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Optimal Feature Selection Technique for Mel Frequency Cepstral Coefficient Feature Extraction in Classifying Infant Cry with Asphyxia

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Abstract

Mel Frequency Cepstral Coefficient is an efficient feature representation method for extracting human-audible audio signals. However, its representation of features is large and redundant. Therefore, feature selection is required to select the optimal subset of Mel Frequency Cepstral Coefficient features. The performance of two types of feature selection techniques; Orthogonal Least Squares and F-ratio for selecting Mel Frequency Cepstral Coefficient features of infant cry with asphyxia was examined. OLS selects the feature subset based on their contribution to the reduction of error, while F-Ratio selects them according to their discriminative abilities. The feature selection techniques were combined with Multilayer Perceptron to distinguish between asphyxiated infant cry and normal cry signals. The performance of the feature selection methods was examined by analysing the Multilayer Perceptron classification accuracy resulted from the combination of the feature selection techniques and Multilayer Perceptron. The results indicate that Orthogonal Least Squares is the most suitable feature selection method in classifying infant cry with asphyxia since it produces the highest classification accuracy.

Keywords*: Feature Selection, Orthogonal Least Square, Mutilayer Perceptron, Cry Signals, F-Ratio*

1. Introduction

Infant cries are unique. A mother's maternal instinct helps them to recognise the needs of a newborn from their cry. Simple signs like hunger, sad or angry, can be recognised easily. Diagnosis of medical conditions from infant cries is possible; however, it may not be simple. The detection of disease or pathological conditions can be performed with the use of computer technology.

It has been proven that Artificial Neural Networks (ANN) can discriminate between complex data [1-12]. Reyes- Galaviz et al. [1] have successfully applied a Time-Delay Neural Network (TDNN) to distinguish between normal, deaf and asphyxiated infants with 86.06% accuracy. In other works [2], a comparison between Feed-Forward Neural Network (FFNN), Recurrent Neural Network (RNN) and TDNN was made to differentiate between pain, hunger, and fear. Their results showed that the FFNN was the most suitable to perform these types of classifications, with 69.23% accuracy.

Two processes are critical for infant cry recognition; feature extraction and pattern classification [1, 2, 13]. Mel-Frequency Cepstral Coefficients (MFCC) analysis, afavourite extraction technique, can be used to derive significant features from voice-based signals [14, 15], such as infant cry. The coefficients obtained from MFCC analysis contain information that can be used to discriminate between individual cases. However, not all coefficients include significant information that can be used for classification. Works by [15, 16] have proven that classifiers trained using a subset of the coefficients can sufficiently represent the entire feature set with increased classification accuracy.

The performance of the classifier can be improved with the use of feature selection techniques to select significant coefficients. F-Ratio and Orthogonal Least Square (OLS) are two types of feature selection techniques that can be combined with Multilayer Perceptron (MLP). F-ratio is a statistical method which analyses variance in multi-cluster data [17], while

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OLS is a technique which determines the structure of the model by identifying the significant feature that can contribute to the model behavior [18-20]. It calculates Error Reduction Ratio (ERR) of the term, the percentage reduction of each term (feature) for the output mean squared error to show the significance of each feature in the model [19].

Extraction of asphyxiated infant cry features using MFCC combined with the classification of the infant cry with asphyxia using ANN has not been carried out using the optimum feature selection technique that can improve the classifier performance. This paper presents a comparison between the performance of two feature selection methods, namely F-ratio and OLS when combined with MLP in classifying asphyxiated infant cry. MLP classification accuracy resulted from the combination of these feature selection techniques with MLP was used to examine the performance the feature selection methods.

2. Research Method

The process of identifying the optimum feature selection technique is depicted in Figure 1. All operations were carried out by an algorithm written in MATLAB version 7.8.0.347 (R2009a) executing on desktop computer Intel® Core™ 2 Duo Central Processing Unit (CPU) running at 3.00 GHz with 2.00 GB of Random Access Memory (RAM) and Microsoft Windows 7 Ultimate installed. In this work, the asphyxia and normal cry signals were obtained from Instituto Nacional de Astrofísica, Óptica. Subjects aged from one day to seven months took part in the cry signal recording. Before MFCC analysis was carried out, the cry signal was passed through resampling and segmentation processes. The feature selection techniques were then performed, followed by MLP classification and selection of the optimal feature selection method. The details of each process are explained in the subsection

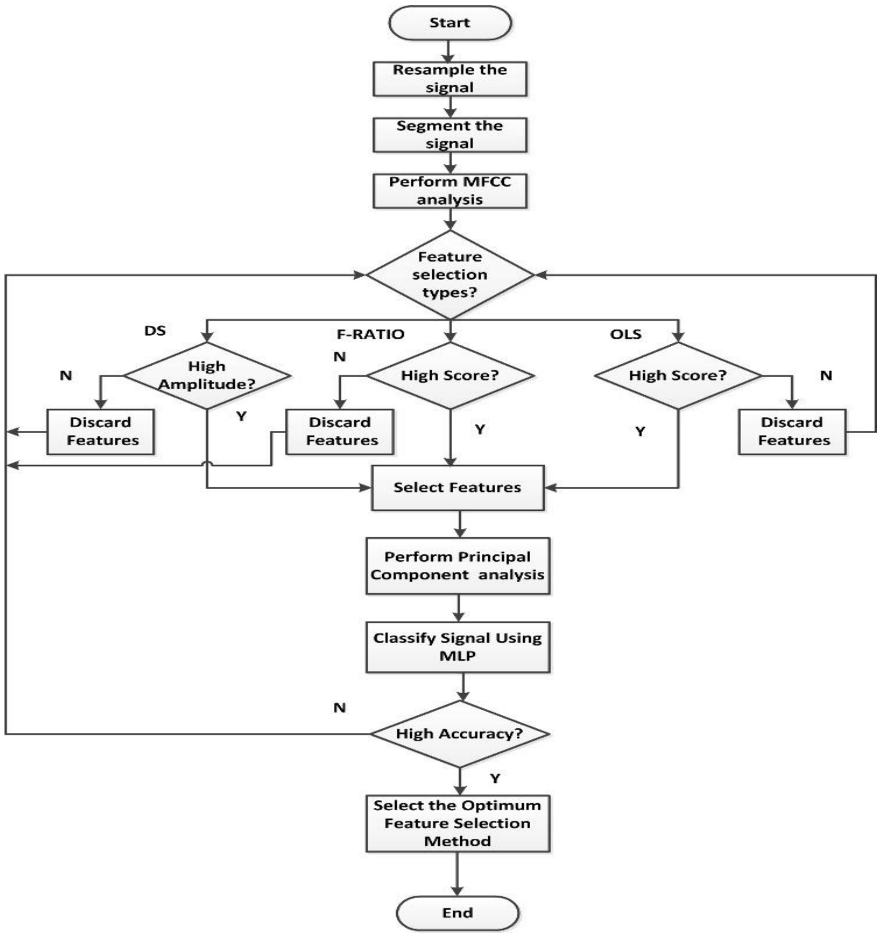

Figure 1. Process of identifying the optimum feature selection technique

2.1. Mel Frequency Cepstral Coefficients Feature Extraction

MFCC is the most suitable representation method for audio signals that lie between 20 Hz to 20 kHz. It is an algorithm that considers human perception sensitivity concerning frequencies in extracting features from audio signals. MFC coefficient, $C_O(n)$ can be computed using Equation 1.

$$C_o(n) = DCT(\log(|FFT(sig(n))|)) \quad (1)$$

Where sig(n) is the original signal at frame which has gone through pre-filtering and windowing process and n=0,1,...N-1.

In this work, the cry signals were first resampled using 8 kHz sampling frequency and segmented into one-second length to preserve the data of each MFCC feature. The original data set was preprocessed with pre-emphasis filter before being segmented to improve the amplitude of the high-frequency components in the samples. In MFCC feature extraction, the input signal was initially decomposed into overlapping frames of time. The frame size used was approximately 16ms per frames, with 50% overlap between them. The overlap was required to capture the temporal characteristic of the signal. Since high-frequency components were introduced at the end of each frame which is called leakage effect, a windowing method was applied to preserve the continuity between the first and the last points in the frame. Each block was then multiplied with a Hamming window to terminate the effect of discontinuity between each frame.

Fourier analysis was then carried out on each frame where Short-time Discrete Fourier Transform (DFT) was computed [21]. The DFT values were passed through a triangular filter called mel-spaced filter bank. The frequencies of mel-spaced filter bank are distributed linearly in the low range and logarithmically in the high range, which mimics the human auditory system. The purpose of this triangular filtering was to group the DFT values together in critical bands. The sampling frequency used influences the number of mel-filter banks produced. The mel-scale frequency, f_{mel} was calculated using Equation 2, which can assist in estimating the number of mel-filter banks.

$$f_{mel} = 2595 \log_{10}\left(1 + \frac{f_s}{700}\right) \quad (2)$$

Where f_s is sampling frequency, the MFC coefficients can be produced by computing the logarithm of the bandpass frequency response followed by the Discrete Cosine Transform calculation for each intermediate signal.

The final data set consisted of 316 normal segments and 284 asphyxiated cry segments. The data set was then randomly divided into training, validation and testing sets with 60%: 20%: 20% ratio.

2.2. Feature Selection

Three different feature selection methods were investigated, namely direct selection, F-ratio, and OLS. F-Ratio is a statistical method of analyzing variance in multi-cluster data [18]. Infant cry classification falls into the category of a multi-cluster data analysis problem since the data went through feature extraction process and the values are unique for each. The F-ratio, $F_r$can be computed using (7).

$$F_r = \frac{\frac{1}{r}\sum_{q=1}^{r}\left(\beta_q - \bar{\beta}\right)^2}{\frac{1}{r}\sum_{q=1}^{r}\frac{1}{n}\sum_{p=1}^{n}\left(\alpha_{pq} - \beta_q\right)^2} \quad (7)$$

Where α_{pq} is an p^{th} element of the q^{th}class, βq is the mean of the q^{th} class which can be expressed as Equation 8.

$$\beta_q = \frac{1}{n}\sum_{p=1}^{n}\alpha_{pq} \tag{8}$$

And $\overline{\beta}$ is the mean of all $\alpha_j$or known as the global mean of the data, and can be expressed as Equation 9.

$$\overline{\beta} = \frac{1}{r}\sum_{q=1}^{n}\beta_q \tag{9}$$

The value of the F-Ratio indicates the data has a discriminative ability. The high F-ratio score means that there is high separability between different clusters or small gap between data of the same group. The feature to be retained and to be removed can be estimated based on the F-ratio score.

OLS is a least-squares solution method which is used to select the model structure and estimate parameter in system identification [18]. It selects the best regressors that describe the output data by calculating Error Reduction Ratio (ERR). The ERR value indicates the contribution of each regressor column in reducing the fitting error between the identification model and the actual output data. Regressors with higher ERR values are given higher priority for inclusion in the final model.

The OLS algorithm can be implemented in feature extraction process to select significant features. Selection of features is performed by ranking the significance of each MFCC coefficient according to their ability to reduce the error between the estimated and the actual output. OLS is carried out on each frame, f_{ik} for each coefficient, k [22]:

$$y_k = \sum_{i=1}^{m} f_{ik}\theta_i \tag{3}$$

where f_{ik} are the MFCC coefficients for each frame, θ is the solution to the linear least squares problem, and y_k is the expected output of the classifier.

It is necessary to transform (3) into an auxiliary model to implement the OLS algorithm as follows:

$$y_k = \sum_{i=1}^{m} w_{ik} g_i \tag{4}$$

Where $w_{ik}$are orthogonal to each another:

$$\hat{g}_l = \frac{\sum_{k=1}^{N} w_{ik} y_k}{\sum_{k=1}^{N} w_{ik}^2} \tag{5}$$

Then, the *err* can be calculated by the following:

$$err_l = \frac{\hat{g}_i^2 \sum_{k=1}^{N} w_{ik}^2}{\sum_{k=1}^{N} y_k^2} \tag{6}$$

The significance of each MFCC coefficient can then be arranged according to the value of err_i. The higher thevalues, the more significant the MFCC coefficients since they contribute more to the reduction inclassification error and hence the discriminative ability ofthe classifier.

Direct selection, F-ratio, and OLS select a subset of the extracted MFCC features and use the reduced features to evaluate the performance of the classifier. Direct Selection (DS) selects the coefficients with the highest amplitude to be employed in the feature subset. This selection method is primarily motivated by the assumption that high-amplitude coefficients contain the most discriminative information. The second and third feature selection method obtained its coefficients in the same way, with the choice being governed by the ranking according to ERR from the OLS algorithm and by discriminative ability from F-ratio analysis. For both OLS and F-ratio, the MFCC feature selection frequency was measured. In all cases, the MLP classification accuracy was determined by some coefficients ranging from 30% to 60% of the number of filter banks while the number of filter banks ranged from 20 to 40 with an increment of 1.

2.3. Feature Reduction

Principal Component Analysis (PCA) was applied to reduce dimensionality redundancy between each MFC selected coefficient. PCA allows the examination of the contributions of each Principal Component (PC), and control how much information is retained. In PCA, the PCs are sorted accordingto their variance contributions and only a small portion of the transformed matrix is used to represent the data [23]. Any data with principal components that contribute less than the total variation defined in the threshold will be discarded.

A method of finding the suitable threshold for PCA was done by experimenting with a set of the filter bank and coefficient combinations acquired using normal MFCC settings found in the previous researches [17], [24-26]. The features were then tested using MLP with several numbers of hidden units ranging from 5 to 30 while the threshold for PCA was in the range of 95% to 99% of the retained total variation in the dataset.

2.4. The Multilayer Perceptron (MLP) Classifier

The features selected using the direct selection, OLS or F-ratio was fed to a three-layer MLP classifier. The top 30%, 40%, 50% and 60% of the best-ranked coefficients from the filter banks were selected as features to train the MLP classifiers. Since the MLP was used for pattern classification, the sigmoid transfer function was used in both the hidden and output layers. The training algorithm used was the scaled conjugate gradient with 5 to 50 hidden units with increments of 5.

The MLP training procedure was repeated on the training set 50 times with different weight initializations to minimize the effect of random weight initializations on MLP performance. The early stopping method was used to avoid over-fitting. At the beginning of stopping, the training set takes an active role in weight updates, while the independent validation set was used to test whether the MLPs were over-fitting. Training was stopped before over-fitting. After the MLPs have been trained, the classification accuracy and Mean Squared Error (MSE) were averaged out over 50 trials.

3. Results and Analysis

3.1. Principal Component Analysis Threshold

Before classification process was performed, a preliminary test was conducted to determine the most suitable PCA threshold to remove the correlated data in the feature subset. Figure 2 shows the classification accuracy for various PCA threshold values. The classification accuracy is affected by the changes in the threshold value. The best results were obtained when the threshold was set to 0.05 (95% retain of the total variation in the dataset), as the classification accuracy was consistently high even with different MLP structures. Therefore, the threshold value of 0.05 was used throughout the work.

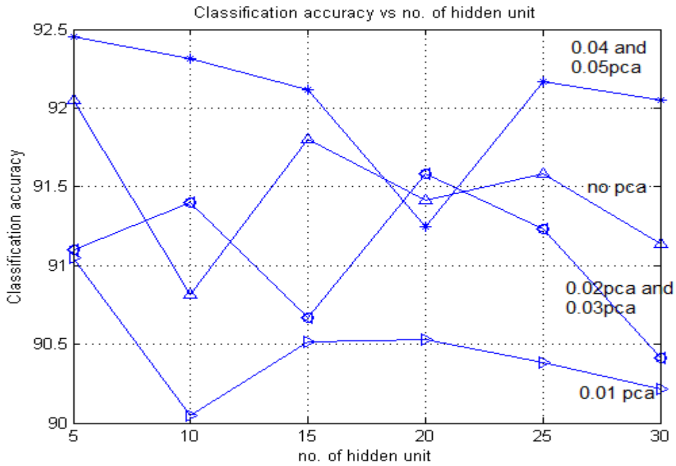

Figure 2. Classification accuracy for various hidden units

3.2. The Effect of Applying OLS

The result of using OLS on the classification accuracy is shown in Figure 3. The classification accuracy was computed for three different input features; all MFCC features (25 coefficients) selected from the 26 filter banks, the 50% best features selected using OLS, and the 50% worst features (discarded by OLS). The results show that using OLS to choose the best subset features, the classification accuracy of the MLPs is higher than using all MFCC features.

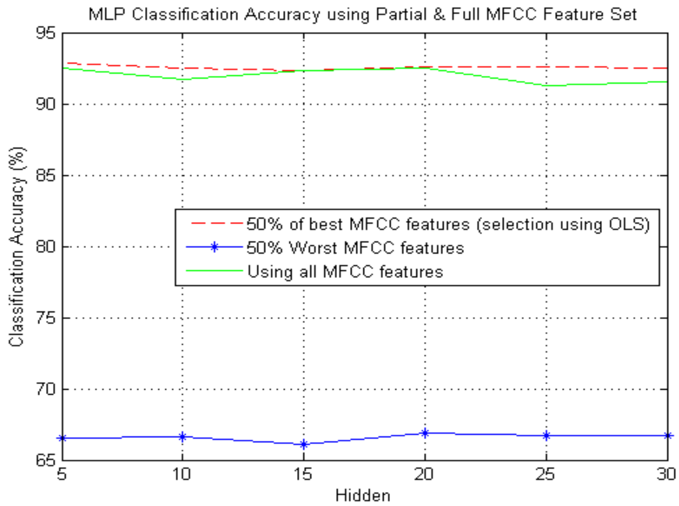

Figure 3. MLP classification accuracy using partial & full MFCC feature set

3.3. Selected Features from OLS

The best 30 MFCC features selected by OLS are shown in Table 1. These are the significant MFCC features that contribute to high classification accuracy. The OLS has ranked the features based on their ERR values. The MFCC features that appear on the top list have high selection frequency which shows that they are significant. The number of frames derived from the sample was 124. OLS ranked coefficients one, two and four on the top as those coefficients were selected in every frame. Coefficients 19, 22, 25, 29 and 30 were not selected at all.

Table 1. OLS Ranking of MFCC Coefficients

Rank	Coeff	Selection Freq.	Rank	Coeff	Selection Freq
1	1	124	16	12	4
2	2	124	17	11	4
3	4	124	18	28	3
4	3	123	19	23	3
5	10	103	20	17	3
6	13	60	21	8	3
7	5	46	22	7	3
8	9	45	23	21	2
9	14	27	24	15	1
10	16	25	25	6	1
11	27	10	26	30	0
12	18	10	27	29	0
13	20	8	28	25	0
14	26	6	29	22	0
15	24	6	30	19	0

As shown in Figure 4, coefficients that were frequently selected resided in the earlier portion of the MFCC coefficient plot. OLS ranked these coefficients among the top because they have higher magnitude compared to other coefficients. The lower MFCC contained the most discriminative information. Most higher coefficients (19, 22, 25, 29 and 30) did not provide discriminative information for classification, which explains why OLS never selected these features.

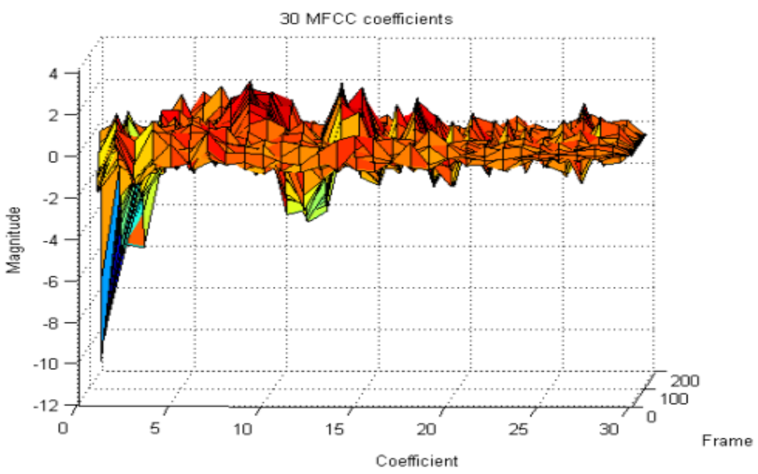

Figure 4. 30 MFCCs of infant cry

3.3. Selected Features from F-Ratio

Table 2 presents the frequency of feature selection using F-Ratio for 30 MFCC features. The F-ratio scores reflect the discriminative ability of each coefficient. A higher F-ratio score indicates that the coefficient is more discriminative compared to other coefficients. F-ratio ranks coefficients one, three and four as the most discriminative. Coefficients 20 to 30 have lower scores and are ranked the least discriminative by F-ratio. Similar to OLS, F-ratio ranks the lower MFCC as the most discriminative, and the higher MFCC as the least discriminative.

Table 2. F-Ratio Ranking of MFCC Coefficients

Rank	Coeff	F-Ratio Score	Rank	Coeff	F-Ratio Score
1	4	284.64	16	16	29.95
2	3	253.88	17	19	29.69
3	1	244.43	18	18	26.57
4	5	98.03	19	17	23.70
5	2	91.92	20	20	22.18
6	10	78.44	21	21	19.44
7	9	72.14	22	23	18.16
8	6	70.63	23	24	16.40
9	12	60.85	24	22	16.23
10	11	57.97	25	27	14.31
11	7	52.85	26	25	13.08
12	13	50.13	27	26	8.85
13	8	48.47	28	29	8.20
14	14	45.76	29	28	7.93
15	15	35.00	30	30	NaN

3.3. Feature Selection Performance for MLP Classification

Table 3 shows the average classification accuracy produced by MLP with three types of selection techniques used; direct selection, OLS, and F-ratio. The best classification accuracy of MLPs trained with DS method is 93.22% when five hidden units and 19 coefficients (50% of filter bank number) generated from 37 filter banks were used.

The MLP classification accuracy increased when OLS and F-ratio feature selection method were employed. With OLS, MLP structure of 15 hidden units and 12 coefficients (30% of 29 filter banks), the highest classification accuracy achieved is 94%. Using F-ratio combined with MLP structure of 45 hidden units and nine coefficients (30% of 29 filter banks) yields the best classification accuracy of 93.38%.

Table 4 shows the average classification accuracy from all possible combinations of 20 to 40 filter banks and MLP with 5 to 50 hidden units. As can be seen in Table 4, feature selections using OLS consistently outperformed F-Ratio and DS regardless of the percentage of coefficients selected. Feature selection using F-Ratio is only effective when it is used to select a small percentage of coefficients (30% to 40% of coefficients from the filter banks). F-ratio performance degrades when a higher percentage of coefficients is selected from the filter banks.

Results shown in Table 3 and Table 4 give clear indication that OLS and F-ratio feature selection methods can improve classification results compared to when feature selection was not used (DS), and OLS has outperformed F-ratio in discriminating between asphyxiated and normal infant cry. The average and maximum classification accuracy for different percentage of coefficients selected from the filter banks shown in Figure 5 also support this finding that OLS is the best feature selection method for classifying asphyxiated infant cry.

Table 3. Best Classification Accuracy provided by MLP with Direct Selection, PLS and F-Ratio

% fb	(a) DS		
	Acc	Hidden	Filterbank
30	92.93	45	31
40	93.13	5	38
50	93.22	5	37
60	93.12	5	37
% fb	**(b) OLS**		
	Acc	Hidden	Filterbank
30	94.00	15	40
40	93.72	40	31
50	93.83	5	28
60	93.95	5	23
% fb	**(c) F-ratio**		
	Acc	Hidden	Filterbank
30	93.38	45	29
40	93.13	5	38
50	93.05	5	30
60	93.12	5	37

Table 4. Average Classification Accuracy between Direct Selection, OLS and F-ratio

%fb	DS	OLS	F-ratio
30	91.65	91.89	91.81
40	91.79	92.10	91.90
50	92.08	92.14	92.01
60	92.05	92.06	91.97

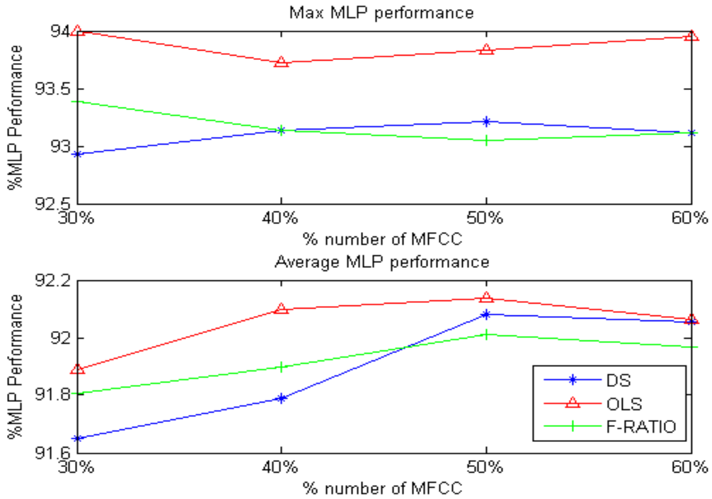

Figure 5. Summary of the MLP classification results

4. Conclusion

The use of the MLP with feature selection methods in classifying infant cries with asphyxia has been discussed in this paper. OLS and F-Ratio selection techniques are useful tools to rank the coefficients according to their discriminative abilities.

This work has shown that OLS algorithm is useful in selecting a subset of features that improve the classification accuracy of the MLPs for diagnosis of infant asphyxia from cry signals. By choosing only a small number of representative features, OLS can reduce the computational load required to perform classification. Both the average and highest MLP classification accuracies have consistently displayed better performance than those with DS. The best classification accuracy obtained was 94% (with MLP structure of 15 hidden units) with the selection of coefficients 30% from 40 filter banks.

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