**INFANT CRY RHYTHM ANALYSIS: A QUANTITATIVE PILOT STUDY**

aN.Sriraam, aTejaswini. S, b A R Someshekar

aCentre for Medical Electronics and Computing,M. S. Ramaiah Institute of Technology, Bangalore, India

bDepartmentof pediatrics, M. S. Ramaiah Medical College, Bangalore, India

ABSTRACT

Infant’s cry, a vocal signal is the first way of communication which carries significant message for the mother. The baby is born with the ability to cry with certain rhythm, which indicates that, something wrong in their world. It contains a lot of information about the infant’s feelings such as hunger, pain, sleepiness, wet diaper etc. The cry rhythm analysis based on Mexican database was already reported in literature. This research pilot study makes use of Indian ethnic group to perform the infant cry rhythm analysis. All the recordings were done in the local hospital, Bangalore by using SONY Voice recorder with a sampling rate of 44.1 KHz. Three conditions namely hunger, wet diaper and pain were considered with n=10 (10 trials for each case). The initial auditory cry rhythms were pre-processed to remove the silence and were segmented with a window of 0.5s. Then Mel Frequency Cepstral Coefficients were estimated for each segment. A recurrent feedback Elman neural network was employed to performthe binary classification: wet diaper versus hunger, wet diaper versus pain and hunger versus pain. The performance of the proposed study was evaluated in terms of classification accuracy. Simulation results showed the accuracy of 99.88%, 99.59% and 99.64% was attained by employing Mel Frequency Coefficients with REN classifier for all the three conditions. Further ROC analysis confirms the suitability of the proposed method for Infant cry rhythm analysis.

Key words: cry rhythm; Mel Frequency Cepstrum Coefficients; REN Classifier.

N Sriraam, Sriraam@msrit.edu

1. **INTRODUCTION**

Babies use different types of cry rhythms to express their needs. Learning to read a baby's rhythm is a skill that all parents should understand in order to respond effectively to the infant’s needs. Of all the infant emotions, crying rhythm is considered the most important parameter. Hence there is a need to translate the cry rhythms into useful message to address the needs of the new born by the mother. Attempts have been made in the recent past to interpret the cry pattern database created by Mexican hospital (Azlee Zabidi et al. 2010 ; Azlee Zabidi et al. 2010).

Infants are capable of communication through different types of cry rhythm. Ability to recognize them is encouraging and fulfilling that can strengthen the bond with the mother. In general, cry rhythms are categorized into hunger, pain, wet diaper, discomfort, boredom, fatigue, anger, colic and irritability. A rhythmic pattern is formed by a basic type of cry continued with a brief silence, then a short whistle higher in pitch than the main cry which is followed by a quick silence before the next cry rhythm (Ronald 2003; Wasz Hockert et al. 1968; Saraswathy et al 2012; Maria et al 2010).

Hunger cry is whispered cry which rises and falls with the rhythm. The sound is less shrill compared to other rhythms. Hunger sounds as an appeal than desperate. This cry rhythm is often pave the way by finger sucking, lip smacking. Boredom rhythm is ill-natured and complaining. It’s almost like a moan. It is usually stopped when baby is picked up. The baby indicates it’s discomfort with a whiny sound of rhythm, which does not stopped when picked up. Thus, baby indicates that it either needs a diaper change or the environment around is too cold or too hot. Anger rhythm is similar to basic rhythm with more air forced through the vocal chords (Ronald 2003).

The baby indicates fatigue as a soft, rhythmic cry as baby tries to soothe and go to sleep. Pain rhythm begins suddenly and it is high pitched with noisy. The cry is high sounding and longer which leaves the infant breathless. Pain rhythm differs from other types because it is stimulated by high intensity stimuli. This type of cry is nonstop and unmanageable. The baby indicates its illness with the signal that they are displeasure with prolonged cry. The rhythm is usually weak, unpleasure and nasal. It is generally lower in pitch than a pain cry. The cry can more readily be identified as a signal of illness when it is considered together with changes in the baby's presence and behavior. The baby may have a flushed face, appear drowsy, refuse to eat, have diarrhea and avoid cuddling. Colic crying rhythm is readily identifiable because it generally occurs regularly every afternoon or evening lasts for several hours each time, and the baby is not readily unsalable (Ronald 2003; Wasz Hockert et al. 1968).

Analysis of infant rhythm signal is an important aid for clinical diagnosis and to identify the demands of infants. Reason for infant rhythm is the same sense of speech in adults which let others knows about their needs and problem. Infant rhythm classification process is a pattern recognition problem which consistsof mainly two stages that are signal processing and pattern classification. The system receives the raw cry signal as the input through the voice recorder. In signal processing stage, the raw signal is preprocessed, normalized and filtered. The continuous signal is analyzed by suitable feature extraction technique. The extracted features of rhythm are statistically analyzed whether to know there is difference between the infant rhythms. Later on features can be classified using pattern classification to differentiate hunger, wet diaper and pain (Wasz Hockert et al. 1968; Saraswathy et al 2012; Maria et al 2010; AliMessaoud & Chakib Tadji 2011).

This research work suggests a quantitative pilot study on infant cry rhythm analysis using a Indian ethnic group. The study is being conducted at the Paediatric clinic of M. S. Ramaiah Memorial Hospital, Bangalore, India to observe the variation in the cry rhythm. Mel Frequency Cepstral Coefficients are used as the feature pattern and the typical Recurrent Elman Neural Network (REN) is employed to perform the cry pattern classification.

1. **RELATED BACKGROUND**

In 1995, M. Petroni et al., [7] has successfully classified three different types of cries using MFCCs and feed forward ANNs, they have achieved an accuracy of 90.4% for three situations like hunger, pain and fear by using cry signals of 16 normal babies [7]. A. Zabidi, et al. [8] used Particle swarm optimization (PSO) with Multi Layer Perceptron (MLP) algorithm to find optimum solution for MFCC computation. They managed to achieve high classification accuracy of 93.9% to classify normal and asphyxiated infant cry. AzleeZabidi et al. [9] used Mel Frequency Cepstrum features as input to Orthogonal Least Square (OLS) Multi Layer Perceptron (MLP) algorithm. It was found that OLS algorithm is effective in enhancing the accuracy of MLP classifier which was high about 94% to classify normal and asphyxiated infant cry. A. Zabidi, et al. [10] used particle swarm optimization algorithm to optimize Mel frequency Cepstrum coefficients parameters, in order to extract optimal feature set for diagnosis of hypothyroidism in infants using Multi Layer Perceptron (MLP) neural network. The results concluded in their work that PSO is suitable technique for adjusting MFCC extraction parameters for classification.

A.Zabidi, W. Mansor, et al., [12] used Mel Frequency Cepstrum Coefficients (MFCC) feature extraction method to extract important information from the cry and Multi layer Perceptron (MLP) classifier to distinguish healthy babies with respect to hypothyroidism babies. The MLP classifier discrimination between positive and negative cases reached up to 89.19% accuracy. Mahmoud Mansouri Jam, et al., [13] used for recognition of two groups: infants with pain and normal infants using Mel frequency multimodal entropy extraction from infant cry. Using multiband spectral entropy,artificial neural network obtained an accuracy of 88.5%. The classification accuracy was improved from 66.9% which was obtained with artificial neural network alone. Therefore, multiband spectral entropy enhanced classification accuracy.

A preliminary work on Infant Cry Detection and Pain Scale Assessment was reported by N. Sriraam and Tejaswini. S [25].Table I highlights the detailed literature review for better understanding.

Table I: Related literature on infant cry rhythm analysis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Sl. No. | Title | Data sets/ techniques adopted | Results | Conclusion |
| 1. | Automatic identification of qualitatives characteristics in infant cry [4] | **Two sets of samples: 20 samples of Mexican infant cry and 13 samples of Cuban infant cry**  **182 unit of cries from first sample and 62 units from second sample**  Threshold was applied to the energy of the signal thus threshold allowed to identify the cries automatically and it also eliminates aspiratory cry signals, eliminates noise | This method identified 238 qualitative characteristics and they were compared with manual identification.  The Melody shape identification accuracy of 90.49% were obtained | Detects cry units even under noisy recordings.  It helps to differentiate normal and pathological cries automatically |
| 2. | Charaterization of Infant Cries Using Spectral and Prosodic Features [6] | **120 infants cry in Neonatal intensive care unit were recorded.**  **Total no. of cry clips recorded for wet-diaper (30), hunger (60) and pain (30)**  **Total Duration : wet-diaper (937 sec), hunger (1874 sec) and pain (725 sec)**  Spectral features: MFCC  Prosodic features: Short time energy and pause duration  Classification: SVM | Spectral features: wetdiaper:86.11%, hunger: 66.7% and pain: 30.56%  Prosodic features: wet diaper: 61.11%, hunger: 27.78% and pain: 83.34% | Performance of ICR system by spectral and prosodic features were observed to be 61.11% and 57.41% .  Average recognition performance of the work was found to be 80.56% |
| 3. | Feature extraction and recognition of infant cries [17] | **722 digital audio recorder was used to record some recordings**  **50 cry samples : 28 hunger, 12 diaper, 11 attention cries**  Linear prediction method and signal boundary detection were introduced to extract features. | Vector quantization with Linear Predictive Coding Coefficients (LPCC) scheme was employed for classification. | All cries are similar to some degree  The overlap of different LPCC create inaccuracies in the analysis and vector training |
| 4. | Infant Cry Classification: Time Frequency Analysis [18] | Three categories namely normal cry, deaf and asphyxia cry with n=340 were extracted from Mexican database.  Short Time Fourier Transform (STFT) features were used with Probabilistic Neural Network (PNN) and General Regression Neural Network (GRNN) classification | The maximum classification accuracy of above 99% was obtained by using PNN and GRNN classifiers. | Results were confined with limited data size. |
| 5. | Modelling and Characterization of an Artificial Neural Network for Infant Cry Recognition Using Mel-Frequency Cepstral Coefficients  [19] | **Two recorders were set with 44100Hz sampling rate, 16 bits, and mono channel. Two microphones were used to pick up the sound from either sides of baby.**  Mel-frequency Cepstral Coefficients (MFCC) with Levenberg-Marquardt(LM) neural network training algorithm was used. | A value of 1 means that a cry has been recognized or detected in the raw audio data. A value of 0 on the other hand if otherwise. | Teaching other sounds to the neural network that are not cry, the ANN can also adapt to those sounds so that those with their own respective MFCC data can be distinguished as not crying sounds. |
| 6. | An Investigation into Classification of Infant Cries using Modified Signal Processing Methods [20] | The data for this study was collected from **Pranaam Hospital, Hyderabad. Cry samples were recorded for infants of age between 3 months to 2 years.**  Database consists of 76 files of infant cry samples.  Auto correlation, Short Time Fourier Transform and LP analysis was used | A larger fluctuation was obtained for pain cry, whereas the fluctuation was relatively flat with lesser fluctuations for discomfort cry. | Quantitative analysis was needed for infant cry due to reason of cry other than pain and discomfort |

Kheddache, et al., in 2013 have used the fundamental frequency and different modes of cries as hyper-phonation, phonation and high pitched cries to differentiate the pathological cries from healthy baby cries. Spectrographic analysis was carried out on healthy and pathologic cries of newborn. The database used contained 2800 cry samples of 1s duration from 48 of newborn babies. The recordings of cries are done using a small recorder, at the distance of 10cm of babies’ mouth with sampling rate of 44.1 KHz. The baby’s age of concern was preterm and full term babies from 1 to 30 days. This study mostly deals with characterization of healthy and pathological babies cry according to the modes of cry such as hyper phonation, phonation and high pitched cry. This work clearly shows the differences in frequency of healthy and pathologic cries. The result obtained in this work is consistent with spectrographic studies of crying newborns [21]. Alejandro Rosales- Perez, Carlos A. Reyes- Garcia, et al., have tried an automatic classification model for infant crying for an early disease detection is been discussed. The model mainly consists of two phases. Firstly, acoustic features acquisitions form the Mel Frequency Cepstral Coefficients and Linear Predictive coding is obtained by signal processing. Secondly, selection or creation of fuzzy model through genetic selection fuzzy model (GSFM) algorithm for classification. For this experiment they have used baby Chillanto infant cry database property of INAOE-CONACyT, Mexico. This approach improves the accuracy for differentiating between normal and pathological cry using Genetic selection fuzzy model (GSFM) algorithm [22].

Nemir Ahmed Al-Azzawi used a new approach to classify two different kinds of cry which come from physiological status such hunger, discomfort, pain etc., and medical disease such as apnea, asphyxia, hypothyroidism etc., based on F transform. The database used in this research was collected from InstitutoNacional de AstrofisicaOptica y Electronica (INAOE). The cry data set had 276 cry samples from both the categories, with different duration. The cry data signal were segmented each signal to segments with 1s of length. Using F transform features a classification accuracy of 96% was reported [23].

Varsharani and Sardar [24] in 2015 have mainly focused on automation of infant’s cry. For the implementation they have used Linear Frequency Cepstrum Coefficients (LFCC) for feature extraction and vector quantization (VQ) code book for matching samples using Linde-Buzo Gray (LBG) algorithm which is similar to K means method in data clustering . The cry samples were recorded form various baby aged 0-6 months of age from Neonatal Intensive Care unit (NICU), Nobal Hospital, Pune. They collected 30 hunger cry, 30 sleepy cries, 30 wanted to burp cries, 30 pain and 30 discomfort (wet diaper, hot or cold and other) cries. The classification of cry was done in two phases. First, training phase where LFCC features are extracted and VQ code codebooks are generated. Second, testing phase in which both feature extraction and codebook generation of samples are repeated. It concluded that LFCC effectively captures the lower as well as higher frequency characteristics than MFCC. The model can produce 94% of accuracy using Euclidean distance [24].

1. **METHODOLGY**

Figure 1 shows the proposed schematic for the pilot research study on infant cry rhythm analysis. The module comprises of data acquisition, pre-processing module, feature extraction, statistical analysis, classification and ROC analysis.

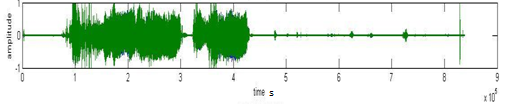


Figure 1: Proposed scheme for infant cry rhythm analysis

For the present pilot study 10 healthy babies of less than 6 months group were considered. A SONY voice recorder was used to collect the raw cry rhythm data under three criteria hunger, pain and wet diaper. The sampling rate of the recorder was 44.1 KHz. The infants cry considered for this research was 10 trails of each type of cry recordings were considered.

1. **PREPROCESSING**

The pre-processing and silence removal was done using Hamming band pass filter. Figure 2 shows the original cry rhythm and cry rhythms with silence removal.



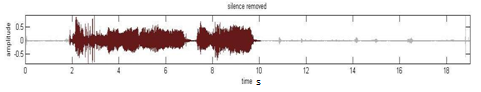


Figure 2: Original cry rhythm and silence removed cry rhythm.

1. **FEATURE EXTRACTION**

Mel Frequency Coefficients (MFC) analysis isa most appropriate voice recognition algorithm to extract features from audio signals and it takes human perception sensitivity with respect to frequencies into consideration. The coefficients compromise a good illustration of the dominant features in acoustic information for a selected window of time.

For a signal with N frames=0, 1...... N-1, MFC coefficient is defined as [8] [9] [10]:

(1)

Where c (n) is the MFC coefficients at frame n; s (n) is the original signal at frame n, after application of pre-filtering and some window method.

The first step is to break the input signal down into frames\ windows of time, in order to comprehensively capture the signal’s temporal features and changes. As a result of frame blocking, high frequency component is produces at the end of every signal block, which is known as leakage effect in spectrum. To minimize the leakage effect to maintain the continuity of the first and last points in frame, Hamming window is used. After windowing, fast Fourier transform is performed on each frame. These values are then grouped together in bands and weighted by a triangular filter bank called Mel filter bank [8] [9] [10].

The Mel filter bank is designed on Mel-scale frequencies, which mimic the human auditory system. Mel-scale frequencies are divided linearly in the low range but logarithmically in the high range therefore human auditory system can detect frequency tones lesser than 1 KHz in linear scale but frequencies higher than 1 kHz in logarithmic scale. The number of Mel-filter banks can be altered depending on the sampling frequency of the signal. The Mel-scale frequency is given by [8],

(2)

The Mel-frequency Cepstral coefficients are then derived by taking the logarithm of the band-passed frequency response and calculating the Discrete Cosine Transform (DCT) for each intermediate signal [9]-[10].

MFC analysis is used extract feature in the cry rhythm signal. The samples are windowed into equal number of length frames. The sampling frequency is 44.1 KHz. In order to smoothen the frame to frame transition, 25% of each successive frame is overlapped. Each block was multiplied with hamming window in order to keep the first and last points of the frame. Fast Fourier transform was applied to the signal to obtain the magnitude of frequency response for each frame. Mel scale was applied to each transformed signal using triangular filter banks to remove the linearity in each frame and the filter banks were adjusted to Mel frequency scale. The logarithm of amplitude spectrum was applied within the frequency scale. Finally DCT was applied to logarithm of amplitude spectrum to reduce the number of parameters in the derived signal. Thus MFC coefficients are obtained for hunger and pain, wet diaper and pain and wet diaper and hunger. Figure 3 shows the flow process for estimation of Mel Frequency Cepstral Coefficients.



Figure 3: Flow chart of Mel Frequency Coefficients



Figure 4: MFCC of Pain and Hunger



Figure 5: MFCC of pain and wet diaper



Figure 6: MFCC of wet diaper and hunger.

It can be seen from figures 4-6 that the distribution of Mel Frequency Cepstral Coefficients for pain- hunger, pain- wet diaper and hunger- wet diaper respectively are easily distinguishable. Therefore, MFCC feature can be used for classification of the pain- hunger, pain- wet diaper, hunger- wet diaper respectively.

1. **STATISTICAL ANALYSIS**

In order to understand the significance of MFCC for pattern classification, statistical analysis was performed. It can be inferred from Figs.4-6 that the MFCC plot shows significant difference for all the three conditions. Most of the biological investigations are carried out on samples as it is not possible to cover the entire population. It is known that repeated samples even though from same population will not yield the same estimates for any characteristic under observation. Here population means the cry rhythm of different babies. Tables II and III depicts the central tendency measures and Wilcoxon statistical results of cry rhythms.

TableII: Central tendency measures of cry rhythm.

|  |  |  |  |
| --- | --- | --- | --- |
| MFCC of Infant Rhythm | Mean | Median | Standard deviation |
| Hunger | -0.220941 | -0.049050 | 4.6127807 |
| Wet diaper | -0.303703 | -0.317600 | 3.0919290 |
| Pain | -0.202810 | -0.25220 | 3.7748134 |

Non parametric tests are performed to check the homogeneity of variance between the groups. We have used Wilcoxon signed rank test to check homogeneity between the groups.

Table III: Wilcoxon signed rank test

|  |  |  |  |
| --- | --- | --- | --- |
| MFCC of Infant Rhythm | Z | p | |
| Hunger vs. pain | -30.431 | 0.000 | P<0.001 |
| Pain vs. wet diaper | -25.504 | 0.000 |
| Hunger vs. wet diaper | -33.598 | 0.000 |

From tables II and III, one can observe the statistical significance of feature MFCC derived under all three conditions. This clearly infers that the MFCC feature can be used for neural network based classification.

1. **Neural Network Based Classification**

Elman neural network found to be potential candidate for processing temporal patterns.The feature trajectories based on Elman neural network can be modeled in a better primitive way by make use of the context units. The context unit’s posses the past hidden layer state through the recurrent links that ensure the stability of the recurrent architecture [26].

The REN Classifier was configured with the following attributes:

1. Single input neuron in the input layer which was presented with 1500 Mel frequency derived hunger, wet diaper, pain pattern respectively.
2. Twenty five hidden neurons with a single hidden layer unit with tan sigmoidal function as activation unit between input– hidden layer.
3. One neuron in the output layer with log sigmoid activation function. This layer performs the binary classification operation.
4. Method of network learning algorithm applied was Gradient descent with momentum algorithm.
5. Maximum number of epochs fixed : 5000
6. Learning rate: 0.6

In order to evaluate the performance of the neural network, the entire datasets were divided into training and testing patterns. 2100 patterns were used for training and 900 for testing. 10 fold cross validation procedure was adopted to validate the entire dataset.

The performance of the REN classifier is evaluated in terms of three parameters such as sensitivity, specificity and classification Accuracy (CA) (3)

(4)

(5)

Table IV: Classification results of REN Classifier

|  |  |  |  |
| --- | --- | --- | --- |
| Case | Sensitivity (%) | Specificity (%) | Classification Accuracy (CA) (%) |
| Pain- wet diaper | 100 | 99.76 | 99.88 |
| Pain- hunger | 100 | 99.18 | 99.59 |
| Wet diaper- hunger | 99.76 | 99.53 | 99.64 |

Figures 7-9 show the performance of REN Classifier. The graphical representation confirms the suitability for the proposed Mel Frequency Cepstral Coefficients. Therefore, REN classifier can be used for classifying the types of cry.

Table IV shows the overall classification result. It can be seen that the REN Classifier yields 99.6% accuracy which ensures the potential application of REN for infant cry pattern classification.

Figure 7: REN classifier output for hunger and pain



Figure 8: REN classification output of pain and wet diaper.



Figure 9: REN classifier output of hunger and pain.

1. **Receiver Operating Curve (ROC) ANALYSIS**

A receiver operating characteristic (ROC) curve allows us to explore the relationship between the sensitivity and specificity of a clinical test for a variety of different cut points, thus allowing the determination of an optimal cut point. Receiver operating characteristic (ROC) curves are used to describe and compare the performance of diagnostic technology and diagnostic algorithms.

The performance of the proposed recurrent feedback classifier is evaluated in terms of ROC Partest graph and RoseplotPartest graph analysis.

It is well known that the performance of binary classification test is examined by statistical measures such as sensitivity and specificity. Sensitivity measures the actual positives that are correctly recognized and specificity measures the actual negative that are correctly recognized. A partest graph is plotted based on the above criteria.

All the partest graph showing the effectiveness of true positive and true negative for all infant cry rhythmic patterns. ROC of pain- hunger [27].



Figure 10: ROC Classification of Pain- hunger.



Figure 11: Partest graph of pain-hunger.



Figure 12: Roseplot of Par test graph of pain-hunger.

ROC analysis of pain- wet diaper



Figure 13: ROC Classification of pain- wet diaper



Figure 14: Partest graph of pain- wet diaper



Figure 15: Roseplot of partest graph of pain and wet diaper.

ROC analysis ofhunger – wet diaper



Figure 16: ROC analysis of hunger wet diaper



Figure 17: Partest graph of hunger- wet diaper



Figure 18: Roseplot ofpartest graph of hunger- wet diaper

Table V:Partest Graph and RoseplotPartest graph considerations.

|  |  |
| --- | --- |
| True Positive (TP) | Baby cry rhythm correctly identified as pain (TP) |
| False Positive (FP) | Baby cry rhythm incorrectly identified as pain (FP) |
| True Negative (TN) | Baby cry rhythm correctly identified as wet diaper/ hunger (TN) |
| False Negative (FN) | Baby cry rhythm incorrectly identified as wet diaper/ hunger (FN) |

It is essential that the values of TP and TN should be always high. It can be inferred from figures (11), (14), (17) that the partest graph of REN classification with rate of FP and FN are found to be absent.

Table VI: ROC analysis for different combination of cry rhythm.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Wet diaper vs hunger | Pain vs hunger | Pain vs wet diaper |
| Prevalence | 50.0% | 50.0% | 50.0% |
| Sensitivity | 99.9% | 100% | 100% |
| Specificity | 99.9% | 99.9% | 99.9% |
| False Positive property | 0.1 | 0.0 | 0.0 |
| False negative property | 0.1 | 0.1 | 0.1 |
| Youden’s Index | 0.997 | 0.998 | 0.998 |
| Positive prediction | 99.9 | 99.9 | 99.9 |
| Positive likelihood ratio | 859 | 860 | 860 |
| Negative Prediction | 99.9 | 100 | 100 |
| Negative likelihood | 0.0 | 0.0 | 0.0 |
| F- measure | 99.9 | 99.9 | 99.9 |
| Test accuracy | 99.9 | 99.9 | 99.9 |
| Miss classification rate | 0.1 | 0.1 | 0.1 |
| Test bias | 1.0 | 1.0 | 1.0 |
| Error odd ratio | 1.0 | ∞ | ∞ |
| Diagnostic odd ratio | 737881 | ∞ | ∞ |
| Discriminant power | 7.4 | ∞ | ∞ |

It can be seen from table VI; ROC analysis confirms the suitability of REN classification for recognizing the infant cry rhythms. All the ROC parameters are found to be within the acceptable range.

1. **CONCLUSION**

This paper discusses quantitative pilot study on the analysis of infant cry rhythm on a specific Indian ethical group. Three conditions are hunger, wet diaper and pain were considered with N=10. The recorded auditory cry rhythms were preprocessing using hamming window to remove the silence segments and the resultant rhythms were segmented using a window of 0.5s. For each segment MFFC’s were calculated and recurrent feedback Elman neural network was applied to perform the binary classification for all the three cry rhythms. The performance evaluation reveled a classification accuracy of 99.9%, 99.9% and 99.9% values for all the three conditions. It can be concluded that proposed pilot study can be applied for validating the large cry rhythm database.

**ACKNOWLEDGMENT**

The authors would like to thank Vision Group of Science and Technology, Government of Karnataka, Bangalore, Karnataka, India for their financial support to carry out this research project (SMYR/2014-2015/GRD No. 294).The authors would like to acknowledge Department of Paediatrics, M S Ramaiah Medical College, Bangalore, India for the assistance and help during recording the cry rhythm. Dr. N Srinivas Murthy, Department of Community medicine, M S Ramaiah Medical College, Bangalore, India for his personal support and assistance for the statistical analysis.

REFERENCES

[1]. Ronald S Illingworth, ”The Normal Child and Some Problems of the Early Years and Their Treatment”, Tenth edition, ISBN: 81-7867-115-8

[2]. O.Wasz-Hockert, J. Lind, V. Vuorenkoski, et al., 1968 ”The Infant Cry A Spectrographic and Auditory Analysis” Spastics International Medical Publications in Association with Willam Heinemann Medical Books Ltd.

[3]. J. Saraswathy, M. Hariharan, SazaliYaacob and Wan Khairuniazam, 2012 “Automatic Classification of Infant Cry: A Review”, International Conference on Biomedical Engineering, 27-28 Feb. 2012,Penang.

[4]. Maria Antonia Ruiz, Luis carlosAltamirona, Carlos Alberto Reyes and Oscar Herrera, 2010 “Automatic Identification Of Qualitatives Characteristics In Infant Cry”, IEEE Spoken Language Technology Workshop, 12-15 Dec 2010, Berkeley, CA.

[5]. Ali Messaoud, ChakibTadj, 2011 “Analysis of Acoustic Features of Infant Cry for Classification Purpose”, 24th Canadian Conference On Electrical And Computer Engineering CCECE, 8-11 May 2011, Niagara falls, ON, Canada.

[6]. Ramu Reddy Venpada, Shiva Ayyappa Kumar. B and K. SreenivasaRao, 2012“ Charaterization of Infant Cries Using Spectral and Prosodic Features”,Indian National Conference Communications (NCC),3-5 Feb 2012,Kharagpur.

[7]. M. Petroni, A. S Malowany, C. C. Johnson and B. J. Stevens, 1995 “ Classifcation of infant cry vocalization using artificial neural network(ANNs) “ International Conference on Acoustics, Speech and Signal Processing, 9-12 May 1995, Detroit, MI.

[8]. A. Zabidi, W. Mansor, Y. K. Lee, A. I. MohdYassin, R Sahak, 2010, “Particle Swarm Optimisation of Mel-frequency Cepstral Coefficients Computation for the Classification of Asphyxiated Infant Cry”, 3rd International Conference on Biomedical Engineering and Informatics, 16-18 Oct. 2010,Yantai.

[9]. AzleeZabidi, Lee YootKhaun, WahidahMansor, IhsanMohdYassin, RohilahSahak, 2010 “Classification of Infant Cries with Asphyxia Using Multilayer perceptron Neural Network”, 2010 Second international Conference on Computer Engineering and Applicarions, 19-21 Mar. 2010, Bali Island.

[10]. A. Zabidi, Lee YootKhaun, W. Mansor, I.M. Yassin, R. Sahak., 2010, “ Optimization of MFCC Parameters using Particle Swarm Optimization for Diagnosis of Infant Hypothyroidism using Multilayer Perceptron”, 32nd Annual International Conference ofEngineering in Medicine and Biology Society , 31 Aug. 2010- 4th Sept. 2010, Buenos Aires.

[11]. Ali Messaound , ChakibTadj, 2011 “ Analysis of Acoustic Features of Infant cry for Classification Purposes”, 24th Canadian Conference On Electrical And Computer Engineering CCECE, 8-11 May 2011, Niagara falls, ON, Canada.

[12]. A. Zabidi, W. Mansor, Lee YootKhuan, I.M. Yassin, R. Sahak., 2010 “ Investigation of Mel Frequency Cepstrum Coefficients Parameters for Classification of Infant Cries with Hypothyroidism using MLP Classifier”, International Joint Conference on Neural Networks, 2010, 18-23 Jul. 2010, Barcelona.

[13]. MahmoudMansouri Jam, HamedSadjedi, 2009” A system for detecting infants with pain from normal infants based on multiband spectral entropy by infants cry analysis”, Second internation Conference On Computer and Electrical Engineering, (Volume 2), 28-30 Dec. 2009, Dubai.

[14]. R. Sahak, W. Mansor, Y. K. Lee, A. I. M. Yassin , A. Zabibi, 2010 “Performance of Combined Support Vector Machine and Principal Component Analysis in Recognizing Infant Cry with Asphyxia32nd Annual International Conference of Engineering in Medicine and Biology Society , 31 Aug. 2010- 4th Sept. 2010, Buenos Aires .

[15]. Jose Orozco Garcia, Carlos A. Reyes Garcia, 2003 “ Mel-Frequency Cepstrum Coefficients Extraction From Infant Cry For Classification Of Normal And Pathological Cry With Feed Forward Neural Networks”, Proceedings on International Joint conference on Neural Network, (Volume 4), 20-24 Jul. 2003.

[16]. Jose Orozco Garcia, Carlos A. Reyes Garcia,2003 ” Implementation and Analysis Of Training Algorithm For The Classification Of Infant Cry With Feed Forward Neural Networks”, International Symposium on Intelligent Signal Processing, 4-6 Sept. 2003.

[17]. Kevin Kuo, 2003, “Feature Extraction and Recognition of Infant Cries”, IEEE International conference on electro/ information technology, 20-22 May 2010,Normal, IL.

[18] J. Saraswathy, M. Hariharan, Wan Khairunizam, SazaliYaacob, N. Thiyagar, 2013, “Infant Cry Classification: Time Frequency Analysis”, 2013 IEEE International Conference on Control System, Computing and Engineering, 29 Nov. - 1 Dec. 2013, Penang, Malaysia

[19] Argel A. Bandala, Allimzon M. Lim, Mark Anthony D. Cai, Allan Jeffrey C. Bacar, and Aynna Claudine G. Mañosca, 2014, “Modelling and Characterization of an Artificial Neural Network for Infant Cry Recognition Using Mel-Frequency Cepstral Coefficients”, 2014- IEEE region 10 Conference TENCON, 22-25 Oct., Bangkok.

[20] Shubham Asthana1, NamanVarma, Vinay Kumar Mittal, 2015 ” An Investigation into Classification of Infant Cries using Modified Signal Processing Methods”, 2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN), 19- 20th Feb, Noida.

[21] YasminaKheddache, ChakibTadj (2013).”Characterization of Pathologic Cries of Newborns based on fundamental frequency estimation”, International journal of scientific Research, 5, 272-276

[22] Alejandro Rosales- Perez, Carlos A. Reyes- Garcia, Jesus A. Gonzalez, Orion F. Reyes- Galaviz, Hugo Jair Escalante, Silvia Orlandi, (2014) “ Classifying Infant Cry patterns by the Genetic Selection of Fuzzy Model”, science direct, biomedical signal processing and control 17, 38-46

[23] Nemir Ahmed Al-Azzawi (2014),”Automatic Recognition system of Infant cry Based on F-Transform”, International Journal of computer applications, volume 102 No-12, 28-32.

[24] BhagatpatilVarsharani V, V.Sardar (2015),” An Automatic Infants Cry Detection Using Linear Frequency Cepstrum Coefficients (LFCC)” International Journal of technology Enhancements And Emerging Engineering research, vol. 2, 29-34.

[25] N. Sriaam, Tejaswini. S, “Infant Cry Detection and Pain Scale management: A Pilot Study”, (2014), International Journal of Biomedical and Clinical Engineering, 3(1), 42-51, January- June 2014.

[26] Elman. J. L 1990, finding structure in time, Cognitive Science, 14, 179-211.

[27] Cardillo G 2006, “Clinical Test Performance of a Clinical test performance of a clinical test based on the Bayes theorem”, http://www.mathworks .com/matlabcentral/fileexchange/12705.