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Pathological infant cry analysis using wavelet packet transform and probabilistic neural network

M. Hariharan *, Sazali Yaacob, Saidatul Ardeenaawatie Awang

School of Mechatronic Engineering, Universiti Malaysia Perlis (UniMAP), 02600 Perlis, Malaysia

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ABSTRACT

A new approach has been presented based on the wavelet packet transform and probabilistic neural network (PNN) for the analysis of infant cry signals. Feature extraction and development of classification algorithms play important role in the area of automatic analysis of infant cry signals. Infant cry signals are decomposed into five levels using wavelet packet transform. Energy and entropy measures are extracted at every level of decomposition and they are used as features to quantify the infant cry signals. A PNN is developed to classify the infant cry signals into normal and pathological and trained with different spread factor or smoothing parameter to obtain better classification accuracy. The experimental results demonstrate that the proposed features and classification algorithms give very promising classification accuracy of 99% and it proves that the proposed method can be used to help medical professionals for diagnosing pathological status of an infant from cry signals.

1. Introduction

Crying is the only way of communication for an infant. From the cry, a trained professional can understand the physical or psychological status of the baby. Infants cry due to some possible reasons such as, hunger, pain, sleepiness, discomfort, feeling too hot or too cold, and too much noise or light. Acoustic analysis of infant cry signal is a non-invasive and has been proven tool for the detection of certain pathological conditions (García & García, 2003; Orozco & García, 2003; Reyes-Galaviz & Reyes-Garcia, 2004; Reyes-Galaviz, Verduzco, Arch-Tirado, & Reyes-García, 2005). In the recent years, simple techniques have been proposed for analyzing the infant cry through linear prediction coding, Mel frequency cepstral coefficients and pitch information (García & García, 2003; Orozco & García, 2003; Reyes-Galaviz & Reyes-Garcia, 2004; Reyes-Galaviz et al., 2005). Little attention has been paid by the researchers based on wavelet and wavelet packet transform. This paper presents the development of an intelligent classification system for classifying normal and pathological cry using wavelet packet transform (WPT) and probabilistic neural network (PNN). The application of wavelet and wavelet packet transform analysis is diversified and has been used in many signal and image processing applications. Avci and Avci have proposed a novel approach for radio signal classification based on wavelet packet energy and multi-class support vector machine (Avci & Avci, 2008). Xian and Zeng have proposed an intelligent fault diagnosing method of rotation machinery based on the wavelet packet analysis and hybrid support vector machines (Xian & Zeng, 2009). Wu and Liu have proposed a fault diagnosis system for internal combustion engines using wavelet packet transform (WPT) and artificial neural network (ANN) techniques (Wu & Liu, 2009). Wu and Lin have conducted an investigation on speaker identification based on discrete wavelet packet transform with irregular decomposition (Wu & Lin, 2009). Hanbay et al. have proposed a method for the prediction of wastewater treatment plant performance based on wavelet packet decomposition and neural networks (Hanbay, Turkoglu, & Demir, 2008).

1.1. Previous works

This section deals with some of the significant works on infant cry signal analysis. Reyes-Galaviz et al. have presented the development of an automatic infant cry recognizer for the early identification of pathologies with the objective of classifying three classes, normal, hypo acoustics and asphyxia (Reyes-Galaviz et al., 2005). They used Mel frequency cepstral coefficients (MFCCs) for feature extraction and a Feed Forward Input Delay neural network with training based on Gradient Descent with Adaptive Back-propagation for classification. The accuracy of their proposed system varies from 96.08% to 97.39%. Orozco and García have developed a method based on linear prediction technique and scaled conjugate gradient neural networks for the detection of pathologies from infant cry. The classification accuracy of their proposed method was 91.08% for 314 samples and 86.20% for

* Corresponding author. Tel.: +60 49798419; fax: +60 49885167.
E-mail addresses: hari@unimap.edu.my (M. Hariharan), s.yaacob@unimap.edu.my (S. Yaacob), saidatul@unimap.edu.my (S.A. Awang).

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1036 samples (Orozco & García, 2003). In another study, the same authors have used MFCC and linear prediction coding techniques for characterizing the infant cry signal and used a feed-forward neural network for classification with several learning methods (García & García, 2003). The accuracy of their proposed system was up to 97.43%. Várallyay et al. have proposed fundamental frequency detection by the smoothed spectrum method (SSM) for the analysis of infant cry signal (Várallyay, Benyó, Illényi, Farkas, & Kovács, 2004). From the previous works, it has been observed that the feature extraction plays an important role in the area of automatic detection of pathological cries. In this paper, the method based on wavelet packet transform is proposed for analyzing the infant cry signals. The infant cry is signal decomposed into five levels. Energy and entropy features are computed from the wavelet packet coefficients and used to characterize the infant cry signals. In order to test the effectiveness of wavelet packet energy and entropy features, a probabilistic neural network is employed. The experimental results elucidate that the wavelet packet features and PNN classifier can be used to detect certain pathological conditions of infant cry medically.

The synopsis of the paper is as follows: Section 2 deals with a brief explanation of the infant cry database used in this work. Section 3 deals with introduction to the design of wavelet packet subband filters and feature extraction of energy and Shannon entropy. The brief introduction of PNN classifier is described in Section 4. In Section 5, inferences from the results of the PNN classifier are presented and it shows the usefulness of the wavelet packet features. Finally, Section 6 deals with the conclusion and suggestion for the future work.

2. Data selection

The database of infant cry is downloaded from the website http://ingenieria.uatx.mx/orionfrg/cry/ called Baby Chillanto database and is a property of the Instituto Nacional de Astrofisica Optica y Electronica (INAOE) – CONACYT, Mexico. The database is described in Reyes-Galaviz, Cano-Ortiz, Reyes-García, y Electrónica, and Puebla (2009). From that, 340 normal cry and 340 pathological cry with asphyxia are used for our analysis. The length of cry signal is 1 s. Asphyxia is defined as the failure to breathe well within 1 min after delivery of the baby. This disease can cause damage to the brain, organs and tissues or even death if subjected to delayed or improper treatment. The sampling frequency of infant cry signals is set to 16,000 Hz for our analysis.

3. Design of wavelet packet filters

This section briefly explains the design of wavelet packet filters and the feature extraction using them.

3.1. Wavelet packets

In discrete wavelet transform (DWT) decomposition procedure, a signal is decomposed into two frequency bands such as lower frequency band (approximation coefficients) and higher frequency band (detail coefficients). Low frequency band is used for further decomposition. Hence DWT gives a left recursive binary tree structure. In wavelet packet (WP) decomposition procedure, both lower and higher frequency bands are decomposed into two sub-bands. Thereby wavelet packet gives a balanced binary tree structure. In the tree, each subspace is indexed by its depth i and the number of subspaces p. The two wavelet packet orthogonal bases at a parent node (i, p) are given by the following forms (Burrus & Haitao Guo, 1998; Raghuveer & Rao, 1998)

$$\psi_{i+1}^{2p}(k) = \sum_{n=-\infty}^{\infty} l[n]\psi_i^p(k - 2^i n) \tag{1}$$

where $l[n]$ is a low pass(scaling) filter

$$\psi_{i+1}^{2p+1}(k) = \sum_{n=-\infty}^{\infty} h[n]\psi_i^p(k - 2^i n) \tag{2}$$

where $h[n]$ is the high pass(wavelet) filter. Wavelet packet decomposition helps to partition the high frequency side into smaller bands which cannot be achieved by using general discrete wavelet transform. The decomposition coefficient of ith depth can be obtained by the $(i-1)$th level, finally we can get the coefficients of all levels through sequential analogy. After it is decomposed by ith depths, the frequency ranges of all subspaces at the ith depth are given as $[0,\ f_s/2^{i+1}], [f_s/2^{i+1}, 2f_s/2^{i+1}], \ldots, [(2^i - 1)f_s/2^{i+1}, f_s/2]$, where f_s is the sampling frequency. In this paper, the infant cry signal is decomposed in to five levels. Table 1 summarizes the frequency bands of each level which has been decomposed. In our analysis, the sampling frequency f_s is 16,000 Hz.

The cry signals are sampled at 16 kHz giving an 8 kHz bandwidth signal. The cry signals are filtered with the wavelet packet filters and four different orders of Daubechies wavelets db1, db4, db10 and db20 are used. In this work, Daubechies wavelet has been chosen due to the following properties (Cohen, Daubechies, & Feauveau, 2006): time invariance – if the time series is time shifted then its wavelet packet coefficients are only time shifted. Fast computation – Daubechies wavelets have fractal-like self-similarity properties that lead to fast wavelet transform techniques. Sharp filter transition bands – Daubechies wavelets have very sharp transition bands which minimizes edge effects between frequency bands. Energy and Shannon entropy are computed using the extracted wavelet packet coefficients in this study. The subband energy can be computed using the extracted wavelet packet coefficients by the following Eq. (3)

$$Energy_n = \sum_{i=1}^{n} |C_{n,k}^P|^2 \quad n = 1, 2, \ldots, N,\ k = 0, 1, \ldots, 2^N - 1 \tag{3}$$

where P is the scale index, n represents the number of decomposition level.

Entropy can be used as a common measure to quantify irregular pattern of the pathological infant cry signals. The measure of

Table 1
Frequency band of each level.

Wavelet packet decomposition level	Frequency band (Hz)
1	0–4000, 4000–8000
2	0–2000, 2000–4000, 4000–6000, 6000–8000
3	0–1000, 1000–2000, 2000–3000, 3000–4000, 4000–5000, 5000–6000, 6000–7000, 7000–8000,
4	0–500, 500–1000, 1000–1500, 1500–2000, 2000–2500, 2500–3000, 3000–3500, 3500–4000, 4000–4500, 4500–5000, 5000–5500, 5500–6000, 6000–6500, 6500–7000, 7000–7500, 7500–8000
5	0–250, 250–500, 500–750, 750–1000, 1000–1250, 1250–1500, 1500–1750, 1750–2000, 2000–2250, 2250–2500, 2500–2750, 2750–3000, 3000–3250, 3250–3500, 3500–3750, 3750–4000, 4000–4250, 4250–4500, 4500–4750, 4750–5000, 5000–5250, 5250–5500, 5500–5750, 5750–6000, 6000–6250, 6250–6500, 6500–6750, 6750–7000, 7000–7250, 7250–7500, 7500–7750, 7750–8000

Shannon entropy can be computed using the extracted wavelet-packet coefficients, through the following Eq. (4)

$$Entropy_n = -\sum_{i=1}^{n} \left|C_{n,k}^{P}\right|^2 log \left|C_{n,k}^{P}\right|^2 \quad n = 1, 2, \ldots, N,\ k = 0, 1, \ldots, 2N - 1 \tag{4}$$

where P is the scale index, n represents the number of decomposition level.

Figs. 1a and 1b shows the two level wavelet packet decomposition of the cry signals pertaining to a normal and an infant with asphyxia. From the figures, it is not easy for us to distinguish between two cry signals. Hence, two parameters are used

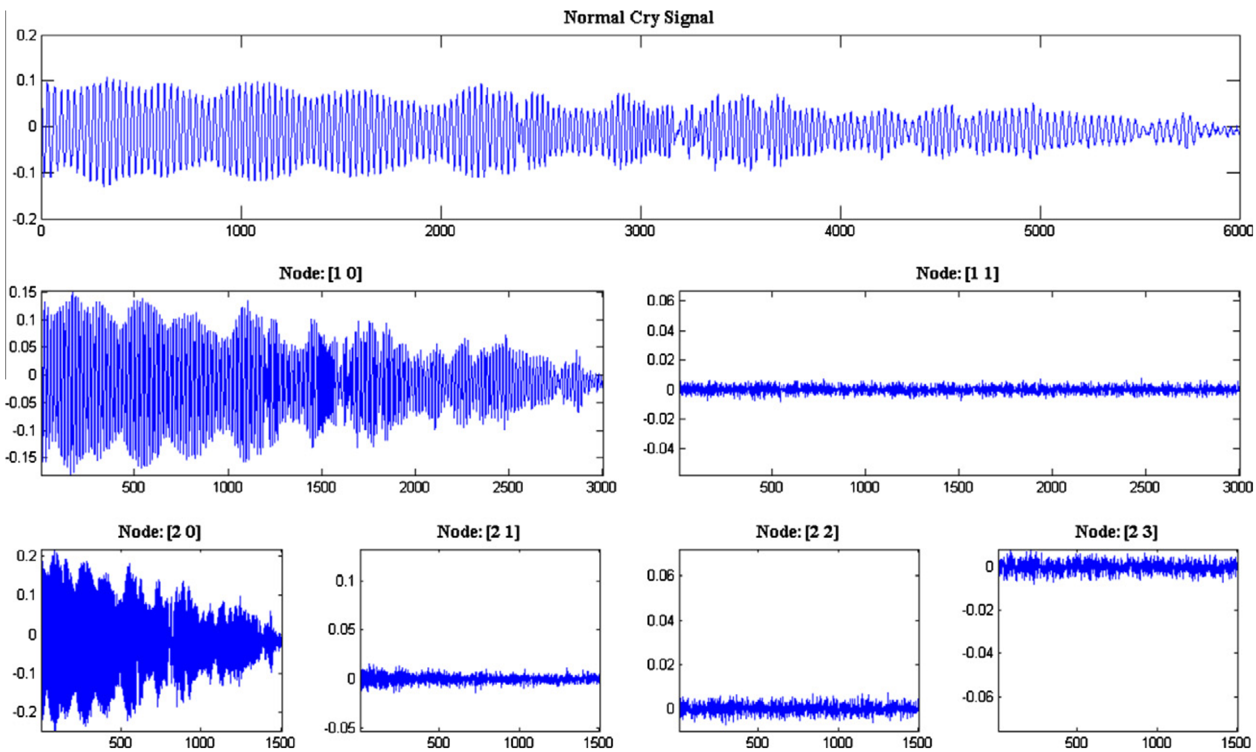

Fig. 1a. Two level wavelet packet decomposition of the normal cry signal with 'db4' wavelet.

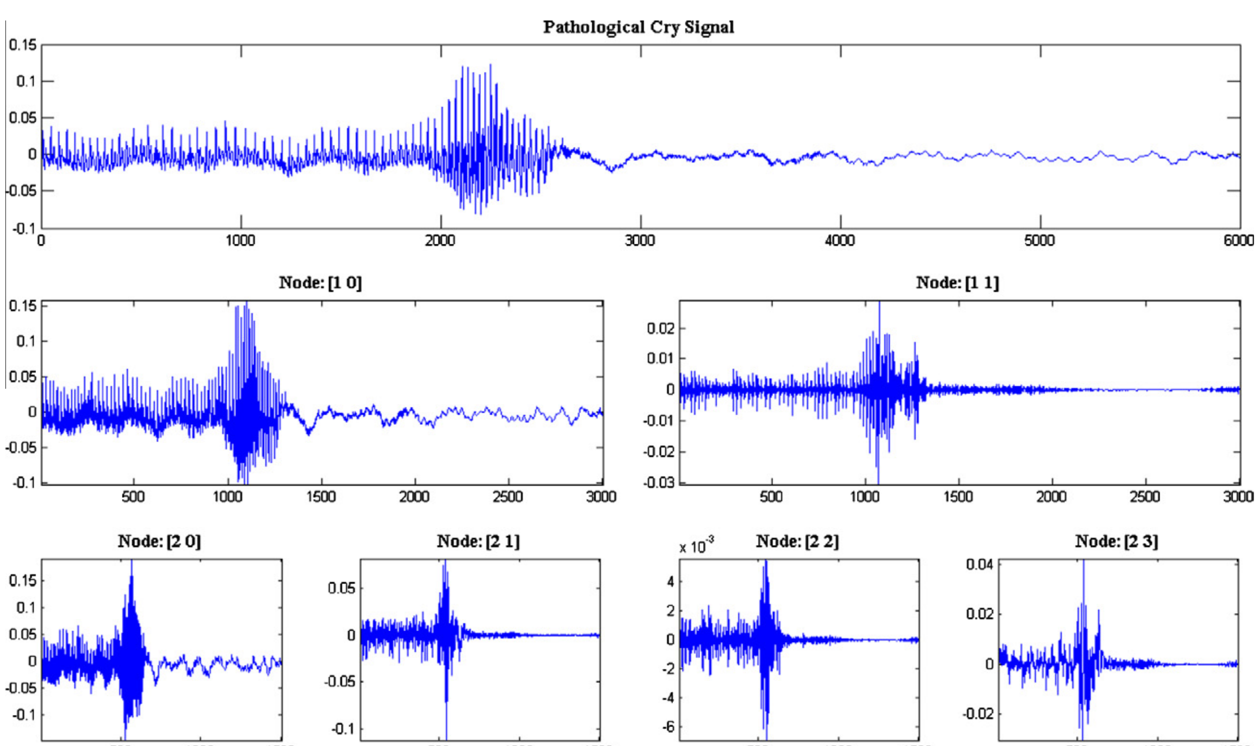

Fig. 1b. Two level wavelet packet decomposition of the pathological cry signal with 'db4' wavelet.

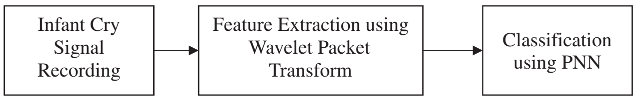

Fig. 2. Block diagram of the feature extraction and classification phase.

Table 2
Confusion matrix.

Actual classification	Predicted classification	
	Pathological	Normal
Pathological	TP	FN
Normal	FP	TN

to quantify wavelet packet coefficients such as energy and entropy.

A feature database is created, after the computation of entropy measures from each subband wavelet packet coefficients and they are used as input features for the classifiers to distinguish the cry signals as normal or pathological. The block diagram of the feature extraction and classification phase is shown in Fig. 2.

4. Probabilistic neural network

Artificial neural networks are widely used in pattern recognition and classification problems by learning from examples. Different neural network paradigms are available for classifying patterns. In this work, PNN structure used for classifying normal and pathological cries. Specht has proposed the probabilistic neural net based on Bayesian classification and classical estimators for probability density function (Specht, 1990). PNN comprises of four units, such as input units, pattern units, summation units and output units. All the units are fully interconnected and the pattern units are activated by exponential function, instead of sigmoidal activation function. The pattern unit computes distances from the input vector to the training input vectors, when an input is presented, and produces a vector whose elements indicate how close the input is to a training input. The summation unit sums these contributions for each class of inputs and produces a net output which is a vector of probabilities. From the maximum of these probabilities, output units produce a 1 for that class and a 0 for the other classes using compete transfer function.

The net can be used for classification as soon as an example of a pattern from each of the two classes has been presented to it. However, PNN generalizes well as it is trained with more examples. Varying smoothing parameter (σ) gives control over the degree of nonlinearity of the decision boundaries for the net. A decision boundary approaches a hyperplane for large values of σ and approximates the highly nonlinear decision surface of the nearest neighbour classifier for small values of σ that are close to zero. In this paper, PNN architecture is constructed using *newpnn*( ) in MATLAB function. The detailed information about the PNN architecture and mathematical equations can be found in the Specht's paper (Specht, 1990).

5. Inferences

In this study, conventional validation was performed to evaluate the efficacy of the proposed features. 680 segments (340 normal + 340 pathological) of cry signals were used. Among them, 60% of data (408 samples) were used for training and remaining 40% of data (272 samples) were used for testing. The PNN was trained with different spread factor or smoothing parameter such as from 0.001 to 0.009 and from 0.01 to 0.09. Though, the network was trained with different spread factors, only the best accuracy results were presented. In order to test the classifier performance, several measures such as, sensitivity, specificity, and the overall accuracy were considered. The sensitivity, specificity and overall accuracy were calculated from the measures true positive (TP), true negative (TN), false positive (FP), and false negative (FN) as presented in Table 2.

TP = true positive, the classifier classified as pathology (Asphysia) when pathological samples were present.
TN = true negative, the classifier classified as normal when normal samples were present.
FN = false negative, the classifier classified as normal when pathological samples were present.
FP = false positive, the classifier classified as pathological when normal samples were present.
Sensitivity = TP/(TP + FN).

Table 3
PNN classification results at each level of wavelet packet decomposition using 'db1'.

Decomposition level	Spread factor	Sensitivity	Specificity	Overall accuracy	Spread factor	Sensitivity	Specificity	Overall accuracy
	Energy features				Entropy features			
1	0.009	82.91	78.65	80.48	0.009	80.43	74.21	76.88
	0.01	83.63	79.39	81.32	0.01	80.33	73.87	76.58
	0.02	87.04	80.37	83.31	0.03	83.37	74.87	78.46
	0.03	88.20	79.30	82.90	0.05	84.89	74.59	78.79
2	0.005	86.23	81.88	83.82	0.006	82.67	80.50	81.43
	0.01	85.88	82.26	83.86	0.009	82.91	79.16	80.85
	0.03	89.10	83.05	85.77	0.01	84.14	79.10	81.32
	0.04	90.01	81.52	85.18	0.02	86.19	77.00	80.85
3	0.005	94.27	89.43	91.65	0.005	88.95	86.57	87.68
	0.007	93.24	90.67	91.88	0.007	90.49	85.40	87.72
	0.01	94.37	90.18	92.13	0.01	89.79	85.00	87.17
	0.02	93.45	89.33	91.25	0.02	92.29	83.43	87.32
4	0.004	94.02	94.54	94.26	0.005	94.38	93.35	93.82
	0.009	95.31	93.76	94.49	0.01	95.01	92.53	93.68
	0.01	96.44	93.00	94.63	0.02	95.15	91.86	93.42
	0.05	97.45	92.09	94.56	0.03	94.54	90.28	92.28
5	0.007	96.17	94.07	95.07	0.009	96.44	95.21	95.77
	0.01	97.38	92.55	94.82	0.01	97.67	95.14	96.36
	0.07	96.87	92.75	94.67	0.02	98.32	94.18	96.14
	0.1	98.80	91.23	94.67	0.03	96.84	94.91	95.85

Specificity = TN/(TN + FP).
Overall accuracy = (TP + TN)/(TP + TN + FP + FN).

Tables 3–6 shows the results of PNN for 'db1', 'db4', 'db10', and 'db20' with energy and entropy features. From tables, it was found that increasing the wavelet packet decomposition level leads to the extraction of a more predominant group of feature vectors, thereby increase in the classification accuracy. The highest classification accuracy was achieved at the fifth level of wavelet packet decomposition. From Table 3, the percentage of increase in classification accuracy was 12% for energy features and 17% for entropy features at the fifth level of decomposition. The best overall accuracy was 95.07% for energy features and 96.36% for entropy features. From Table 4, the percentage of increase in classification accuracy 15% for energy features and 23% for entropy features. For Daubechies wavelet 'db4', entropy features perform better than energy features. From Table 5, the percentage of increase in classification accuracy was 17% for energy features and 23% for entropy features.

For 'db10, both the features equally perform well at the fifth level of decomposition. From Table 6, the percentage of increase in classification accuracy was 12% for energy features and 15% for entropy features. The number of features at the fifth level of decomposition was 32. All the 32 features were used to provide better representation of cry signal. From the above discussion, it can be observed that the maximum of classification accuracy can be obtained regardless of the different order of Daubechies wavelets. In this paper, two-class pattern recognition was carried out such as normal or pathological cry signal. In Section 2, some of significant works were reported and the maximum classification accuracy of 97.43% was obtained. At the fifth level of wavelet decomposition, the maximum classification accuracy of 99.49% for 'db20' was obtained and it shows that the proposed features

Table 4
PNN classification results at each level of wavelet packet decomposition using 'db4'.

Decomposition level	Spread factor	Sensitivity	Specificity	Overall accuracy	Spread factor	Sensitivity	Specificity	Overall accuracy
	Energy features				Entropy features			
1	0.009	77.52	82.03	79.56	0.009	77.89	72.65	74.93
	0.01	77.10	83.76	79.96	0.01	80.92	73.74	76.73
	0.02	77.04	89.45	82.02	0.03	83.90	75.35	78.90
	0.03	75.46	92.13	81.69	0.05	84.33	73.46	77.72
2	0.005	89.16	87.21	88.13	0.006	86.53	87.15	86.80
	0.01	89.52	87.23	88.27	0.009	88.53	85.32	86.76
	0.02	91.37	85.84	88.24	0.01	87.26	85.41	86.21
	0.04	93.22	83.50	87.72	0.03	90.95	81.57	85.63
3	0.006	94.98	94.00	94.45	0.007	92.80	90.26	91.43
	0.008	96.37	93.09	94.63	0.008	92.72	90.41	91.47
	0.04	97.42	92.08	94.56	0.01	93.49	90.96	92.17
	0.05	98.42	91.86	94.89	0.03	95.49	89.28	92.13
4	0.005	95.11	95.42	95.26	0.007	95.60	95.32	95.44
	0.007	96.95	94.16	95.44	0.009	96.18	95.49	95.81
	0.06	98.48	93.40	95.74	0.03	95.88	95.48	95.66
	0.07	98.32	93.62	95.81	0.04	95.88	95.06	95.44
5	0.008	79.92	95.59	86.03	0.009	95.08	97.44	96.21
	0.01	88.44	95.57	91.65	0.01	95.36	96.59	95.96
	0.08	92.32	97.66	94.82	0.02	98.50	96.42	97.43
	0.09	92.20	97.52	94.67	0.03	98.49	95.87	97.13

Table 5
PNN classification results at each level of wavelet packet decomposition using 'db10'.

Decomposition level	Spread factor	Sensitivity	Specificity	Overall accuracy	Spread factor	Sensitivity	Specificity	Overall accuracy
	Energy features				Entropy features			
1	0.009	82.37	79.89	81.03	0.009	78.39	73.98	75.81
	0.01	82.53	80.41	81.36	0.01	79.77	73.82	76.36
	0.02	86.52	80.79	83.35	0.03	84.90	74.64	78.82
	0.04	87.90	81.73	84.26	0.05	84.16	74.93	78.75
2	0.008	95.88	95.12	95.48	0.002	95.28	94.03	94.60
	0.009	96.30	94.82	95.51	0.005	95.63	93.97	94.74
	0.02	95.62	95.48	95.51	0.02	95.94	92.84	94.30
	0.03	97.47	93.60	95.40	0.03	95.21	90.06	92.43
3	0.006	98.03	94.51	96.18	0.006	97.06	96.65	96.84
	0.008	98.77	94.03	96.25	0.009	97.98	96.19	97.06
	0.01	98.10	94.25	96.07	0.02	97.33	96.10	96.69
	0.06	98.60	93.69	95.99	0.03	96.61	96.13	96.36
4	0.008	98.35	95.87	97.06	0.006	96.41	98.44	97.39
	0.009	98.28	96.49	97.35	0.008	97.38	97.72	97.54
	0.04	98.51	96.69	97.57	0.02	97.63	96.66	97.13
	0.07	99.17	96.36	97.72	0.04	97.88	97.04	97.43
5	0.009	95.91	99.39	97.57	0.009	96.64	99.10	97.83
	0.01	98.37	97.11	97.72	0.01	97.88	97.87	97.87
	0.04	99.77	97.22	98.46	0.07	99.55	97.63	98.57
	0.08	99.85	97.36	98.57	0.08	98.97	98.11	98.53

Table 6
PNN classification results at each level of wavelet packet decomposition using 'db20'.

Decomposition level	Spread factor	Sensitivity	Specificity	Overall accuracy	Spread factor	Sensitivity	Specificity	Overall accuracy
	Energy features				Entropy features			
1	0.008	88.82	85.55	87.02	0.008	84.08	84.12	84.04
	0.01	88.59	87.39	87.90	0.01	85.64	82.48	83.90
	0.02	91.11	87.66	89.26	0.02	83.94	82.95	83.27
	0.03	88.71	88.68	88.60	0.04	84.87	80.21	82.32
2	0.006	98.30	97.32	97.79	0.008	97.60	98.45	98.01
	0.01	98.74	97.05	97.87	0.01	97.89	98.24	98.05
	0.03	98.33	98.10	98.20	0.02	97.90	97.89	97.87
	0.05	97.98	98.19	98.05	0.04	96.39	97.55	96.95
3	0.007	98.90	98.05	98.46	0.006	98.39	98.04	98.20
	0.009	98.98	98.55	98.75	0.007	98.53	97.68	98.09
	0.01	99.19	98.48	98.82	0.02	98.25	98.18	98.20
	0.05	98.90	98.11	98.49	0.04	98.39	98.31	98.35
4	0.008	99.63	99.34	99.49	0.008	98.90	98.47	98.68
	0.009	99.70	98.26	98.97	0.009	99.05	98.40	98.71
	0.04	99.56	98.70	99.12	0.01	98.91	99.12	99.01
	0.07	99.63	98.48	99.04	0.05	98.97	98.54	98.75
5	0.009	91.50	99.44	95.11	0.009	98.34	99.19	98.75
	0.01	97.14	99.32	98.20	0.01	99.27	99.49	99.38
	0.03	99.85	98.48	99.15	0.02	99.63	99.20	99.41
	0.09	99.85	98.42	99.12	0.03	99.56	99.06	99.30

and classification algorithm provides better classification compared to earlier works. Finally, the experimental results indicates that the propose features has the potential in detecting pathological problem of an infant from cry signals.

6. Conclusion

This paper presents the analysis of infant cry signals based on the wavelet packet transform and PNN. The infant cry signals were decomposed into five levels. At each level, energy and entropy features were extracted using wavelet packet coefficients. The effect of the proposed features was tested at every level of decomposition of cry signals. The sensitivity, specificity, and overall accuracy were used as performance measures, in order to test the reliability of the PNN classifier. The maximum classification accuracy of 99% was obtained at the fifth level of decomposition. The classification results indicate that the proposed method could be used as a valuable tool for clinical diagnosis of the infant cry signals.

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