INTERNATIONAL JOURNAL OF AUTOMOTIVE AND MECHANICAL ENGINEERING (IJAME)
ISSN: 2229-8649 e-ISSN: 2180-1606
VOL. 18, ISSUE 1, 8454 – 8463
DOI: https://doi.org/10.15282/ijame.18.1.2021.05.0640

ORIGINAL ARTICLE

Automatic Voice-Based Recognition for Automotive Headlights Beam Control

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ABSTRACT – Driving comfort plays an important role in modern automotive technologies. One of the ways of comforting the driver is the voice-based recognition to control car headlights. The driver uttered a 'specific word' that is taken as an input to the proposed voice-based recognition system. The proposed mechanism then determines if the signal was either 'high beam' or 'low beam' to control the car headlights. To activate the headlight's beam, this voice recognised signal is sent to a processing board. Mel Frequency Cepstral Coefficient (MFCC) is used in the recognition mechanism to extract the uttered word before being fed into Artificial Neural Networks (ANN) and Support Vector Machines (SVM) as a classification engine. The proposed automatic voice-based recognition was evaluated via experimental work. The results show that the proposed automatic voice-based recognition for headlights activation control involving MFCC feature works effectively in which SVM gives slightly better performance accuracy when compared to ANN. In addition to a lesser training time, the resulting accuracy using SVM in the training and testing phase is 93.595% and 91.74% respectively. Meanwhile, ANN has an accuracy of 89.39% and 88.16% in the training and testing respectively.

ARTICLE HISTORY
Received: 17th Aug 2020
Revised: 3rd Oct 2020
Accepted: 22nd Jan 2021

KEYWORDS
Voice-based recognition; Automotive headlight beam control; Artificial neural networks; Support vector machines; Mel frequency cepstral coefficient

INTRODUCTION

The development of technology in the automotive field has increased dramatically. Many parts of the automotive have been developed, for example, automotive headlight beam. Most of the current commercial automotive headlight beam activation control uses a mechanical switch that lies under the steering wheel. The signal is activated by moving up and down based on the beam needed, i.e. the high and low beam is managed manually with quite substantial physical movement. This system is sometimes inconvenient since the driver still needs to switch on and off the signal, which may cause mistakes to happen. Furthermore, many other technologies introduce automated high-low headlight beam control such as proposed by Asaduzzaman et al. [1]. The system work based on the detection of head and tail lights under night-time road conditions. The system depends on the detection device which will acknowledge that the neighbouring vehicle exists. On the other hand, Viswanadha, et al., [2] developed an Automatic Driver Assistance system (ADAS). This system provides detecting vehicles based on the camera to detect the condition of the road. This system is considered expensive and still need physical activity of the driver to activate the headlight's beam.

The voice-based recognition system to activate the high-low headlights beam is developed in this work. The system applied in modern automotive applications is mainly proposed to assist the driver to perform multitasking tasks. It uses spoken words (voice) as the input that helps the computer to interpret and execute the result by recognising specific words. This method helps drivers perform the task more effectively and safely based on their specific speech style as biometric fingerprinting. The use of voice recognition systems is not only advocated for multitasking and safety purposes but is also used as an independent voice source in traffic management surveillance systems [3].

In the voice word recognition system, there are two essential stages, namely extraction of features and matching of pattern. Features are certain property or characteristics that are extracted from the pre-processed speech signal representing the original signal of the speech. Many features extraction techniques have been used in literature such as Fast Fourier transform [4], linear predictive coding (LPC) [5], linear predictive cepstral coefficient (LPCC) [5], and Mel-frequency cepstral coefficient (MFCC) [6]. Among the above-mentioned feature extraction methods, MFCC is considerably the best feature extraction techniques for voice word recognition. The second stage is called pattern matching. This process is the identification of signal patterns using the extracted features from the voice recorder to recognise the speaker's command. Besides, other design techniques such as using dynamic time wrapping and multi-layer neural networks [8] have been proposed in the literature.

There are much work has been done in recognising the voice data based on intelligent system, Nichi, and Millis, combine the Artificial neural network (ANN) and Gaussian Mixture Model (GMM), and the system having an accuracy of 70% [7]. Furthermore, many works have been done based on the Support Vector Machines (SVM) which are applied to voice recognition [8-9]. The result shows that the voice recognition based on the SVM has good accuracy above 90% based on that result SVM is applied in this work. Based on that observation, this work implemented the intelligent system to develop automotive headlight beam activation control automatically. Moreover, this work also compared the method

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of an intelligent system which applied to the automatic headlight beam based on voice recognition system; Artificial Neural Network (ANN), and Support Vector Machines (SVM), since this two methods are often used for voice recognition. In the beginning, the paper discusses the proposed methodology of the voice-based recognition system. Next, the detailed discussion of the voice-based mechanism is presented. In the end, an experimental test for the proposed voice-based headlights beam control is discussed and the results are analysed.

SYSTEM OVERVIEW

System Description

In this study, there are five important components involved, including voice data recording, intelligent recognition based on voice, Arduino controller board, car's relay, and car headlights. The schematic diagram of the system can be seen in Figure 1. In the voice-based recognition system, the recorded voice is processed that identifies the person's uttered words. The voice recognition is then used as the Arduino input to activates the car relay to trigger the car headlights.

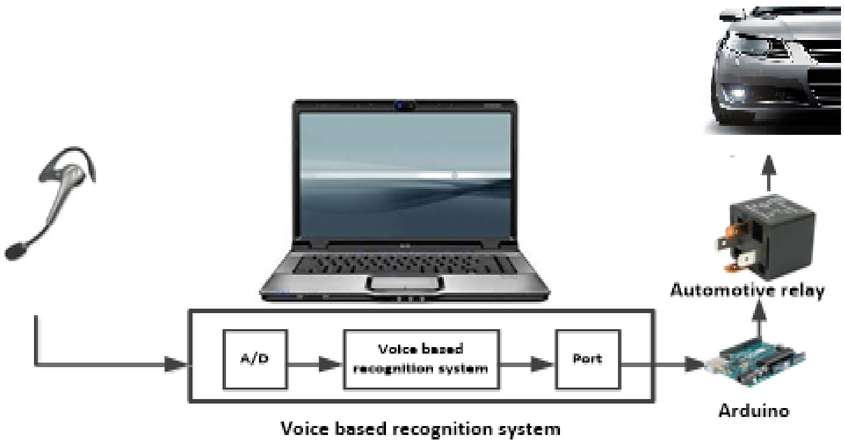


Figure 1. Proposed intelligent automatic automotive front lamp based on word recognition.

Figure 2 shows the schematic illustration for the voice (uttered word) recognition system. A pre-processing procedure is used to convert a digital speech signal. The pre-processing step is carried out to compress the signal spectrally and make it less sensitive at a later stage to finite precision effects. The pre-processed signal is then used as input for the feature extraction step. The extraction of the feature is the way to transform the original voice data to the function vector that later is used as input to the recognition mechanism in classification mode. In a recognition engine using AI (machine learning), two imperative phases are involved i.e.: training and testing process. The system is trained in the training phase to recognise a person's command (voice) and create the model for the voice pattern. The model that fit the training data is then tested in the testing phase to produce outcome from the new data (testing data).

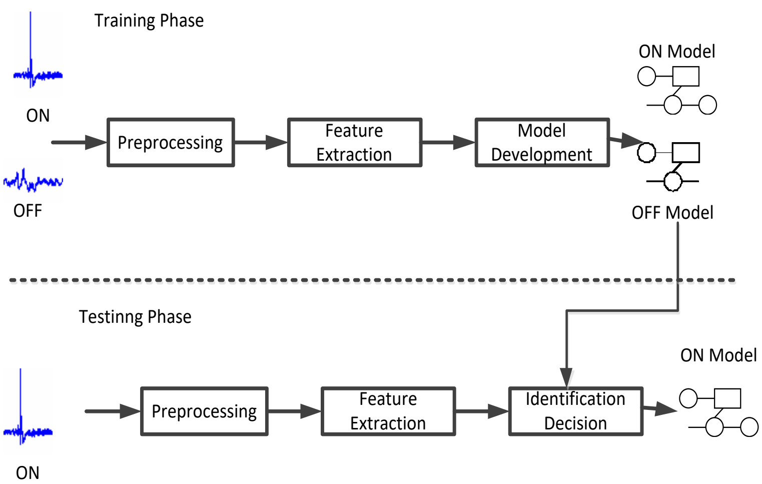


Figure 2. The voice recognition system in the training and testing stage [10].

The implementation of the voice recognition system is carried out using a computer with a sound card and processor of 2.5 MHz Intel Core i5. The installed sound card records the voice signal with a sampling frequency of 44 kHz. The used personal computer has MATLAB software installed to incorporate both voice signal processing and intelligent identification mechanism. The decision signal that will turn on the headlights is sent to the Arduino (Arduino UNO type) via the USB port on the computer. The Arduino output is then used to activate the car relay to control the headlight's beam. As shown in Figure 3, a car's relay and headlights set are installed. The relay works on a 12 V DC power supply and is set to NC (normally close) state. The parallel port passes through the signal to the car's automatic relay as shown in Figure 4, which is connected to the car's headlights unit to activate high or low beam according to the specified voice command signal from the driver.

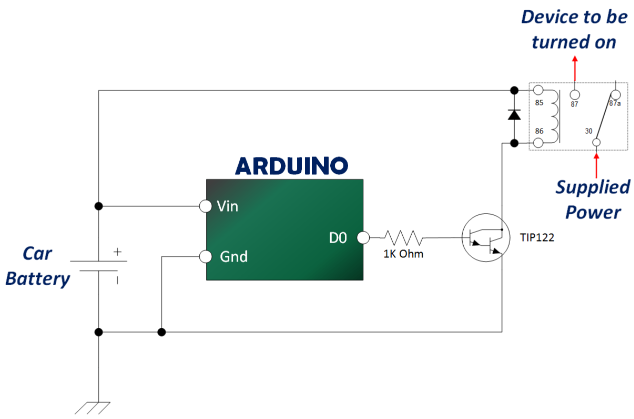


Figure 3. The setup of Arduino and automotive relay.

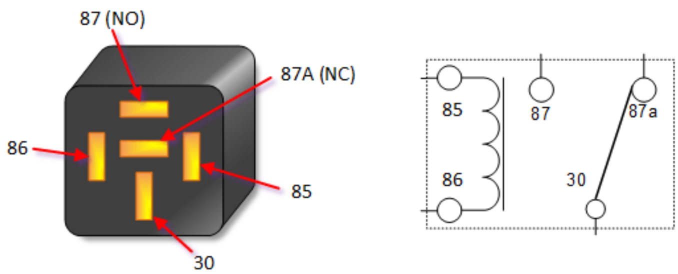


Figure 4. The automotive relay.

Feature Extraction

Extraction of features is a crucial process in many applications involving machine learning tasks including the system discussed in this study. Features indicate quantities or properties that are derived from the pre-processed signal (speech signal in this case) to be representative of the raw signal. The MFCC method is applied to the recognition system in this work. The MFCC engages some well-known auditory characteristics and offers relatively good efficiency in its implementation [11]. The block diagram showing the extraction process using MFCC function is shown in Figure 5.

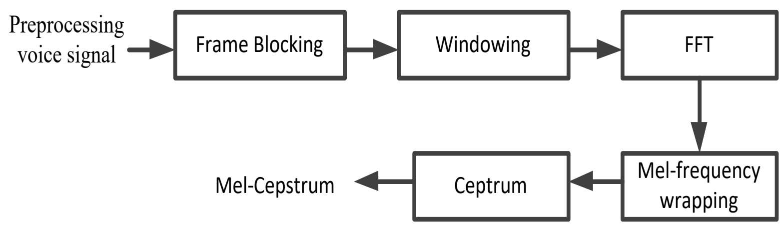


Figure 5. Feature Extraction processed using MFCC approach.

The processing step begins with the capture of the voice data/signal using ADC (Analog to Digital Converter) device at the sampling frequency (fs). Then the signal is then filtered in the form of a first-order FIR filter as follows:

$$H(z) = 1 - \alpha z^{l} \tag{1}$$

where α is the filter coefficient, usually between 0.9 and 1.0, representing the grade of pre-emphasis. Windowing is the next step. This process is performed to interrupt the discontinuity at the beginning and the last part of the signal. The most common type of windowing is Hamming and Hanning. In this study, a hamming window is used. The hamming length of 30 ms is used and the blocking signal is measured and multiplied as:

$$w(k+1) = 0.54 - 0.46\,cos(\,2\prod(k/(n-1))), k = 0, \ldots, n-1. \tag{2}$$

After the resulting signal is fed to the windowing, the outcome is given to the next phase using the Fast Fourier Transform (FFT), resulting in signal as follows [11]:

$$X_n = \sum_{k=0}^{N-1} x_k\, e^{-2\partial jkn/N} \tag{3}$$

where $N = 0,1,2,\ldots,N-1$ and $j = \sqrt{-1}$.

The outcome of this FFT is called a spectrum. After that, the spectrum reaches the Mel-Frequency (F_{mel}) wrapping stage expressed as:

$$F_{mel} = \begin{cases} 2595 * log_{10}\left(1 + \frac{F_{HZ}}{700}\right), & F_{HZ} > 1000 \\ F_{HZ}, \quad F_{HZ} < 1000 \end{cases} \tag{4}$$

The frequency-domain signal during the wrapping process is expressed as follows:

$$X_i = log_{10}\left(\sum_{k=0}^{N-1} |X(k)|\ H_i(k)\right) \tag{5}$$

with $i = 1, 2, 3, \ldots, M$**.** Here M is the number of triangle filter and $H_i(k)$ is the i^th^ value of the filter for the acoustic frequency of k.

Furthermore, the Mel-spectrum is transformed into the time domain using DCT (Discrete Cosine Transform). The outcome is called Cepstrum Coefficient (C_j) of MFCC which can be expressed as:

$$C_j = \sum_{i=1}^{M} X_i \cos\left(j(i-1)/2\frac{\pi}{M}\right) \tag{6}$$

with $j = 1,2,3,\ldots,K$. K denotes the number of the coefficient. The Cepstrum Coefficient component is then used as the input to the AI machine learning-based voice recognition using SVM-based and ANN-based classification techniques in this study. In the future, some other machine learning algorithms other than SVM and ANN can be used for this classification task.

The role of the two intelligent SVM and ANN are applied to classify and identify the voice based on the voice model develop by MFCC method. The result of these two methods is compared in order of knowing the best suitable identification method used in this system.

Support Vector Machines

SVM is one of the most well-known supervised machine learning algorithms that can perform well for classification and regression tasks. The fundamental idea of SVM is to map non-linear training data through the kernel function into a higher-dimensional feature space. For a linear separable case, as shown in Figure 6, SVM tries to find a hyperplane that best split the data into two or more classes. Therefore, there exists a separating hyperplane whose function is:

$$w \cdot x + b = 0 w \in R^N, b \in R, \tag{7}$$

With the output labels indicated by Y=±1 for binary classification, the resulting equations are:

$$y_i\ (w \cdot x + b = 0) \geq 1, i = 1, \ldots, N \tag{8}$$

By optimising ||**w**|| subject to this constraint, the SVM seeks a unique separating hyperplane. Here, ||**w**|| is the Euclidean norm of **w**. The distance *1/*||**w**|| is set for each class between the hyperplane and the nearest data points called support vectors. By introducing the Lagrange multiplier $\boldsymbol{\alpha_i}$, the SVM mechanism seeks to solve the solution during training, which is a unique globally optimised result ($\boldsymbol{w_{opt}}$) with the following expression:

$$\boldsymbol{w}_{opt} = \textstyle\sum_i^N \boldsymbol{\alpha_i\, y_i X_i}, \tag{9}$$

with $\boldsymbol{\alpha_i} \neq 0$. Data points nearest to the hyperplane ($\mathbf{X_i}$) are called the support vectors. Once SVM was properly trained, a decision boundary can be found by comparing each new test data $\mathbf{X^T}$ with the support vector ($\mathbf{X_i}$) only, $i \in SV$ (Support Vector data);

$$\boldsymbol{y} = sign\left(\sum_{i \in SV} \boldsymbol{\alpha_i y_i (X_i X^T)} + b\right) \tag{10}$$

where $\mathbf{X}^{\mathrm{T}}$ is the new test data.

Figure 6 also demonstrates separable non-linear data with misclassification data added. This extension is performed by adding so-called "slack" variable, $\xi \geq 0$, for each training sample. As a result, Eq. (10) can be expressed as:

$$\boldsymbol{y_i}(\boldsymbol{wX} + b = 0) \geq 1 - \xi, i = 1, \ldots, N \tag{11}$$

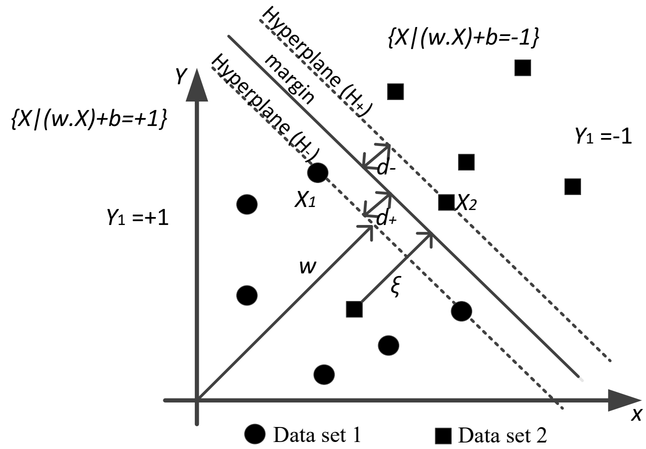
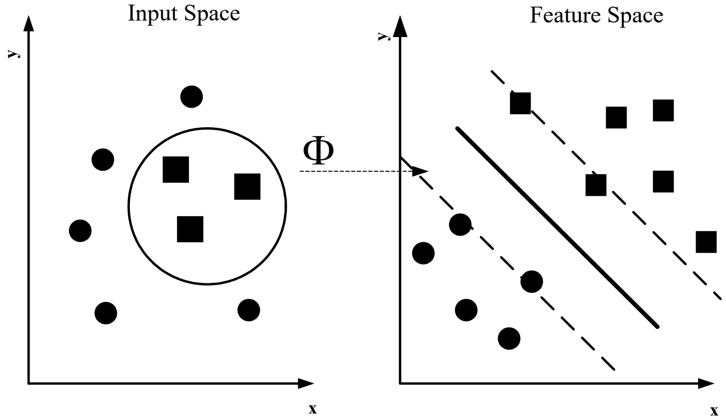


Figure 6. SVMs with linearly separable data [12].



(a) Nonlinearly separable data (b) Transformed to linear separable

Figure 7. Mapping of non-linear into higher-dimensional feature space [13].

For the case of non-linear separable data, it is often known to be a mixture of linear separable cases in many practical situations. A case of non-linear separable data with some miss-classified data is shown in Figure 7. Initially, the non-linear separable data in Figure 7(a) is transformed by the Kernel function (Φ) into a feature space as shown in Figure 7(b). Once transformed, it is possible to obtain the linear separating hyperplane like a linearly separable case. This approach is carried out based on data mapping to space where new features can be linearly separable [14]. The kernel transformation can be mathematically expressed as:

$$\Phi : R^D \longrightarrow R^F \tag{12}$$

where D and F are the input space dimension and higher-dimensional space respectively. The higher-dimensional space F can be referred to as the feature space. Table 1 lists three common kernel functions. The selection of the SVM kernel function relies on the data. To achieve a good classification result, a specific kernel function must have opted precisely. It also depends on the nature of data to properly set the degree (d) in the polynomial type kernel and to choose the free parameter (σ) in the Gaussian RBF (Radial Basis Function) type kernel [15].

Artificial Neural Networks (ANN)

ANN algorithm is another popular machine learning algorithm. ANN in its various type has been applied in many studies involving classification and regression problems [8, 16]. ANN can be trained in supervised mode to model a specific input-output data mapping by updating the connection weights of neurons, .i.e. the value of the connections between neurons. Supervised ANN is commonly trained so that specific input results in a specific target output. The main problem in ANN is usually overfitting when the training treatment is not properly handled. For this reason, many studies outlined that SVM can perform better than ANN.

Table 1. Common Kernel function for SVM

Kernel	$K(x, xi)$
Linear	$x^T \cdot x^j$
Polynomial, degree (d)	$(x^T \cdot x^j + 1)^d$
Gaussian RBF	$exp(-\frac{\left\|x^T - x^j\right\|^2}{2\sigma^2})$

The most common type of supervised ANN is the multi-layer perceptron (MLP) network architecture which uses a backpropagation learning algorithm to train the networks. This is a gradient descent type of learning. An MLP consists of three neural network layers; input layer, hidden layer, and output layer. The input layer is a node to be responsible for feeding the inputs to the ANN. The layer in the middle is called the hidden layer which can contain many neurons. The remaining layers are characterised by their weighted inputs and non-linear activation functions. Each neuron in the output layer is directly assigned to indicate a class value in classification.

The algorithm of backpropagation is iterative, where each iteration refines the weights of the MLP which are initially set as a random value between -1 to 1. As shown in Figure 8, the algorithm operates in two phases namely the forward phase and the backward phases.

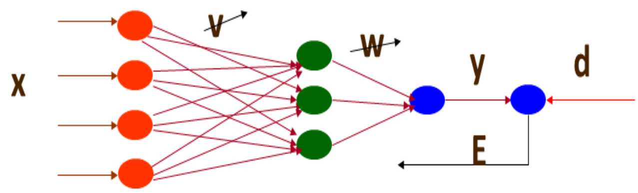


Figure 8. MLP neural network.

All training vectors and their corresponding labels are introduced to the MLP in the forward process and an overall error is observed. Given the n^{th} training vector (y_n), the output of the k^{th} output neuron is:

$$O_k(n) = f(\sum_i w_{ki} \ f(\sum_j w_{ij} \, y_n(j))) \tag{13}$$

where the summation j above is from all input neurons input and where the summation i above is from all hidden neurons. In addition, w_{ij} is the weight associated with the connection of the given layer's i^{th} neuron to the following layer's j^{th} neuron. The activation function can be a non-linear sigmoid function such as:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{14}$$

The weight (w) is updated to minimise the error in the backward process, beginning at the output layer and moving into the hidden layer. In the forward phase, the process of calculating error E and refining the weights converges to a minimum error. The error function can be for example mean squared error as:

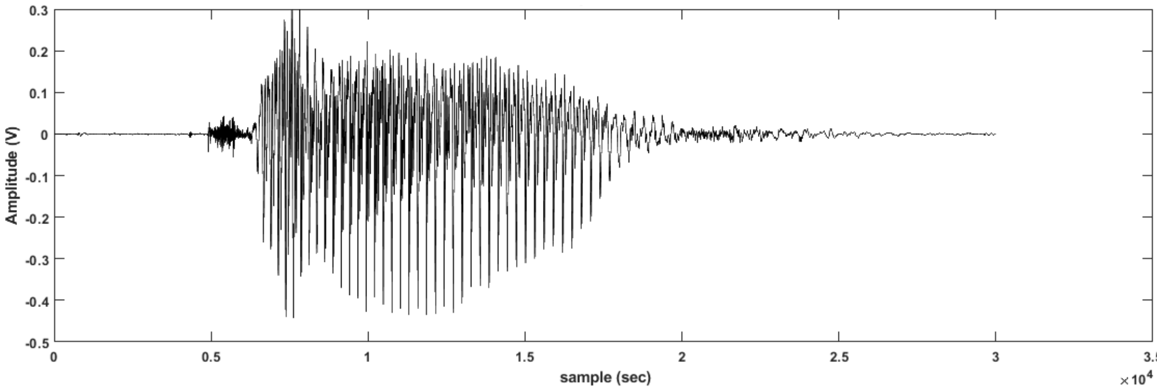
$$E = \sum_n \sum_k (O_k(n) - d_k(n))^2 \tag{15}$$

with $d_k(n)$ represents the desired output/target of the k^{th} output neuron is given the n^{th} training data vector.

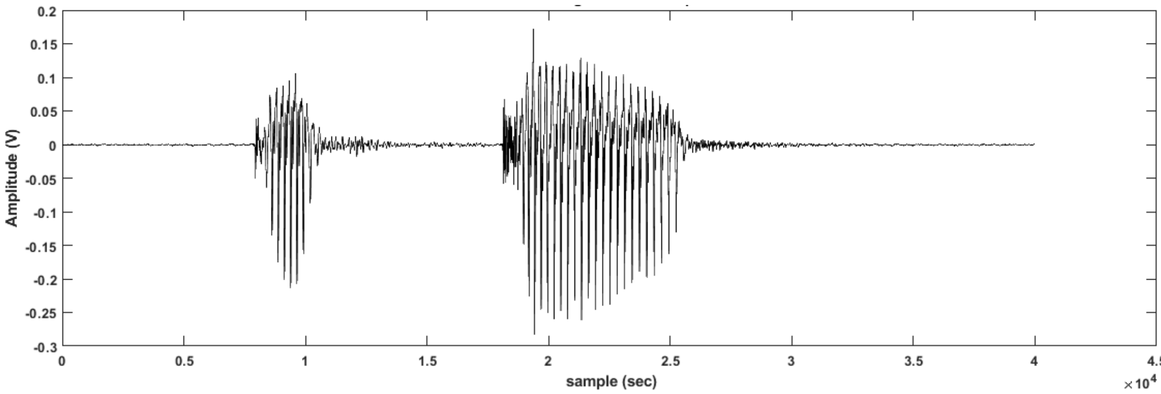
Results and Discussion

The experiment is carried out using headlights automotive equipment to evaluate the proposed intelligent automatic headlights control based on word (voice) recognition system. During the experiment, the speaker (i.e. driver of the car) has to say the word ‘Far’ and ‘Close’. The ‘Far’ and ‘Close’ voices are included throughout the experiment. This is to represent ‘High’ and ‘Low’ headlights beam respectively. Figure 9(a) and 9(b) show the examples of ‘Far’ and ‘Close’ words, respectively. To obtain the MFCC coefficients, a number of 12 Cepstral coefficients are applied. By combining the FFT spectrum of 20-ms Hamming-window speech segments and the frame rate of 10-ms, these filters are simulated. Figure 10(a) and 10(b) displayed the 12 MFCC Cepstral coefficient for ‘Far’ and ‘Close’ voice signals respectively. As can be seen, the signal consists of 12 Coefficient which is used respectively as an input signal to the ANN and SVM classifier.

There are 20 words for 'Far' and 'Close' respectively as the training and testing dataset in this study. A number of ten data of each word are used to train the system and the other ten data are used to test the system. The intelligent voice recognition is developed to build the model of each word that will be evaluated in the accuracy of the training. The testing accuracy indicates how well the algorithm is to classify the system's new word. The captured voices are then processed using the technique of extraction of features, resulting in the recognition of the extracted voice. The extraction process resulting in 2232 data from the word 'Far' and 2356 data from the word 'Close' is then used to train the proposed system. The intelligent word recognition is trained respectively using ANN and SVM methods, and the results are compared.

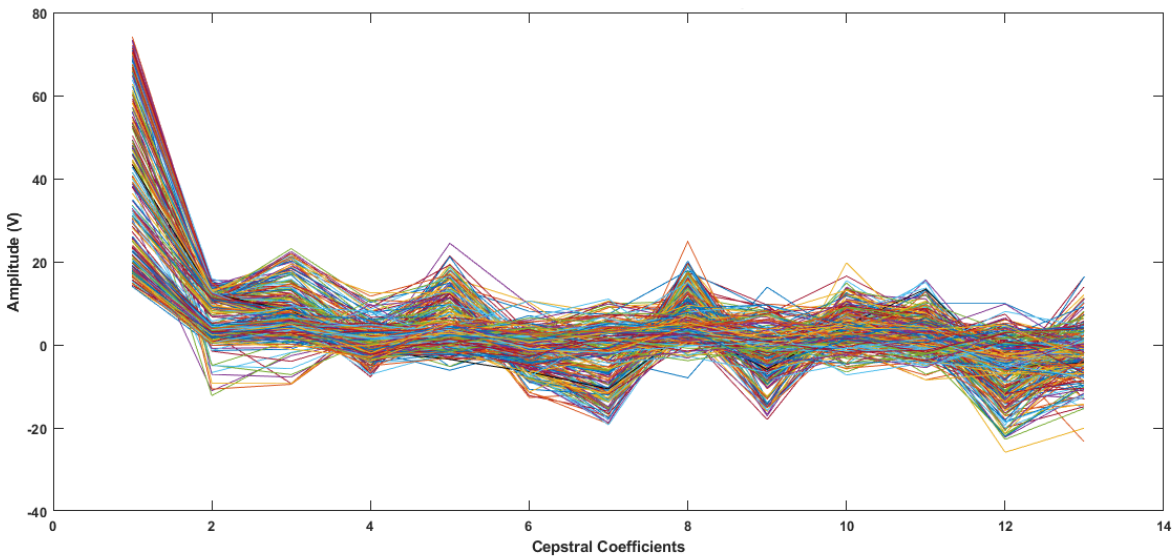


(a)

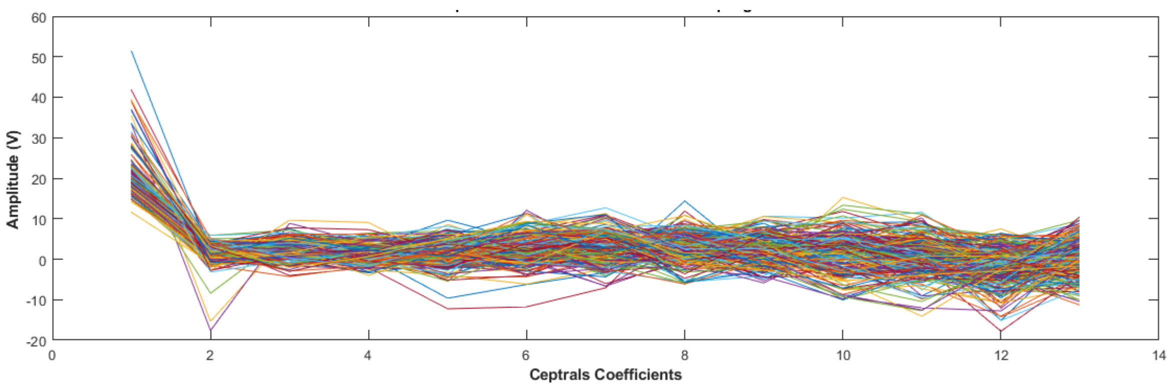


(b)

Figure 9. Raw signal for (a) 'Far' beam and (b) 'Close' beam.



(a)



(b)

Figure 10. Cepstral Coefficient of the (a) ‘Far’ voice signal and (b) ‘Close’ voice signal.

The binary classification based on SVMs is used to conduct the process of classification. The RBF kernel function is used in this study. Table 2 shows that the SVM-based word identification system provides results with a classification rate of 93.59% during the training stage. The identification of the SVM-based system can classify acceptably well the word based on its voice. Further experiments are conducted using other voice data (test dataset). The proposed system can produce a classification rate of 91.74%, as shown in Table 2.

Furthermore, ANN of multilayer perceptron (MLP) network with the backpropagation learning algorithm is also used as a binary classifier. The numbers of neurons in the input, hidden and output layers are respectively 12, 1 and 1. As shown in Table 2, 89.59% accuracy of the training stage is produced by the ANN. It means that speakers’ signals are notably classified by the ANN with lower accuracy. Besides, an experimental test with another voice data testing yield a classification rate of 88.16% using ANN, as shown in Table 2. Besides that, the training time based on SVM is faster compared to the neural network, since SVM only used the data which lies on the hyperplane. That data becomes the reference model of each of the words. Ever since adding the training data, as long as the data is not located in the hyperplane will not impact the training model.

Based on the results shown in Table 2 in this study, the proposed SVM-based word identification system can achieve a better classification rate than that of the ANN method. Furthermore, as opposed to the ANN system, this SVM training can be accomplished in a shorter time. Then the obtained SVM-based word identification system is applied to the real implementation by connecting to the Arduino UNO board that is interfaced with the car headlight.

Table 2. Comparison of speaker classification using SVM and ANN.

Number of data	Word identification	Classification Rate (%) (fs = 44 kHz)				Training time (s)	
		Training		Testing			
		SVMs	ANN	SVMs	ANN	SVMs	ANN
2.232	Far	90.84	86.23	91.19	88.20	42.56	56.08
2.356	Close	96.35	92.95	92.28	88.12		
	Avr. Acc.	93.595	89.59	91.74	88.16		

In the experiment, the ‘High’ or ‘Low’ signal from the SVM-based classifier is fed to the Arduino board. The decision of the high - low beam of the classifier system used as input to the Arduino as shown in Figure 11. Furthermore, the output side of the Arduino board is connected to an automotive relay which is certainly further connected to the light unit to produce output accordingly. Figure 11 shows the implementation using LED lamp during Arduino circuit testing. Figure 12 shows the overall system implemented in the real car headlight unit. The system applied in the car simulation in the lab, and has been tested several times with applied the Automatic voice-Based Recognition system.

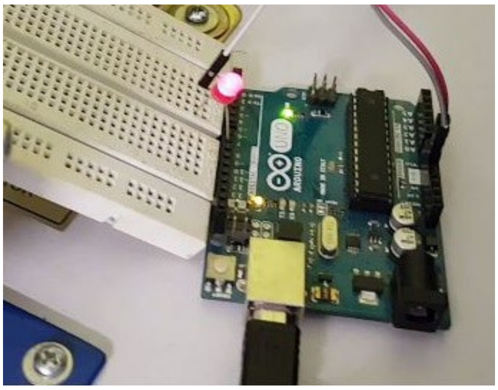


Figure 11. Implementation of the system connected to the simulation LED lamp.

Figure 12. Implementation of the real car headlight.

CONCLUSION

This work has developed an intelligent automatic voice-based headlight beam control for automotive applications. The proposed system applied Mel-Frequency Cepstral Coefficient (MFCC) as a feature extraction technique for the person's voice signal. The feature extraction output from the MFCC is then used as input to the intelligent voice recognition system using SVM and ANN respectively. The results of the experimental study showed that the proposed system using SVM produced a slightly better performance, particularly in terms of training and testing accuracy as well as faster training time as compared to ANN. The obtained SVM-based classification model is then implemented in the real system using an Arduino UNO board that is connected to the relay and car headlight unit. This real experiment is carried out to further confirm the effectiveness of the proposed method during the simulation. In addition, the future development of this system can also be developed for other automotive instruments and other fields of application. This is an intelligent approach for biometric-based access, especially for voice-based recognition control.

For future development, it is important to carry out the command with the aid of hands-free operation in the control system. In a real driving situation, this will help the driver to use features such as when the driver uses a helmet. This is also for considerations such as start and stops driving mode. These implementations would require additional voice processing and enrichment to minimise the disruption due to unwanted noise in the signal.

ACKNOWLEDGEMENT

We thank Dr. Zener Lie, as the head of Lab of Binus Aso School of Engineering (ASE), Binus University, for his valuable support, permission and discussion of this work.

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