2) \in \hat{\mathbb{R}}^2, |\xi_2| \geq 1/8, |\xi_2/\xi_1| \leq 1,\}$ then $\hat{\psi}^{(1)}$ is defined as:

$$\hat{\psi}^{(1)}(\xi) = \hat{\psi}^{(1)}(\xi_1, \xi_2) = \hat{\psi}_1(\xi_2)\hat{\psi}_2\left(\frac{\xi_1}{\xi_2}\right) \quad (3)$$

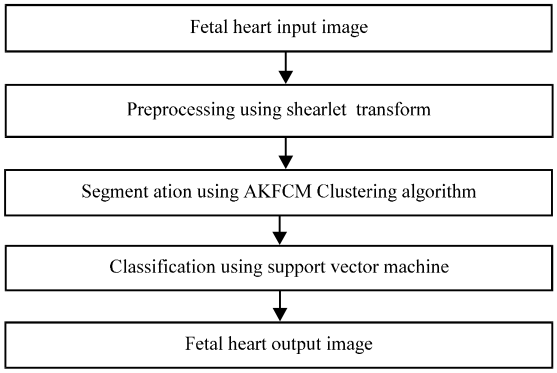

Fig. 1: Process flow diagram of the proposed method

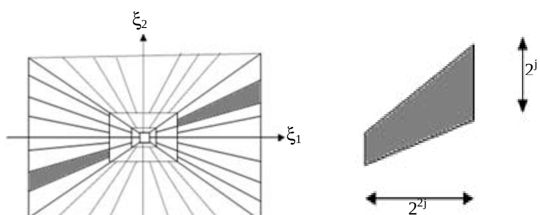

Fig. 2: Tiling frequency of shearlets and frequency support of shearlets

$$W_{j,1}^{(1)}(\xi)=\begin{cases}\hat{\psi}_2\left(2^j\frac{\xi_2}{\xi_1}-1\right)\chi D_0(\xi)+\hat{\psi}_2\left(2^j\frac{\xi_1}{\xi_2}-1+1\right)\chi D_1(\xi) \text{if} 1=-2^j\\ \hat{\psi}_2\left(2^j\frac{\xi_2}{\xi_1}-1\right)\chi D_0(\xi)+\hat{\psi}_2\left(2^j\frac{\xi_1}{\xi_2}-1-1\right)\chi D_1(\xi) \text{if} 1=2^j-1\\ \hat{\psi}_2\left(2^j\frac{\xi_1}{\xi_2}-1\right) \quad \text{otherwise}\end{cases} \tag{4}$$

Where, $\psi_2 \subset [-1, 1]$. For $1-2^j \leq 1 \leq 2^j-1$, here $W^{(d)}_{j,1}(\xi)$ is a window function on a pair of trapezoids, outlined as Fig. 1. When $1 = -2^j$ or $1 = 2^j-1$, at the junction of the horizontal cone and vertical cones D_0 and D_1, $W^{(d)}_{j,1}(\xi)$ is the superposition of two such functions.

Utilizing this information for $j \geq 0, -2^j \leq 1 \leq 2^j-1, k \in \mathbb{Z}^2$, $d = 0, 1$, compose the Fourier transform of the shearlets in the mathematical statement (Eq. 5):

$$\hat{\psi}^{(d)}_{j,l,k}(\xi)=2^{\frac{3j}{2}}V\left(2^{-2j}\xi\right)W^{(d)}_{j,l}(\xi)e^{2pi\,\xi A_d^{j}B_d^{l}k} \tag{5}$$

Where:

- $V(\xi_1, \xi_1)$ = The $\hat{\psi}_1(\xi_1)\chi D_0(\xi_1, \xi_2)+\hat{\psi}_2(\xi_2)\chi D_1(\xi_1, \xi_2)$, the dilation matrices
- A^j = The connected with scale transformations such as rotations
- B^l = The connected area preserving geometrical transformations such as shear:

$$A_0=\begin{pmatrix}4&0\\0&2\end{pmatrix}, B_0=\begin{pmatrix}1&1\\0&1\end{pmatrix}, A_1=\begin{pmatrix}2&0\\0&4\end{pmatrix}, B_1=\begin{pmatrix}1&0\\1&1\end{pmatrix} \tag{6}$$

The shearlet transform of $f \in L^2(\mathbb{R}^2)$ can be calculate as:

$$SH_\psi f(a,s,t)=\langle f,\psi^{(d)}_{j,l,k}\rangle=2^{\frac{3j}{2}}\int_{R^2}\hat{f}(\xi)\overline{V(2^{-2j}\xi)W^{(d)}_{j,1}(\xi)},\ e^{2i\pi\xi A_d^{-j}B_d^{-l}k}d\xi \tag{7}$$

Absolutely, one can without much of a stretch verify that:

$$\sum_{d=0}^{1}\sum_{l=-2j}^{2j-1}\left|W^{(d)}_{j,l}(\xi_1,\xi_2)\right|^2=1 \tag{8}$$

And from Eq. 8 it takes after that:

$$\left|\hat{\varphi}(\xi_1,\xi_2)\right|^2+\sum_{d=0}^{1}\sum_{j\geq 0}\sum_{l=-2j}^{2j-1}\left|V\left(2^{2j}\xi^{2j}_{1,2}\xi_2\right)\right|\left|W^{(d)}_{j,l}(\xi_1,\xi_2)\right|^2=1$$
$$\text{for}(\xi_1,\xi_2)\in\hat{R}^2 \tag{9}$$

Segmentation using Adaptive K-means Fuzzy C-Means (AKFCM) clustering algorithm: The image processing segmentation is mostly performed to extract the information from images. AKFCM clustering algorithm is the procedure of organizing objects into groups where in members are similar on specific perspectives. In most clustering models, the idea of similarity depends on distances such as the euclidean distance. Along these lines, the proposed algorithm establishes the fuzzy concept to be applied and then the member is assigned to its particular centre by means of the euclidean distance. Next acquainted the idea of belongs to measure the relationship between the centre and to guarantee that its membership meets certain criteria. The level of membership is the redesigned based on its level of belongingness. Consequently, the positions of the centers are recalculated based on the updated membership function. These features are acquainted all together with provide a better and more adaptive clustering process.

Adaptive K-means Fuzzy C-Means (AKFCM) Clustering algorithm: For segmentation, AKFCM clustering algorithm is extensively utilized in various sorts of data analysis. It segments n objects into k clusters. Every object fits in with the distances between centroids and objects. While expanding the distance between the global centroid and cluster centroid, adaptive K-means Fuzzy C-Means algorithm minimizes the distance between the cluster centroid and objects.

Let input image $X = \{x_1, x_2, ..., x_n\}$ with n pixels to be segmented into $1<c<N$ clusters. And $X_i = \{x_{i1}, x_{i2}, ..., x_{im}\}$ is an object with a set of m dimensional measurements. The membership matrix $U = u_{ik}$ is a $n\times k$ where $u_{ik} = 1$ means the object i is allocated to cluster k. The centroid of k clusters is $z = \{z_1, z_2, ..., z_k\}$. The neighborhood window has 3×3 or 5×5 sized square window around the pixel. The neighborhood distance $d_N(x_i, z)$ can be detailed as:

$$d_N(x_i, z) = \sum_{j\in N_i} w_{ij} d_{x_j, z} \tag{10}$$

where, $d_{xr,z}$ is the separation in the middle of x_r and z:

$$d_{x_j, z} = \sum |\{x_j\}_q - z_q| \tag{11}$$

Here $\{x_j\}_q$ and z_q, represents the qth element vector x_j and z, respectively. $\sum_{j\in N_i} w_{ij} = 1$ for each pixel. Where w_{ij} calculates the closeness between the central pixel i and its neighbor pixel j. Furthermore, similarity window $S = \{S_i\}_{i\in N}$ is also expected to avoid the confusion. The restriction of X to S_i can be detailed as:

$$X(S_i) = (x_k, k\in S_i)$$

The comparability window with size (2p+1)×(2p+1), here p is a positive integer. The weight distance w_{ij} will be planned as:

$$w_{ij} = \frac{1}{z_i}\exp\left(-\frac{\left\|G_s\times\left(X(S_i)-X(S_j)\right)\right\|^2}{\lambda_g \sigma_i^2}\right), r\in N_i \tag{12}$$

Here, $\|G_\sigma\times(X(S_i)-X(S_j))\|^2$ is the a Gaussian weighted euclidean distance between two window estimated size images. The variance of Gaussian is $\sigma = p/2$:

$$z_{ij} = \sum_{j\in N_i}\exp\left(-\frac{\left\|G_s\times\left(X(S_i)-X(S_j)\right)\right\|^2}{\lambda_g \sigma_i^2}\right) \tag{13}$$

Finally, the AKFCM can be formulated as:

$$P(U,Z) = \sum_{k=1}^{p}\sum_{i=1}^{n} u_{ik} \sum_{j=1}^{m} \frac{d_N^2(x_{ij}, z_{kj})}{d_N^2(z_{kj}, z_{0j})} \tag{14}$$

With the constraints $\sum_{k=1}^{p} u_{ik=1}$, $u_{ik} = \{0, 1\}$, $\forall i$ and $0<\sum_{i=1}^{n} u_{ik} < n$, $\forall k$:

$$u_{ik} = \begin{cases} 1, & \text{if } d_N^2(x_{ij}, z_{kj}) \le d_N^2(x_{ij}, z_{0j}) \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

z_{0j} is the jth feature of the centroid z_0. At that point, z_{0j} can be computed as:

$$z_{0j} = \frac{\sum_{i=1}^{n} x_{ij}}{n} \tag{16}$$

$$z_{kj} = \begin{cases} z_{0j}, & \text{if } \sum_{i=1}^{n} u_{ik} d_N(x_{ij}, z_{0j})| = 0 \\ \dfrac{\sum_{i=1}^{n} u_{ik} d_N(x_{ij}, z_{0j}) xij}{\sum_{i=1}^{n} u_{ik} d_N(x_{ij}, z_{0j})}, & \text{otherwise} \end{cases} \tag{17}$$

Classification using Support Vector Mchine (SVM): SVM (Leonarduzzi *et al*., 2015; Spilka *et al*., 2015) goes for developing an ideal hyperplane which can isolate the positive and negative classes such that the margin, i.e., the separation from the nearest sample of the prepare training set to the hyperplane is expanded. The improvement issue of SVM is as per the following:

$$\min_{w,\rho}\left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i\right) \tag{18}$$

$$\text{s.t.}: \forall_{i=1}^{N}: y_i(w^T x_i - \rho) \ge 1-\xi_i \tag{19}$$

$$\forall_{i=1}^{N}: \xi_i \ge 0 \tag{20}$$

Where:

$\xi = [\xi_i]_{i=1}^{N}$ = The vector of slack variables

C = The trade-off parameter

The decision function is the accompanying form:

$$f(x) = \text{sign}(w^T x - \rho) \tag{21}$$

RESULTS AND DISCUSSION

Data set comprises of 30 ultrasound images. MSE and PSNR values are computed for the denoised images using shearlet transforms shows that it can denoise more effectively. The performance of shearlet transform is compared with other LET techniques like contourlet, curvelet and wavelet as follows in Table 1.

AKFCM cluster algorithm performs the fully automatic segmentation without the manual involvement. The following figures shows the segmentation of normal ultrasound fetal heart.

Figure 3a is degraded by speckle noise and (Fig. 3b) shows the restored image of the preprocessing technique. Figure 3c shows the segmented image using AKFCM. The four chambers can be viewed clearly. The performance of Navie bayes and K-NN classifiers are also

Table 1: Comparision of the various LET techniques for preprocessing

Transforms	MSE	PSNR
Shearlet	2.120	73.4208
Contourlet	2.090	64.9207
Curvelet	8.540	58.7080
Wavelet	6.654	49.7083

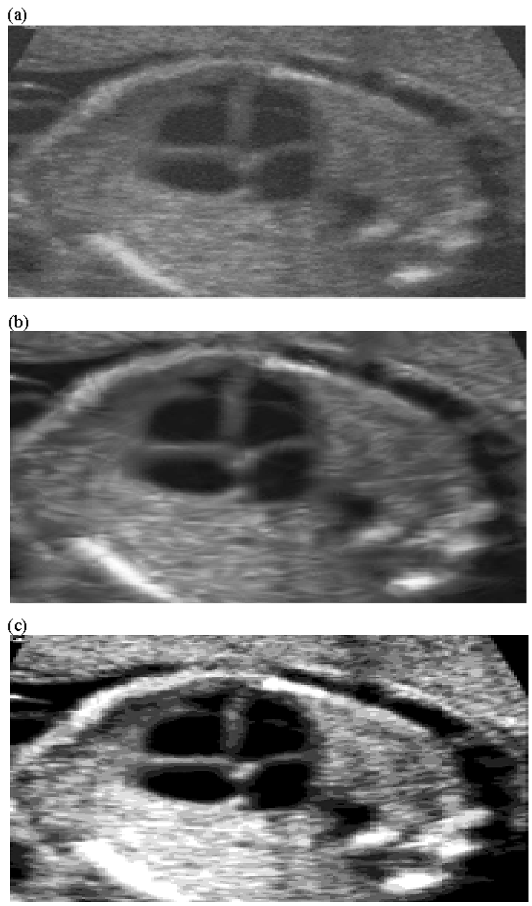

Fig. 3: a) Noisy image; b) Restored image after preprocessing and c) Segmented image using AKFCM

compared with SVM classifier. Navie bayes classifier best suits for data rather than images. K-NN classifier is commonly known as lazy classifier.

To analyse the performance of the classifier, various measures are used. The commonly preferred measures are accuracy, sensitivity and specificity are listed below:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Table 2: Comparison of measures of classifiers

Parameters	Accuracy (%)	Sensitivity (%)	Specificity (%)
Proposed method	93.43	96.02	92.77
K-NN classifier	88.20	87.50	89.01
Navie bayes classifier	82.90	83.40	81.30

Where:

TP = The ultrasound fetal heart images with the characteristic and tested positive

FN = The ultrasound fetal heart images with the characteristic and tested negative

FP = The ultrasound fetal heart images without the characteristic and tested positive

TN = The ultrasound fetal heart images without the characteristic and tested negative

SVM classifier provides the improved accuracy, sensitivity and specificity. The comparison of measures of classifiers are listed in Table 2.

CONCLUSION

This study examined the fetal heart images using shearlet transform for preprocessing, AKFM clustering algorithm for segmentation and SVM for classification. In the preprocessing technique, the shearlet transform is the utilization of shearing to control directional selectivity as opposed to rotation utilized by curvelets. In the segmentation technique, AKFCM clustering algorithm is the process of organizing objects into groups wherein members are similar on certain aspects. In most clustering models, the concept of similarity is based on distances such as the Euclidean distance. In the classification technique, SVM provided a good out-of-sample generalization can be robust. This experimental results shows that the SVM gives the accuracy (93.43%), specificity (96.02) and sensitivity (92.77 %) as compared with other techniques.

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