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Improved binary dragonfly optimization algorithm and wavelet packet based non-linear features for infant cry classification

M. Hariharan[a,*], R. Sindhu[b], Vikneswaran Vijean[c], Haniza Yazid[c], Thiyagar Nadarajaw[d], Sazali Yaacob[e], Kemal Polat[f]

[a] *Department of Biomedical Engineering, SRM Institute of Science and Technology, (Deemed to be University under section 3 of UGC Act 1956), Kattankulathur, 603203, Tamil Nadu, India*
[b] *School of Computer and Communication Engineering, Universiti Malaysia Perlis (UniMAP), Campus Pauh Putra, Perlis 02600, Malaysia*
[c] *School of Mechatronic Engineering, Universiti Malaysia Perlis (UniMAP), Campus Pauh Putra, Perlis 02600, Malaysia*
[d] *Consultant Pediatrician & Adolescent, Department of Pediatrics, Hospital Sultanah Bahiyah, Alor Setar, Kedah 05460, Malaysia*
[e] *Universiti Kuala Lumpur Malaysian Spanish Institute, Kulim Hi-Tech Park, Kulim, Kedah, Malaysia*
[f] *Department of Electrical and Electronics Engineering, Faculty of Engineering and Architecture, Abant Izzet Baysal University, Bolu 14280, Turkey*

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Background and objective: Infant cry signal carries several levels of information about the reason for crying (hunger, pain, sleepiness and discomfort) or the pathological status (asphyxia, deaf, jaundice, premature condition and autism, etc.) of an infant and therefore suited for early diagnosis. In this work, combination of wavelet packet based features and Improved Binary Dragonfly Optimization based feature selection method was proposed to classify the different types of infant cry signals.
Methods: Cry signals from 2 different databases were utilized. First database contains 507 cry samples of normal (N), 340 cry samples of asphyxia (A), 879 cry samples of deaf (D), 350 cry samples of hungry (H) and 192 cry samples of pain (P). Second database contains 513 cry samples of jaundice (J), 531 samples of premature (Prem) and 45 samples of normal (N). Wavelet packet transform based energy and non-linear entropies (496 features), Linear Predictive Coding (LPC) based cepstral features (56 features), Mel-frequency Cepstral Coefficients (MFCCs) were extracted (16 features). The combined feature set consists of 568 features. To overcome the curse of dimensionality issue, improved binary dragonfly optimization algorithm (IBDFO) was proposed to select the most salient attributes or features. Finally, Extreme Learning Machine (ELM) kernel classifier was used to classify the different types of infant cry signals using all the features and highly informative features as well.
Results: Several experiments of two-class and multi-class classification of cry signals were conducted. 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% J Vs Prem was achieved using the features selected (only 204 features out of 568) by IBDFO. For the classification of multiple cry signals (multi-class problem), the selected features could differentiate between three classes (N, A & D) with the accuracy of 100% and seven classes with the accuracy of 97.62%.
Conclusion: The experimental results indicated that the proposed combination of feature extraction and selection method offers suitable classification accuracy and may be employed to detect the subtle changes in the cry signals.

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1. Introduction

Crying is a common symptom in the first 3 months of life and carries the information about the neurological and medical status of infants [1]. According to statistics in 2015, highest rate of infant deaths within the first year of life was recorded in the African region (55 per 1000 live births) than the European region (10 per 1000 live births) [2]. Every year, 15 million babies are born too early and this number is rising. The rate of preterm birth ranges from 5% to 18% of babies born across 184 countries [3]. Due to congenital anomalies, an estimated 303,000 new-borns die within 4 weeks of birth every year worldwide [4].

Annual infant deaths have declined from 8.9 million in 1990 to 4.5 million in 2015 [2]. These statistics are completely independent of the information present in the infant cries. Parents and other

* Corresponding author.
E-mail address: hariharan.m@ktr.srmuniv.ac.in (M. Hariharan).

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care-givers respond to the needs of infant's only by hearing the sound of crying. Parents of infants who suffer from excessive crying seek medical care in the first few months of life, since they are more likely to experience behavioural problems in childhood [5]. The focus of the cry researches is to look for differences between the cry signals of typically developing infants as well as the infants who are at risk of several diseases and developmental disorders. Differences in acoustic parameters are due to the disturbances of vocal neuromuscular maturation, to brain disorders, to central nervous system insults, to various developments disorders (hearing impairment or autism), and to genetic defects (the down syndrome, morbus crabbe and cri-du-char syndrome) [6]. Crying is originated in the central nervous system and it involves a coordinated effort of several brain regions, mainly brainstem and limbic system [7]. Hence, cry signals may be useful in the early detection of the infants who are at risk of several diseases and developmental disorders. Early detection of risks for vulnerable children would allow implementing prevention strategies and policies in childhood [8]. The aim of this paper is to examine the ability of information embedded in infant cries to distinguish between several pathologies thereby cry analysis could be applied successfully in identifying the cause of crying and in the early detection of the infants who are at risk of developmental difficulties.

Many studies have been carried out in recent years to effectively classify the different types of cry signals [9–19]. Data collection, feature extraction, feature reduction and classification are four major stages in infant cry signals classification. Statistically significant database is required for the development of reliable infant cry analysis tools. Most of the researchers have carried out their study and presented the results based on the self-collected database with different types of infant cry, varied recording conditions, age groups, diverse pathologies and different weights [9]. Self-collected databases are not available for research purpose and comparison of the proposed algorithms. Representation of cry signals using quantifiable parameters is a challenging task to differentiate subtle changes present in the cry signals. Researchers have applied and extracted features from the recorded cry signals using time, frequency and time-frequency domain based signal processing algorithms [10–13,17,18,20–22]. Mel-frequency Cepstral Coefficients (MFCCs) and Linear Predictive Coding based features (LPCs) were widely used as signal processing techniques to represent the recorded cry signals [10–13,17,18,20–22].

Wavelet packet transform based energy and entropy features [23,24], statistical features derived from time-frequency plots [17,25] and bi-spectrum based features [26,27] were also used to quantify the recorded signals in terms of features. Several acoustic characteristics (fundamental frequency, phonation, hyper phonation, dysphonation, number of changes in cry mode and unvoiced sound) were measured from the infant cries and found a significant difference between the cries of healthy new-borns and newborns with pathologies [13,28]. Using the above feature extraction methods, reasonable success has been achieved. However, as signal processing algorithms are advancing, it is suitable to explore new signal processing algorithms to improve the current performance of the infant cry classification system both in binary and multiclass experiments. After the extraction of many features, dimensionality reduction and feature selection techniques are applied to beat the curse of dimensionality issue. In the area of automatic recognition infant cry system, researchers have applied Principal Component Analysis (PCA) [22,29–31] and meta-heuristic optimization (Genetic Algorithm -GA and Particle Swarm Optimization-PSO) based feature selection algorithms [11,12,15,30,32–35] to select the most discriminative features from the extracted features. To classify the recorded cry signals as normal or abnormal, researchers have used various classifiers namely feed-forward neural network trained by adaptive learning rate backpropagation [22,30,35,36], time-delay neural network trained by scaled conjugate gradient algorithm [22,30,35,36], probabilistic neural network [17,20,23], general regression neural network [25,37], support vector machine [38,39], genetic selection of fuzzy model [11,15], adapted boosting mixture learning method based Gaussian mixture model [10,14], fuzzy relational neural network [34,40] and Extreme Learning Machine (ELM) [41]. Some of the researchers have used feature extraction and statistical analysis to depict their findings [13,42,43].

Normal (N) cry signals and different types of cry (hunger-H and pain-P) or pathological cry signals (asphyxia -A, deaf-D, pre-term- Prem, jaundice-J, autistic) and several other diseases were used by the researchers [10–12,27]. Binary/two class classification/recognition experiments (normal Vs pathological) were conducted and reported in most of the published works [10–12,14,17,18,23,26,32,33,39] and less research works have been conducted on the classification of different types of pathological cry signals along with normal cry signals [20–22,29–31,35,36,40,44]. Classification of different types of cry signals using a single classifier becomes difficult as several factors affect the cry characteristics. In binary/two-class classification experiments (normal Vs pathological), overall accuracy between 90.68% and 99.42% was obtained [10–12,14,17,18,23,26,32,33,39]. Classification of infant cry signals as a multi-class problem is less explored, however, researchers have conducted the experiments of classification of three classes of cry signals from Baby Chillanto® infant cry database (Normal, Deaf and Asphyxia) and they have reported the accuracies between 88% and 98.67% [20–22,29–31,35,36,40,44].

Various signal processing and classification algorithms have been proposed for infant cry classification. Researchers have not yet found sufficient or suitable features for reliably describing the minute changes in the cry signals which means that the problem of determination of the most informative features for infant cry classification is an open issue. Infant cry classification performance can be improved significantly if appropriate and reliable features are extracted. Feature selection/reduction techniques are to be applied before classification to select highly informative features for reducing the processing time without degrading the classifier performance.

Selection of most suitable classifier for infant cry classification is a challenging issue as each classifier has its own advantages and limitations. Higher classification accuracies were achieved for binary classification task, but multi-class or classification of different cry patterns is still a challenging task. Hence, in this work, wavelet packet transform based energy and non-linear entropies (Shannon Entropy- ShEn, Renyi Entropy – ReEn, Tsallis Entropy – TsEn, Fuzzy Entropy – FuEn, Permutation Entropy – PeEn, Approximate Entropy – ApEn, Sample Entropy – SaEn) were proposed for better representation of infant cry signals. After feature extraction, highly informative features were selected using Improved Binary Dragonfly Optimization (IBDFO) algorithm. A wrapper based feature selection algorithm was developed and ELM with kernel [45] was used as classification algorithm. Two-class and multi-class classification experiments were conducted before and after feature selection. Best feature set was obtained with less number of features compared to the size of the original feature set and thereby the accuracy of infant cry classification has been improved.

2. Cry database

In this work, two different databases were used for analysis. First database is from the property of INAOE-CONACyT, Mexico (Baby Chillanto® infant cry database) [46–49]. This database consists of different types of cry signals such as normal (full-term infants), asphyxia (infants who are suffered from birth asphyxia), deaf (Infants who are hearing impaired), and pain (cry signals

Table 1
Details of databases used in this work.

Database	Types of cry signals	Number of infants	Number of 1 s samples
Database 1 (Baby Chillanto® database, Mexican Infants)	Normal (N)	5	507
	Asphyxia (A)	6	340
	Deaf (D)	6	879
	Hungry (H)	32	350
	Pain (P)	21	192
Database 2 (Malaysian Infants)	Normal (N)	5	45
	Jaundice (J)	17	513
	Pre-term (Prem)	24	531

were recorded during immunization process) and hunger (cry signals were recorded only after infant gets hungry). In this database, cry signals were recorded at two different sampling frequencies (8 kHz, 11.025 kHz and 22 kHz). The cry signals were segmented into 1 s samples and labelled according to their cry type by researchers of INAOE-CONACyT, Mexico. The infant cry samples were collected directly by specialized paediatricians from just born to 6 months old infants. The second database was developed using cry samples of Malaysian infants (Normal -N, Infants with Jaundice (J) and Pre-term -Prem). Infants with jaundice were diagnosed with bilirubin blood test and their bilirubin levels are between 9 and 17 mg/dL. Gestational period of pre-term infants is between 25 and 35 weeks. Normal infants are full-term i.e., they are delivered after the completion of 37 weeks. All the cry samples were recorded using standard operating procedure. Cry signals were recorded by a high performance Shotgun microphone (condenser type, EM-9600), which was placed 10–30 cm away from the infant's mouth. The recordings were made in a neonatology (neonatal intensive care unit – NICU) department of Hospital Sultanah Bahiyah Alor Setar, Kedah. The sampling frequency of the recorded signals was fixed to 44.1 kHz. Prior to an infant's participation in the recording, the written informed consent was taken from the parents or guardians of the infants. Then, a copy of the same was given to the parents or guardians of the infants. Data collection procedure of second database was approved by the Ministry of Health, Malaysia (NMRR-13-530-15,160). Details of types of cry signals, number of infants and number of 1 s samples were tabulated in Table 1.

Cry samples from these two databases are combined together and used for analysis. Therefore, the database contains 3357 cry samples. Length of cry samples was fixed at 1 s. All the cry signals were recorded at different sampling frequencies. Hence, all of them were down-sampled to 8 kHz before feature extraction. In the second database, the down-sampled cry signals were segmented into non-overlapping frames with a length of 32 ms (256 samples) to separate cry and non-cry/silent portions from premature and jaundice cry signals based on the energy of the frames. Low energy frames were discarded and the frames with high energy (cry portions) were merged for further analysis [50].

Fig. 1 shows the block diagram of the proposed infant cry classification system. The proposed system includes analysis of cry signals using proposed feature extraction method, Meta-heuristic optimization based feature selection (wrapper based) and classification using the selected features with ELM kernel classifier.

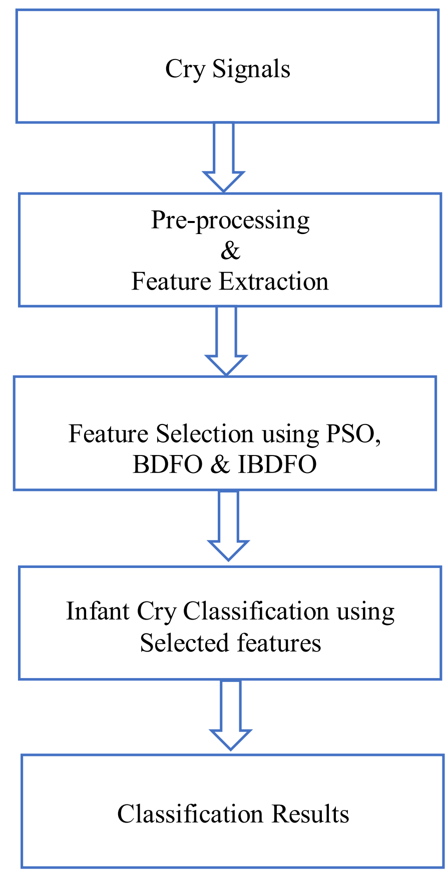

Fig. 1. Block diagram of the proposed infant cry classification system.

3. Feature extraction

Extraction of salient features for accurate classification of different types of infant cries is an open issue. Several feature extraction methods (MFCCs, LPC based cepstral parameters, time-frequency analysis based features and HOS based features) have been proposed for the representation of cry signals in the literature. In this work, wavelet packet transform based energy and non-linear entropies were extracted for better representation of infant cry signals and also for improved classification accuracy. MFCCs and LPC based cepstral parameters were also extracted in addition to the proposed features.

3.1. Extraction of MFCC and LPC based features

Fig. 2 depicts the steps involved in the extraction of Mel frequency cepstral coefficients and LPC based cesptral parameters(LPC, LPCCs and WLPCCs) [51,52].

In the extraction of MFCCs and LPC based cepstral features, the cry signals were passed through a first order low pass filter to spectrally flatten the signal and to make it less prone to finite precision effects later in the signal processing [52]. The first order pre-emphasis filter is defined as

$$H(z) = 1 - a * z^{-1} \qquad 0.9 \le a \le 1.0 \tag{1}$$

The commonly used a value is $15/16 = 0.9375$ or 0.95 [52]. In this work, the value of a was set equal to 0.9375.

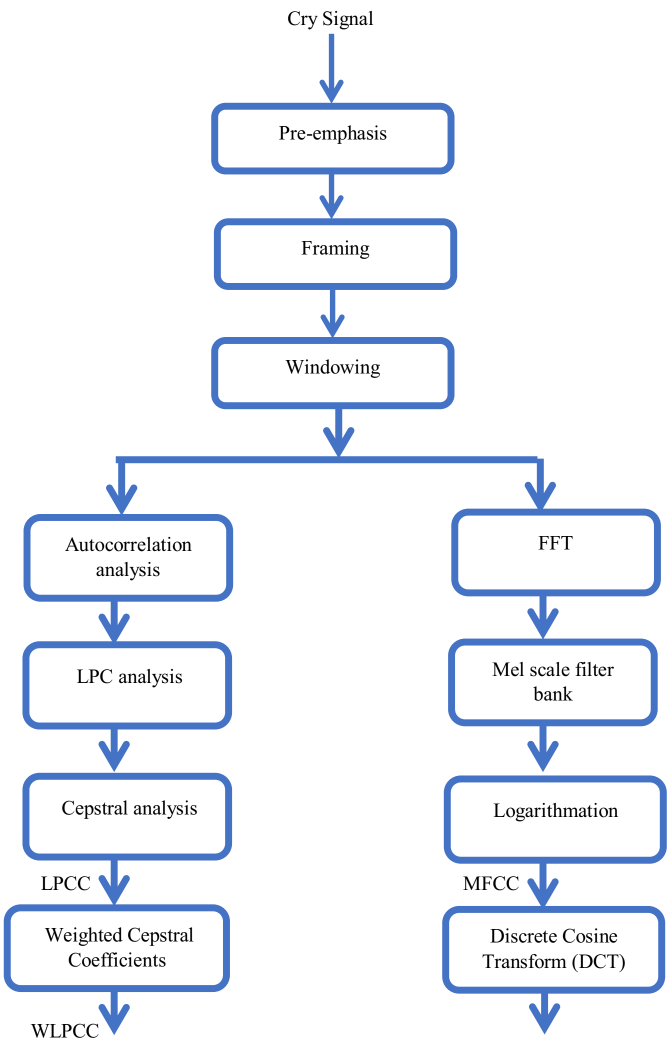

Fig. 2. Steps involved in the extraction of MFCCs and LPCs based cepstral features.

After pre-emphasis, the cry signals were segmented into frames (50 ms) with 50% overlap and windowed by Hamming window to minimize the signal discontinuities and spectral distortion. The fast Fourier transform (FFT) was applied to calculate the spectrum of the each frame, followed by Mel-scaled mapping to get the spectrum in Mel domain. The Mel-frequency scale is linear frequency spacing below 1 kHz and a logarithmic spacing above 1 kHz (13 linear filter banks +27 logarithmic or non-linear filter banks). Logarithmic Mel spectrum was obtained by taking the logarithm value of the signal after the Mel filters. Finally, discrete cosine transform was applied to 40 logarithmic Mel filter bank energies and only 16 cepstral coefficients were kept, while others have been discarded [51]. From each frame, 16 MFCCs were extracted and averaged over all the frames. The steps involved in the LPC based coefficients are as follows: pre-emphasis, framing, windowing, autocorrelation analysis and conversion of autocorrelation coefficients to an LPC parameter set using Durbin's method [52]. LPCCs can be derived directly from the LPCs using recursion technique. The weighted LPCCs were derived from LPCCs by appropriate weighting. The suitable value for order of LPC was found between 8 and 16 and set at 16. From each frame, 56 coefficients (16 LPCs + 24 Linear Predictive Cepstral Coefficients-LPCCs + 16 Weighted LPCCs) were extracted and averaged over all the frames.

3.2. Extraction of wavelet packet based energy and Non-linear entropies

Wavelet or wavelet packet transform has been applied in various signal and image processing for the past three decades [24,37,46,53–62]. Wavelet packet transform is a generalization of wavelet transform and offers rich signal analysis. In both wavelet and wavelet packet transform, signals are decomposed into approximation and detail. In wavelet transform, only approximation is used in further decompositions, while in wavelet packet transform both approximation and detail are used in further decompositions. Infant cry signals are decomposed into 5 levels using the wavelet packet transform with 'dmey' wavelet [24] and a total of 62 sub-bands were obtained. After that, energy and entropy based features have been calculated. Shannon, Renyi, Tsallis, permutation, fuzzy, approximate and sample entropy were computed. For each cry signal, a total of 496 (62×1 energy + 62×7 entropies) features was extracted.

3.2.1. Energy

Energy [59] of each wavelet packet sub-band coefficients was calculated using the following equation

$$EGY = \sum_{j,k} \left| C_{j,k} \right|^2 \tag{2}$$

$j = 1,2,3, \ldots., J$ and $k = 1,2,3, \ldots, N$, where J is the number of decomposition level and N is the number of wavelet packet coefficients in the respective sub band.

3.2.2. Shannon entropy

Entropy [17] of each wavelet packet sub band coefficients was calculated using the following equation

$$ShEn = -\sum_{j,k} C_{j,k} \log\left(C_{j,k}\right) \tag{3}$$

$j = 1,2,3,\ldots J$ and $k = 1,2,3,\ldots N$, where J is the number of decomposition level and N is the number of wavelet packet coefficients in the respective sub band.

3.2.3. Renyi entropy

Using the principle suggested by Renyi [63], it is used to approximate the spectral complexityof a time series signal [63,64] and is given by

$$ReEn = \frac{1}{1-\alpha} log\left(\sum_{j,k} C_{j,k}^{\alpha}\right) \tag{4}$$

$\alpha \neq 1$ and α was fixed as 2 in this work.

3.2.4. Tsallis entropy

Tsallis entropy is an extension of extensive entropy and used to study the complexity of non-additive systems [64–66]. The abnormal experimental phenomena of complex systems cannot be explained by extensive entropy. The expression to compute Tsallis entropy is given as follows [64–66]:

$$TsEn = \frac{1}{\alpha - 1}\left(1 - \sum_{j,k} C_{j,k}^{\alpha}\right) \tag{5}$$

$\alpha \neq 1$ and α was fixed as 2 in this work.

3.2.5. Permutation entropy

Bandt and Pompe have introduced permutation entropy to measure the complexity of the time series by comparing neighbouring values [67]. Embedded dimension m and time lag τ are to be determined in advance for the computation of permutation entropy.

Embedded vector is formed based on the parameters m and τ from a time series and permutation entropy is calculated. The details of mathematical description of PeEn can be found in [67–69]. Parameters m and τ were fixed as 3 and 1 respectively.

3.2.6. Fuzzy entropy

Zadeh introduced the concept of "fuzzy sets" and Fuzzy entropy was computed by employing the family of exponential functions as the fuzzy membership function to get a fuzzy measurement of two vectors' similarity based on their shapes [70,71]. Three parameters (m, r f and n) must be fixed for the calculation of fuzzy entropy, where m is the length of the sequence, r is the width of the boundary of the exponential function and n is the gradient of the boundary of exponential function. In this work, these three parameters ($m = 4$, $r = 0.2$ and $n = 2$) were fixed through experiments. The detailed mathematical description of FeEn can be found in [70,71].

3.2.7. Approximate entropy

Approximate entropy was proposed by Pincus to measure the randomness or the regularity of a time series [72,73]. Initially, it was applied to relatively short, noisy datasets. ApEn measure is approximately equal to the negative average natural logarithm of the conditional probability that the trends of time series that is close to each other will remain close at the next point [64,72,73]. ApEn is scale invariant and model dependent. Higher degree of regularity can be measured from the low values of ApEn, while a low degree of regularity from high values of ApEn. In the computation of ApEn, two parameters, run length m and tolerance window r must be fixed. More details of ApEn can be found in [64,72,73]. In this work, m and r values were fixed as 2 and 0.2 respectively.

3.2.8. Sample entropy

Richman and Moorman have proposed the modified version of ApEn, which was named as sample entropy [74]. It can also be used as a measure of data regularity. It is a measure equal to the negative natural logarithm of the conditional probability that two sequences similar for m points remain similar at the next point, where self-matches are not included in calculating probability [64,74]. SaEn is largely independent of the length of time-series and displays relative consistency. In the computation of SaEn, two parameters, run length m and tolerance window r must be fixed. More details of SaEn can be found in [64,74]. In this work, m and r values were fixed as 2 and 0.2 respectively. All the parameters in entropies were fixed empirically through simulations.

4. Feature selection

The main aim of feature selection is to select most relevant features/attributes from a huge number of available features/attributes to achieve comparable or even better classification accuracy than using all the attributes/features [75–78]. Generally, feature selection methods are divided into three categories namely filter, wrapper and embedded. In filter based methods, the quality of the features is evaluated by using either 'relevance/redundancy index' or scoring' . Using these criteria, features can be effectively ranked in descending order based on their individual score and then a certain number of top features are selected. These methods focus on the utility of an individual feature only and ignore the combination of features and hence the optimal size of a feature subset is hard to be determined [75–78]. Wrapper methods include search strategy and a learning algorithm as part of the evaluation function. Though these methods guaranteed good results in some fields, feature subset produced is very specific to the used learning algorithm. Wrapper methods are computationally expensive and their results are not stable due to its stochastic nature of search strategy whereas filter methods are computational inexpensive (helps to reduce the size of feature set quickly) [75–78]. Both filter and wrapper based feature selection approaches have its own advantages and limitations. In this work, binary version of dragonfly optimization algorithm (BDFO) based feature selection was proposed to select information rich features from the extracted features. A wrapper based feature selection method was developed and ELM kernel was used as learning algorithm in the wrapper model. Elitism and new updating mechanism were introduced in the basic BDFO to enhance its performance during optimization of cry features.

4.1. Dragonfly optimization

DFO was recently developed by Mirjalili based on the static and dynamic swarming behaviours of dragonflies in nature [79]. In meta-heuristics optimization, exploration and exploitation are the two essential phases and they are designed in DFO by modelling the social interaction of dragonflies in searching for foods and avoiding enemies when swarming dynamically or statistically. Dragonflies are fancy insects and their life cycle includes two main stages namely nymph and adult. Major portion of their lifespan was spent in nymph and become adult after they undergone metamorphism. Exploration phase is modelled by flying behaviour of sub-swarms over different areas in a static swarm. Exploitation phase is achieved as dragonflies fly in bigger swarms and along one direction. Three important behaviour of swarms are explained and mathematically shown as follows [79]:

Individuals are separated from other individuals in the neighbourhood to avoid static collision, which is known as separation and is calculated as follows [79]:

$$S_i = -\sum_{j=1}^{N} X - X_j \tag{6}$$

where X and X_j are the position of the current individual and position of jth neighbouring individual respectively. N is the number of neighbouring individuals.

Velocity matching of individuals with the other individuals in the neighbourhood is known as alignment and is expressed as follows [79]:

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N} \tag{7}$$

where V_j is the velocity of jth neighbouring individual.

Attraction of individuals towards the centre of the mass of the neighbourhood is called as cohesion [79].

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - X \tag{8}$$

where X and X_j are the position of the current individual and position of jth neighbouring individual respectively. N is the number of neighbouring individuals.

The main aim of any dragonfly is survival; all the individuals should be attracted towards food sources and distracted from enemies. Attraction towards a food source is calculated as below [79]:

$$F_i = X^+ - X \tag{9}$$

Distraction from the enemy is calculated as follows [79]:

$$E_i = X^- + X \tag{10}$$

where X, X^+, X^- are the position of the current individual, position of the food source and position of the enemy respectively. The above five concepts helped to simulate the behaviour of dragonflies in both dynamic and static swarms. There are two vectors considered: step (ΔX) and position (X) to update the position of artificial dragonflies in a search space and simulated their movements. The step vector is analogous to the velocity vector in particle swarm optimization (PSO), and the DFO algorithm is developed based on the framework of the PSO algorithm [79]. The step vector [79] is updated using the following Eq. (11):

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_t \quad (11)$$

where s, a, c, f and e are the weight vectors for separation, alignment, cohesion, food and enemy respectively. w is the inertial weight and t denotes iteration counter.

Then, the position vectors are calculated as follows [79]:

$$X_{t+1} = X_t + \Delta X_{t+1} \quad (12)$$

With the five different factors, different explorative and exploitative behaviours are simulated during optimization. To enrich the randomness, stochastic behaviour and exploration behaviour of the dragonflies can be increased by introducing a levy flight in the search space using a random walk when there is no neighbouring solutions [79].

Pseudo Code of the BDFO algorithm [79]

```
Initialize the dragonflies population Xi(i=1,2,3,...,n)
Initialize step vectors ΔXi (i=1,2,3,...,n)
While the end condition is not met
    Calculate the objective values of all dragonflies
    Update the food source and enemy
    Update w,s,a,c,f and e
    Calculate S, A, C, F and E using Eqs. (6)–(10).
    Update step vectors using Eq. (11)
    Calculate the probabilities using Eq. (13)
    Update position vectors using Eq. (14)
End While
```

Continuous DFO is converted to binary DFO without modifying the structure by employing a transfer function. s-shaped and v-shaped transfer functions are commonly used. The v-shaped transfer functions are better than the s-shaped transfer functions as they do not force the particles to take values of 0 or 1. Transfer functions receive velocity (step) values as inputs and return a number between 0 and 1. The following transfer function is utilized to calculate the probability of changing position for all artificial dragonflies [79].

$$T(\Delta X) = \left| \frac{\Delta X}{\sqrt{1 + \Delta X^2}} \right| \quad (13)$$

To update the position of search agents in binary search spaces, the following new updating position formula is then employed [79].

$$X_{t+1} = \begin{cases} \sim X_t & rand < T(\Delta X_{t+1}) \\ X_t & rand \geq T(\Delta X_{t+1}) \end{cases} \quad (14)$$

With the transfer function and new position updating equations, the BDFO will be able to solve binary problems. The main step in the BDFO based feature selection is the goodness/fitness evaluation procedure. Generally, the two popular measures such as classification accuracy and error rate will be used in designing a fitness function. In this work, the following equation was used to evaluate the fitness of the each dragon fly.

$$Fitness = \alpha * (Error\ Rate) + (1 - \alpha) * \frac{number\ of\ selected\ features}{Total\ number\ of\ features} \quad (15)$$

where α is fixed between 0 and 1 to give relative importance to classification performance (error) and the number of features. The value for α was fixed as 0.9 since the classification performance is more important than the number of features. Based on the fitness function (Eq. (15)), the quality of each search agent was calculated. After evaluating the fitness of all dragon flies, best or highly fit two dragonflies and its fitness were saved. Food source and enemy were updated and then the velocity (step) and position of each dragon fly were updated.

Flow chart of the proposed IBDFO was shown in Fig. 3, which explains the implementation of IBDFO. Food source (best solution and position) was updated in two situations. In the first situation, current food fitness and position were updated, if the classification performance (Error rate) of the dragon fly's new position was better than that of previous dragon fly's food position. In the second situation, current food fitness was updated, if the number of features was smaller than previous best food position and the classification performance (Error rate)of the new position was the same or better than the current food fitness. After that, elitism was applied i.e, least fit or worst two dragonflies and its fitness was replaced with highly fit dragonflies and its fitness. BDFO simulation will stop when a pre-defined stopping criterion, e.g the maximum number of iterations or an optimal fitness value has been reached. Maximum number of iterations was fixed as 100.

5. Results

From the literature, it can be observed that the high infant cry recognition accuracies can be achieved for the recognition between two classes of infant cries, however the recognition of different cries (multi-class) is still challenging. To enhance the infant cry recognition accuracy, wavelet packet based non-linear entropies were proposed. These entropies were concatenated with conventional short-term cepstral parameters and used for analysis. Cry signals from two different databases were mixed and subjected to feature extraction. A total of 568 (496 wavelet packet based features + 56 LPC based cepstral features + 16 MFCCs) features were derived from the recorded cry signals. Improved BDFO based feature selection was proposed which consists of a new food source update mechanism and elitism strategy to select the most salient features and to enrich the feature selection process as well. A wrapper based feature selection technique was implemented. ELM kernel was used as learning algorithm. In this ELM kernel implementation, the hidden layer feature mappings need not to be known to users and Gaussian kernel was used [45]. Best values for positive regularization coefficient (ε) and Gaussian kernel parameter were found and fixed empirically after several experiments. The proposed method was implemented under MATLAB platform using a LAPTOP with Intel Core i7–2.2 GHz and 8 GB RAM. The performance of IBDFO was compared with its basic BDFO and PSO. Twenty-five independent simulations (runs) of IBDFO, BDFO and PSO based feature selections were conducted. Most frequently selected features were identified during twenty-five independent simulations and used for infant (two-class and multi-class) cry recognition experiments. Table 2 shows the list of original features and number of selected features from each feature set using PSO, BDFO and IBDFO.

As observed from Table 2, number of features selected using IBDFO is less, when compared to BDFO and PSO. Average number of features selected was 204, 251 and 276 using IBDFO, BDFO and PSO respectively. Fig. 4 shows the convergence curve of three optimization algorithms. From the Figure, it can be seen that IBDFO converged quickly than BDFO and PSO. The convergence of IBDFO tends to accelerate as iteration increases. This is due to the improved food source update mechanism proposed for BDFO which assists it to look for the promising regions of the search space.

Figs. 5 and 6 illustrates the comparison of classification accuracy and geometric mean of three methods. The results obtained from IBDFO were better than results obtained from BDFO and PSO.

Tables 3–5 tabulates the two-class, three-class and seven-class infant cry recognition experiments. For two-class experiments, sensitivity (SE), specificity (SP), overall accuracy (ACC), area under re-

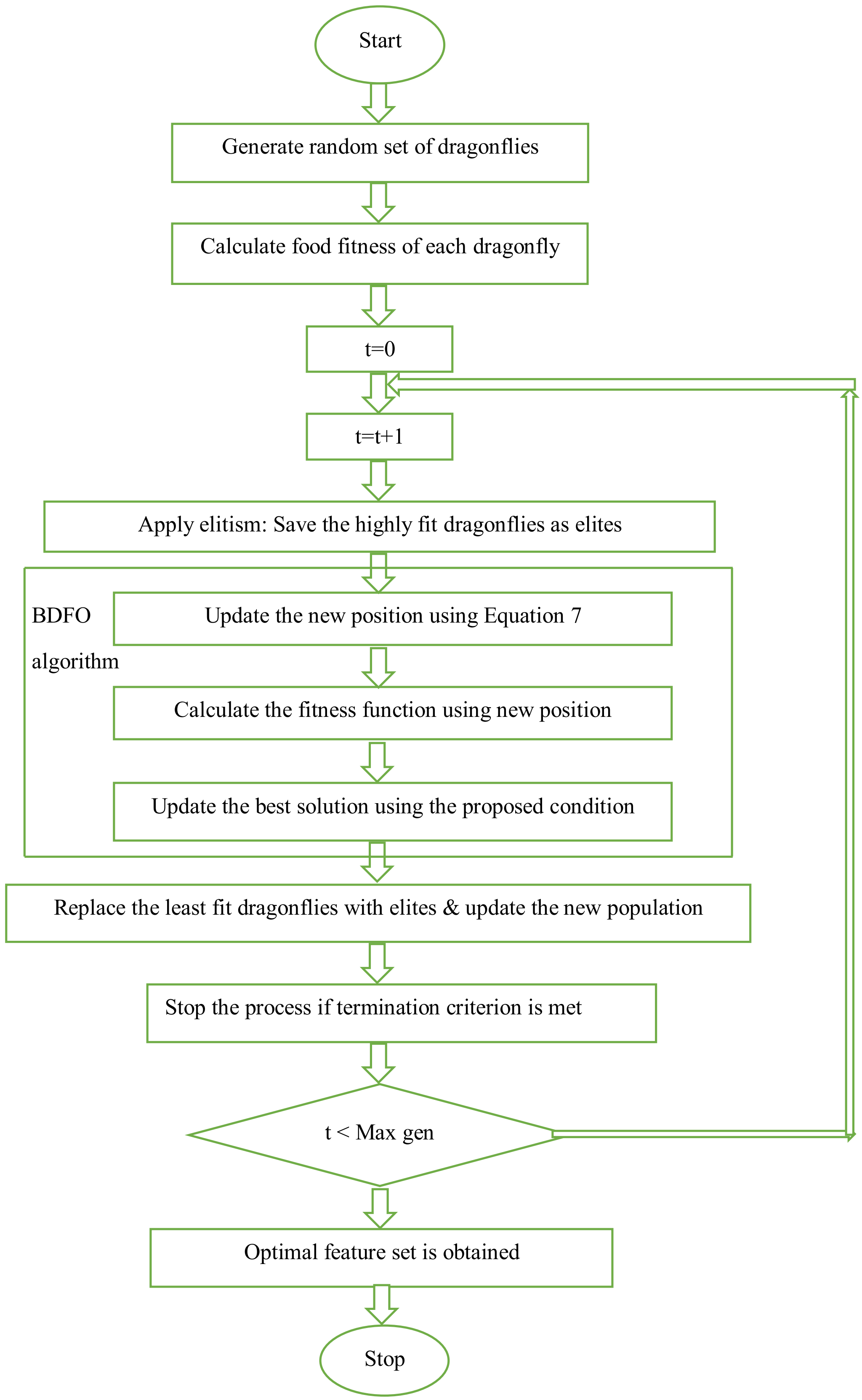

Fig. 3. Flowchart of the proposed IBDFO.

Table 2
List of original features and number of features selected using PSO, BDFO and IBDFO.

Feature list	Size of original feature set	Selected features using PSO	Selected features using BDFO	Selected features using IBDFO
MFCCs	16	12	11	11
LPCs	16	4	9	8
LPCCs	24	15	17	13
WLPCCs	16	8	7	9
EGY	62	31	36	27
ShEn	62	30	28	20
ApEn	62	39	36	18
SaEn	62	39	23	19
TsEn	62	32	25	20
ReEn	62	23	19	18
PeEn	62	21	21	16
FuEn	62	22	19	25
Total	**568**	**276**	**251**	**204**

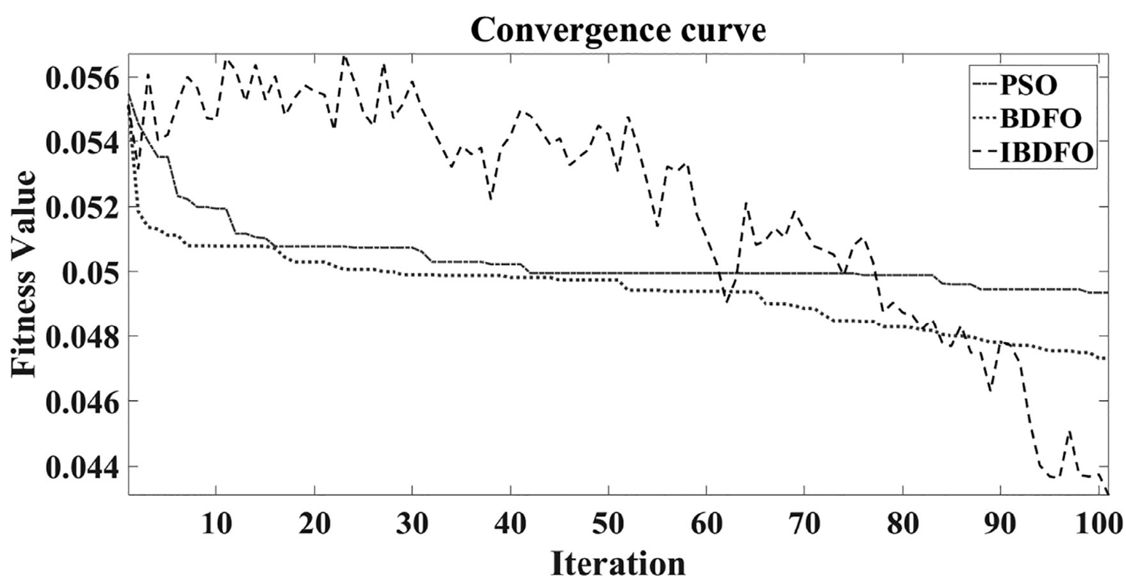

Fig. 4. Convergence curve of PSO, BDFO & IBDFO.

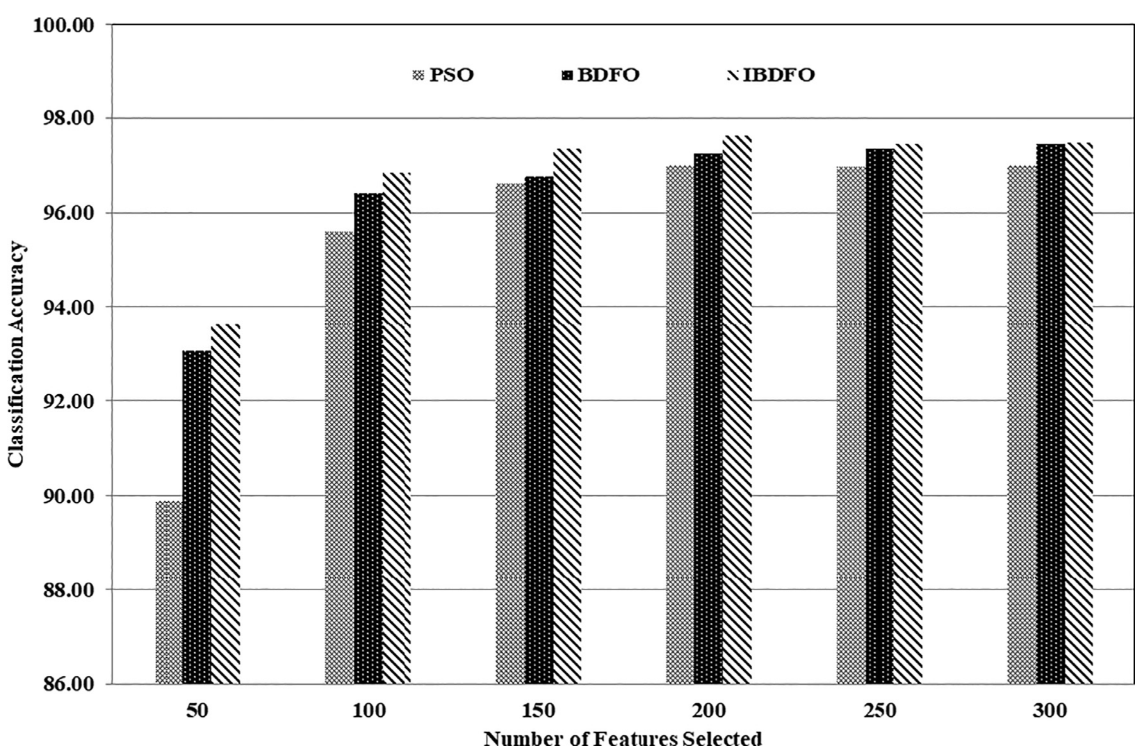

Fig. 5. Number of features selected Vs overall classification accuracy.

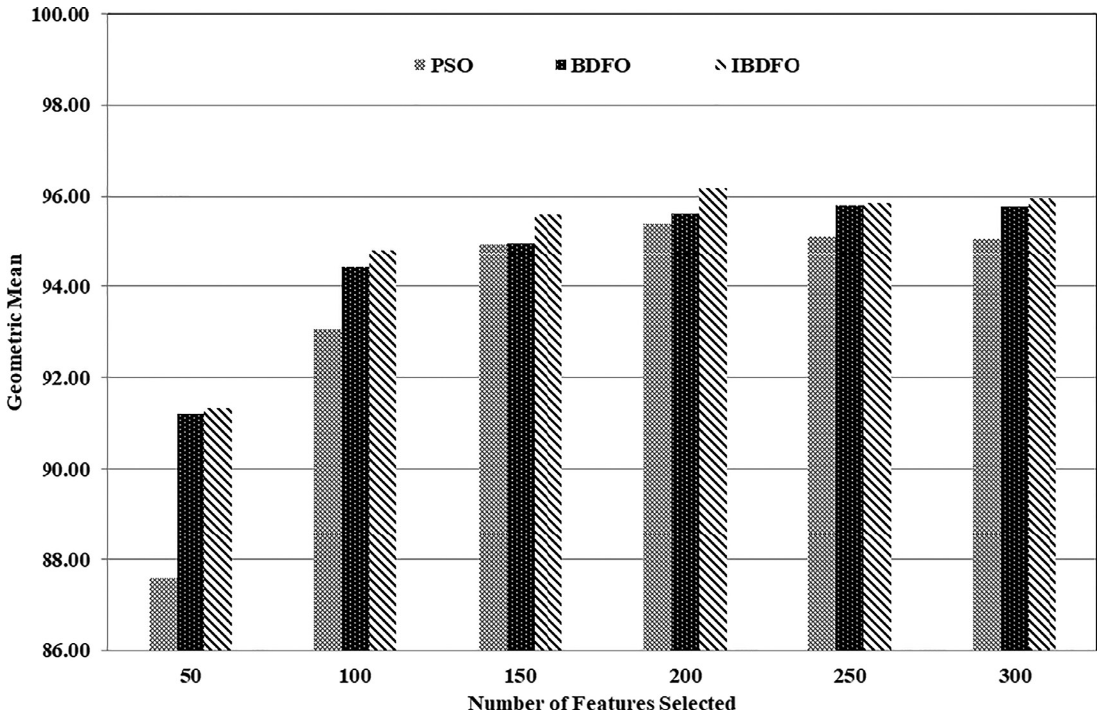

Fig. 6. Number of features selected Vs geometric mean.

Table 3
Classification Results for Binary/Two-class Experiments.

Features	Experiments	SE	SP	ACC	AUC	Fmea	Kappa	G_mean
Using All Features	A Vs N	100	99.98	99.99	1.00	1.00	1.00	99.99
	D Vs N	100	99.96	99.99	1.00	1.00	1.00	99.98
	H Vs P	90.71	80.63	87.14	0.86	0.90	0.72	85.52
	J Vs Prem	95.51	96.07	95.80	0.96	0.96	0.92	95.79
Using Features Selected using IBDFO	A Vs N	100	100	100	1.00	1.00	1.00	100
	D Vs N	100	100	100	1.00	1.00	1.00	100
	H Vs P	93.8	83.59	90.18	0.89	0.93	0.78	88.54
	J Vs Prem	97.27	97.93	97.61	0.98	0.98	0.95	97.6
Using Features Selected using BDFO	A Vs N	100	100	100	1.00	1.00	1.00	100
	D Vs N	100	99.98	99.99	1.00	1.00	1.00	99.99
	H Vs P	92.20	82.14	88.63	0.87	0.91	0.75	87.02
	J Vs Prem	97.19	97.59	97.39	0.97	0.97	0.95	97.39
Using Features Selected using PSO	A Vs N	100	100	100	1.00	1.00	1.00	100
	D Vs N	100	99.95	99.98	1.00	1.00	1.00	99.97
	H Vs P	91.00	81.72	87.71	0.86	0.91	0.73	86.23
	J Vs Prem	96.39	96.10	96.25	0.96	0.96	0.92	96.25

Table 4
Classification results for three-class experiments.

Features		N	D	A
Using All Features	**N**	100.00	0.00	0.00
	D	0.00	100.00	0.29
	A	0.00	0.00	99.71
	Overall Accuracy	**99.99**	**Geometric Mean**	99.98
		0.02		0.04
Using Features Selected using IBDFO	**N**	100.00	0.00	0.00
	D	0.00	100.00	0.00
	A	0.00	0.00	100.00
	Overall Accuracy	**100**	**Geometric Mean**	**100**
		0.00		**0.00**
Using Features Selected using BDFO	**N**	100.00	0.00	0.00
	D	0.00	100.00	0.03
	A	0.00	0.00	99.97
	Overall Accuracy	**99.99**	**Geometric Mean**	**99.99**
		0.02		**0.03**
Using Features Selected using PSO	**N**	100.00	0.00	0.00
	D	0.00	100.00	0.00
	A	0.00	0.00	100.00
	Overall Accuracy	**100**	**Geometric Mean**	**100**
		0.00		**0.00**

Table 5
Classification results for seven-class experiments.

		N	D	A	H	P	J	Prem
Using All Features	**N**	**99.02**	0.00	0.00	1.26	0.73	0.19	0.00
	D	0.00	**100**	0.00	0.29	0.10	0.00	0.00
	A	0.00	0.00	**100**	0.11	0.00	0.00	0.00
	H	0.47	0.00	0.00	**90.23**	17.19	0.00	0.00
	P	0.43	0.00	0.00	8.11	**81.98**	0.00	0.00
	J	0.00	0.00	0.00	0.00	0.00	**95.87**	3.28
	Prem	0.07	0.00	0.00	0.00	0.00	3.94	**96.72**
	Overall Accuracy		Mean	**96.64**	Geometric Mean		Mean	**94.62**
			Std	**0.11**			Std	**0.18**
Using Features Selected using IBDFO	**N**	**99.13**	0.00	0.00	1.31	0.52	0.19	0.00
	D	0.00	**100**	0.00	0.00	0.42	0.00	0.00
	A	0.00	0.00	**100**	0.00	0.00	0.00	0.04
	H	0.47	0.00	0.00	**93.31**	13.54	0.00	0.00
	P	0.40	0.00	0.00	5.37	**85.52**	0.00	0.00
	J	0.00	0.00	0.00	0.00	0.00	**97.08**	1.62
	Prem	0.00	0.00	0.00	0.00	0.00	2.73	**98.34**
	Overall Accuracy		Mean	**97.62**	Geometric Mean		Mean	**96.07**
			Std	**0.04**			Std	**0.16**
Using Features Selected using BDFO	**N**	**99.28**	0.00	0.00	0.86	0.00	0.35	0.00
	D	0.00	**100**	0.00	0.00	0.10	0.00	0.00
	A	0.00	0.00	**100**	0.00	0.00	0.00	0.00
	H	0.33	0.00	0.00	**92.00**	14.17	0.00	0.00
	P	0.40	0.00	0.00	6.97	**85.63**	0.00	0.00
	J	0.00	0.00	0.00	0.17	0.10	**96.34**	2.41
	Prem	0.00	0.00	0.00	0.00	0.00	3.31	**97.59**
	Overall Accuracy		Mean	**97.41**	Geometric Mean		Mean	**95.95**
			Std	**0.14**			Std	**0.19**
Using Features Selected using PSO	**N**	**99.09**	0.00	0.00	1.14	0.00	0.19	0.00
	D	0.00	**100**	0.00	0.06	0.52	0.00	0.00
	A	0.00	0.00	**100**	0.00	0.00	0.00	0.00
	H	0.51	0.00	0.00	**90.63**	15.52	0.12	0.00
	P	0.36	0.00	0.00	7.89	**83.96**	0.00	0.00
	J	0.00	0.00	0.00	0.29	0.00	**95.98**	2.26
	Prem	0.04	0.00	0.00	0.00	0.00	3.70	**97.74**
	Overall Accuracy		Mean	**96.99**	Geometric Mean		Mean	**95.17**
			Std	**0.10**			Std	**0.24**

ceiver operating characteristics (AUC), F-measure (Fmea), Kappa and Geometric mean (G_mean) were recorded and presented as results in Table 3. Using all features, overall accuracies of 99.99% for A Vs N, 99.99% for D Vs N, 87.14% for H Vs P and 95.80% for J Vs Prem were obtained. Using the features selected from IBDFO, 100% accuracies for both A Vs N and D Vs N, 90.18% for H Vs P and 97.61% for J Vs Prem were achieved. This indicates that the percentage of recognition accuracies was improved significantly using the most salient features selected from IBDFO when compared to features selected from BD.

For three-class experiments (Classification of N, A and D), results were calculated in terms of confusion matrices and presented in Table 4. There was not much difference in the infant cry recognition accuracies before and after feature selection. However, same or better results were obtained using only top 204 features selected from IBDFO than using all the features (568) and the features selected from BDFO (251) and PSO (276). No confusion among the three classes of cry signals (N, A and D) using the proposed feature set.

Results of seven-class experiments were tabulated in Table 4 in terms of confusion matrices for different feature sets. Overall infant cry recognition accuracy and G-mean of 96.64% and 94.62% were obtained using all the extracted features. Best overall accuracy of 97.62% and G-mean of 96.07% were achieved using the selected features from IBDFO (207 features), which are better/comparable results than the results achieved (BDFO - 97.42% (overall accuracy) & 96.07% (G-mean) and PSO - 96.99% (overall accuracy) & 95.17% (G-mean)) using the selected features from BDFO and PSO. Among the seven classes of cry signals, higher confusion between hunger and pain cry signals, moderate confusion between jaundice and pre-term cry signals and less confusion among normal, deaf and asphyxia cry signals.

Statistical results using Wilcoxon rank sum test were tabulated in Table 6. Fitness value obtained and number features selected using IBDFO are statistically different from BDFO and PSO.

6. Discussion

In this work, wavelet packet transform based energy and non-linear entropies were proposed and extracted from the recorded infant cry signals to characterise them into normal and different types of cries. Non-linear entropies were extracted to evaluate the subtle changes present in the infant cry signals. The effectiveness of the non-linear entropies in analysing non-stationary signals like speech signals and various bio-signals was investigated by several researchers. Well-known acoustic feature sets such as MFCCs and LPC based cepstral parameters were also extracted and concatenated with the proposed feature set. After extracting the pertinent features from the cry signals, most information-rich features were selected using IBDFO. IBDFO is different from conventional BDFO in terms of new updating mechanism and elitism strategy. By introducing two modifications in the existing BDFO, its performance was enriched which results in higher cry classification accuracy with less number of features.

In [10], authors have proposed a method based on MFCCs and its dynamic features and boosting mixture learning (BML) with GMM-UBM for cry signal classification of healthy (39 infants, full-term) and sick infants (22 infants with heart problems, neurological disorders, respiratory diseases and blood abnormalities). Cry signals were recorded in several hospitals in Canada and Lebanon.

Table 6
Statistical results of Wilcoxon ranksum test over all runs.

		IBDFO Vs PSO	IBDFO Vs BDFO	BDFO Vs PSO
Fitness Value	*p*-value	1.48E-06	4.04E-10	2.46E-09
	h-value	1.00	1.00	1.00
Number of features selected	*p*-value	5.51E-15	9.32E-11	2.00E-33
	h-value	1.00	1.00	1.00

Average accuracies of 69.59%, 64.57% and 85.21% were obtained for detection of healthy infant, infants with neurological disorders and infants with respiratory problems respectively [10]. Lederman et al. have used two different databases for infant cry classification [80]. The first database (Israel infants) contains 21 healthy pre-term infants and 19 pre-term infants with respiratory distress syndrome (RDS). The second database (German infants) consists of cry signals of seven infants with cleft palate. MFCCs and their derivatives and LPCs were used as features and continuous density hidden Markov model (CD-HMM) was used as classifier. Cry classification accuracies of 63% for healthy Vs RDS and 90% for infants with cleft palate (age and subject dependent, age dependent – subject independent, and age independent – subject dependent) were achieved [80]. In [12], Orlandi et al. have used twenty-two acoustical parameters and four classifiers (logistic curve, multi-layer perceptron, support vector machine and random forest) for classification of full-term and pre-term infants (Italian, 28 full-term and 10 pre-term). They achieved a maximum accuracy of 87% with 10 best acoustical parameters. In the literature, several works (two-class experiments) can be found using Baby Chillanto database [11,15,17,21–23,30,34–36,81]. Few works (two-class) can be found using self-collected database, however they are not available for research purpose [9,10,12,14,16,18,26,27].

In [23], wavelet packet transform based energy and Shannon entropy features were extracted from the cry signals of normal and abnormal (Asphyxia) of database 1 (Mexican Infants) and classified using a probabilistic neural network. Maximum classification accuracy of 99.42% was obtained using 10-fold cross validation experiment [23] . In [24], authors have conducted a study how to select best mother wavelets among the available mother wavelets (Haar, Daubechies, Symlet, Coiflet, Biorthogonal, Reverse Biorthogonal and Finite impulse response (FIR) based approximation of Meyer) based on three criteria namely similarity measure, regularity of wavelets and classification results. Authors have extracted energy and Shannon entropy with different mother wavelets from the recorded cry signals of database 1 (Mexican Infants) and compared their performances. From the experimental analysis, authors have found and concluded that Meyer's wavelet was the best candidate mother wavelet for accurate classification of cry signals [24]. Using the cry signals from the database 1 (Mexican Infants), the authors have reported 90.68% accuracy for A Vs N, 99.42% for D Vs N and 97.96% for H Vs P in [11]. For the classification of hunger and pain cry signals, our proposed method yielded lower accuracy (90.18%), but for other experiments our approach yielded higher classification accuracy (100% for A Vs N and 100% for D Vs N). Maximum average classification accuracy of 97.61% was achieved using the features selected (204 features) from IBDFO with ELM classifier for the classification of Jaundice and pre-term cry signals.

Classification of infant cry signals as a multi-class problem is less explored. Researchers have conducted the experiments of classification of three classes of cry signals from Baby Chillanto® infant cry database (Normal, Deaf and Asphyxia) and they have reported the accuracies between 88% and 98.67% [20,30,31,35,36,40,79]. Using our proposed method, maximum average classification accuracy of 100% was attained which means that the entire cry signals were perfectly classified. Experiments of classification of seven classes of cry signals using the proposed feature set and IBDFO based feature selection with ELM classifier were conducted. Maximum average accuracy of 97.62% was obtained using the selected features (204 features) from IBDFO with ELM classifier for the classification of seven classes of cry signals.

7. Conclusions

Cry signals can be used to study the several levels of information about the infants. Several works can be found in the literature for two-class or binary classification experiments. In this work, wavelet packet based energy and non-linear entropies were proposed for improved classification of cry signals. Originally 568 features which include 496 ($1 \times 62 + 7 \times 62$) wavelet packet based energy and non-linear entropies, 16 MFCCs and 56 LPC based cepstral parameters were extracted from the recorded cry signals. IBDFO was proposed to select most relevant and discard the irrelevant or noisy features. Several experiments were conducted before and after feature selection. 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% J Vs Prem) was achieved using the features selected (204 features) by IBDFO. For the classification of multiple cry signals (multi-class problem), the selected features could differentiate between three classes with the accuracy of 100% and seven classes with the accuracy of 97.62%. From the experimental results, it can be evidently seen that the proposed method offers suitable classification accuracy and may be employed to investigate the subtle changes in the cry signals. In the future works, other state-of-art meta-heuristics optimization based algorithms will be explored and hybridized to enhance the performance of conventional algorithms thereby the infant cry classification accuracy can further be improved.

Conflict of interest

None declared.

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