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A Multi-Stage Adaptive Singular Value Decomposition Approach for Fetal ECG Signal Extraction in Multichannel Input System for Prenatal Health Monitoring

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Abstract: A novel methodology for denoising and extraction of Fetal ECG signal is presented. The study is extended for the classification of the fetal ECG. A hybrid multistage adaptive filtering with singular value decomposition technique to remove the noise and to extract the Fetal Electrocardiogram signal from the abdominal signal is proposed. The proposed architecture is a combination of Singular Value Decomposition (SVD) method and Adaptive extraction method using QR-decomposition and affine projection algorithm. This method leads to enhancement of fetal ECG by canceling maternal ECG and noises in the first stage using SVD. The proposed method is applied to simulate and real time ECG signals to demonstrate its superior effectiveness. The Proposed methods are superior in its performance when compared to existing methods like independent component analysis, wavelet transform and others.

Key words: Singular value decomposition, affine projection, QR-decomposition, fetal ECG, maternal ECG, adaptive filtering, multistage filtering, wavelet transform, support vector machines, neural networks

INTRODUCTION

The objective of this research is to develop a method for the extraction and classification of the fetal ECG signal. The basic idea behind the proposed method is to improve the performance of the currently existing techniques and to design a new novel methodology for extraction and classification of the fetal information. In literature, several researchers is carried out for removal of noise from abdominal ECG and extraction of fetal ECG from abdominal ECG. The average pattern subtraction (Alaluf *et al*., 1989) is the oldest and obsolete method due to deficiency of proper patterns. The most widely used algorithm in communication field is the adaptive noise cancellation using matched filtering is used in the denoising process. The other methods includes linear regression, IIR adaptive filtering combined with Genetic algorithm (Kam and Cohen, 1999), adaptive impulse correlated filter (Martinez *et al*., 1997), adaptive least mean square linear prediction methods. Even though, wavelet method (Khamene and Negahdaripour, 2000) plays a vital role in the extraction and classification operation, proper wavelets have to be chosen or new mother wavelet is to be found. Similar implementation issues happens in the work which extracts the fetal ECG using wavelet analysis and adaptive filtering. Hilbert Transform (Wei *et al*., 2014) and non linear state space projection is the latest work carried out for the extraction of fetal information using envelope detection. Other methods used for the extraction of FECG from mixed signal are Principal Component Analysis (PCA) or Singular Value Decomposition (SVD) and Independent Component Analysis(ICA) (Wan and Chai, 2008; Yu and Wakai, 2011; Lee and Jiang, 2009). The Blind Source Separation BSS methods produce better results only when the system uses large number of recorded ECG leads . Extended state kalman filtering based fetal extraction provides good feature extraction for single channel recordings but faces adaptation problem (Niknazar *et al*., 2013). The blind source separation method is combined with other methods like adaptive noise cancellation (Zarzoso *et al*., 2000), independent component analysis and adaptive enhancer, singular value decomposition with ICA (Gao *et al*., 2003) to extract the Fetal ECG signal. Few works is been carried out on kurtosis maximization and blind extraction with power method (Hua and Su, 2015). In another research the ICA is combined with the neural network (Ye *et al*., 2007; Hasan *et al*., 2009) and n-support vector regression (Han *et al*., 2015) to extract the fetal ECG in noninvasive methods.

Some already proposed ICA-based techniques are INFOMAX (Poursoltani *et al*., 2006), JADE

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(Poursoltani *et al*., 2006), fastica (Poursoltani *et al*., 2006), subspace decomposition. The BSS in wavelet domain (Ming *et al*., 2009) and adaptive-ICA method (Waldert *et al*., 2007) also gives better results but the processing time and memory requirements are more. The ICA method is integrated with the neural network method for classification purpose. The neural network methods are mostly used for classification purpose and delineation purpose. In this research, two multi-channel adaptive approaches using QR-decomposition and Affine Projection algorithms with singular value decomposition are proposed for the extraction of the fetal ECG signal. A large number of the medical diagnosis procedures can be converted into intelligent data classification tasks. The classifier classifies the abdominal ECG information into maternal and fetal heart rate. The fetal heart rate is separated and among the same further, classification is done for diagnosis. In the literature several classifiers are proposed. Some of the works carried in past are Hidden Markov Models (HMM), Artificial Neural network, adaptive neuro Fuzzy Inference System (ANFIS), SVM-based methods. Performance evaluation of classifiers is a fundamental step for determining the best classifier or the best set of parameters for a classifier. For many classification problems, especially in the medical diagnosis, the overall classification accuracy is not adequate alone because in general not all errors have the same consequences. Wrong diagnoses can cause different cost and dangers depending on which kind of mistakes have been done. Therefore, for such situations, in addition to overall classification accuracy Receiver Operation Characteristic (ROC) analysis is usually performed.

Fetal ECG monitoring system: The basic components of the fetal monitoring system is the maternal ECG, fetal ECG and noise represented by $m_i(t)$, $f_i(t)$ and ($N_l(t) + n_h(t)$) . The composite and the thoracic signal are represented by composite signal (CECG):

$$Ab_i(t) = N_l(t)[f(t) + m(t) + n_h(t)] \quad (1)$$

Where $N_l(t)$ is the low frequency noise signal due to baseline wander, electrode contact noise. Thoracic signal:

$$Ab_i(t) = N_l(t)[m(t) + n_h(t)] \quad (2)$$

In order to evaluate the effect of noise in ECG, we have adopted the dipole theory of heart for generating the synthetic abdominal and thoracic ECG signal (McSharry *et al*., 2003; Sameni *et al*., 2007) with different amplitudes, widths and rotational angle. In our research, the model for orthogonal lead VCG co-ordinates are altered using different scaling factors for attenuation of volume conductor. The various stages of the Fetal ECG monitoring system is shown in Fig. 1.

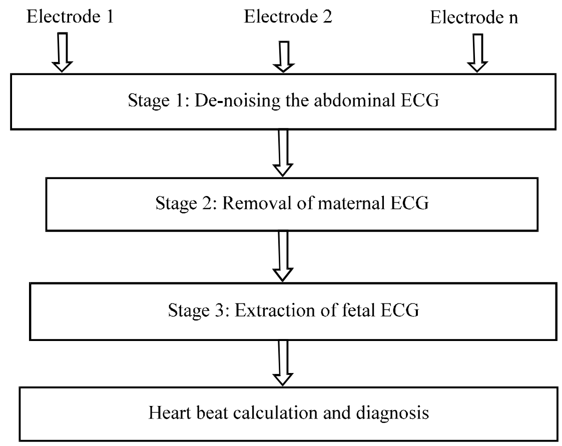

Fig.1: Stages of fetal ECG monitoring system

Preprocessing stage: In this research, the pre processing stage is implemented using non-adaptive filters like Butterworth, zerophase filter, Savitzky Golay (SG), median filter and wavelet transform . The non-adaptive filters performance is less when compared to wavelet transform. In wavelet transform technique, 3 and 5 level decomposition using daubechies, biorthogonal wavelets gives better performance. The BSS methods singular value decomposition or Principal Component Analysis (PCA) and those that take advantage of the higher-order statistical information contained in the available data, performing the Independent Component Analysis (ICA).

Extraction of fetal ECG stage: Even though, in literature several methods like average pattern subtraction, correlation technique, adaptive using matched filtering, wavelet tranform, Principal Component Analysis (PCA) or singular value decomposition and ICA methods are used still new hybrid methods are need for the day for the extraction of the fetal ECG. The need for classification methods for diagnosis purpose is also increased.

Delineation and classification of fetal ECG signal: Some arrhythmias are signs of more serious heart problems and others are not. So, the detection of parameters and classification of the fetal ECG is performed with the help of RR interval. The RR intervals and the heart rate values are used for diagnosis. In literature several methods like

Hidden Markov Models (HMM), Artificial Neural network adaptive neurofuzzy Inference System (ANFIS), SVM-based methods are used for the classification based on various parameters.

The mathematical modeling of the proposed method: In fetal monitoring system, the input stage contains "m" sensors and "n" samples are taken from each sensor. We represent the matrix by x, whose size is n x m. The number of samples is varied based on the sampling frequency about 300-500Hz .The sampling frequencies increases the size of the matrix n x m by which the memory requirements becomes larger and computing becomes complex. So, the data is approximated with low rank method SVD.

Singular Value Decomposition for MIMO system: For the matrix n x m the SVD decomposes the matrix into:

$$X = U\ D\ V' \tag{3}$$

Now, xi(t) be the signal recorded at the ith electrode placed on the abdomen or thorax. In this work the Number of electrodes is chosen as 3-5 numbers If the sampling time is T_S then, the sampled signal is given by $x_{ij}=x_i(jT_s)$ Where i=1 2 3 ………………n. n represents number of electrodes. Ts-Time sample rate. From the Eq. 12 the SVD of data matrix X is given by:

$$X = \sum_{K=1}^{N} ?_K U_K V_K^T \tag{4}$$

Where $U = [U_1,U_2,U_3.......U_k, ...U_n]$ is an n x m orthonormal matrix made up of left singular vectors U_k ? R^n $V = [V_1,V_2,V_3.......V_k, ...V_m]^T$ is a m x n orthonormal matrix made up of right singular vector $V_k R^m$. T-indicates transpose:

$$D = \text{diag}\ [\lambda_1, \lambda_2, \lambda_3..................\lambda_K] \tag{5}$$

Where d=n x m pseudo diagonal matrix D is made of singular values. $\lambda_k \geq n$ Where $\lambda_1 \geq \lambda_2 \geq \lambda_3 .... \geq \lambda_m \geq 0$ The term UV^T is a m x n unitary rank matrix named the K^{th} Eigen image of data matrix x. The signal recorded through the electrodes placed in the abdomen and thorax as a whole is given by a sum of Eigen values pondered by the singular values. The samples data X_{ij} at time j can be expressed as:

$$X_{ij} = \sum_{K=1}^{N} \lambda_K U_{Ki} V_{Kj} \tag{6}$$

The SVD can be further elaborated as:

$$X = \lambda_1 U_1 V_1^T + \lambda_2 U_2 V_2^T + \lambda_3 U_3 V_3^T + ...\lambda_m U_m V_m^T \tag{7}$$

For the multidimensional sensors where the electrodes been placed in mothers abdominal and thorax is represented by:

$$X = \lambda_1 U_1 \otimes V_1 + \lambda_2 U_2 \otimes V_2 + \lambda_3 U_3 \otimes V_3 + ...\lambda_m U_m \otimes V_m \tag{8}$$

By using the singular value decomposition the correlated variables are transformed to uncorrelated details. The SVD provides the information about the various relationships among the recorded data of electrodes placed in abdomen and thorax. The SVD approximates the original data into new data with fewer dimensions. SVD method is the effective and simplest technique for data reduction. So, from the equation, we can observe that the matrix x containing the original data can be decomposed into a product of three matrix. The equation can be transformed to fewer dimensions:

$$X \approx \lambda_1 U_1 \otimes V_1 + \lambda_2 U_2 \otimes V_2 + \lambda_3 U_3 \otimes V_3 + ...\lambda_q U_q \otimes V_q \tag{9}$$

Now, the SVD have minimized the matrix to only n x q size instead of n x m matrix. This reduction is done by omitting the singular values which are zero/minimum value with the threshold (hard thresholding). In soft thresholding methodology the singular values which have minimum values are replaced with zero. The N-Dimensional matrix is divided into 2-Dimensional array and SVD is applied. From the literature, we found that a direct SVD for multisensory or multi electrode system is not possible .

So, in this research the SVD is calculated like combining the individual electrode and combining the rest:

$$X_{ij} \approx \lambda_1 U_1^{(1)} \times U_1^{(2)} \times U_1^{(3)} \times U_1^{(4)} ... + \lambda_2 U_2^{(1)} \times U_2^{(2)} \times U_2^{(3)} \times U_2^{(4)} ... + \lambda_q U_q^{(1)} \times U_q^{(2)} \times U_q^{(3)} \times U_q^{(4)} ... U_q^{(k)} \tag{10}$$

Where:

$$U_1^{(1)}, U_2^{(1)}, U_3^{(1)}, ... U_q^{(1)} \varepsilon R^{n1}$$
$$U_1^{(2)}, U_2^{(2)}, U_3^{(2)}, ... U_q^{(2)} \varepsilon R^{n2}$$
$$U_1^{(k)}, U_2^{(k)}, U_3^{(k)}, ... U_q^{(k)} \varepsilon R^{nk}$$

But, the orthogonality condition is not satisfied. In the proposed methodology, the SVD is used as a preprocessing stage for initial removal of noise. In the SVD preprocessing, the SVD method is applied to the dataset of 3-5 electrodes. The noises are completely removed since the noise signal is uncorrelated with the source signal. Consider for one channel:

$$X = U\ D\ V' \tag{11}$$

$$X = [U_a, U_{a,n}, \ldots U_n] \begin{bmatrix} D_a & 0 & 0 \\ 0 & D_{a,n} & 0 \\ 0 & 0 & D_N \end{bmatrix} [V_a, V_{a,n},, \ldots V_m]^T \tag{12}$$

Where a-main signal, n-noise for multichannel (m) the singular values are:

$$D_1 = \begin{bmatrix} D_{a_1} & 0 & 0 \\ 0 & D_{a_1,n_1} & 0 \\ 0 & 0 & D_{n_1} \end{bmatrix} \ldots D_n = \begin{bmatrix} D_{a_m} & 0 & 0 \\ 0 & D_{a_m,n_m} & 0 \\ 0 & 0 & D_{n_m} \end{bmatrix} \tag{13}$$

Optimizing or nullifying the singular values corresponding to the various noise $D_n \ldots\ldots D_{nm}$ and applying the inverse SVD gives noise free signal. The random noise values whose values are minimum than threshold value is zeroed for soft threshold and the entire row is removed for hard thresholding.

Adaptive filter design for extraction of fetal ECG for MIMO system: The number of channels chosen here is 5 and individual adaptive noise canceller is implemented for each channel. For MIMO case the estimation is done at each ANC channel. From the results of the experiments it is been proved that the use of parallel and cascaded adaptive methodology gives effective results. The Multistage LMS algorithm uses instantaneous estimates of vector based on sample values of input x (n) and error e(n) of previous stage in which no matrix inversion required and it does not require correlation measurement instead of expected value:

$$\nabla(n) = -2e(n)[x(n)] \tag{14}$$

The filter coefficients are updated along the direction of gradient vector estimate:

$$[h(n+1)] = [h(n)] + \mu e(n)[x(n)] \tag{15}$$

In LMS algorithm gradient vector estimate requires the knowledge of data x(n) and not the cross correlation estimate:

$$e(n) = [h(n)] + \mu e(n)[x(n)] \tag{16}$$

but to note down that LMS algorithm provides only an approximation to optimum wiener solution. For the present research of multi channel modeling of adaptive filter we once again use x as input which would be:

$$x(n) = N_1(n)\left[F(n) + M(n) + N_h(n)\right] \tag{17}$$

for multichannel FIR system the I^{th} channel $x_i(n)$ is convolved with the channel response

MATERIALS AND METHODS

The proposed method: An hybrid method is proposed which combines the effectiveness of Singular Value Decomposition, multistage adaptive filtering using QR decomposition (Sameni *et al*., 2007) and Affine Projection algorithm and support vector machine classifier. The proposed hybrid method reduces the size of the data without information loss, better estimation of the fetal parameters from the recorded signal without using the source signal and classification of the same. The block diagram is given in Fig. 2. The algorithm consists of 3 stages. The first stage is SVD where the signal undergoes data compression. The fetal ECG is extracted from the abdominal ECG using the proposed algorithm.

Most of the adaptive fast algorithms are numerically unstable due to finite-precision effects. But, the proposed multistage QR-Decomposition (QRD) technique is numerically stable. The algorithm is very fast and stable since the solutions to all lower order problems are obtained as a byproduct upon solving an Nth-order filtering problem. The second method which is been implemented is the multistage Affine Projection(AP) algorithm which has low memory requirement for implementation and is efficient. In addition to that the proposed method causes no delay in the input or output signals but the performance is robust when colored noise is present in the system.

In addition, to the proposed methodology this research is extended for a multichannel system implemented using various combination of optimizing techniques along with the QR-decomposition and affine projection algorithm. The method suits well to our problem as the noise changes in time and the frequency of the maternal signal and the maternal noise overlaps with the fetal ECG information. Normally, the adaptive filters are used where signals are non-stationary.

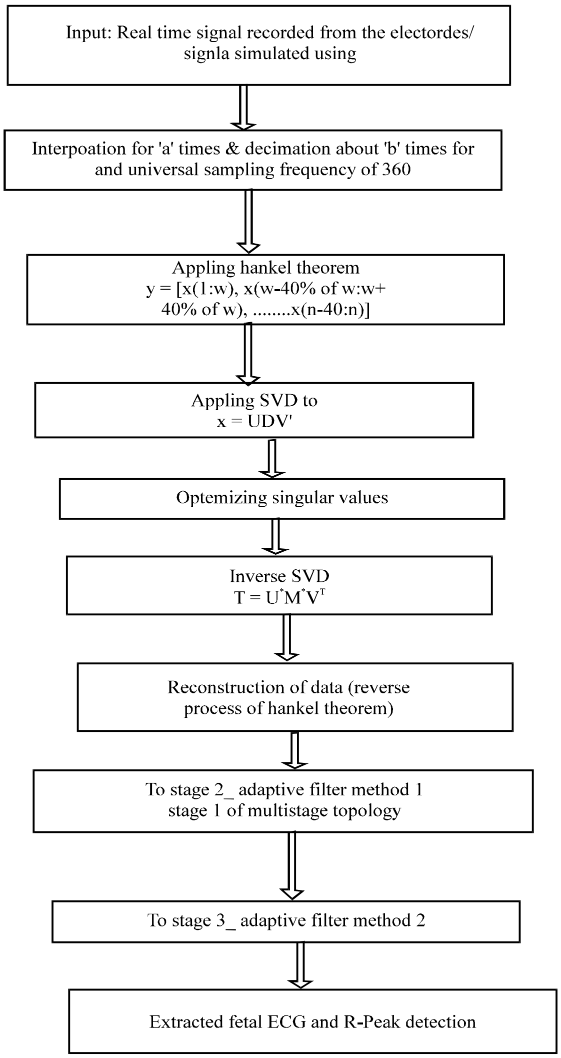

Fig. 2: Block diagram of the Proposed algorithm

RESULTS AND DISCUSSION

The proposed methodology for denoising, extraction and classification of fetal ECG from abdominal ECG is been tested with the real time database available in MIT-BIH Physionet database, European database and DaISy (Database for the Identification of Systems). The data consists of signals recorded from pregnant woman of different gestational age. Each data contains seven channels out of which four are signals recorded from abdominal electrodes and three were thorax signal. Some of the data contains 8 channels out of which five were abdominal signal and 3 were thorax. Table 1 shows the performance of various methods. The parametric values in Table 1 show that the adaptive method is dominant in the comparative analysis using non-adaptive filters like zerophase, median filter, wavelet transform using different wavelets and statistical methods like independent component analysis and singular value decomposition are used. The statistical methods like ICA and SVD are efficient but they require more number of input channels which increases the complexity of design and implementation. All ICA algorithms extract the fetal ECG when the noise components /energy is very less. The extraction performance is good only when there are more number of electrodes involved (5 at least) which is practically difficult during labor and its impossible. When compared to non adaptive methods where the scope for multichannel is less adaptive filter becomes dominant. So the adaptive algorithm is more efficient when compared to all other methods. The proposed methodology is compared with various LMS algorithm/filters like direct form LMS FIR adaptive filter, direct form LMS FIR adaptive filter, direct form NLMS FIR adaptive filter, direct form DLMS FIR adaptive filter, direct form BLMS FIR adaptive filter, FFT based block LMS. Direct form Sign-sign, sign-error, sign-data along with this RLS algorithm like fast RLS algorithm, LS lattice FIR AF. gradient adaptive lattice FIR AF. In the multi stage, AF various combination of LMS, NLMS, RLS, AP and lattices based AF are used. The mean square error is been calculated and compared for various step size and leakage factor.

The research is extended for the classification of fetal ECG using support vector machine. R-peaks of the fetal ECG signal are delineated using adaptive threshold method which is used for classification and analysis of heart beat during prenatal care. RR-interval ratio is very effective in distinguishing normal and arrthymia beats. In literature several classification algorithm are proposed like support vector machine (Melgani and Bazi, 2008), particle swarm optimization, Neural network, k-nearest neighbor algorithm, wavelet feature extraction and Neural network (Lim, 2009). The feature extraction process in a work (Ince *et al.*, 2009) utilizes morphological wavelet transform features which are projected onto a lower dimensional feature space using principal component analysis and temporal features from the ECG data. The research is extended towards the classification of the fetal ECG. For the same several methods have implemented for the RR interval details. We propose the derivative method of RR interval measurement. For the obtained observation of fetal and maternal the fetal signals are extracted and classified. In this method the R peaks are detected with amplitude and location. The RR intervals with amplitude is given to the classifier. The classifier separates the information into Maternal and fetal R peaks .The fetal RR

Table 1: Performance comparison of various methods for denoising

	Non adaptive type name												Adaptive type name			
Methods	Savitzygolay		Butterworth		Median		Zerophase		Wavelet db54		Wavelet rbio354		nlms	QRD	ap	SVD
Noise (DB)	20	60	20	60	20	60	20	60	20	60		60	60	60	60	60
PSNR	73.003	91.6767	62.069	62.069	71.3986	76.5689	61.671	61.6685	69.247	69.47	69.268	69.4773	70.94	72.524	70.106	72.36
MSE	0.0033	4.42E-05	0.0404	0.0404	0.0047	0.0014	0.0443	0.0443	0.0077	0.0073	0.0077	0.0073	0.005	0.0036	0.0063	0.003
MAXERR	0.1971	0.0663	0.9805	0.9751	0.2366	0.1374	1.0204	1.0192	0.4518	0.417	0.458	0.4237	0.337	0.3713	0.3628	0.361
L2RAT	1.0619	0.9795	0.0146	0.014	1.0617	0.9795	0.0016	0.0016	0.6996	0.6839	0.6827	0.6677	0.896	0.923	0.9844	0.982

Table 2: Performance comparison of various adaptive filters for the extraction of fetal ecg

	LMS algorithm					RLS algorithm				Affine Projection algorithm		
Parameters	LMS	NLMS	DLMS	BLMS	SS	RLS	SWRLS	QRDRLS	FTF	AP	QRDLSL	GAL
Stage 1												
PSNR	80.47688	80.40436	80.3656	80.43424	80.47402	78.73604	77.07008	78.73349	78.73788	78.05683	79.02878	79.03368
MSE	0.000855	0.000869	0.000876	0.000863	0.000855	0.001224	0.001836	0.001224	0.001224	0.001428	0.001224	0.001224
MAXERR	0.236742	0.303348	0.334152	0.28509	0.236334	0.403104	0.267648	0.254286	0.278256	0.307428	0.315894	0.252348
L2RAT	1.390872	1.382916	1.380876	1.38516	1.388322	1.226754	1.336914	1.226142	1.22349	1.435548	1.305906	1.31019
Stage 2												
PSNR	77.33181	77.06926	77.39944	77.13444	77.24562	76.21889	75.49663	76.50082	76.51663	76.00836	76.49572	76.67554
MSE	0.001734	0.001836	0.001734	0.001836	0.001734	0.002244	0.002652	0.002142	0.00204	0.002346	0.002142	0.00204
MAXERR	0.474198	0.45696	0.416976	0.378726	0.570996	0.419424	0.416772	0.391272	0.391068	0.393516	0.485622	0.383724
L2RAT	1.764498	1.784796	1.736448	1.794384	1.7901	1.632714	1.676778	1.583244	1.579368	1.809276	1.68657	1.669434

Table 3: Performance comparison of various classification methods

Classifier	Positive predictive value	Negative predictive value
Neural network	100	100
SVM	100	100
KNN	100	100
Naive bayes	89.21	93.7
Daubechies	94	93
Symle	95	94
PSO-based	96	95

interval is then classified into normal fetal signal, fetal bradycardia and fetal tachycardia. Table 2 gives the performance of the various classification algorithm for RR interval .From the table its been observed that the Neural network, SVM and KNN gives 100% performance in the positive predictive and negative predictive value. The number of features given to the classifier is 2, the amplitude of the extracted R-peaks and RR interval. The performance will be optimum even more features are given to the classifier. In our work, we used 300 data for training and 100 data for testing. In the validation process, the classifier achieves minimum mean square error at 6 epochs beyond 6 epochs the MSE is stable (constant). Hence, the point at which MSE is minimum will be taken as best validation performance. The MSE value for 10, 20 and 30 neurons are MSE-0.021813, MSE-0.022488 and MSE-0.00585, respectively. The SVM classifier is been trained with 2 classes of class 1 contains maternal information and class 2 fetal information. The algorithm is tested with the fetal information extracted from the proposed method. The support vectors are data points from both classes which are closer to the separating hyper plane. The sensitivity and specificity of the classifier is 80 and 60%, respectively. The results is compared with the classifier implemented using naive bayes classifier and K-nearest neighbour classifier. The cross validation errors of the naive bayes classifier is evaluated with different distributions Table 3.

CONCLUSION

The research is extended for the classification of fetal ECG using support vector machine. R-peaks of the fetal ECG signal are delineated using adaptive threshold method which is used for classification and analysis of heart beat during prenatal care.

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