Infant Crying Classification by Using Genetic Algorithm and Artificial Neural Network

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Abstract- Cry as the only way of communication of babies with the surrounding environment can be happened for many reasons such as diseases, suffocation, hunger, cold and heat feeling, pain and etc. So, the analysis and detection of its source are very important for parents and health care providers. So the present study designed with the aim to test the performance of neural networks in the identification of the source of babies crying. The present study combines the genetic algorithm and artificial neural network with (Linear Predictive Coding) LPC and MFCC (Mel-Frequency Cepstral Coefficients) to classify the babies crying. The results of this study indicate the superiority of the proposed method compared to the other previous methods. This method could achieve the highest accuracy in the classification of newborns crying among the previous studies. Developing methods for classification audio signal analysis are promising and can be effectively applied in different areas such as babies crying.

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Keywords: Crying; Mel-frequency cepstral coefficients; Linear predictor coefficients; Neural networks; Genetic algorithms

Introduction

Crying is a physiological action used by infants to communicate with the outside environment. Crying can occur for many reasons, such as diseases, choking, hunger, feeling cold and heat, pain and etc. It seems that all cries are similar, but they are actually very different, and depending on the reasons, have different types and characteristics (1,2). The first studies related to infants' crying were begun in 1964 by the Wasz-Hockert Research Group. Their findings showed that four basic types of infant crying, including pain, hunger, pleasure, and birth, can be identified (2). Analyzing the infants crying signals makes it possible to identify their illness and needs, and therefore it is important for parents as well as health care providers. In recent decades, various studies have been conducted on baby crying to identify diseases (such as hearing problems, central nervous and respiratory systems diseases) or to investigate conditions such as pain, hunger, fear, and sleepiness (3-9). The aim of the present study is to evaluate the functioning of the artificial neural network (ANN) to identify the source of crying in newborn babies.

Materials and Methods

The proposed method in the present study is using a combination of genetic algorithm (GA) and ANN, which was organized according to Figure 1.
Based on Figure 1, each of these steps, including data formation, preprocessing, feature extraction, feature selection, and classification are described below.

Database

The Baby Chillanto database, with 2268 babies' cries, was used in this study. This data collection includes 340 coughing, 350 starvations, 879 deaf, 192 pain, and 507 normal samples. This dataset is accessible from http://ingenieria.uatx.mx/orionfrg/cry.

Preprocessing

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Pre-processing is a necessary step in any successful process in the signal and image analysis, and in fact, it is a correct basis for doing the calculation. The following steps were performed in the pre-processing phase.

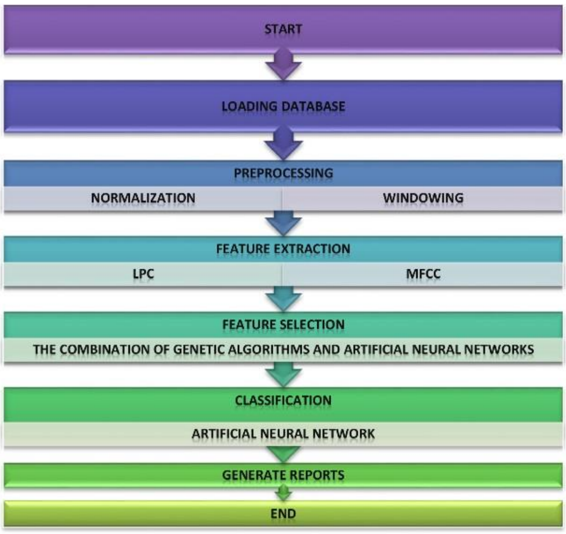

Figure 1. Flowchart of the proposed research method

Windowing

At this stage, each frame is multiplied in a single-window separately in order to reduce the effect of the signal discontinuity at the beginning and end of each frame. Selecting the window is very important because the edges of a frame affect the signal errors. For this reason, the window should be used to narrow the edges of the frame uniformly. Hamming window is an example of windows, which is commonly used in such applications and, hence it was used in this study. If the window displayed with W (n), applying the window will be done according to the following formula (9):

2. $$W(n) = 0.54 - 0.46\ \cos\frac{2\pi n}{N-1}$$

$$0 \leq n \leq N-1$$

* N is the number of samples in a frame, and k is the frame number.

The Hamming window at the beginning and end has values that are close to zero, and the value in the center of the window is close to the one.

Normalization

Normalization is used for better signal analyzing and removing the noises. The signal normalization is accomplished using formula (2).

2. $$Z_i = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

Feature extraction

Feature extraction is a process in which data is linearly or non-linearly forms, is mapped from a higher-dimensional space to a new lower-dimensional one. With regard to the one-second windows which were extracted from the signals, the use of frequency analyzers can provide suitable information for describing the signal (10-13). Such an analysis can be done with the help of LPC and MFCC features. In this study, 354 features (304 features are based on the MFCC, and 50 features are based on the LPC method) have been extracted.

Linear predictive coding LPC

LPC method is widely used in the field of ASR (Automatic Speech Recognition) (14-16). LPC is one of the strongest analytical techniques (17) and can be considered as a subset in the signal processing tools (1). Basically, the LPC function imitates the resonance of the human voice structure (18). The LPC method divides the input signal into the voices to extract the sound features, and then, based on a Hamming window, the LPC analysis takes place by analyzing the correlation coefficients (17,18).

Mel-Frequency cepstral coefficients (MFCC)

The main idea of using the MFCC is to simulate the sensitivity of the human hearing system in speech reception. A lot of applications have used the Mel's frequency (19-22). One of the important reasons for using these coefficients is the high degree of clarity; it means that it demonstrates the minor changes very well. The other strong point of this method is the use of a discrete cosine transform, which can summarize the data and remove the details of the spectral structure (22). For acquiring a real Cepstral, at the first phase, the audio signal is divided into 20-30-ms frames and passed through the hamming window to reduce the discontinuity effect of the edge. Then the signal spectrum is calculated and passes from the filter of the MEL bank. The logarithm is obtained from the previous stage energy, and at the final stage, the discrete cosine transform (DCT) is used. The above process is shown in Figure 2.

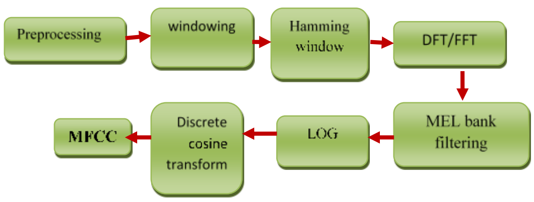

Figure 2.

Then, the MFCC using the sinusoidal transformation are obtained from the following equation:

$$3.\quad CJ = \sum_{i=1}^{M} X_i \cos\left(j \times \left(i - \frac{1}{2} \right) \times \frac{\pi}{M} \right)$$

In the above equation, M and j are the numbers of MFCC and the number of bases, respectively. After calculating these coefficients, the average coefficients in all parts are used as the final attribute vector.

Feature selection

The high number of extracted features (over 350) was not suitable as an input of the neural network. So it was necessary to significantly reduce the number of features. Because the evaluation of all combinations of features is in exponential order as 2^350, which can defeat any modern computer. So, the necessity of using smart features selection techniques was well understood. In this study, to select the appropriate features, the GA has been used. This algorithm was developed by Holland as an innovative optimization technique based on the natural behavior of species optimization. This method is a kind of computer simulation for solving a group optimization problem (23). A GA is a special type of evolutionary algorithm in which there are a number of runs called generations and the number of members called populations. GA uses statistical methods to guide the search operation towards the optimal point in the process that depends on natural selection. Then some of the members are selected for genetic operations such as combination and mutation, and new population members are created. After that, the new population was replaced with the worst fitness among the old population, and this cycle will continue in generations to reach the stopping criteria.

The used GA

In the current study, chromosomes are the selected features in binary form. The number of the population set to 100, the number of generation to 30, the combination parameter equal to 0.5, and the mutation parameter equal to 0.5. In this study, the GA was used to select the features, and the fitness function was derived from the assessment of the accuracy of the ANN in the classification of the status. In fact, in this combination, the ANN does the task of the evaluation function.

Classification

Several pattern recognition techniques have been used to classify infants crying. One of the most widely used techniques is ANN (5,6,24). Also, the other methods such as support vector machine (15,16), Hidden Markov Model (25,26), as well as the other hybrid methods such as the combination of fuzzy logic with the ANN (27-30), or with support vector machine (31), have also been used. In order to simplify the classification problem, binary classifications were selected as follows:

- Natural (class 1: combined 1&2) against Pain (class 3)
- Natural (class 1) against Deafness (class 4)
- Natural (class 1) against Choking (class 5)

Hence three ANN trained separately, each of them used for one of the binary classifications.

Multilayer ANN

In this paper, the three layers' ANN with one hidden layer was used for classification. The number of input neurons was equal to the number of selected features. These features which had been selected by the GA. Subsequently, the data were classified by the ANN.

Training algorithm

The best method to train ANNs is back propagation. To train the network, the Bayesian-regularization (a special version of back propagation) was used. The obvious property of this algorithm is its high accuracy. In order to assess the ANN performance, the following parameters were used. These parameters are defined as:

Table 1. The accuracy parameters based on the confusion matrix

	Confusion matrix
1	True Negative (TN)
2	True Positive (TP)
3	False Positive (FP)
4	False Negative (FN)

The equations of accuracy, sensitivity, and specificity are obtained as follows:

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

6. Sensitivity= $\frac{TP}{TP+FN}$

7. Specificity= $\frac{TN}{TN+FP}$

Results

In the current study, GA was used to select (a subset of 50) features that were injected as inputs of the ANN. Based on the selected features, ANN with selective features was created, trained, and tested on the classification of crying data. Figures (3,4,5), respectively illustrate the training process for classification in classes 1 vs. 3, classes 1 vs. 4, and classes 1 vs. 5:

Figures (6,7,8) show Receiver operating characteristic (ROC) in classes 1 vs. 3, classes 1 vs. 4, and classes 1 vs. 5, respectively.

The ROC chart represents the prediction power of the classifier by displaying the predictive true positive against false positive. The ROC result is a graph that, if it is closer to the upper-left corner, the classifier is better. These diagrams imply the acceptable performance of designed classifiers. Figures (9,10,11) show the confusion matrices of the networks.

Table 2 shows the comparison of the performance of the introduces a method which has presented in this study with methods in the past studies. Based on the findings of this table, the proposed method has better accuracy than other methods

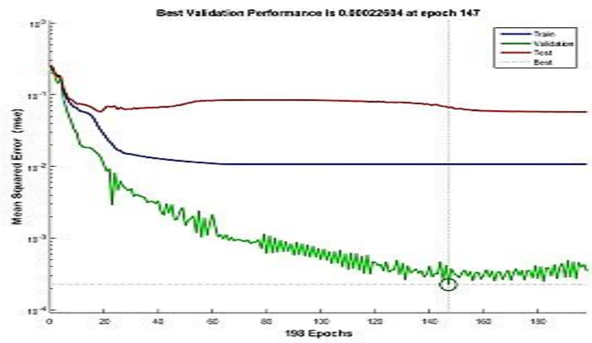

Figure 3. The networks training process in classifying 1 vs. 3

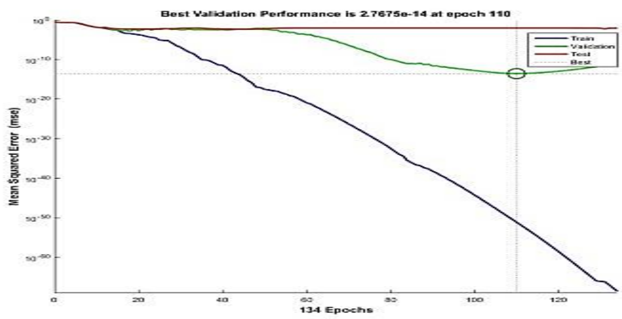

Figure 4. The networks training process in classifying one vs. 4

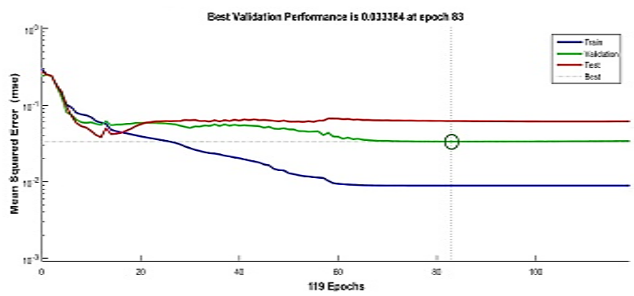

Figure 5. The networks training process in classifying 1 vs. 5

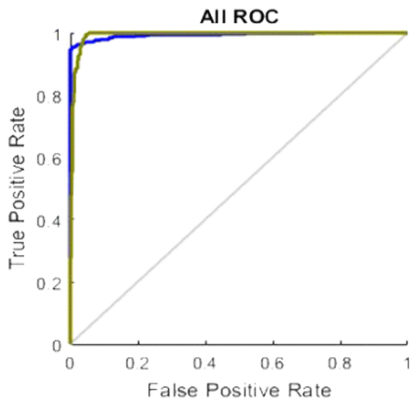

Figure 6. ROC Chart in Classifying 1 vs. 3

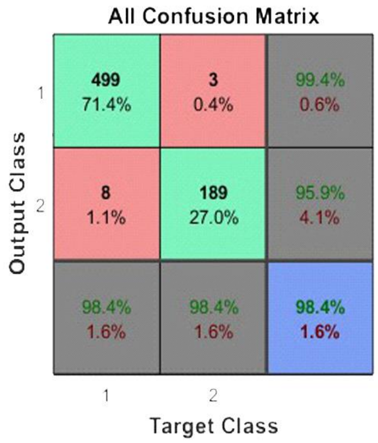

Figure 9. Confusion matrix in classifying 1 vs. 3

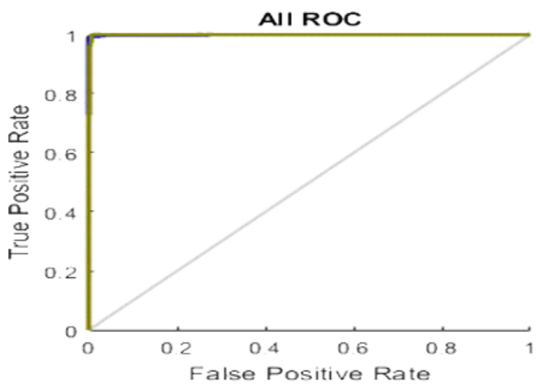

Figure 7. ROC Chart in Classifying 1 vs. 4

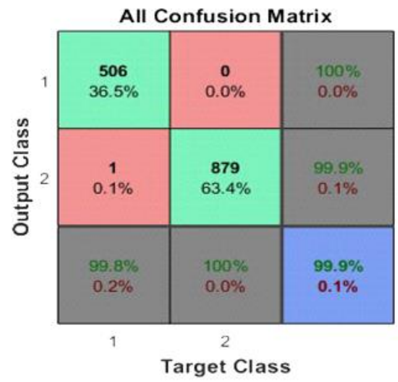

Figure 10. Confusion matrix in classifying 1 vs. 4

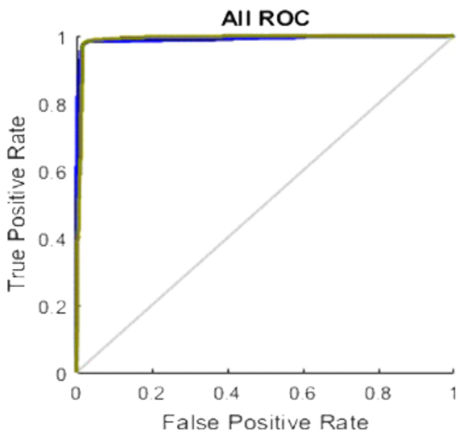

Figure 8. ROC Chart in Classifying 1 vs. 5

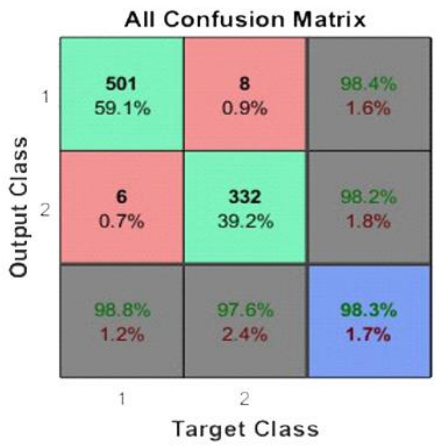

Figure 11. Confusion matrix in classifying 1 vs. 5

Table 2. Comparison of the performance of the proposed method in this study with other methods in the previous studies

First Author	Database / (Number of babies)	Feature Extraction	Classifiers	Best Accuracy
Mahmoud Mansouri Jam (2009) (32)	Baby Chillanto database (2268 crying samples) [8]	Mel-frequency entropy cepstrum spectral coefficients (MFECs)	Multi-layer perceptron ANN (MLP)	88.3 %
R. Sahak (2010) (33)	Database from the University of Milano-Bicocca	Mel-frequency cepstrum coefficients (OLS)	Support Vector Machine	93.16%
Azlee Zabidi (2010) (34)	Baby Chillanto database(2268 crying samples)	Mel- frequency cepstrum coefficients (BPSO)	Multi-layer Perceptron ANN	95.07 %
J.O. Garcia (2003) (20)	53 (Real database)	Mel-frequency cepstrum coefficients and linear prediction coefficients	Scaled Conjugate Gradient ANNs	96.80 % (314 samples)
M. Hariharan (2012) (8)	Baby Chillanto database(2268 crying samples)	Short-time Fourier transform (STFT)	General regression neural network (GRNN	99 %
Gyorgy Varallyay JR. (2004) (35)	37 (Real database)	Fundamental frequency using the smoothed spectrum method (SSM)	--	--
M. Hariharan(2011) (6)	Baby Chillanto database	Wavelet packets	Probabilistic ANN (PNN)	99.49%
Krittakom Srijiranon (2014) (36)	251 (Real database) MPEG-4 video file	MFCC PLP RASTA	Neuro-fuzzy	96.00%
Silvia Orlandi(2016) (37)	38 (Real database)	WEKA software	Random Forest, Logistic curve , Multilayer Perceptron, Support Vector Machine,	87.34
Hesam Farsaie Alaie (2016) (38)	190 (Real database) *	Mel Frequency Cepstral Coefficient(MFCC) static Mel-Frequency Cepstral Coefficients (MFCCs)	Gaussian Mixture Model-Universal Background Model (GMM-UBM)	89.76
Sheinkopf (2012) (9)	39 (Real database)	--	Fundamental frequency(F0) 2-phonation	--
M. Hariharan(2018) (39)	1- Baby Chillanto database(2268 crying samples) 2- database developed using cry samples of Malaysian infants(1089 cry samples)	Wavelet packets Linear Predictive Coding (LPC) Mel-frequency Cepstral Coefficients (MFCCs)	Extreme learning machine (ELM)	In binary or two-class experiments, maximum accuracy of 90.18% for H Vs. P, 100% for A Vs. N, 100% for D Vs. N and 97.61% accuracy for J Vs. Prem was achieved
Wei jer lim (2016) (40)	Baby Chillanto database	Dual-Tree Complex Wavelet Packet Transform (DT-CWPT)	Extreme learning machine (ELM) Support Vector Machine	The results demonstrate that the DT-CWPT feature extraction and classification methods give a high accuracy of 97.87%, 87.26%, 100.00% for asphyxia versus normal, hunger versus pain, and deaf versus normal, respectively.
Asthana et al. (2015) (41)	(Real database)	• short-time Fourier transform, • auto-correlation, • LPC	--	--
Present Study	Baby Chillanto database(2268 crying samples)	*2-LP Analysis* Linear Predictive Coding (LPC) Mel Frequency Cepstral Coefficient(MFCC)	ANN	99.9 %

Discussion

Infants crying are a biological signal through which they can communicate with their surrounding environment. By analyzing baby crying, valuable information can be obtained about the condition of the infants (41). Different studies using different techniques in cry analysis have achieved a variety of findings. The present study was done to identify the source of newborn crying using ANN, and its results indicate that the proposed method has superiority over other methods that were used in the newborn crying classification. So far, several studies have been carried out to analyze the crying signals using various techniques. Studies such as García in 2003, Asthana *et al.*, in 2015, and Hariharan in 2017 with the purpose to determine the cause of the cry, focused on the classification of two types of normal and hypo acoustic crying in newborns. They achieved a high degree of accuracy in the classification using LPC and MFCC to extract audio features and applying the scaled conjugate gradient ANNs and the Gaussian Mixture Model-Universal Background Model (GMM-UBM) as classification algorithm (3,41,42). Also, the study of Rosales-Pérez *et al*., in 2015 by using LPC and MFCC techniques and GSFM classifier, highlighted the application of baby crying analyzing in the early diagnosis of the disease (1). However, the current study is similar to Garcia's study in terms of extracted features and also in the classification method. The difference in the present study is the application of the GA to select and reduce the dimension of the features.

The use of the GA selects the features cleverly, and in fact, the advantage of the current research is the use of GA, which resulted in an accuracy of 99.9%. Some studies, such as the Orlandi *et al*., in 2016, also used this algorithm to select features, except that they used Logistic Curve classifiers instead of the ANN. The result of their study was one of the first steps in establishing a babies' identification system to identify the risk of premature infants (37).

Various feature extraction techniques, such as short-time Fourier transform, auto-correlation, linear prediction analysis, and support vector machine, are modified and used to the classification of cry as an audio signal. Alaie *et al*., (2016), to classify the baby crying pathology, used the Gaussian Mixture Model-Universal Background Model (GMM-UBM); Cano Ortiz *et al*., (2004) and Hariharan (2011) to classify the baby crying in 2 categories (natural and abnormal) used RBF ANN and probabilistic ANN (PNN) respectively (5,6,38). Along with these studies, current research similar to the studies of Alaie *et al*. and Diaz *et al*, used the MFCC to extract the features, and such as the study of Cano Ortiz *et al*., used the ANN classifier and could achieve high accuracy in classification (5,38,43). However, in contrast to the current study, the study by Hariharan *et al*., (2018) and Lim *et al*. (2016) was based on the wavelet analysis, which is, in fact, the simultaneous time-frequency analysis of the signals (6,40)

In some studies, such as Varallyay *et al*., (2004) and Sheinkopf (2012), the crying signals were analyzed in the frequency domain for differential evaluation (4,9). The present study by using MFCC and LPC as a feature extraction technique can analyze the crying frequency. However, the features which had been used in some studies, such as Sheinkopf (2012), were the analysis of the crying signal from the frequency aspect, which was different from the current study (9). In order to achieve the highest accuracy in classifying, some studies such as Srijiranon *et al*., (2014) used the Neuro-fuzzy technique as the hybrid techniques and proved that the use of these combined techniques brings better results (36). The proposed method in the current study, by applying the GA and the ANN, could achieve the highest accuracy in the classification of newborns crying among the previous studies.

The results of the present study indicate the efficacy of the proposed method in comparison to the other methods so that they are promising and can be effectively applied in audio signal analysis in other areas. On the other hand, different types of methods can be tested by replacing each of the three parts of this study: feature extraction, feature selection, and classification. For example, wavelet-based feature extraction can be used. Even more other evolutionary algorithms, such as PSO, can be used in the feature selection phase. This can happen in the classification phase too.

Conflicts of Interest

The authors declare that there is no conflict of interest

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