Analysis of Visual Colour Perception using EEG Spectral Features

Paulraj M P1, Abdul Hamid Adom1, Hema C R2, Divakar Purushothaman1

ABSTRACT

Electroencephalography signals are the electrophysiological measures of brain function and used to develop a brain machine interface (BMI). BMI system is used to provide a communication and control technology for the differentially enabled people having neuromuscular disorders. In this paper, a simple BMI system based on EEG signal emanated while visualizing of different colours has been proposed. The proposed BMI uses the color visualization tasks (CVT) and aims to provide a communication link using brain activated control signal. For each EEG signal, using spectral analysis, alpha, beta and gamma band frequency statistical spectral features such as spectral energy, mean spectral energy and standard deviation spectral energy are obtained. The extracted features are then associated to different control signals and a probabilistic neural network model has been developed to observe the classification accuracy of this three features.

Keywords— Spectral Features, Brain Machine Interface, Colour Visualization Tasks, Neural Network.

I. INTRODUCTION

Electroencephalography (EEG) is defined as an electrical activity recorded from the scalp using surface electrodes [1]. EEG signals are the electrophysiological measures of brain function. While performing visual, mental and physical actions, EEG signals are produced. Thus the difference in EEG signals while performing various actions helps us to develop a brain machine interface (BMI). BMI is a system that provides communication link between the human brain and a digital computer. BMI aims to help the people who are suffering with neuromuscular disorders such as paralysis, quadriplegics, amyotrophic lateral sclerosis brain stem stroke, and spinal cord injury to drive computers directly by brain activity rather than by physical means. In recent years many research works have been carried out in developing BMI systems and it is mainly involved in recording an EEG signals using surface electrodes [2]. Many significant technological advancement have occurred in the past decade towards developing a BMI, such as using visual evoked potential (VEP), slow cortical potential (SCP), P300 evoked potential, sensorimotor activity mental tasks and multiple neuromechanisms [3-6]. Few researchers have investigated the effect of colour on the EEG signal activity and analyzed whether different colours affect can the behavior of EEG signals [7]. Using this theoretical concept, the BMI using CVT has been proposed and analyzed to help the differentially enabled people.

In this paper, a simple protocol has been proposed for visualization of different colors namely black, blue, cyan, green, magenta, red, white and yellow. As a preliminary of the research, these eight colours were chosen as it emanates high brain activity responses [7]. The features corresponding to the alpha, beta and gamma bands were
extracted from the EEG signals using spectral energy entropy. The extracted features are fed as input to probabilistic neural network (PNN) model. The block diagram of the proposed BMI system is shown in Figure 1. The rest of the paper is organized as follows: Section II describes the data collection and feature extraction method. Section III illustrates the designed network model and its performances. Section IV and V presents the results and conclusion, showing the potential of EEG signals derived from vision perception for BMI.

II. FEATURE EXTRACTION

A. Protocol and Data Collection

EEG brain signals were recorded using the Mindset-24 topographic neuro-mapping instrument along with an electrode cap [8, 9]. This instrument is also called as 1.5 to 34 Hz data acquisition system. Ten healthy volunteers (10 men), aged between 21 and 25, have participated in this experiment. All the ten subjects had no prior experience in EEG experiments. The subjects were requested to get seated in a silent room and also requested not to make any overt movement while performing the CVT. A 19 channel (FP1, FP2, F7, F3, FZ, F4, F8, T3, T5, C3, CZ, C4, T4, T6, P3, PZ, P4, O1 & O2) electrode cap was used for recording the brain signals from the scalp as per the 10-20 system of electrode placement [10] and the measurements were made with reference to electrically linked mastoids, A1 and A2. A 19 channel electrode cap along with the internal 10-20 electrode positions are shown in Figure 2.

In the experimental study, the subjects were asked to perform eight different CVTs and their corresponding EEG signals were recorded. All the subjects were free from illness at the time of EEG recording. Before starting the data collection, the data collection procedures were explained clearly to the subject. The subjects were seated comfortably in front of a color LCD monitor and were asked to view the displayed colors. All the ten subjects were asked to view the colour screen in a relaxed condition during the data collection. Before starting the real data collection, for each colour task, a sample data collection was conducted to find the difficulties in performing the tasks and a feedback was also obtained from the subjects. Each color was displayed on the color
LCD and subjects were asked to visualize each colour for 10 seconds and the EEG signals were recorded. Before recording the next CVT, the subjects were asked to be in a relaxed state for 20 seconds and this process was repeated for all the trails. For each subject, EEG signal was recorded for 10 seconds at a sampling frequency of 256 Hz [9] and ten such trials session were performed for all the tasks. After completing each session, the subjects were asked to sit in a relaxed manner for 2 to 5 minutes.

A. Feature Extraction Process

In this section, feature extraction processes using spectral features are described and carried out. Three spectral features namely spectral energy, mean spectral energy and standard deviation spectral energy were proposed and analyzed based on the statistical approach [16]. First the raw EEG data was preprocessed and then feature extraction was performed. The recorded signals were segmented into number of frames with a overlapping of 75% [11]. Each frame has 256 samples (corresponding to 1 second). The segmented signals were then filtered using passband elliptic filters and the alpha (7 to 14 Hz), beta (14 to 21 Hz) and gamma (21 to 34 Hz) from all the 19 channels [1, 11]. In this spectral feature extraction process, the filtered data, \( x_j \) were first Fourier transformed to \( X(\omega) \) using Equation (1).

\[
X(\omega) = \sum_{n=1}^{N} x(\omega) w_{\omega n} e^{-j2\pi(\omega-\omega_0)}
\]

where \( w_{\omega n} = e^{-j2\pi(\omega-\omega_0)/N} \) is the complex exponential and \( N \) is the total number of data in the filtered signal. For the Fourier transformed signal \( Y(\nu) \), the spectral energy (SE) value is calculated using Equation (2).

\[
SE = \sum_{\nu=1}^{N} |Y(\nu)|^2
\]

Then the corresponding mean spectral energy (MSE) and standard deviation spectral energy (SDSE) is calculated using Equation (3) and (4) respectively,

\[
MSE = \frac{\sum_{\nu=1}^{N} |Y(\nu)|^2}{N}
\]

\[
SDSE = \sqrt{\frac{1}{N-1} \sum_{\nu=1}^{N} [Y(\nu)^2 - \bar{Y}(\nu)^2]}
\]

where \( N = 256 \), is the number of samples. Similarly, the features corresponding to the CVTs performed by all the ten subjects (for all trials) were extracted and associated to their respective colour codes. Each CVT has 57 (19 channels x 3 bands) feature values and it is given as input to the network model.

III. Neural Network

To discriminate the colour perception using visualization tasks, probabilistic neural network (PNN) has been developed. PNN is a supervised neural network proposed by Donald F. Specht [14, 15] and it is a variant of radial basis network suitable for classification problems. The PNN is a direct continuation of the work based on Bayesian classification and classical estimators for probability density function [14]. The only factor that needs to be selected for training is the smoothing factor/spread factor which affects the classification accuracy.

The network structure of PNNs is similar to that of backpropagation [12, 13]; the primary difference is that uses exponential activation function instead of sigmoidal activation function and also the training time is lesser compared to multi-layer feed forward network trained by back propagation algorithm.

PNN consists of four types of units, namely, input units, pattern units, summation units, and an output unit. The pattern unit computes distances from the input vector to the training input vectors, when an input is presented, and produces a vector whose elements indicate how close
the input is to a training input. The summation unit sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes. Furthermore, the shape of the decision surface can be made as complex as necessary, or as simple as desired, by choosing an appropriate value of the smoothing parameter.

In this paper, PNN architecture and the feature extraction process are constructed and analysed using MATLAB software. For the CVTs, the eight different colours are to be classified into eight different clusters. This problem requires 57 input neurons. In the experimental study, EEG signals corresponding to eight different visualization tasks were recorded and separate neural network model was developed for each subject. The master data set has 2960 samples. The network is trained with 1776 samples of data and tested with 1184 samples with a testing tolerance of zero. The accuracy results of each subject for the corresponding smoothing parameter (K) ranges from 0.10 to 0.20 are tabulated in Table 1, 2 and 3. 60% (1776 samples) of training samples are taken randomly from the total samples and the remaining 40% (1184) samples are tested using the network models. This process of training and testing is repeated for 10 times. From the Table 1, 2 and 3, the highest classification performance of three features and its smoothing parameter value for each subject were highlighted. The highest average classification accuracy of SE, MSE and SDSE features has been tabulated in Table 4.

**TABLE 1. CLASSIFICATION PERFORMANCE OF PNN USING**

<table>
<thead>
<tr>
<th>K</th>
<th>Sub 1</th>
<th>Sub 2</th>
<th>Sub 3</th>
<th>Sub 4</th>
<th>Sub 5</th>
<th>Sub 6</th>
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<tr>
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<td>84.40</td>
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</tr>
<tr>
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<td>84.01</td>
<td>89.61</td>
<td>81.29</td>
<td>83.30</td>
</tr>
<tr>
<td>0.14</td>
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<td>84.65</td>
<td>84.70</td>
<td>86.04</td>
<td>91.59</td>
<td>83.56</td>
<td>85.84</td>
</tr>
<tr>
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<td>85.21</td>
<td>82.42</td>
<td>83.26</td>
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</tr>
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<td>82.41</td>
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<td>77.64</td>
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</tr>
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</table>
To discriminate the colour perception using visualization tasks, PNN has been developed. In this case, eight-class classification was carried out using PNN to categorize these different CVTs. The highest mean classification accuracies of three spectral features for each subject were tabulated in the Table 4. While comparing the classification accuracy of three features, it has been also observed that MSE feature performs well when compared to other two features (SE and SDSE) for all ten subjects.

From the Table 4, it could be observed that, the highest mean classification accuracy of 95.04% (for subject 5)
and the lowest mean classification accuracy of 87.86% (for subject 6) were obtained for MSE feature. Further, it can be observed that the performance of the subject 5 is better than the other subjects.

V. CONCLUSION

In this paper, SE, MSE and SDSE features were extracted from the EEG signal while performing the CVTs and the results were compared. The extracted features were associated to their respective tasks and the neural network models were developed successfully. The performance of the neural network models were tabulated and compared. From the above experimental study, it has been observed that the MSE feature using PNN model performs better when compared to the other two features. The proposed BMI using CVT is new in the development of BMI and it will be easy to implement, hence it involves less mental stress and no need of special training to control the BMI. In future, the proposed system will be implemented in a real time analysis.

Acknowledgement

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REFERENCE


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Author’s Biography

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Stationary and Non-Stationary Vehicle Cabin Noise Level Identification Using Spectral Composite Features and Neural Networks

Paulraj M P, Sazali Yaacob, Allan Melvin Andrew

ABSTRACT

Determination of vehicle comfort is important because continuous exposure to the noise and vibration leads to health problems for the driver and passengers. In this paper, a vehicle comfort level classification system has been proposed to detect the comfort level in cars using artificial neural network. A database consisting of sound samples obtained from 30 local cars is used. In the stationary condition, the sound pressure level is measured at 1300 RPM, 2000 RPM and 3000 RPM. In the moving condition, the sound is recorded while the car is moving at 30 km/h up to 110 km/h. Subjective test is conducted to find the Jury’s evaluation for the specific sound sample. The correlation between the subjective and the objective evaluation is also tested. The relationship between the subjective results and the sound metrics is modelled using Probabilistic Neural Network. It is found from the research that the Spectral Composite Feature gives better classification accuracy for both stationary and moving condition model, 94.21% and 90.45% respectively.

Keywords- noise comfort, subjective evaluation, noise level, frequency band, neural network.

I. INTRODUCTION

Riding Comfort is the comfortness of noise, vibration and motion inside a vehicle, experienced by both driver as well as the passengers.

ISO 2631 whole-body vibration certification testing covers the comfort, safety and health of the passengers subjected to it [2]. The assessment of ride comfort consists of the four domains, namely, seat vibration, steering wheel vibration, interior noise and general handling in motion of the vehicle. Seat vibration deals with ISO whole-body vibration and absorption of vibration by the passenger and driver when on-board. Steering wheel vibration is due to tire unbalance. Interior noise in the vehicle deals with the averaged overall sound pressure level and sound metrics such as loudness, sharpness and roughness of the noise. General handling in motion of the vehicle is due to braking force, where it will affect the comfort of the passenger and driver in terms of drivability comfort. Measuring and quantifying ride comfort can help meeting the necessary standards and regulations. It also helps to troubleshoot, understand and improve the noise and vibration comfort in the vehicles [1].

The comfort in the car interior is already become a need for the passengers and the buyers. Due to high competition in car industries, all the car manufacturers are concentrating in improving the interior noise comfort of the car [7]. Although various researches and testing have been conducted, the researches are privatised for
internal usage and are not commercialised. No specific device has been developed to test the comfort level in a vehicle commercially. Thus, there is a need to develop a user-friendly device which can be available to test the interior noise comfort commercially.

The rest of the paper has been organised as follows: Section 2 narrates the establishment of vehicle interior noise database. In Section 3, the feature extraction of the vehicle interior noise has been discussed. Section 4 shows the feature reduction using Principal Component Analysis. Section 5 discusses the formulation of Spectral Composite Feature. The subjective evaluation on the noises is described in Section 6. Section 7 discusses about the experimental prediction and verification. The paper is concluded in Section 8.

II. ESTABLISHMENT OF VEHICLE INTERIOR NOISE DATABASE

The methodology for the research is divided into two sections, namely objective evaluation and subjective evaluation.

Data is required to train and test the artificial neural network for maximum classification accuracy. Thus, a simple data recording protocol is formulated to record the noise level inside the car. A measurement mannequin is used to place the microphones and the wirings as per ISO 5128-1980 (E) Acoustic- Measurement of noise inside motor vehicles standard [6, 15]. The sampling frequency of the recorded sound is 51200 Hz. It is further re-sampled to 8000 Hz [10]. Human ears are sensitive from 8 Hz to 4000 Hz and the sensitivity will decrease gradually when the frequency approaches 20 kHz. 8000 Hz is chosen based on two times the maximum frequency required as defined by Nyquist sampling theorem.

During the measurement sessions, the measurement mannequin is placed on the front passenger seat. Figure 1 shows the position of the mannequin in the car. Two microphones need to be placed at front portion and another at the rear portion of the car interior [15]. The front microphones are attached to the headphone which is placed on the mannequin’s head. Figure 2 shows the position of microphones on the mannequin’s head. The measurement device is placed on rear seat of the car as shown in Figure 3. All the microphones are connected to the measurement device, Orchestra. The Orchestra’s input channels are used to capture the input signals. One crew is required to operate the car while another to control the data recording [15].

Figure 1. Experimental Set-up using Measurement Mannequin

For data collection, two measurement sessions are conducted. The first measurement session is conducted when the car is in stationary condition (SC). The engine has been accelerated to three different speeds, namely, 1300 RPM, 2000 RPM and 3000 RPM [15]. The relationship between the speed of the car and the Revolution per Minute (RPM) has been utilised. For each trial, the noise inside the car is recorded for 10 seconds. For the measurement during moving condition (MC), the car is driven at a constant speed at 30 km/h, 60 km/h, 70 km/h, 80 km/h, 90 km/h and 110 km/h respectively and the noise inside the car is measured [18].
Figure 2. Microphone Positions on Measurement Mannequin

The recorded sound samples contain additional environmental noise. The data collection has to be done in a sound-proof room to get the data with minimum noise, but it is not feasible to implement in the outdoor condition, especially for data collection when the car is moving. Hence, a simple pre-processing is performed on the recorded signals. The low frequency component below 8 Hz and high frequency noise components above 4000 Hz are removed using band-pass Butterworth Filter with order 1 [9, 11]. 25 One-third Octave frequency bands with 25 centre frequencies are used for signal filtration.

III. FEATURE EXTRACTIONS OF CAR INTERIOR NOISES

Feature extraction involves simplifying the amount of resources required to describe a large data accurately. For sound signal, basic statistical features such as the mean, median, standard deviation, energy and kurtosis can be taken. Many popular researchers those involved in acoustic researches prefer sound quality metrics such as the loudness, sharpness, fluctuation strength and roughness to be used as the features [8, 16]. In this paper, One-third frequency band power, $L_{eq}$, energy entropy and loudness are used as features [17].

Each signal is divided into frames such that each frame has 1024 samples [13, 18]. 1024 samples were chosen since it gives a better result when compared to other $2^n$ values; where $n$ is a value from 1 onwards. The frame signals are filtered using 25 one-third octave band Butterworth filters with band range between 8 Hz to 4000 Hz. The high frequency noise is filtered since the significant comfort variation happens mainly between 8 Hz to 4000 Hz [18]. The features values are normalised between values 0.1 to 0.9 using binary normalization technique and have been randomised [3].

Four features were discussed and compared. The four features are discussed below:

A. Spectral Power (SP)

In SP feature extraction process, the signal was first Fourier transformed. Using Equation (1), the SP values for the twenty five bands corresponding to a frame are computed.

$$p^k = \frac{1}{N} \sum_{q=1}^{N} \left[ Y^k_q(\cdot) \right]^2$$

(1)

where,

$N = 1024$, is the number of samples,

$Y^k_q(\cdot)$ represents the $q^{th}$ sample of the $k^{th}$ frame corresponding to the $i^{th}$ frequency band, and

$p^k$ represent the $i^{th}$ frequency band of the $k^{th}$ frame signal.

$$p^k = [p^k_1, p^k_2, p^k_3, \ldots, p^k_{25}]$$

(2)

The SP corresponding to the $k^{th}$ frame is represented in Equation (2). A data set consisting of 720 (30x4x6)
feature sets along with its associated target vector has been formulated and this dataset has been named as SC Spectral Power (SC-SP) database. The data collection formulation is repeated for the MC protocol and a dataset consisting of 480 (30x4x4) features sets has been formulated for the MC set. This data set has been named as MC Spectral Power (MC-SP) database.

B. Spectral Equivalent Continuous Sound Pressure Level (SLEQ)

The signal was first Fourier transformed. The SLEQ values for the twenty five bands corresponding to a frame are computed using Equation (3).

\[ l_{eq}^k = \sum_{i=1}^{25} \left[ \frac{1}{N} \log_{10} \left( \frac{1}{\log_{10}(25)} \sum_{q=1}^{N} \left( Y_{eq}^k(q) \right) \right) \right] \]  

where, \( N = 1024 \), is the number of samples, \( Y_{eq}^k(q) \) represents the \( q^{th} \) sample of the \( k^{th} \) frame corresponding to the \( i^{th} \) frequency band, and \( Y_{eq}^k \) represents the \( i^{th} \) frequency band of the \( k^{th} \) frame signal.

\[ \left( Y_{eq}^k \right) \]  

The SLEQ corresponding to the \( k^{th} \) frame is represented in Equation (4). A data set consisting of 720 (30x4x6) feature sets along with its associated target vector has been formulated and this dataset has been named as SC Spectral Equivalent Continuous Sound Pressure Level (SC-SLEQ) database. The data collection formulation is repeated for the MC protocol and a dataset consisting of 480 (30x4x4) features sets has been formulated for the MC set. This data set has been named as MC Spectral Equivalent Continuous Sound Pressure Level (MC-SLEQ) database.

C. Spectral Energy Entropy (SEE)

In SEE feature extraction process, the signal was first Fourier transformed. Using Equation (5), the SEE values for the twenty five bands corresponding to a frame are computed.

\[ l_{se}^k = -\sum_{i=25}^{2} \left[ \frac{1}{N} \log_{10} \left( \frac{N}{\log_{10}(25)} \sum_{q=1}^{N} \left( Y_{se}^k(q) \right) \right) \right] \]  

where, \( N = 1024 \), is the number of samples, \( Y_{se}^k(q) \) represents the \( q^{th} \) sample of the \( k^{th} \) frame corresponding to the \( i^{th} \) frequency band, and \( Y_{se}^k \) represent the \( i^{th} \) frequency band of the \( k^{th} \) frame signal.

\[ \left( Y_{se}^k \right) \]  

The SEE corresponding to the \( k^{th} \) frame is represented in Equation (6). A data set consisting of 720 (30x4x6) feature sets along with its associated target vector has been formulated and this dataset has been named as SC Spectral Energy Entropy (SC-SEE) database. The data collection formulation is repeated for the MC protocol and a dataset consisting of 480 (30x4x4) features sets has been formulated for the MC set. This data set has been named as MC Spectral Energy Entropy (MC-SEE) database.

D. Spectral Loudness (SL)

The signal was first Fourier transformed. The SL values for the twenty five bands corresponding to a frame are computed using Equation (7).

\[ l_{sl}^k = -\sum_{i=2}^{25} \left[ \frac{1}{N} \log_{10} \left( \frac{N}{\log_{10}(25)} \sum_{q=1}^{N} \left( Y_{sl}^k(q) \right) \right) \right] \]  

where, \( N = 1024 \), is the number of samples, \( Y_{sl}^k(q) \) represents the \( q^{th} \) sample of the \( k^{th} \) frame corresponding to the \( i^{th} \) frequency band, and \( Y_{sl}^k \) represent the \( i^{th} \) frequency band of the \( k^{th} \) frame signal.

\[ \left( Y_{sl}^k \right) \]  

The SL corresponding to the \( k^{th} \) frame is represented in Equation (8). A data set consisting of 720 (30x4x6) feature sets along with its associated target vector has been formulated and this dataset has been named as SC Spectral Loudness (SC-SL) database. The data collection formulation is repeated for the MC protocol and a dataset consisting of 480 (30x4x4) features sets has been
formulated for the MC set. This data set has been named as MC Spectral Loudness (MC-SL) database.

**IV. FEATURE REDUCTION USING PRINCIPAL COMPONENT ANALYSIS**

The most well known linear method for data analysis is the Karhunen-Loeve transform or the Principal Component Analysis (PCA) method, which maximises the variance of the projected vectors. It is defined by a matrix having as rows the eigenvectors of the feature space covariance matrix. The PCA removes any redundancy between the components of the projected vectors, since the covariance matrix in the transformed space becomes diagonal as shown in (9):

\[ \sum y = eig[\lambda_1, \lambda_2, \lambda_3 ... \lambda_n] \]

where, \( \lambda_i; i = 1,2,3,...,n \) stand for the eigenvalues of the decomposed data covariance matrix.

The PCA performs the vector projection without any knowledge of their labels. This transformation is defined in such a way that the first principal component has as high a variance as possible and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components. It is therefore, an unsupervised data analysis method.

In this research, PCA was used to remove any redundancy between the components of the projected vectors in each frequency bands. Only relevant data were chosen, ignoring components whose variance explained is less than 1. Table 1 shows the number of reduced data column using PCA. The most number of data column were reduced for SLEQ, showing that the feature has the most redundancy of data.

**Table 1. Comparison of Number of Data Columns Before and After PCA**

<table>
<thead>
<tr>
<th>Features</th>
<th>Before PCA</th>
<th>After PCA</th>
</tr>
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<tbody>
<tr>
<td>SP</td>
<td>25</td>
<td>22</td>
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<tr>
<td>SLEQ</td>
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<td>21</td>
</tr>
<tr>
<td>SL</td>
<td>25</td>
<td>20</td>
</tr>
</tbody>
</table>

**V. FORMULATION OF SPECTRAL COMPOSITE FEATURE**

Using PCA, the best set of values of each features were obtained. The obtained features can be combined to form a more robust and better feature. This is called Composite Feature (CF). In this research, a set of CF was formed, namely, Spectral Composite Feature (SCF). SCF is formed by combining all the reduced data columns of the time domain features.

Procedure to extract the frame based SCF features is described below:

Step 1: The reduced data columns after the PCA (Table 1) of each spectral feature for SC protocol were combined. The SCF set for the \( k^{th} \) frame corresponding to the \( i^{th} \) data column obtained from the four spectral features can be represented as:

\[ SCF^k = [z_1^k, z_2^k, z_3^k, z_4^k, z_5^k, z_6^k, z_7^k, z_8^k, z_9^k, z_{10}^k] \]

Step 2 : A data set consisting of 720 (30x4x6) feature sets along with its associated target vector has been formulated and this dataset has been named as SC Spectral Composite Feature (SC-SCF) database.

Step 3 : Repeat step 1 for the MC protocol and a dataset consisting of 480 (30x4x4) features sets has
been formulated for the MC set. This data set has been named as MC Spectral Composite Feature (MC-SCF) database.

VI. SUBJECTIVE EVALUATION ON CAR INTERIOR NOISES

The recorded signal is converted from \texttt{.cmg} into \texttt{.wav} files to be played back to the juries [14]. The \texttt{.cmg} format raw data file is obtained using the dBFA32 post-processing software. 20 Jury members are chosen from the School of Mechatronics Engineering, University of Malaysia Perlis (UniMAP).

Hearing screening is conducted using pure tone audiometric test. The test is vital to identify whether the subject is having normal hearing capability or not. The subjects can only proceed to the listening test if they passed the pure tone audiometric test [4, 19]. The test is conducted in the Acoustic lab using the Audiometric chamber. Prior to the test, the audiometric booth was calibrated by the certified vendor, so that the results from the test are acceptable. The baseline audiogram for each subject is stored for future references [14].

The subjects are allowed to sit for the listening test only if they pass the hearing screening test. The listening test is conducted in a small closed room to generate the environment of car interior. The recorded sample is stored in compact disks in randomized manner and played to the subjects [10]. The subjects need to listen to the samples played using the laptop and give the evaluation for the specific recorded sample. The subjects need to give the evaluation for the noise comfort based on the scale 1 to 10, where the scale 1 indicates least comfort and 10 indicates the most comfort level [12].

<table>
<thead>
<tr>
<th>Table 2. Subjective Evaluation Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subjective Rating</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td>6</td>
</tr>
<tr>
<td>7</td>
</tr>
<tr>
<td>8</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>10</td>
</tr>
<tr>
<td>Total:</td>
</tr>
</tbody>
</table>

The recorded sample is played at the actual sound pressure level recorded in the car, so that the subjects can have the same sound exposure experienced during the measurement sessions. The sound samples are played back using headphones, so that the subjects get the same sound exposure and are protected from unwanted disturbing noise [5, 10]. The maximum allowed sound pressure level to be played is 90dB. Continuous exposure to noise above 90 dB can leads to temporary deafness and permanent deafness.

After obtaining the subjective indices from all the subjects, the average index is computed and used as the target value for training the neural network. It is important that the outlier removal is made on the subjective ratings to ensure that the subjective rating is reliable. The standard deviations of the sound samples are shown in Table 2. From Table 2, it can be inferred that most of the subjects rate the sound samples from 4 to 7. The extreme ratings are the least rated by the subjects.
VII. EXPERIMENTAL PREDICTION AND VERIFICATION

Artificial neural network is a powerful tool used in many applications such as pattern recognition, data processing and classification. Artificial Neural Network imitates the biological neural network of human brain. It produces the output pattern when given the input pattern. It is an information processing system developed as a generalisation of mathematical models of human cognition [20]. In this research, Probabilistic Neural Network (PNN) is used to classify the cars comfort at different conditions [20]. PNN is chosen since it gives better classification accuracy and has less computational time when compared to the conventional Multilayer Perceptron classifier. For every feature, two neural network models are developed, one for stationary condition and another one for moving condition. Both the network model consists of 28 input neurons in the input layer and two hidden layers with 40 hidden neurons each. The 28 input neurons are the values from 25 frequency bands and the remaining 3 inputs indicate the speed information (each recorded speed was represented using a 3-bit binary code). The SCF model has total number of 85 input neurons, 82 input neurons obtained from the four features after PCA and 3 input neurons to indicate the speed information. All the network model has ten output neurons. The binary sigmoid activation function is used since the data samples are normalised from 0.1 to 0.9. The SC-SCF contains 720 samples and the MC-SCF database contains 480 samples. The ratio for training and testing data is modelled as 60/40 [20].

Table 3 shows the neural network training result for the stationary condition for all the four features and the composite feature. From the table, it is observed that SCF offers better mean classification rate of 94.21%. SLEQ recorded the least mean classification rate of 89.53%.

<table>
<thead>
<tr>
<th>Feature</th>
<th>SP</th>
<th>SLEQ</th>
<th>SEE</th>
<th>SL</th>
<th>SCF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum Classification Rate (%)</td>
<td>90.12</td>
<td>88.00</td>
<td>88.33</td>
<td>87.33</td>
<td>91.12</td>
</tr>
<tr>
<td>Maximum Classification Rate (%)</td>
<td>92.31</td>
<td>90.81</td>
<td>90.67</td>
<td>90.86</td>
<td>95.88</td>
</tr>
<tr>
<td>Mean Classification Rate (%)</td>
<td>91.42</td>
<td>89.53</td>
<td>89.62</td>
<td>89.57</td>
<td>94.21</td>
</tr>
</tbody>
</table>

Based on the comparison in Figure 4, SCF gives the best result for both the condition. Both moving and stationary models are used to evaluate the noise comfort level in the vehicle.

Table 4 shows the neural network training result for the moving condition for all four features and the composite feature. From the table, it is observed that SCF offers better mean classification rate of 90.45%. SL value records the least mean classification rate of 85.43%.

Table 4. Classification Accuracy Of Stationary Condition

Table 5 and Table 6 show the confusion matrix of SCF feature for both stationary and moving models respectively. From Table 5, it is observed that the first, second, ninth and tenth indices have no level of confusion and it is classified accurately. Further, it is observed that the seventh index has high level of confusion when compared to the other indices. From Table 6, it is observed that the first index has low level of confusion and it is classified accurately. Further, it is observed that the fourth index has high level of confusion when compared to the other indices.
Table 4. Classification Accuracy of Moving Condition

<table>
<thead>
<tr>
<th>Minimum Classification Rate (%)</th>
<th>SP</th>
<th>SLEQ</th>
<th>SEE</th>
<th>SL</th>
<th>SCF</th>
</tr>
</thead>
<tbody>
<tr>
<td>86.18</td>
<td>84.51</td>
<td>85.32</td>
<td>84.33</td>
<td>88.56</td>
<td></td>
</tr>
<tr>
<td>Maximum Classification Rate (%)</td>
<td>88.83</td>
<td>87.57</td>
<td>87.75</td>
<td>87.75</td>
<td>91.75</td>
</tr>
<tr>
<td>Mean Classification Rate (%)</td>
<td>87.40</td>
<td>86.37</td>
<td>86.59</td>
<td>85.43</td>
<td>90.45</td>
</tr>
</tbody>
</table>

Figure 4. Comparison between the features

TABLE 5. CONFUSION MATRIX OF SC-SCF

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>Index 1</th>
<th>2</th>
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<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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</tr>
<tr>
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<td>0</td>
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<td>1</td>
<td>0</td>
<td>87.50</td>
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<td></td>
<td></td>
<td>10</td>
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<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
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TABLE 6. CONFUSION MATRIX OF MC-SCF

<table>
<thead>
<tr>
<th>Actual</th>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>Accuracy (%)</th>
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</tr>
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<td>0</td>
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<td>13</td>
<td>0</td>
<td>92.86</td>
</tr>
<tr>
<td>10</td>
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<td>0</td>
<td>0</td>
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<td>8</td>
<td>88.89</td>
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</tbody>
</table>

VIII. SUMMARY AND CONCLUSIONS

The research covers the concepts of digital signal processing techniques and artificial neural network. Measurement device, Orchestra is used to capture the noise emanated from the vehicle interior. The frequency-based features, namely, Spectral Power, Spectral $L_{eq}$ value, Spectral Energy Entropy, and Spectral Loudness were extracted from the signals. The sound is played back to 20 subjects with good hearing capabilities to find out the associative index for the respective sound file. Based on the neural network training, it has been observed that Spectral Composite Feature gives the best result for both moving and stationary models. Confusion matrices of Spectral Composite Feature for both models have been tabulated.

Acknowledgement

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Stationary and Non-Stationary Vehicle Cabin Noise Level Identification Using Spectral Composite Features and Neural Networks

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Fuzzy Logic Inference System for Voiced-Unvoiced-Silence Classification of Malaysian English Isolated Words based on Time-domain Features

Yusnita MA¹  Paulraj MP²  Sazali Yaacob²  Shahriman AB²  Satheesh Kumar Nataraj²

Abstract

The ability of a system to automatically detect speech signals such as, voiced-unvoiced-silence can have a great impact to the accuracy and computation time in isolated-word speech recognition systems. The presence of a long inter-syllable silence in Malaysian English speech is due to the habit of spelling and reading methods in syllabic manner of the national Malay language at school. Further, manual segmentation is very tedious, laborious and error-prone for large vocabularies and sample size. Time-domain features such as short-time energy and zero-crossing rate are proven to be very efficient and simple computations. Since frame-based speech analysis does not consider the start and end of a particular phoneme, the best and easiest way to make decision for the important features should be inferred from human expert knowledge. In this paper, fuzzy inference system is build from membership functions and fuzzy rules derived from a simple statistical analysis of the speech data from males and females and three ethnic groups of Malaysian English speakers. The study of voiced-unvoiced-silence classification using fuzzy logic method with energy and zero-crossing rate input vectors are based on the simplest settings of three two-syllabic words and under noise-free environment. The experimental results show highest accuracy rates of 99% for voiced speech and 94% for silence.

Keywords – Voiced/Unvoiced/Silence classification, Malaysian English, Short-time energy, Zero-crossing rate, Fuzzy logic.

I. INTRODUCTION

There are basically two methods to segment speech signals. Traditional automatic speech recognition systems (ASRs) try to separate blocks into the same characteristics which represent a single phoneme, which is the smallest unit of speech construction in a particular language. Malcangi [1] and Tolba [2] performed analysis based on phoneme segmentation. The other method and perhaps most of the modern ASRs practice is using fixed-frame segmentation due to its simplicity and straightforward process. While the earlier is claimed to have better representation, however, it is complicated by the fact that phonemes can blend together under certain circumstances and variety of imperfect articulation of a spoken word could make this task disputable to detect correct boundaries. According to [3, 4], frames are made in the size of 10 ms to 30 ms due to the theory that temporal variation of the vocal tract shape is relatively slow thus maintain a constant characteristics within this time frame length. This is also a compulsory condition for using fast Fourier transform and Linear Predictive Coding (LPC) techniques. In speech preprocessing, automatic speech segmentation is a key processing task to overcome manual
segmentation which is time consuming, laborious, tedious, error prone and expert dependent. The classification of speech into voiced, unvoiced and silence abbreviated as V-UV-SIL or the decision of endpoint detection has been intensely researched in the field of speech applications such as speech recognition, synthesis and coding. Not all key information embedded in the pre-recorded speech is contained in the short-time frames of the uttered speech. Discarding the unnecessary frames of non-speech part is preliminarily important to have an efficiently less computational and more accurate isolated-word ASRs. These systems are used primarily for handling voice commands such as in voice dialing and security control to access confidential information area.

The model of speech can be best described using source-filter model [5] which describes speech sounds as the product of convolution between the vocal tract filter and the glottal source and assuming that these components are independent from each other, giving it the second name as linear separable model as well. The mechanism of having voiced speech is the vibration of the vocal folds in response to airflow from the lungs and it is periodic in nature. Conversely unvoiced speech is caused by turbulent airflow due to a constriction in the vocal tract and exhibited by a noise-like signal. All vowels and semivowels sounds and some consonants are voiced while most of the consonants are unvoiced. The vowels are 12 dB louder than consonants [6] in general. Malaysian English (MalE) is colored by different pronunciations as it is influenced by various ethnicities [7], thus complicating the structure in comparison to native English pronunciations such as British English. Some voiced sounds like /z/ is pronounced unvoiced and a Chinese Malaysian replaces the phoneme with voiced /θ/. Final unvoiced plosive /t/ is realized as unvoiced glottal stop /ʔ/ for a Malay speaker. MalE speakers tend to speak in a syllabic manner (syllable-stress) as they are taught to spell and read by that manner. As the result they tend to prolong the gap between syllables in a word.

The advent of fast computer hardware and algorithms has witnessed many techniques implemented to achieve this goal. The appropriate ways of extracting features of a spoken word such as simple time-domain features namely short-time energy (STE), zero-crossing rate (ZCR) and pitch contour. However, pitch has some drawback [8] as it depends very much on voice periodicity wherein a single frame might be just quasi-periodic or non-periodic. Pattern recognition technique and statistical decision theory have been successfully used such as in [8, 9] in determining the decision threshold. In [9] three algorithms were developed based on histogram of STE only for speech detection. Multiple features such as log STE, ZCR, first autocorrelation coefficient, first LPC coefficient and log energy of prediction error were used in [8] to calculate mean vector and covariance matrix of probability density functions of each V-UV-SIL class. Based on lower and upper threshold limits of energy of speech and ZCR threshold of silence, a backward and forward search algorithm for endpoint detection was establish in a well known paper [10] for isolated utterances. This algorithm was further investigated [11] and features were extended using frame-based Teager’s energy and energy-entropy to compare the performance in detecting Malay isolated-words speech recognition. An even simple decision barely made based on just the amount of energy and ZCR count algorithm was establish in [12] for the word 'four'. Spectral features are less encountered in V-UV decision probably due to its more computation cost but it was reported in [13] using Mel frequency cepstral coefficient and LPC with Gaussian mixture model. The attempt to apply fuzzy logic to V-UV-SIL is quite new although it has been applied to segment phonetic unit of vowels and consonants in [1] and voiced-silence classification for pathological speech in [14]. Thus separating V-UV from SIL using simple features namely log STE and ZCR and fuzzy logic as simple and human-like rules predictor is inevitably important in speech processing of MalE speech which is the focus of the study.
in this paper. The attempt to evaluate the developed system in comparison to manual labeling is also presented.

This paper is organized as follows. In section II, a brief description about MalE speech database is presented. Section III describes methodologies used for extracting speech features and classifier used to do the classification of V-UV-SIL frames. The experimental setup and findings are discussed in section IV. Lastly, section V gives the concluding remarks based on the studied problem and methodology.

II. MALAYSIAN ENGLISH SPEECH DATABASE

For the purpose of analysis, speech utterances recorded from seven males and females from two major ethnicities i.e. Malay and Chinese and from seven males and five females Indian MalE speakers uttering three two-syllable words i.e. bottom, student and zero. Two-syllabic words were selected to prove that some words have great inter-silence. Each word was replicated five times to generate more samples from a speaker. The average duration of each word is about 0.5 s to 0.7 s and was hand-segmented prior to analysis. Subjects were postgraduate students of Universiti Malaysia Perlis aged from 18 to less than 30 years. The dataset contains total utterances of 200 samples for each word under the study. The recording was carried in an acoustic chamber room which is semi-anechoic using a handheld condenser and unidirectional microphone. The background noise in that room was approximately 22 dB. This level is considered very quiet and controlled as compared to normal quiet room about 40 to 50 dB. The speech was recorded using a laptop computer sound card and MATLAB program where the sampling rate was set to 16 kHz and bit resolution was set to 16 bps.

III. METHODOLOGY

Firstly, the DC components captured in the raw data due to microphone setup was removed or zero-adjusted. Next, frame-blocking into 256-point frame with 128-point overlapping between consecutive frames were made on each word sample prior to log STE and ZCR extractions. The flowchart in Fig. 1 summarizes the process of classifying V-UV-SIL speech

![Figure 1. Block Diagram of V-UV-SIL System](image)

A. Short-time Energy

Time-domain feature such as STE is efficient and easy to compute, thus simplify the hardware implementation. Higher energy is an indicator of voiced speech as unvoiced is spoken at less power and very much less energy should be in silence. Energy is associated positively with loudness of the acoustic signal and also related negatively to its frequency. It is found that the spectrum decreases in amplitude with increasing frequency at a rate of around 12dB per octave. This feature measures the sum of squared magnitude of the sample values in each frame and can be expressed as in (1) as log-energy.

\[
E(k, n) = 10 \cdot \log_{10} \left( \frac{1}{N} \sum_{n=0}^{N-1} |x(k, n)|^2 \right) \tag{1}
\]

where variables \( E(.) \) and \( x(.) \) represent frame-energy and input speech respectively and \( k \) is the \( k \)th frame and \( n \) is the \( n \)th sample point in a frame. \( N \) is the length of the frame.

B. Zero-crossing Rate

Another simple yet powerful time-domain feature is ZCR. It is a measure of how many times the waveform crosses the zero-axis in a particular frame. Also, it can be a crude estimation of pitch determination wherein the number of crossings per second is equal to twice the frequency
and best used in the absence of noise environment. Generally, the ZCR of both unvoiced speech and background noise are higher than voiced speech which has obvious fundamental periods and has most of the energy concentrated at low frequencies. The equation to count zero-crossings is given in (2).

\[ ZCR(k, n) = \frac{1}{2N} \sum_{n=0}^{N-1} |\text{sign}[x(k, n)] - \text{sign}[x(k, n-1)]| \]  

(2)

where variables ZCR(.) and x(.) represent frame-ZCR and input speech respectively and \( k \) is the \( k \)th frame and \( n \) is the \( n \)th sample point in a frame. \( N \) is the length of the frame. The function \( \text{sign}[.] \) is defined as follow

\[ \text{sign}[x(n)] = \begin{cases} +1 & \text{if } x(n) \geq 0 \\ -1 & \text{if } x(n) < 0 \end{cases} \]  

(3)

C. Fuzzy Logic Inference System

Fuzzy logic was first introduced by Zadeh in 1965 who defined fuzzy set theory to describe fuzziness. In Zadeh’s second most influential paper [15], human knowledge was suggested to be captured in fuzzy rules. Thus, fuzzy logic leads to more human-like intelligent system as it models our sense of word and decision making based on common sense. It is basically a set of mathematical principles for knowledge representation based on degrees of membership [16]. The behavior of the collected speech data from MaIE utterances was studied using statistical analysis (minimum, mean and maximum values) of STE and ZCR measures to derive fuzzy membership functions and fuzzy rules. To ensure that the rules fit our data, the inferred knowledge was also based on experimental observations that correlate to these three classes to tune the fuzzy engine. This system was designed using MATLAB fuzzy logic toolbox GUIs. Manual hand-labeling of V-UV-SIL of frames of each word were made to evaluate the fuzzy inference system (FIS). Since this task was laborious and time-consuming, only three words were analyzed. Fig. 2(a)–(c) depict the membership functions for STE and ZCR inputs and speech output for the word ‘bottom’. A triangular membership function was chosen as it is practical and one of the simplest linear-fit functions. To keep the design simple, a minimum number of three membership functions in input and output were generated.

![Figure 2(a). Membership function for STE](image)

![Figure 2(b). Membership function for ZCR](image)

![Figure 2(c). Membership function for system output](image)

There were five steps involved in developing FIS. (1) Fuzzification of inputs—the crisp measures STE and ZCR were taken to determine their degree of membership in each fuzzy subset. (2) Application of fuzzy operators—only AND operators were used in five rules using \( \min \) built-in method. (3) Application of implication method—\( \min \) was used to truncate output fuzzy sets. (4) Aggregation of all outputs—fuzzy sets that represents the outputs of each rules were combined using \( \max \) method into a single fuzzy set. Lastly (5) Defuzzification—resolves the single fuzzy set to a single crisp value. The fuzzy rules in V-UV-SIL FIS are tabulated in Table 1.
TABLE 1. A SET OF RULES for V-UV-S SYSTEM

<table>
<thead>
<tr>
<th>Rule#</th>
<th>STE Operator</th>
<th>ZCR Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>if LOW</td>
<td>NONE</td>
</tr>
<tr>
<td>2</td>
<td>if MEDIUM</td>
<td>MEDIUM</td>
</tr>
<tr>
<td>3</td>
<td>if MEDIUM</td>
<td>HIGH</td>
</tr>
<tr>
<td>4</td>
<td>if MEDIUM</td>
<td>LOW</td>
</tr>
<tr>
<td>5</td>
<td>if HIGH</td>
<td>NONE</td>
</tr>
</tbody>
</table>

IV. RESULTS & DISCUSSION

In this section, the experimental setup and results are reported. Three experiments based on three isolated words i.e. 'bottom', 'student' and 'zero' were conducted to find the thresholds for generating fuzzy membership functions. Each word consists of the following phonemes sequences according to British English:

bottom - /'b, *, t, m/

student - /s, t, j, u:, d, n, t/

zero - /'z, I, r, * /

Only a great detail of the word 'bottom' is shown and discussed as example for analyzing the results. Fig. 3 depicts the waveform 'bottom' consisting of its phonemes sequence and silence.

It is obvious that the MalE speech is characterized by syllabic stress and a long inter-syllable silence which can cause a waste in processing. The silence was produced before the release of plosive /t/. Table 2 and 3 tabulate the results of STE and ZCR measures of ten test samples of 'bottom'. This test dataset is 5% fraction of the available data.

TABLE 2. TEST DATASET WITH STE MEASURES

<table>
<thead>
<tr>
<th>No</th>
<th>Speaker ID</th>
<th>Gender</th>
<th>Ethnic</th>
<th>Min STE</th>
<th>Mean STE</th>
<th>Max STE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Spk5</td>
<td>Female</td>
<td>Malay</td>
<td>-50.11</td>
<td>-20.18</td>
<td>5.67</td>
</tr>
<tr>
<td>2</td>
<td>Spk7</td>
<td>Male</td>
<td>Indian</td>
<td>-52.23</td>
<td>-15.01</td>
<td>9.58</td>
</tr>
<tr>
<td>3</td>
<td>Spk13</td>
<td>Male</td>
<td>Malay</td>
<td>-59.93</td>
<td>5.85</td>
<td>6.83</td>
</tr>
<tr>
<td>4</td>
<td>Spk19</td>
<td>Male</td>
<td>Chinese</td>
<td>-50.95</td>
<td>-11.12</td>
<td>10.27</td>
</tr>
<tr>
<td>5</td>
<td>Spk25</td>
<td>Female</td>
<td>Chinese</td>
<td>-53.16</td>
<td>-20.31</td>
<td>2.83</td>
</tr>
<tr>
<td>6</td>
<td>Spk95</td>
<td>Female</td>
<td>Indian</td>
<td>-58.30</td>
<td>-14.04</td>
<td>8.5</td>
</tr>
<tr>
<td>7</td>
<td>Spk112</td>
<td>Male</td>
<td>Chinese</td>
<td>-51.88</td>
<td>-14.29</td>
<td>11.04</td>
</tr>
<tr>
<td>8</td>
<td>Spk141</td>
<td>Female</td>
<td>Indian</td>
<td>-53.12</td>
<td>-13.35</td>
<td>6.06</td>
</tr>
<tr>
<td>9</td>
<td>Spk97</td>
<td>Female</td>
<td>Malay</td>
<td>-50.74</td>
<td>-10.84</td>
<td>10.70</td>
</tr>
<tr>
<td>10</td>
<td>Spk81</td>
<td>Male</td>
<td>Malay</td>
<td>-51.74</td>
<td>-12.65</td>
<td>8.73</td>
</tr>
</tbody>
</table>

TABLE 3. TEST DATASET WITH ZCR MEASURES

<table>
<thead>
<tr>
<th>No</th>
<th>Speaker ID</th>
<th>Gender</th>
<th>Ethnic</th>
<th>Min STE</th>
<th>Mean STE</th>
<th>Max STE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Spk5</td>
<td>Female</td>
<td>Malay</td>
<td>0</td>
<td>17.56</td>
<td>59</td>
</tr>
<tr>
<td>2</td>
<td>Spk7</td>
<td>Male</td>
<td>Indian</td>
<td>3</td>
<td>23.71</td>
<td>97</td>
</tr>
<tr>
<td>3</td>
<td>Spk13</td>
<td>Male</td>
<td>Malay</td>
<td>0</td>
<td>14.38</td>
<td>72</td>
</tr>
<tr>
<td>4</td>
<td>Spk19</td>
<td>Male</td>
<td>Chinese</td>
<td>3</td>
<td>16.58</td>
<td>60</td>
</tr>
<tr>
<td>5</td>
<td>Spk25</td>
<td>Female</td>
<td>Chinese</td>
<td>7</td>
<td>30.51</td>
<td>83</td>
</tr>
<tr>
<td>6</td>
<td>Spk95</td>
<td>Female</td>
<td>Indian</td>
<td>0</td>
<td>15.91</td>
<td>51</td>
</tr>
<tr>
<td>7</td>
<td>Spk112</td>
<td>Male</td>
<td>Chinese</td>
<td>2</td>
<td>17.21</td>
<td>92</td>
</tr>
<tr>
<td>8</td>
<td>Spk141</td>
<td>Female</td>
<td>Indian</td>
<td>6</td>
<td>23.05</td>
<td>80</td>
</tr>
<tr>
<td>9</td>
<td>Spk97</td>
<td>Female</td>
<td>Malay</td>
<td>0</td>
<td>14.35</td>
<td>64</td>
</tr>
<tr>
<td>10</td>
<td>Spk81</td>
<td>Male</td>
<td>Malay</td>
<td>6</td>
<td>22.55</td>
<td>86</td>
</tr>
</tbody>
</table>

Next, the frames having different ranges of STE and ZCR values were analyzed to discuss the results for Spk5. Fuzzy rules generated in Table 1 were justified based on manual observations and the computed features values in Figure 4(a)–(f).

It was observed that the waveform in Fig. 4(a) i.e. frame 28 displayed as noise-like signal, was the inter-syllable silence between the first syllable /bRt/ and the release of /t/ at its final position in the speech. These characteristics justified Rule 1 in the FIS.
Fuzzy Logic Inference System for Voiced-Unvoiced-Silence Classification of Malaysian English Isolated Words based on Time-domain Features

Fig. 4(a). Frame #28 of Spk5 with min STE and max ZCR

Fig. 4(b) is another inter-syllable silence but with very low STE and minimum silence (ZCR = 0). This condition might be due to the microphone setting. These characteristics also justified Rule 1 in the FIS.

Fig. 4(c). Frame #9 of Spk5 with max STE and medium ZCR

Frame 71 in Fig. 4(d) originated from phoneme /n/ and it was a voiced nasal consonant characterized by a single frequency sound. These characteristics justified Rule 4 in the FIS.

Fig. 4(b). Frame #31 of Spk5 with low STE and min ZCR

Frame 9 in Fig. 4(c) justified Rule 5 with max STE and medium ZCR. All frames with high STE regardless of ZCR count was considered voiced part. This frame was a voiced open back rounded short vowel /R/ in the word as characterized by the stable pitch of multiple combinations of frequencies.

Fig. 4(d). Frame #71 of Spk5 with medium STE and low ZCR

Frame 63 in Fig. 4(e) originated from voiced vowel schwa /Y/. These characteristics justified Rule 2 in the FIS.
Lastly the analysis for fuzzy rule involved Rule 3, wherein frame 40 in Fig. 4(f) was postulated to originate from a rapid burst of unvoiced consonant /t/ preceding the voiced vowel schwa /ʌ/.

For the purpose of system evaluation, accuracy rate was computed based on the difference between manual labeling of human expert and FIS output. The results are tabulated in Fig. 5. With reference to the experimental results, the overall classification rates for bottom, student and zero are 92.64%, 92.22% and 92.27% respectively.

The breakdown of accuracy rates for voiced, unvoiced and silence is presented as bar chart and clustered across each word.

In further analysis, the accuracy rates for speech and non-speech were obtained by combining the voiced and unvoiced frames. By doing this, the averagely low accuracy rate of unvoiced can be solved. It is proven that frame reduction is achieved by eliminating the inter-syllable silence. The results for speech and non-speech classification and frame reduction rates of each word can be visualized in Fig. 6 and Fig. 7.
Fuzzy Logic Inference System for Voiced-Unvoiced-Silence Classification of Malaysian English Isolated Words based on Time-domain Features

V. CONCLUSION AND FUTURE WORK

This paper has presented a classification of speech into V-UV-SIL of MalE isolated words using an intelligent FIS. Based on the distribution of crisp data from short-time log-energy and zero-crossing rate and using simple statistical data analysis, membership functions and fuzzy rules were derived to build the system. Classification results shows that FIS has demonstrated a great potential in detecting voiced speech with a high accuracy rate ranging from 93% (‘zero’) to 99% (‘bottom’), followed by silence 88% (‘bottom’) to 94% (‘zero’). However, it is a non-trivial problem to detect unvoiced from voiced and silence because of its partially low energy and overlap characteristic of zero-crossings like silence. The accuracy obtained was in between 18% (‘zero’) to 67% (‘student’). However the accuracy rate of detecting speech and non-speech parts are satisfactory i.e. in average 93.4% and 89.4% respectively. This should enable to capture the important speech features and at the same time, resulted in speech compression of as much as 24% via eliminating the inter-syllable silence problem which has been shown quite signifcant in MalE speech. The plan for future work is to demonstrate that classification of accent types of MalE speakers can be more efficient using the results of this V-UV-SIL classification.

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REFERENCES


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Fuzzy C-means Clustering Technique For Cancer Detection In Ultrasound Images

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ABSTRACT
Detecting tumor areas in breast Ultrasound (US) images is a challenging task. The occurrence of benign areas in breast may result in false identification of malignant areas which may have serious outcome. The CAD system can act as a major function in the early detection of breast cancer and can decrease the death rate among women with breast cancer. This challenge is especially daunting in non homogenous noisy US Images where benign and malignant images are difficult to identify. The US images possess speckle noise which is its inherent property. This study is an attempt to reduce false alarm in Breast cancer detection using computationally efficient fuzzy based image clustering. The images are obtained from the famous American Cancer database for conducting experiments.

Keywords: Cancer detection, Speckle noise, Fuzzy C-Means with repulsion, Ultrasound images

I INTRODUCTION
Fuzzy logic is one of the powerful soft computing tools in the field of pattern recognition of US images [1], [2], [3]. These imperfections could possibly relate with image during image capture or while transmission phase. Presence of speckle noise is one of the major imperfections linked with the US image and it may hamper the performance of CAD diagnostic tools. Fuzzy based image segmentation could be used to identify important pattern in noisy breast US images. It can be categorized into following classes: fuzzy clustering, fuzzy rule, fuzzy geometry, fuzzy thresholding and fuzzy integral based clustering techniques [4] [5].

In this study we have performed image clustering using Fuzzy C-means (FCM) algorithm [8] [13] in Ultrasound images which have the property of speckle noise. The motivation of this study is to devise a better diagnostic imaging for breast cancer detection.

Ultrasound imaging systems may introduce some amounts of speckle noise or artifacts in the signal, so the quality assessment is an important factor. Therefore, a matrix based image quality assessments method MSE and PSNR are used to measure the quality of these images.

Mean Square Error (MSE) - Mean Square Error assesses the quality of image based on variation and its unbiasedness. MSE is given by the mean square distance between the pixels of the original image Aij and the pixels in the reconstructed image Bij. It is given as:

\[
MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (A_{ij} - B_{ij})^2
\]

(1)

Peak Signal to Noise Ratio (PSNR) - Peak Signal to Noise Ratio is used to analyze the quality of the two images – original and reconstructed image after the de-noising process. Mathematically PSNR is represented as:

\[
PSNR = 10 \log \left( \frac{255^2}{MSE} \right)
\]

With comparison with Ultrasound images

II EXPERIMENTAL
Fuzzy logic is one of the powerful soft computing tools and can be employed to solve a wide range of image processing problems. The Fuzzy C-Means (FCM) clustering algorithm is used in this study to cluster the images into two classes: benign and malignant. The images are divided into training and testing sets. The training set is used to find the cluster centroids while the testing set is used to evaluate the performance of the FCM algorithm. The performance of the algorithm is evaluated using the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR).
The outline of the paper is as follows: A brief discussion of Fuzzy C-Means based clustering technique is presented in Section-II. Section-III discusses the methodology used for US image clustering. Section-IV presents the experiments and results. The paper is concluded with Section-V with future implementations.

II. FUZZY C-MEANS (FCM) BASED CLUSTERING TECHNIQUE

The Fuzzy Filters are non-liner filters used to preserve the details in an image. Fuzzy Filters was proposed by Dunn [8] and refined by Bezdek [7][12][14] and others. The fuzzy inference model is composed of a group of logic connectors and IF-THEN statements. The outputs of the filters depend on the defuzzifying process, which is a combination of the effects of the established rules [5].

Fuzzy C-Means (FCM) Algorithm has been an admired choice for pattern recognition using clustering. In fuzzy clustering, each point has a degree of belonging to clusters. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the center of cluster. Any point \( x \) has a set of coefficients giving the degree of being in the \( k \)th cluster \( w_k(x) \). With fuzzy c-means, the centroid of a cluster is the mean of all points, weighted by their degree of belonging to the cluster:

\[
C_{\text{perf}} = \frac{\sum w_i(x)x}{\sum w_i(x)}
\]  

(3)

The degree of belonging, \( w_i(x) \), is related inversely to the distance from \( x \) to the cluster center as calculated on the previous pass. It also depends on a parameter \( m \) that controls how much weight is given to the closest centre.

III. METHODOLOGY

The proposed methodology describes fuzzy c-means clustering of breast malignant areas in noisy US images with the following steps.

First we synthesis breast image by inducing speckle noise across the breast image [6].

To maintain the consistency among different images Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) is used as metrics.

Fuzzy C-Means clustering [16], [14] is performed on the images obtained in step i of this algorithm. Compare with the original image the noise induced image as in fig.4 and fig.5 to indentify the tumor cells.

Evolutionary Neuro-Fuzzy techniques used to de-noise the images. Repulsive C-Means Fuzzy clustering is again performed on these images obtain after step iv.

Compare with original image [11], the results are as in fig.5 which show a significant improvement in clustering.

IV. EXPERIMENTS AND RESULTS

The experiment is simulated using Matlab7.5 [18] and the performance of the proposed method is evaluated using 255 X 255 grayscale images [17] with prominent malignant areas. The region of interest (ROI) is the identification of tumor. The effect of increasing noise level on the quality of the image is shown in Table1. MSE is the mean square error between the original and noisy image and original and de-noised image. The improvement in PSNR in the experiments is shown in Table 2. It is inversely related with the MSE. PSNR is the peak signal to noise ratio between the original and noisy image and the original and de-noised image.
Table 1. Standard Deviations (STD) in terms of Mean Square Error (MSE)

<table>
<thead>
<tr>
<th>σ (Standard Deviation)</th>
<th>MSE (Original and Noisy Image)</th>
<th>MSE (Original and De-Noised Image)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.010</td>
<td>0.5100</td>
<td>0.4854</td>
</tr>
<tr>
<td>0.015</td>
<td>0.4819</td>
<td>0.4623</td>
</tr>
<tr>
<td>0.020</td>
<td>0.4726</td>
<td>0.4452</td>
</tr>
<tr>
<td>0.025</td>
<td>0.4999</td>
<td>0.4926</td>
</tr>
<tr>
<td>0.030</td>
<td>0.4996</td>
<td>0.5014</td>
</tr>
</tbody>
</table>

Figure 1(b) demonstrates suppression of homogenous noise at $\sigma = 0.015$. Figure 1(c) shows the affect of Noise Reduction using Evolutionary ANFIS technique as the presence of speckle noise can hinder the detection of malignant areas.

Figure 2(b) shows the image clustering using Standard Fuzzy C-Means Clustering applied on Original image. In Figure 2 (c) shows how Standard FCM can be used for finding the region of interest (ROI).
In Figure 3 (b) original image corrupted with speckle noise at \( \sigma = 0.015 \). The presence of speckle adversely affects the detection of artifacts. The proposed method is applied on the image corrupted with noise as shown in Figure 3.

FCM analysis on various images is shown in Table 3. This analysis broadly divides into three categories: FCM applied on original image, FCM applied on noise induced image [9] and Repulsive FCM applied on de-noised image. FCM analysis is performed by calculation of cluster centers and then the assignment of members to these centers using the Euclidian distance. It is an iterative process and stabilized after certain computations. In the above experiment the iterations stabilize at 15. The execution time is proportionate with the number of clusters. Since we have only one cluster the time taken is 1.005 sec. In Table 3 the clustering results using Repulsive FCM, the impact of speckle noise on the performance of FCM algorithm is shown and the proposed de-noising technique incorporated into the Repulsive FCM algorithm shows a significant improvement in the clustering of the image.

Table 3. Clustering Results

<table>
<thead>
<tr>
<th>US Image</th>
<th>Data FCM</th>
<th>FCM for Speckle Noise Induced Image</th>
<th>FCM for De-Noised Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>904.3</td>
<td>1415.967</td>
<td>1240.65</td>
</tr>
<tr>
<td>Image 2</td>
<td>703.4</td>
<td>1216.467</td>
<td>1189.45</td>
</tr>
<tr>
<td>Image 3</td>
<td>960.1</td>
<td>1473.367</td>
<td>1266.25</td>
</tr>
<tr>
<td>Image 4</td>
<td>503.5</td>
<td>1015.967</td>
<td>1185.05</td>
</tr>
<tr>
<td>Image 5</td>
<td>889.8</td>
<td>1400.967</td>
<td>1205.85</td>
</tr>
</tbody>
</table>

V. CONCLUSION AND FUTURE RESEARCH

Fuzzy image processing has widely been used in the context of image segmentation and noise reduction [15] [16]. In this study Repulsive FCM [8] [14] Algorithm has been tested on noisy breast US image. Results showed that our technique effectively clusters the breast malignant areas, which could take more computations by conventional clustering methods. The clustering system identifies various important artifacts, such as cyst, tumor and micro calcifications. Patient clinical history together with better detection mechanisms could be beneficial for early diagnosis. Based on our study we have found number of areas for future research including detecting of tiny micro calcification. In future, we can extend FCM class 2 for non-homogenous noisy image to increase the computational complexity and when applied to de-noised image complexity is expected to decrease. Other potential area could be the classification of tumor based on the sharpness of the contours of artifacts.

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Fuzzy C-means Clustering Technique For Cancer Detection In Ultrasound Images


Author’s Biography

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A Novel Parallel Architecture for Elliptic Curve Cryptography
Based on Modified Programmable Cellular Automata

B. MuthuKumar¹, S. Jeevananthan²

ABSTRACT

An elliptic curve cryptography co-processor using the Modified Programmable Cellular Automata (MPCA) is proposed, which can perform the scalar multiplication over the GF ($2^{211}$). The novel elliptic curve cryptography (ECC) co-processor is parallel and polynomial basic with high throughput, better efficiency and less memory area. The proposed architecture can perform the doubling operation maximum of 187 MHz frequency and occupy 418 slices, and addition operation is performed maximum of 185 MHz and occupies 163 slices. With projective coordinate, the co-processor is implemented using very-high-speed integrated circuits hardware description language (VHDL) and simulated using OrCAD simulator.

Keywords - Elliptic Curve Cryptography (ECC), Modified Programmable Cellular Automata (MPCA), Scalar Multiplication.

I. INTRODUCTION

When the sensitive information is stored and accessed via networked environment, considerable attention must be taken to ensure data protection. A suitable encryption and decryption methodology is adopted both at the server and at the client end to safeguard the critical data. Very recently, the field of cryptography has grown unprecedentedly because of the rapid growth in data communications and internet services. The main characteristics of the cryptography are data confidentiality, authentication, data integrity, and non-repudiation, access control and availabilities of service. There are two types of cryptography, viz. secret-key cryptography and public-key cryptography. Secret-key cryptography [1]-[4] has a secrete key, which is used for both encryption and decryption. Public-key cryptography has two pairs of key; one pair is used for encryption while another pair is used for decryption also having technology for key agreement and digital signatures. Public key cryptography has been widely used today for Information security and E-commerce. The security of public cryptosystems is based on number-theoretic hardness of discrete logarithm problem.

In 1978, Rivest, Shamir and Adleman [5] had proposed a well-known public key cryptography scheme is RSA. The security of RSA is based on the difficulty of the integer factorization problem. Elliptic curve cryptography (ECC) was introduced by Victor Miller [6] in 1985 and Neal Koblitz [7] in 1987. The ECC operations can be implemented either over binary field $GF (2^n)$ or prime field $GF(p)$[8]. The ECC over $GF(2^{211})$ is easy to implement on field programmable gate array (FPGA) because it is having only logic operations and shift operations.

A fast parallel architecture for the implementation of the elliptic curve scalar multiplication using a novel Modified Programmable Cellular Automata (MPCA) is proposed. The proposed co-processor is parallel and
polynomial basic with high throughput, better efficiency and less memory area. The architecture can perform the doubling operation maximum of 187 MHz frequency and occupy 418 slices, and addition operation is performed maximum of 185 MHz and occupies 163 slices.

II. STATE-OF-THE-ART

The cellular automata (CA), proposed by Von Neumann and Stanislav Ulam, are a bio-inspired paradigm highly addressing the soft computing and hardware for a large class of applications including information security [9]. The cellular automata technique used in parallel processing and number theory applications. Jun–Cheol Jeon [9] has proposed an efficient division architecture using restricted irreducible polynomial on ECC based on CA. An arithmetic computations architectures using programmable cellular automata has been proposed by Zhang et al[10], P.P. Choudhury et al [11], have proposed a LSB multiplier based on CA. Petre Anghelescu et al [12] have proposed an efficient encryption algorithm based on hybrid additive programmable cellular automata (HAPCA).

Anghelescu, P[13] has proposed a high-performance encryption system base on bio-inspired based cryptosystems. Sheng-Uei Guan [14] has developed a new class of cellular automata, self programming cellular automata (SPCA), with specific application to pseudorandom number generation. Petre Anghelescu et al [15] has presented an originally encryption system implemented on a structure of hybrid additive programmable cellular automata (HAPCA), which support both software and hardware implementation. Petre Anghelescu [16] has proposed an encryption and decryption modules and a cascadable structure of PCA is used in order to ensure the security of the algorithm.

Nandi.S et al [24] has presented the theory and application of Cellular Automata (CA) for a class of block ciphers and stream ciphers to provide better security against different types of attacks. Based on CA state transitions certain fundamental transformations are defined for block ciphering functions to generate the simple (alternating) group of even permutations which in turn is a subgroup of the permutation group and these functions are implemented with a class of programmable cellular automata (PCA) built around rules 51, 153, and 195. For stream ciphers, high quality pseudorandom pattern generators built around rule 90 and 150 programmable cellular automata with a rule selector (i.e., combining function).K.N. Vijeyakumar et al [25] , have proposed Low- Power High-Speed Error Tolerant Shift and Add Multiplier, which enables the removal of input multiplexer, switching of adder cells and bypassing adder for zero bit values of the multiplier constant. Ning Zhu et al [26],[27] , have proposed Low-Power High-Speed Truncation-Error-Tolerant Adder, which is able to ease the strict restriction on accuracy, and at the same time achieve tremendous improvements in both the power consumption and speed performance.

III. ECC MATHEMATICAL BACKGROUND

Many public key cryptosystems are based on the finite field GF(2^m) in order to achieve a high level of security. The factoring large numbers or computing discrete logarithms for integers are computational complexity of an underlying mathematical problem for providing the security of public cryptosystems. An ECC cryptosystem is defined as the tuple $T = (a, b, G, n, h, GF(2^m))$, where, ‘a’ and ‘b’ define the elliptic curve on GF(2^m), G is a generator point of the elliptic curve, ‘n’ is the order of ‘G’, that is, the smaller integer such that ‘nG = O’ (identity point in the additive group).’ $H$ is called the co-factor and it is equal to the total number of points in the curve divided by ‘n’, and GF(2^m) is a finite field.

The most time consuming operation on the ECC is the scalar multiplication, which is depending on the tuple T. In ECC
security services perform the key agreement, digital signature and bulk encryptions. The hierarchy of various ECC operations is given in Fig.1. A scalar multiplication can be defined as adding the point ‘P’ to itself ‘(n – 1)’ times. That is, kP = P + P + P + · · · + P to k times. To perform the Scalar multiplication, the first operation is Finite field arithmetic, and the next level performance using two kinds of sums: the Elliptic curve addition which consist of the sum of two different points (P + Q) and Elliptic curve doubling which consist of the sum of the same point (P + P).

There are two types of coordinates, affine coordinates and projective coordinates. Non-super singular elliptic curve equation defined over a binary field GF (2^n) in affine coordinates can be denoted as

\[ y^2 + x^3 + ax^2 + b = 0 \]  

(1)

To perform addition,

let \( P = (x_P, y_P) \in GF(2^n) \) and \( Q = (x_Q, y_Q) \in GF(2^n) \),

if \( P \neq -Q \), then \( P + Q = (x_3, y_3) \),

where

\[ x_3 = \bar{e}^2 + \bar{e} + x_1 + x_2 + a \]  
\[ y_3 = \bar{e} (x_1 + x_3) + x_3 + y_1, \]

with \( \bar{e} = (y_1 + y_2) / (x_1 + x_2) \).

To perform doubling

let \( P = (x_P, y_P) \in GF(2^n) \),

where \( P \neq -P \), then \( 2P = (x_3, y_3) \),

where \( x_3 = \bar{e}^2 + \bar{e} + a \) and \( y_3 = x_1^2 + \bar{e} x_3 + x_3 \),

with \( \bar{e} = x_1 + y_1 / x_1 \).

Lopez and Dahab [28] proposed alternative projective coordinates’ operations, which avoid the inversions operation. The projective point \( (x: y: z) \neq 0 \), corresponds to the affine point \( (x / z, y / z^2) \). The elliptic curve equation in projective coordinate is

\[ y^2 z + x y z^2 = x^3 + a x^2 z^2 + b z^4 \]  

(2)

IV. PROGRAMMABLE CELLULAR AUTOMATA

The CA is a computing model of complex system using simple rule[21],[23]. In CA the problem space into number of cell and each cell can be one or several final state. Cells are affected by the simple rule of their left and right neighborhood. CA is completely parallel and
discrete dynamical systems and said to be reversible in the sense that the CA will always return to its initial state. Each cell in grid is one of a finite number of states, such as “on” or “1” and “off” or “0”. The neighborhood of the each cell is defined as all cells which are relative to the specified cell including the cell itself. The neighborhood conditions are determined by a pattern invariant in time and constant over the cells. At the time \( t = 0 \), cells in the grid are in arbitrary states and the CA evolves changing the state of all cells in the grid at discrete times, according to a local rule. Cellular automata are also called “cellular spaces”, “tessellation automata”, “homogeneous structures”, “cellular structures”, “tessellation structures”, and “iterative arrays”.

The one-dimensional nontrivial CA is base model, which consist of two possible states per cell and a cell’s neighbors are defined as the adjacent cells on either side of it. The possible patterns of a neighborhood are \( 2^3 = 8 \), because of a cell and its two neighbors form a neighborhood of 3 cells. There are 2\(^8\)=256 possible rules have been generated, which are number from 0 to 255. The next-state function describing a rule for a three neighborhood CA cell can be expresses as follows

\[
a_i(t+1) = f(a_{i-1}(t), a_i(t), a_{i+1}(t))
\]

(3)

Where \( i \) is the position of an individual cell in one dimensional array of cells, \( t \) is the time step, and \( f \) is the rule of CA.

The rule 30 and rule 110 CAs [20] are particularly interesting. The rule 30 says that, an infinite one-dimensional array of cellular automaton cells with only two states is considered, with each cell in some initial state. At discrete time intervals, every cell spontaneously changes state based on its current state and the state of its two neighbors. Table 1, shows the Rule 30, the rule set which governs the next state of the automaton.

Rule 30[20] has also been used as a random number generator in Wolfram’s program Mathematical, and has also been proposed as a possible stream cipher for use in cryptography. The function of the universal machine in Rule 110 requires an infinite number of localized patterns to be embedded within an infinitely repeating background pattern. The background pattern is fourteen cells wide and repeats itself exactly every seven iterations. The pattern is 00010011011111. Table 2, describes the Rule 110 for cellular automaton.

The behavior of cellular automata are defined in four classes, they are

Class 1: All initial patterns evolve quickly into a stable, homogeneous state.

Class 2: All initial patterns evolve quickly into stable or oscillating structures. Local changes to the initial pattern tend to remain local.

Class 3: All initial patterns evolve in a pseudo-random or chaotic manner. This class is suitable for pseudo-random number generation.

Class 4: All initial patterns evolve into structures that interact in complex and interesting ways.

Programmable CA (PCA)[18] is a structure where the combination logic (CL) of each cell is not fixed but it’s controlled by a number of control signals such that different rules can be realized on the same structure. This architecture used PCA based modular multiplication algorithm1 [18]-[19].

<table>
<thead>
<tr>
<th>Current Pattern</th>
<th>111</th>
<th>110</th>
<th>101</th>
<th>100</th>
<th>011</th>
<th>010</th>
<th>001</th>
<th>000</th>
</tr>
</thead>
<tbody>
<tr>
<td>New state for center cell</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
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</tbody>
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Table 1 Rule 30 for cellular automaton

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<td>1</td>
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</tr>
</tbody>
</table>

Table 2 Rule 110 for cellular automaton
A Novel Parallel Architecture for Elliptic Curve Cryptography
Based on Modified Programmable Cellular Automata

PCA based modular multiplication algorithm 1
Input: A(x), B(x), P(x)
Output C = AB mod P(x)
Reset PCA
Configure Coefficients of B(x) as Cm, and
Coefficients of P(x) as Cr
Run PCA m clock cycl

V. PROPOSED ARCHITECTURES

The proposed architecture is based on the projective coordinate over the GF(2^m). Let us take two points on the curve from (2), P = (x, z) and Q = (x, z). The point doubling 2P = (x, y, z) is converted to projective coordinate representation, becomes,

\[ x_1 = x^4 + b, z_1^{1/2} \]  
\[ z_1 = x_1^2, z_1^{1/2} \]  

\[ x_2 = x^4 + b, z_2^{1/2} \]  
\[ z_2 = x_2^2, z_2^{1/2} \]  

Fig. 2 Montgomery point doubling architecture

The architectures [18] of point doubling formulas are shown in Fig. 2. In Fig. 2, the ‘sqr’ perform the squaring operation of eight bit, thirty two bit and sixty four bit values. ‘Mux’ act as multiplexer for select appropriate input and ‘Mult’ is used to perform the multiplication operation. Reg A, B, C and D are used to store the temporary values. The algorithm describes the Montgomery point multiplication algorithm [18] is used to perform the scalar multiplication. The advantage of the Montgomery point multiplication algorithm is that it occupies the less memory and it is very difficult to cryptanalysis in timing attacks and power analysis attacks because of main loop perform same operation in every iteration.

Input = (K_{n-1}, k_{n-2}, ..., k_1, k_0)
P(x,y) ∈ GF(2^m)
Output: Q(x_3, y_3) = kP
Procedure: MontPointMult (P,K)
1. Set X ← x, Z ← 1, X_2 ← x^4 + b, Z_2 ← x^2
2. for i from n-2 down to 0 do
   2.1 if (k_i =1) then
      Madd(X_1, Z_1, X_2, Z_2);
      Mdouble(X_2, Z_2);
   2.2 else
      Madd(X_2, Z_2, X_1, Z_1);
      Mdouble(X_1, Z_1);

Fig. 3 Montgomery point adding architecture

In Fig. 3[18], the ‘Mux’ is used to select required input from x1, x2, z1 and z2 inputs. ‘Sqr’ module is used to perform the squaring operation and ‘Mult’ for performing the multiplication operation. Reg A, B, C and D are used to store the temporary values. The algorithm describes the Montgomery point multiplication algorithm [18] is used to perform the scalar multiplication. The advantage of the Montgomery point multiplication algorithm is that it occupies the less memory and it is very difficult to cryptanalysis in timing attacks and power analysis attacks because of main loop perform same operation in every iteration.

Input = (K_{n-1}, k_{n-2}, ..., k_1, k_0)
P(x,y) ∈ GF(2^m)
Output: Q(x_3, y_3) = kP
Procedure: MontPointMult (P,K)
1. Set X ← x, Z ← 1, X_2 ← x^4 + b, Z_2 ← x^2
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      Madd(X_1, Z_1, X_2, Z_2);
      Mdouble(X_2, Z_2);
   2.2 else
      Madd(X_2, Z_2, X_1, Z_1);
      Mdouble(X_1, Z_1);

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3. \( x_3 \leftarrow X_1 / Z_1 \)

4. \( y_3 \leftarrow (x+x_1/z_1)(X_1+xZ_1)(X_2+xZ_2)+(x^2+y)(Z_1Z_2) \)

\( (xZ_1Z_2)^{-1} + y \)

5. Return \((x_3, y_3)\).

In proposed architecture is shown in the Fig.4. It consists of input and output buffer interface, MPCA module and ECC operation module. ECC operation module performs the fundamental ECC operations. Several architectures are available for restricted irreducible polynomial on ECC based on CA. The parallel architecture is proposed for the implementation of the elliptic curve scalar multiplication using programmable cellular automata. But the scalar multiplication adds hardware latency and degrades the performance of the ECC system when put in real time data encryption. Hence a modified CA that uses an efficient scalar multiplier is coined. Since the scalar multiplication is a process of repetitive addition, the Modified CA uses an efficient adder that minimizes the hardware latency and increases the performance of the system to a considerable extent. Conventional adder circuit, the delay is mainly attributed to the carry propagation chain along the critical path from the least significant bit (LSB) to the most significant bit (MSB). Therefore, if the carry propagation can be eliminated or curtailed, a great improvement in speed performance can be achieved. The design of the Modified cellular Programmable Automata computation Engine using high performance adders is based on the following procedures (part-1 – part-3) [25]–[27],.

**Fig.4 Proposed architecture**

**Part – 1**

- First, the input operands are split into two parts:
  a) An accurate part that includes several higher order bits
  b) Inaccurate part that is made up of the remaining lower order bits
  c) The length of each part need not necessary be equal

**Part – 2**

- The addition of the higher order bits (accurate part) of the input operands is performed from right to left (LSB to MSB) and normal addition method is applied.
  a) This is to preserve its correctness since the higher order bits play a more important role than the lower order bits.

**Part – 3**

- The lower order bits of the input operands (inaccurate part) require a special addition mechanism.
  a) No carry signal will be generated or taken in at any bit position to eliminate the carry propagation path.
  b) To minimize the overall error due to the elimination of the carry chain, a special strategy is adopted, and can be described as follow:
i. Check every bit position from left to right (MSB to LSB).

ii. If both input bits are "0" or different, normal one-bit addition is performed and the operation proceeds to next bit position.

iii. If both input bits are "1," the checking process stopped and from this bit onward, all sum bits to the right are set to "1".

The main feature of proposed architecture is eliminating the carry propagation path in the inaccurate part and performing the addition in two separate parts simultaneously, the overall delay time is greatly reduced and hence the latency is minimized and throughput is increased. Moreover, significant proportion of the power consumption of an adder is due to the glitches that are caused by the carry propagation. Since the carry propagation is eliminated, it makes the system extremely power conservative. However proposed architecture is applicable only for the error tolerant systems since the accuracy of the system is compromised for performance.

VI. SIMULATION RESULTS

The proposed architecture stimulated using OrCAD stimulator version. The results shows that proposed architecture efficiently perform the scalar multiplication using MPCA. Fig.5 describes that MPCA achieves the high throughput, high efficiency and low combinational logic block compare to normal ECC.

Fig. 6 implies the performance results of Normal ECC and MPCA of Point doubling. MPCA achieves the point doubling operation in 418 slices at the frequency of 187MHz. Fig. 7 shows the performance of Normal ECC and MPCA of Point addition. MPCA achieves the point addition operation using 163 slices at the frequency of 185MHz. Fig. 8 shows the squaring performance of Normal ECC and MPCA. MPCA achieves the squaring operation using 230 slices at the frequency of 372MHz. In point addition and point doubling operation one and five squaring operations are used respectively. Inversion operation is performed during the coordinate conversion. Fig.9 shows the performance analysis of inversion regarding ECC and MPCA. MPCA occupies less number of slices at higher frequency compare to normal ECC during inversion process. Synthesis results of ECC fundamental operations are shown in the Table 1.

Fig. 5 Performance Comparison

Fig. 6 Performance Analysis for Doubling

Fig 7: Performance Analysis of Addition
In this work, OrCAD simulator is used to stimulate the key generation process. For generating the proposed architecture select the random number in the elliptic curve and obtain the different key for each process. Fig. 10 shows the results of key generation.

**Table 1 Synthesis Results**

<table>
<thead>
<tr>
<th>Operations</th>
<th>Frequency (MHz)</th>
<th>Occupation (slices)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inversion</td>
<td>190</td>
<td>890</td>
</tr>
<tr>
<td>Squaring</td>
<td>372</td>
<td>230</td>
</tr>
<tr>
<td>Doubling</td>
<td>187</td>
<td>418</td>
</tr>
<tr>
<td>Addition</td>
<td>185</td>
<td>163</td>
</tr>
</tbody>
</table>

In this work, an efficient, high throughput and less area elliptic curve cryptography co-processor over GF (2^{211}) using the modified programmable cellular automata (MPCA) is proposed, which is performed in parallel and polynomial basis. A Cellular Automata is a computing model of complex System using simple rule. Using Lopez and Dahab proposed projective coordinates operations the point addition and doubling is performed.

The Montgomery point multiplication algorithm used to perform the scalar multiplication. Source code is written in VHDL, synthesized using Xilinx Spartan EXCS30 prototype. The experimented result shows that the proposed co-processor having better throughput, frequency and less number of slices.

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A Novel Parallel Architecture for Elliptic Curve Cryptography Based on Modified Programmable Cellular Automata

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A Sequential Analysis based Approach in Wireless Sensor Networks

Punam Borah

ABSTRACT

Security is crucial for wireless sensor networks deployed in hostile environments. The selection of dropping nodes may be random. Identifying such attacks is very difficult and sometimes impossible. Selective forwarding attack is one such attack which is hard to detect. In this paper, the problem of identifying compromised and packet dropping nodes is considered. Two methodologies are presented and analyzed for this purpose. In the first method, the disconnected nodes are detected. In the second method, properly connected nodes are tested with packet transfer from source node to the destination node to identify the random dropping of nodes. Further an effective method for detecting the selective forwarding attack is proposed called the sequential mesh test which helps in the identification of nodes suffering from this attack. It is shown through experiments that this method can provide a higher detection accurate rate and a lower false alarm rate than the existing detection scheme.

Keywords: Malicious nodes, packet dropping, selective forwarding attack, wireless sensor networks.

I. INTRODUCTION

Wireless sensor networks (WSN) are composed of small sensors that are able to sense some phenomenon in the environment, and communicate the sensed data. Data is wirelessly communicated between sensors until it reaches a central processing unit, referred to as the sink. The node-patterned deployment of WSNs, however, can be the focus of certain types of malicious attack. One such strategy is the selective forwarding attack. Fig. 1 shows an example sensor network under selective forwarding attack.

As shown in Fig. 1, two compromised nodes selectively drop sensitive packets. Two algorithms have been identified and analyzed for identifying the malfunctioning nodes. The first algorithm identifies the disconnected nodes in a network. The second algorithm identifies the nodes causing the random dropping of packets in the network. In selective forwarding attack, a compromised node drops some of the packets for which it needs to relay while forwards other packets.

In this paper, we propose the sequential mesh test based selective forwarding attack detection scheme in wireless sensor networks. The sensor node will need to send the packet drop report message through another path to the cluster head if it does not observe the forwarding data message from the next hop sensor node in a fixed interval.

Fig.1 A sensor network under selective forwarding attack
The cluster head will run the sequential mesh test based detection scheme against the suspicious node after receiving the packet drop reports. We show through experiments that our scheme can provide a higher detection accurate rate and a lower false alarm rate than the existing detection scheme.

A. Related Work

Several solutions have been proposed to identify and overcome node failures and dropping of packets. One such approach as seen in [1] is based upon their dynamically measured behavior. They use a watchdog that identifies misbehaving nodes and a pathrater that helps routing protocols avoid these nodes. A lightweight solution called DPDSN [2] identifies paths that drop packets by using alternate paths that WSN finds earlier during route discovery. CHEMAS (CHEckpoint-based Multi-hop Acknowledgement Scheme) [3], is a lightweight security scheme for detecting selective forwarding attacks. Intanagonwiwat et al. [4] proposed the concept of directed diffusion data-centric in that all communication is for named data.

A countermeasure to the selective forwarding attack exists [5] in which a multidataflow topology (MDT) scheme is utilized to defend against the selective forwarding attack. Brown et al. [6] proposed the SPRT scheme for detecting selective forwarding attacks in heterogeneous sensor networks. The scheme utilizes powerful high-end sensors and is based on the sequential probability ratio test. Another security scheme for detecting selective forwarding attacks uses a multi-hop acknowledgement technique [7]. Kaplantzis et al. [8] proposed a centralized intrusion detection scheme. It suggested that the system can detect black hole attacks and selective forwarding attacks. Further [9] shows that there were several studies carried out on the attacks against sensor networks and its countermeasures.

B. Paper Organization

The remainder of this paper is organized as follows. Section 2 gives the overview of the system, showing the various modules that the entire system is made up of. Section 3 outlines the scheme used for generating and reporting packet drops. The Sequential mesh test scheme is presented in Section 4. Performance evaluation is discussed in Section 5. We present our conclusions and future work in Section 6.

II. Overview of System

The important issues in the sensor network are the coverage problem and the successful transmission of data to the base station [16]. The sensors send the collected data within their communication range to the base station without failure. But the base station may not receive all data sent by these nodes due to transmission problems or node malfunctions. Therefore, it is our duty to identify and report the malfunctioning nodes. Fig. 2 shows the overview of the entire system. The system proposed here consists of four basic modules:

- Determination of disconnected nodes: The nodes which are compromised and always lead to dropping of packets are identified.
- Identification of random packet drops: Apart from the disconnected nodes, there can be several other nodes causing random dropping of packets. These nodes are identified here.
- Generation of packet drop reports: For the base station to run tests on accused nodes, nodes causing suspicion needs to be identified. This is done by a source sensor node, which after detecting a suspicious node informs the base station through the packet drop reports.
- Sequential Mesh Test: After receiving packet drop reports, the base station runs the sequential mesh test to confirm the accusations and determine whether the node has undergone the selective forwarding attack or not.
A. Determination of Disconnected Nodes

The determination of disconnected nodes helps in the identification of nodes which are compromised and drop all packets that it receives. The identification of these disconnected nodes is accomplished through the use of Algorithm-H. This algorithm is run from the base station which sends broadcast packets to all the nodes. The nodes receiving this packet send an acknowledgement back to the base station. The nodes from which the base station receives acknowledgements are the connected nodes, otherwise they are considered to be disconnected nodes.

Pseudocode for Algorithm-H:

Objective: Determines which sensor nodes in the field are not connected to the sensor network i.e., it finds the holes.

Algorithm-H (graph, base)
{
    disconnectedNodes ← empty list
    for each node in graph
        do
            if (node not connected to base station)
                then
                    disconnectedNodes ← disconnected
                    Nodes+node
                    return disconnected

B. Identification of Random Packet Drops

The identification of random packet drops helps in determining the nodes which are not fully compromised but at times result in dropping of packets randomly [10].

The identification of these random dropping of packets is facilitated through the use of Algorithm-F. The algorithm begins at the source sensor node which needs to send number of packets to the base station. Each time a packet is sent, the counter value is increased. A mismatch of this value between the current node and the previous node at any point of time indicates a random drop of packet in the path.

Pseudocode for Algorithm-F

Objective: Detects if packets were dropped during transmission from a node A to the base station.

Algorithm-F (node A, path)
{
    transmit packets from node A to base station along path
    if (number of packets received != packet_count at current node)
        then
            return True
        else
            return False
}

III. Generation of Packet Drop Reports

For identification of nodes suffering from selective forwarding attacks, the sequential mesh test needs to be executed on the accused nodes [11]. Therefore, the first step here is determining the accused node. The packet dropping reports are generated by the source sensor node, which observes the network closely after sending a packet to its neighbors.
Alternate paths are selected when a node becomes suspicious and reports of it dropping a packet, is sent to the base station by the source node. These reports are called as the packet dropping reports. Here, the wireless sensor nodes should listen promiscuously to the network after sending their data packets. If the sender node has not observed the forwarding message after a fixed period of time, it can suspect that the intermediate relay node has dropped its packet [12]. Then the sender node will report packet dropping event to the cluster head through another path. Consider the sample scenario shown in Fig. 3.

Here, node ‘u’ is the original sender of the data packet to the base station ‘C’. Sensor node u sends data packet to C through intermediate node ‘v’. If, after certain interval of time, ‘u’ does not observe the message to have been forwarded, then it assumes ‘v’ to be the accused node then it will report this packet dropping event to the base station C through another path u->w->C. Node ‘u’ now needs to send the ID of the accused node (i.e., node ‘v’) as well as the packet which was dropped to the base station [13]. The following steps are followed to encrypt the data along with the accused node ID and sent to the base station.

a. Generate key $K_{uc}$ which is the key shared between node ‘u’ and the base station ‘C’.

b. Encrypt data and ID of ‘v’ with $K_{uc}$ to give $K_{uc}(data||v)$.

c. ‘seq’ used is a newly generated sequence number.

d. Encrypted result of step ‘b’ concatenated with ‘seq’, to give $K_{uc}(data||v)||seq$.

e. Resend message obtained in step ‘d’ to ‘C’ through node ‘w’.

f. At node ‘w’ concatenate the message sent at step ‘e’ with the ID of the last hop sensor, this gives seq||$K_{uc}(data||v)||u$.

g. Node ‘w’ encrypts the message obtained at step ‘f’ with $K_{cw}$, where $K_{cw}$ is the key shared between node ‘w’ and C, this gives $K_{cw}(seq||K_{uc}(data||v)||u)$.

h. Message obtained at step ‘g’ sent out until it reaches C.
i. C decrypts the packet drop report obtained layer by layer by using the keys.

j. The included node ID indicates the suspicious selective forwarding attack node.

IV. SEQUENTIAL MESH TEST

Sequential Mesh Test (SMT) is used to confirm the accusations made on a node under suspicion. After receiving the packet drop reports, the base stations needs to verify whether the accused node has undergone the attack or not [12]. For this purpose the sequential mesh test is used which is a form of statistical analysis wherein based on a predefined rule, results are obtained. The variable ‘p’ is used to denote the probability that a node drops a packet. The interval [p1, p0] denotes the acceptable probability interval of dropped packets [15].

After the base station receives the packet drop reports, it is able to identify the accused node and hence runs the sequential mesh test on this node to confirm the attack. To perform the sequential mesh test, the following steps are carried out:

a. A number of samples containing the status of packet forwarding need to be collected; this is represented as ‘m’ samples.

b. A variable ‘x’ is used where x=1 indicates a successful packet forwarding and x=0 denotes packet drop.

c. Variable ‘p’ denotes the probability of dropped packets among all forwarding packets.

d. The range specified as [p1, p0] denotes the acceptable probability interval of dropped packets.

• If p>p0: Accused node is a selective forwarding attack node.

• If p<p1: Accused node is not a selective forwarding attack node.

• If p1<p<p0: More samples having the status of packet forwarding are required to be collected.

e. The symbol ‘α’ denotes the acceptable missed detection rate.

f. The symbol ‘β’ denotes false alarm rate.

g. Further, the detection of selective forwarding attack is transformed into the following hypothesis test:

i. Null hypothesis H0: p=p0.


• Null hypothesis H0: p=p2, Alternative hypothesis H1: p=p1.

• Null hypothesis H0: p=p2, Alternative hypothesis H1: p=p1.

• Here p2 = 1 - (log( p0 / p1 ) / (log( ( p0 (1-p1) ) / ( p1 (1-p0) ) ) )).

h. Let S_n = ΣS i=1 xi be the times of successfully test until ‘n’.

i. Then,

• a 1 = log( β / (1-α) ), b1 = log( (1-β) / α )

• h1 = b1 / log( ( p0 (1-p1) ) / ( p1 (1-p0) ) )

• S1 = [log( (1-p1) / (1-p0) )] / [log( ( p0 (1-p1) ) / ( p1 (1-p0) ) )]

• h2 = b1 / [log( ( p0 (1-p2) ) / ( p2 (1-p0) ) )]

• S2 = [log( (1-p2) / (1-p0) )] / [log( ( p0 (1-p2) ) / ( p2 (1-p0) ) )]

j. SMT starts from n=1 (where ‘n’ is the number of samples collected, i.e., n = 1….m).
• If $S_n \geq S_1 + h_1$: Reject $H_1$, accept $H_0$, which means accused node is a selective forwarding attack node.

• If $S_n \leq S_2 - h_2$: Reject $H_2$, which means accused node, is not a selective forwarding attack node.

• If $S_2 - h_2 < S_n < S_1 + h_1$: Collect more samples and continue test.

\[ n_0 = \left\lfloor \frac{(h_2 + h_1)}{(S_2 - S_1)} \right\rfloor. \]

The base station needs to run SMT to verify which nodes are attackers and which nodes are not.

V. PERFORMANCE EVALUATION

In this system the Sequential Mesh Test (SMT) based detection method is compared with Sequential Probability Ratio Test (SPRT) based detection method [17]. This system has been designed, developed and implemented using the powerful tool “Java 1.6, Prowler Simulator and NetBeans IDE” with the high degree of user friendliness and accuracy.

Fig. 4 shows the average detection accuracy ratio of this method at different attack package drop rate for values corresponding to Table I. It is seen that the detection accurate ratio of SMT method is higher than that of SPRT method. Furthermore, the result shows that the higher the attack package drop rate, the higher the detection accurate ratio this method can achieve.

The values for Table I and Table II have been obtained based on the following configured parameter values:

- Square area side for the test field: 100,
- Number of nodes: 100,
- Malicious nodes: 5, 6, 7,
- Random Walk: 5,
- Disconnected nodes: 5, 6, 7, 30, 33, 34, 41, 42,
- Sink hole nodes: 45, 21, 84,
- Node to run algorithm-F: 36,
- Packet dropping node: 84,
- Selective Forwarder: 21, 22, 23, 24, 25,
- True Attacker: 22, 23,

Table I
Average Detection Accuracy Ratio

<table>
<thead>
<tr>
<th>Accuracy</th>
<th>Attack Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.005</td>
<td>0.005</td>
</tr>
<tr>
<td>0.015</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Fig. 5 shows the average false alarm ratio of this method at different attack package drop rate for values corresponding to Table II. It is seen that the false alarm ratio of SMT method is lower than that of SPRT method.

The attack package drop rate has no obvious influence on the false alarm ratio of this method.

![Fig. 5 The Average Detection Accuracy Ratio of SMT scheme](image-url)
A Sequential Analysis based Approach in Wireless Sensor Networks

Table II
Average False Alarm Ratio

<table>
<thead>
<tr>
<th>False Ratio</th>
<th>Attack Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.010</td>
<td>0.005</td>
</tr>
<tr>
<td>0.000</td>
<td>0.02</td>
</tr>
<tr>
<td>0.005</td>
<td>0.02</td>
</tr>
<tr>
<td>0.020</td>
<td>0.02</td>
</tr>
<tr>
<td>0.010</td>
<td>0.03</td>
</tr>
<tr>
<td>0.020</td>
<td>0.04</td>
</tr>
<tr>
<td>0.000</td>
<td>0.05</td>
</tr>
<tr>
<td>0.020</td>
<td>0.06</td>
</tr>
<tr>
<td>0.040</td>
<td>0.07</td>
</tr>
<tr>
<td>0.020</td>
<td>0.08</td>
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</table>

VI. CONCLUSION AND FUTURE WORK

In this paper, we propose a sequential mesh test based selective forwarding attack detection scheme in wireless sensor networks. First we describe an efficient scheme for reporting packet drops in a sensor network. Sensor nodes report the status of each transmission to the cluster head. Based on the reports, the cluster head performs the sequential mesh test and determines if a sensor node is compromised or not. A study about packet dropping by a partially compromised node is also carried out. Two methods are used to identify the partially compromised nodes in the path. Our experiment results show that our scheme can achieve a higher detection accurate rate and a lower false alarm rate than the existing detection scheme.

Identification of the fully compromised nodes [14] and the sink holes detection work can be left for future research.

REFERENCES


**Author’s Biography**

Punam Borah received his Bachelor of Engineering degree in Electronics and Instrumentation Engineering from Annamalai University in Chidambaram, Tamil Nadu and Master of Engineering in Information Technology from Rajiv Gandhi Technical University in Bhopal, Madhya Pradesh in 2002 and 2006 respectively. He is currently working as an Asst. Professor in the Department of Information Science and Engineering, SJB Institute of Technology in Bangalore, Karnataka. His research interests include Security Issues in Wireless Sensor Networks and Cloud Computing. He has participated and presented technical papers in various national and international level conferences.
Data Reduction Techniques in Data Mining

A. Anbarasi & S. Santhosh Baboo

ABSTRACT

Dimension reduction of datasets is very useful in different application including classification, compression, Text documents, microarray gene-expressions, images, etc. The challenge in distributed data mining is how to learn as much knowledge from distributed databases as we do from the centralized database without costing too much communication bandwidth. In this paper we propose a data reduction algorithm, which is different from all of these methods, to encode the transactions which reduce the size of transaction that in turn reduces the transfer time, size of the transaction, cost as well as increase the security level of data.

Keywords: Reduction, compression, & encode

INTRODUCTION

A dimension refers to a capacity of a certain aspect of an entity. Dimensionality reduction is the learning of methods for reducing the number of dimensions relating the entity [4]. Its general objectives are to remove irrelevant and redundant data to reduce the computational cost and avoid data over-fitting [1], [2] and to improve the quality of data for efficient data-determined processing tasks such as Data transmission and storage system in distributed data mining. Dimensionality reduction is an useful solution to the problem of “curse of dimensionality”[3].

In practice, researchers and practitioners interchangeably use dimension, feature, variable, and attribute[5]. Correspondingly, we will interchangeably use entity, example, vector, and instance. Consider an application in which a system processes data (speech signal, images, or patterns in general) in the form of a collection of vectors[8]. For a particular application, it is more often than not that a subset of features is relevant and in some cases, a large number of features are irrelevant. This problem can be caused by factors such as: (1) many dimensions will have variation smaller than the measurement noise and thus will be irrelevant, and (2) many dimensions will be correlated (through linear combinations or functional dependence) to others and thus will be redundant[7]. Therefore, in many situations, it is recommended to remove the irrelevant and redundant dimensions, producing a more economical

II. PROBLEM METHODOLOGY

Data Storage System transforms a transaction into a single dimension transaction with all attributes that appears in its original form. The encoded transactions are represented by a sequence of numbers. The sum of subset approach techniques should be followed. By this way, the new transaction is smaller than the original form and hence the cost of storage is reduced.

Certain transaction set of data items $Z=\{x, y, z\}$, the power set of $Z$, is in fact written as possible $P(Z)=\{\emptyset, \{x\}, \{y\}, \{z\}, \{xy\}, \{xz\}, \{yz\}, \{x,y,z\}\}$. If set $S$ is assumed as set of powers of 2, i.e. for example $S = \{2, 4, 8, 16\}$, then the power set $P_1(Z) = \{\{2\}, \{4\}, \{8\}, \{16\}, \{2, 4\}, \{2, 8\}, \{2, 16\}, \{4, 8\}, \{4, 16\}, \{8, 16\}, \{2, 4, 8, 16\}\}$. In this fashion, the sum of the subsets are matchless i.e. $2, 4, 8, 16, 6, 10, 18, 12, 20, 24, 30$.

2.1 Algorithm

For Calculating Dimension

Input: Number of data’s needed from set

Output: Extract the data’s as per rows and columns
k = input('Enter the Datasets to be extracted :');
c = k;
disp(c);
row = round(c/2)
col = round(k-row)
for i=1:m:n
    for j=1:m:n
        p = [i:m,j:n];
        X = A(p);
    end
end
K = X
The above algorithm gives us the extract data’s from the
set based on the calculation of rows and columns.

For making the given data’s as set and perform for
checking.
N = input('Enter the number of values:');
names = cell(1,N);
for t=1:N
    e2 = input('Enter the items:','s');
    names {t} = e2
end
The above algorithm creates a cell arrays for the user
defined data’s that is need to be checked with the data
set.

Comparing the values in dataset and Encoding
if(strcmp(names(t),K(i1,j1)))
    fprintf('an Item Found\n')
    K1 = 2^j1;
k2=cell(1,N);
    names{t}=K1
else
    fprintf('an Item Not Found\n')
end
The above algorithm performs the comparison operation
between the user data and the data set. If the item is found
in the set it encodes the data based on the sum of subset
approach specified and creates a cell arrays which gives
the encoding data’s in the form of numerical
representation values.

2.2 Process of Algorithms
Mention the dimension of the matrix (cell arrays) so that
the specified items will be displayed. From the dataset,
which is available to sort and select the needed items.
The needed items are chosen based on the number of
values needed. After that the position of the selected data
are taken and based on the formulae which is depicted
the values are calculated and applied to cell array. If the
item is not found in the dataset which is available go for
the selection of next item. Or else if the data set seems
to be empty or the searched item is not found, insert the
needed items in the data set and again continue the same
process. If the selected item is there continue the
calculation of values and update the newly created dataset
or cell arrays.

2.3. Comparison of Centralized and Decentralized
Mining of Data
The comparative performances of these two cases are
shown in figure 1. From figure-1, it is clear that, this kind
of data transformation better in terms of time and network
bandwidth usage compared with traditional system built
over client and server technology. The percentage
improvement of performance increases with decrease in
the number of patterns find in each site because, more
the number of patterns, implies, more data to be carried
by migration to central site.
Data Reduction Techniques in Data Mining

III. CONCLUSION

As computers become increasingly powerful, many applications can produce massive data of high dimensionality. Dimensionality reduction is an efficient way of dealing data with high dimensionality. The purpose is to reduce the data so that computational load decreases and better quality can be extracted in data mining algorithms. In this paper, we described the concepts of feature extraction and feature selection, and briefly introduced some representative methods. The need of dimensionality reduction techniques presents new challenges, and novel methods are expected to be developed.

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