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Enhancing Single Speaker Recognition Using Deep Belief Network

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ABSTRACT

Recognition in speech is complex phenomena study, and the reason for this is the complexity of human language. The barrier of the problem in speech recognition study now can be handled from speech signal using machine learning methods. Nowadays, Deep Belief Networks (DBN) automatically is able to find out the representation of speech signal.

This paper tries to approach a structure optimization of DBN which based on the combined technique of evolutionary computation to enhance the single speaker speech. It firstly extracts from the feature of speech signal then applies them to construct lots of random subspaces. The result of the conducted experimental in the evolutionary computation of DBN indicates the structure have an improvement for speech recognition.

Keywords: Deep Belief Network; Evolutionary Computation; Speech Recognition; Speech Signal; Random Subspace.

1 Introduction

Speech is the audio form for communication in human behaviors, which is spoken continuously states. In the speech recognition the continuously spoken states convert an acoustic signal, it captured by a microphone or telephone to a length of words. The characteristics of signal it reflects the different speech sound being spoken. The information from a speech that we are gathering is represented by a spectrum of amplitude from speech waveform. Based on this speech characteristic allows us to recognize the feature information from the waveform of the speech signal. Recognizing word from the acoustic signal is a though work, many researchers are emerging in the area of speech recognition and signal processing [1].

Speech Recognition as well-known as computer speech recognition is the process learning from the computer to understand our spoken by an algorithm implemented as a computer program. The main goal of the speech recognition area is developing speech recognition technology and systems into machines. The basic communication from a human being is a speech of human speech ability of the machine, the desire to automate simple tasks requiring machine interaction with humans in an automatic speech [2].

Nowadays, the application in tasks that require human-machine interfaces, such as automatic call processing in telephone networks, and query-based information systems find widespread in the statistical modeling of speech, automatic speech recognition systems. That provides updated travel information, stock price quotations, weather reports, data entry, voice dictation, access to information: travel, banking,

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commands, transcription, disabled people (blind people) supermarket, railway reservations, etc. [3]. Speech recognition technology was increasingly used within telephone networks to automate as well as to enhance the operator services [4].

In the sixth decades of speech, recognition area has attracted many researchers' attention for the reason of curiosity about technology and the mechanism of realization. The speech feature extraction is a key issue for all classification methods to obtain better generalization. The extracted features should minimize the distances between samples with the same speech class and maximize the distances between samples with the different speech classes [5]. If the features are not well defined, the best classifier could have difficulty in reaching the good performance. Most typical features are predefined by hand-engineered ones, including newly proposed nonlinear dynamic features [7].

They have achieved the great success in specific fields where the small speech training data can be available only. However, these features perform inconsistently on different speech recognition tasks [8]. They are on the lower level to make themselves difficult to extract and organize the discriminative features from the speech signals. It is not clear which speech features are most powerful in distinguishing recognition [2, 8]. They are easily influenced by speakers, speaking styles, sentences, and speaking rates because these factors directly affect the extracted speech features such as pitch and energy contours [5]. Besides, they are not easily tuned for the newly coming speech signals-pitch and energy contours [5]. Besides, they are not easily tuned for the newly coming speech signals.

Recently, the development of machine learning based on speech has been made in a deep neural network similar as a neural network. One of approaching algorithm in deep neural networks is Deep Belief Network (DBN) [3]. For example, speech signal utilizes the higher level features to represent the more abstract concepts [10]. This is the reason that they succeed in breaking most of the world records of the recognition tasks. Among deep learning methods, deep belief network (DBN) is the most representative one [11, 12]. It applies the unsupervised learning algorithms such as auto-encoders and sparse coding to learn higher level feature representations from the unlabeled data [13]. It has produced the state-of-the-art results on recognition and classification tasks [10]. On the other hand, typical classification methods used for speech recognition include hidden Markov model (HMM) [14], Gaussian Mixture Model (GMM) [15], artificial neural networks such as recurrent neural network (RNN) [16], support vector machine (SVM) [17, 18], and the fuzzy cognitive map network [19]. These methods are confronted with the complicated decision boundary of the classification.

In such case, the ensemble learning can be applied that can learn any nonlinear boundary through appropriately combining the simple classifiers. It has potential ability to reduce over fitting problems greatly, to decrease the risk of a single classifier, and to obtain better performance than its single classifiers [20]. The usual ensemble classifiers are boost-based, bagging-based approaches [21], random subspace [22], and so forth. Some of them have been applied to perform speech recognition but still fail to reach the performance as expected. For example, it seems that random forest and AdaboostDT have the bad effect for speech classification [23]. The possible reason is that the diversity of the base classifiers is not guaranteed [24]. As to random subspace, the classifiers trained with different features should have certain diversity inherently. However, in the neural networks (NN) are prone to over fitting. Especially, the deep neural networks in some cases where the training data are not abundantly clear [24]. For instance, there are two different features sets, but the classifiers trained by the two features sets may have the similar classification results, leading to no rich diversity between them [24]. To ensure the diversity among base classifiers, the features in random subspace should be further abstracted from different viewpoints using DBN.

This paper presents an evolutionary computational method for speech recognition, which is composed of the DBN and Tabu Search. Hayashida et al. [25] describes a number of subspace the implementation of tabu search is applied. Each subspace can be directly fed into DBN to generate the high-level features. The rest of this paper is organized as follows: In Section 2, several related works are briefly introduced about speech recognition techniques, DBN and RBM. The evaluated system and some experiments on simple voice dataset are presented in Section 3. Then Section 4 describes about the results and discussion. Finally, Section 5 concludes this paper.

2 Speech Techniques and Structural Optimization

2.1 Speech Recognition.

This section will introduce about speech recognition technique.

Speech is a moving signal. When we speak, our articulatory apparatus (the lips, jaw, tongue, and velum) modulates the air pressure and flow to produce an audible sequence of sounds [12]. Although the spectral content of any particular acoustic signal in speech may include sequences up to several thousand hertz, our articulatory configuration (vocal-tract shape, tongue movement, etc.) often does not undergo dramatic changes more than 10 times per second [13]. The acoustic properties of a waveform corresponding to a phone can vary greatly depending on many factors - phone context, speaker, style of speech, etc.

The main process in the speech recognition is feature extraction, it would be reduced variability of spoken words signal. Particularly, eliminating various information, such as whether the sound is voiced or unvoiced, it eliminates the effect of periodicity or pitch, the amplitude of excitation signal and also the fundamental frequency etc. The feature extraction techniques for speech recognition describes about reducing dimensionality of input vector while maintaining the discriminating power of signal. Many researchers have some point of important work in speech recognition area [14]. The related works for speech recognition techniques follows by:

- Principle Component Analysis (PCA)
- Independent Component Analysis (ICA)
- Mel-Frequency Scale Analysis
- Filter Bank Analysis
- Mel-Frequency Cepstrum (MFCC)
- Integrated Phoneme Subspace method (PCA, LDA and ICA)

Recently, the common technique in order to desire processing task in speech recognition is MFCC. The characteristics such as peak, pitch spectrum mean and standard deviation of the signal are extorted from denoised signal [15].

All modern descriptions of speech are to some degree probabilistic. That means that there are no certain boundaries between units, or between words. Speech to text translation and other applications of speech are never 100% correct. That idea is rather unusual for software developers, who usually work with deterministic systems. And it creates a lot of issues specific only to speech technology [16]. Therefore, a number of problems with the standard method of hidden Markov model (HMM) and features that come from fixed and frame based spectra (eg MFCC) are discussed [17].

On the other hand, the approaches method for speech recognition is acoustic phonetic, pattern recognition, artificial intelligence [26]. Acoustic approach that stated by hemdal and hughes 1967 [27], this method was based on finding speech sound and label it.

The process of acoustic approach is analyst the spectral from speech combined with feature detection to set of feature that describe the wide acoustic properties. Then, segmenting and labeling the speech signal becomes a stable acoustic area followed by one or more phonetic labels that produces the result in phoneme lattice characterization in speech. Finally, in this approach tries to determine the correct words or string of word.

Next approach is pattern recognition. This method is known generically as pattern matching. In they studied Itakura 1975; Rabiner 1989; Rabiner and Juang 1993) [28] pattern matching involves two essential step; this step was namely pattern training and pattern comparison. The most important feature of this approach is that it uses well-formulated mathematical structures and determines the representation of appropriate utterance patterns and a reliable pattern comparison of a set of labeled training samples through a formal training algorithm. The most widely used statistical method in pattern recognition is Hidden Markov Model (HMM).

In 1994, Moore [29] studies about template based approach. The underlying idea of this method is easy to understand. The prototype collection of speech patterns is stored as a reference pattern representing the dictionary of candidate words. At this stage the algorithm will match unknown speech utterances with each template reference and choose the best category as the matching pattern. Typically, templates for all words are built This has the advantage of it, because of less acoustic segmentation fault or classification of more variable units such as phonemes can be avoided. The other main idea is to use a dynamic form of programming approach to temporarily align the pattern to account for the difference in speech levels across the speaker as well as the repetition of words in the same way the speaker. For more detail about the speech recognition techniques, see table 1.1

Table 1. Speech Techniques

Approach	Representation	Recognize Function	Typical
Acoustic Phonetic	Phonemes	Lexical Probability	Log Likelihood Ratio
Pattern Recognition:			
● Template	Pixel from speech samples	Correlation distance	Classification error
● DTW	Spectral sequences	Dynamic wrapping algorithm	Euclidian Distance
● Statistical	Spectral vectors	Clustering Function	Classification error
Neural Network	Speech Features	Network function	Mean Square Error (MSE)
SVM	Kernel	Max Margin	Minimizing bound of error

2.2 Speech Recognition Development (year vise).

In 1950 the researchers tried to exploit the basic idea of phonetic acoustics in the earliest attempt to design a system that could communicate with machines. During the 1950s, most voice recognition systems learned about spectral resonance over the span of each utterance extracted from the signal output of the bank's analog filter and the logic circuit [30]. In 1952, at Bell's laboratory, Davis, et.al built a system for the introduction of isolated digits for one speaker [31]. In this system is very dependent on the measurement of resonance time on the pronunciation.

In an independent venture at RCA Laboratories in 1956, Olson and Belar tried to recognize 10 different syllables from one speaker, embodied in 10 two-syllable words [32]. The system also relies on spectral measurements (already available analog filter banks) especially during vulnerable conversations. In 1959, at University College in England, Fry and Denes tried to build phoneme recognition to recognize four vowels and nine consonants [34]. Actually the development of speech recognition is significantly fast. In this paper development information of speech recognition recognize start at 2009-2017s.

2.2.1 2009-2017s

In the early 2009, the development of speech recognition technology becomes inexpensive and powerful. Nowadays, the development of technology is supported by advances in artificial intelligence and the increasing number of data words that can be easily mined, it is possible the development of technology has recently become the next dominant interface.

In the long history of speech recognition, both shallow form and deep form (e.g. recurrent nets) of artificial neural networks had been explored for many years during 1980s, 1990s and a few years into the 2000s.[35][36][37] But these methods never won over the non-uniform internal handcrafting Gaussian mixture model/Hidden Markov model (GMM-HMM) technology based on generative models of speech trained discriminatively.[38] A number of key difficulties had been methodologically analyzed in the 1990s, including gradient diminishing[39] and weak temporal correlation structure in the neural predictive models.[40][41].

In contrast to HMMs, neural networks make no assumptions about feature statistical properties and have several qualities making them attractive recognition models for speech recognition. When used to estimate the probabilities of a speech feature segment, neural networks allow discriminative training in a natural and efficient manner. Few assumptions on the statistics of input features are made with neural networks. However, in spite of their effectiveness in classifying short-time units such as individual phonemes and isolated words, [41] neural networks are rarely successful for continuous recognition tasks, largely because of their lack of ability to model temporal dependencies.

All these difficulties were in addition to the lack of big training data and big computing power in these early days. Most speech recognition researchers who understood such barriers hence subsequently moved away from neural nets to pursue generative modeling approaches until the recent resurgence of deep learning starting around 2009–2010 that had overcome all these difficulties. Hinton et al. and Deng et al. reviewed part of this recent history about how their collaboration with each other and then with colleagues across four groups (University of Toronto, Microsoft, Google, and IBM) ignited a renaissance of applications of deep feed-forward neural networks to speech recognition. [42] [43] [44] [45].

Today [47], A Microsoft research executive called this innovation "the most dramatic change in accuracy since 1979."[48] In contrast to the steady incremental improvements of the past few decades, the application of deep learning decreased word error rate by 30%. [46] This innovation was quickly adopted across the field. Researchers have begun to use deep learning techniques for language modeling as well. A deep feed-forward neural network (DNN) is an artificial neural network with multiple hidden layers of units between the input and output layers. [44] Similar to shallow neural networks, DNNs can model complex nonlinear relationships. DNN architectures generate compositional models, where extra layers enable composition of features from lower layers, giving a huge learning capacity and thus the potential of modeling complex patterns of speech data [49].

A success of DNNs in large vocabulary speech recognition occurred in 2010 by industrial researchers, in collaboration with academic researchers, where large output layers of the DNN based on context dependent HMM states constructed by decision trees were adopted.[50][51] [52] See comprehensive reviews of this development and of the state of the art as of October 2014 in the recent Springer book from Microsoft Research.[53] See also the related background of automatic speech recognition and the impact of various machine learning paradigms including notably deep learning in recent overview articles [54][55].

One fundamental principle of deep learning is to do away with hand-crafted feature engineering and to use raw features. This principle was first explored successfully in the architecture of deep auto encoder on the "raw" spectrogram or linear filter-bank features, [56] showing its superiority over the Mel-Cepstral features which contain a few stages of fixed transformation from spectrograms. The true "raw" features of speech, waveforms, have more recently been shown to produce excellent larger-scale speech recognition results [57].

2.3 Neural Networks Involve into Deep Belief Network (DBN).

This section will introduce about several models of neural networks involvement.

Since a decade the development of artificial neural networks has been used in artificial technology applications. It has been consisted of pattern recognition, voice and speech analysis and natural language processing. Due to lack of effectiveness of networks performance in Neural Network some cases, deep models and architectures with many layers were suggested. The theorem of Deep Belief Network (DBN) is first introduced by Hinton et.al [8]. DBN is a basic network that consists of belief network composed of multiple layers of Restricted Boltzmann Machines (RBM) [9]. In DBN feature extraction works under unsupervised learning, it's called pre-training process then fine-tuning is performed in remaining process. Figure. 1 shows DBN consisting of three layers of RBM as the standard models.

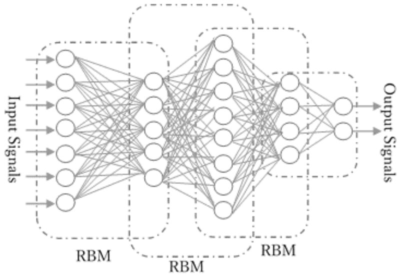


Figure 1. Standard Deep Belief Network Model

2.3.1 Deep Belief Network in RBM

An invention of Boltzmann Machine was first introduced by Smolensky in 1986 [21] with the characteristic of one hidden layer and one visible layer. In 2000, Hinton et.al improved the Boltzmann Machine into Restricted Boltzmann Machine which is used as generative models of different types of data. A Restricted Boltzmann Machine models consist of two sets of units visible and hidden units. A visible unit can be derived as the units that are directly observed in RBM. Hidden units are not directly connected to training data but the models dependencies between components. This structure of RBM can adjust the parameter in order to make the probability distributions of RBM fits in the training data as much as possible.

To understand bipartite graph of RBM, we have commonly example of study [8], Hinton et.al conducts the experiment of DBN in Modified National Institute of Standards and Technology (MNIST) database. In his experiment the binary images of MNIST as training set for RBM. The training of MNIST model are represented random binary pixels as visible units and the connected of stochastic binary feature vectors modeled as hidden units. In this paper work, we would like try to conduct similar experiment like MNIST but in the speech format database.

$$\mathrm{E}(v,h) = -\sum_{j} b_j v_j - \sum_{i} c_i h_i - \sum_{j}\sum_{i} v_j W_{ji} h_i \qquad (1)$$

Where in equation (1) that each layer undirected edge represents dependencies only between hidden unit $h = (h_1, h_2, \dots, h_n)$; $h_i \in \{0,1\}$ where $i = 1,2,\dots,n$ and visible units $v = (v_1, v_2, \dots, v_k)$; $v_j \in \{0,1\}$ where $j = 1,2,\dots,k$. The binary data and labels so they can also be used to model the joint distribution.

The term of W_{ji} is the recurrent weight between visible unit j and hidden units i in the symmetric interaction, b_j and c_i are respectively referred to bias term between connection of hidden and visible units. The structure itself assigns a probability to each connection vector between hidden and visible units. This probability can be defined as mathematical equation with the help of energy functions:

$$\mathrm{P}(v,h) = \frac{exp\big(-\mathrm{E}(v,h)\big)}{Z} \qquad (2)$$

Where Z:

$$Z = \sum_{v,h} exp\big(-\mathrm{E}(v,h)\big) \qquad (3)$$

where Z as normalization constant between hidden and visible units can be obtained by summing over all possible pairs of visible and hidden unit vectors.

According to Hinton`s paper work [8] the probability of the network assigns to training images can be improved by adjusting the weights and the biases to lower the energy of that's image and improve the other energy of images.

Due to predictive the data from the model in the speech to spectrograms, so we considered converting the spectrogram into image to create the same dimensional. The predictive between real data and the prediction model distribution as a vector with respect to a weight can be computed as follows:

$$-\frac{\partial \log \mathrm{P}(v)}{\partial \mathcal{W}_{ji}} = \langle v_j h_i \rangle_{real} - \langle v_j h_i \rangle_{predict} \tag{4}$$

In equation (3), $\langle v_j h_i \rangle$ means to denote the expectation under the distribution specified by the subscript that follows. With simple learning rate rule to perform the stochastic ascent in the log probability of the training data can be shown as follows:

$$\Delta \mathcal{W}_{ji} = \alpha\big(\langle v_j h_i \rangle_{real} - \langle v_j h_i \rangle_{predict}\big) \tag{5}$$

The learning rate can be described as α. The function of using learning rate in DBN to search for momentum in updating weight and biases.

In RBM theorem shown that there is no connection between hidden and visible units so the hidden units are independent given by visible units. Now given a selected image v as randomly, the binary units product h_i of each hidden unit i^{th}, is set to 1 where the probability of the image can be calculated as:

$$\mathrm{P}(h_i = 1|v) = g\left(b_i + \sum_j v_j \mathcal{W}_{ij}\right) \tag{6}$$

As shown in equation (5) the derivate of $g(x)$ is a *logistic sigmoid function*. The sigmoid can be written as $g(x) = 1/\big(1 + exp(-x)\big)$. So that's equation can be summarized as hidden unit also can be written as;

$$\mathrm{P}\big(v_j = 1\big|h\big) = g\left(c_j + \sum_i h_i \mathcal{W}_{ij}\right) \tag{7}$$

2.3.2 Contrastive Divergence

Once RBM is learned using *Contrastive Divergence* (CD) algorithm [19], the DBN is able to initialize the weights of feed forward back-propagation neural network then it is used for classification to predict the image model. RBM can be learnt better when the predictive model is used before the step sampling in Gibs before collecting statistical step in learning rule but for the purposes of pre-training.

In many cases when we are facing in continuous rather than binary the Gaussian Bernoulli RBM should be used to approach the data distribution. Continuous data such as MFCC can be naturally modeled by linear variable with Gaussian and the RBM energy function has been modified to approach such as variable, so the GRBM can be shown as:

$$E(v, h) = \sum_j \frac{\big(v_j - b_j\big)^2}{2\sigma_j^2} - \sum_i c_i h_i - \sum_j \sum_i \frac{v_j}{\sigma_i} \mathcal{W}_{ji} h_i \tag{8}$$

Where σ_i is the standard deviation of the Gaussian for visible units in . Since the binary data in the hidden layer we used the conditional distribution to sample the state. In the CD we enabled to create the conditional distribution both of hidden and visible layer.

The equation can be written as:

$$\mathrm{P}(h_i|v) = g\left(b_i + \sum_j \frac{v_j}{\sigma_j} \mathcal{W}_{ij}\right) \tag{9}$$

$$\mathrm{P}(v_j|h) = \mathcal{N}\left(b_i + \sigma_i \sum_i \frac{h_i}{\sigma_j} \mathcal{W}_{ij}, 1\right) \tag{10}$$

(12)

Where $\mathcal{N}(\mu, \sigma^2)$ is defined as Gaussian normal distribution. For some distribution, the RBMs may be not achieving representation as efficient as unrestricted Boltzmann Machine. However, if the layers have enough number of units hidden layers any distribution can represented with RBMs. In addition, the number of hidden layer units with weight and bias helps to improve the performance of DBN using the log-likelihood. Log-likelihood represents the gradient of $\log p(v; \theta)$ the weights for the RBM can update as follows;

$$\Delta \mathcal{W}_{ji} = E_{real}\langle v_j h_i \rangle - E_{predict}\ \langle v_j h_i \rangle \tag{11}$$

Where $E_{real}\ \langle v_j h_i \rangle$ representative of observed data in training set and $E_{predict}\ \langle v_j h_i \rangle$ is the prediction from the model.

RBM basically can be applied in speech recognition system. Using a RBM as a standard conversion model between speaker and speech spectral envelop, it is possible to recognize speech [31]. In this paperwork, we try to reconstruction the speech signal using Gaussian Mixer Model (GMM) as representatives from Hidden Markov Model (HMM) based voice conversion methods that are benefited from use of multiple RBM. The voiced subspace is used to train RBM in spectrogram perform feature.

2.4 Enhancing Feature Structure

This section describes a structure of optimization process by neural networks theorem. Some researcher focus on this works called Elman Network with a feedback layer which only connects to the hidden layer and they proposed the structural optimization to find the optimum characteristic parameters stated by Delgado et al [9]. After training the binary data in RBM, data from previous process can be used for training another model of first RBM significantly in hidden units this process can be repeated as much as desired for creating many layers of non-linear feature detectors and more complex data. The RBM stack can be associated in multi-layer generative model is called deep belief net [10].

This paper proposes enhancing method with setting parameters of each hidden layer and unit number of each layer in RBMs following by DBN.

This approaching method includes local search based on taboo search for structural optimization and the modularization based on solution space improves learning efficiency on calculation time. Here, the DBN structure optimization that the paper purposed can be described as follows:

Step 1: Optimization of number of hidden layer.

- Step 1-1: Set the n be the number of hidden layers and let $n = \underline{n}$. Let setting number of units in initial layer is 500. Using equation 6 to define probabilities from visible unit and hidden units. learning and verification are performed, the error at that time is ε_{st}, ε_{ve} respectively. Evaluation value of structure in DBN(E_n) is calculated from ε_{st} and ε_{ve} as the evaluation and classification value.

$$E_n = \frac{1}{\varepsilon_{st} + \varepsilon_{ve}} \tag{12}$$

- Step 1-2: When $E_n \geq E_n^*$ then update the best solution $E_n^* = E_n$, where $n^* = n$
- Step 1-3: if $\bar{n} > n$ then let n = n+1 and go to step 1-1, if $\bar{n} = n$, let n^* be the number of hidden layers.

Step 2: Optimize number of units of each layer using split the hidden layer with optimized solution space. The number of units is determined with the number of hidden layers. The number of units of hidden layer let be $(x_1,\ x_2,\ x_3, \dots,\ x_n)$.

- Step 2.1: Searching unit number of i^{th} hidden layer using the multilayer perceptron.
- Step 2.2: Let the center of gravity of subspace j be $x_1^j, x_2^j, \dots, x_n^j$and let $\hat{x}_i^j = x_i^j$ as the current solution.
- Step 2.3: Let E_i^jcalculated from equation above from the learning error ε_{st} and the verification error ε_{ve} of DBN structure for the representative point and used it as the evaluation value.
- Step 2.4: The highest value is selected and its set as D_t
- Step 2.5: Continue to search the highest value by repeating from step 2.1.

Step 3: Structure determination by optimizing the number of hidden layer units by taboo search.

- Step 3.1: Generate an solution $A_0 = (x_1 x_2, \dots, x_n)$ is chosen randomly from solution space D_t, set A^*=A_0 and made the axis of neighbor search: calculate the evaluation value at initial solution and set A_0 as the taboo list save to *t = 0*.
- Step 3.2: Evaluate each neighborhood solution by equation (11) as a set of neighboring solutions excluding the solutions included in the taboo list among neighborhood solutions of A^* learning. The most evaluated value A' be the high solution, then E_{tb} be the evaluation value and store it as A' in the taboo list.
- Step 3.3: When $E_{tb} > E_{tb}^*$, update $E_{tb}^* = E_{tb}$ to $A^* = A'$.

Step 3.4: If t $< T_{tb}$ go to step 3.2 with *t=t+1*. Otherwise if $t = T_{tb}$ the solution is finished with A^* as a solution. In this step, the structural optimization cannot decrease and seems monotonically increases.

3 Speech Recognition Using DBN

3.1 Experiment Preparation

In this section we describe the general idea in our system and also evaluate the DBN that has modularization system in simple dataset of voices. We try to process the speech signal using the traditionally simple voice dataset. That simple voice dataset consists of acoustic signal and expected containing meaningful of sound in the human range from 20 Hz to 20,000 Hz [12]. In the simple dataset that we chose shows the simple utterance experiment tried to test our system whether working well or not. We do not pick up the long of utterance due to our limitation time in study.

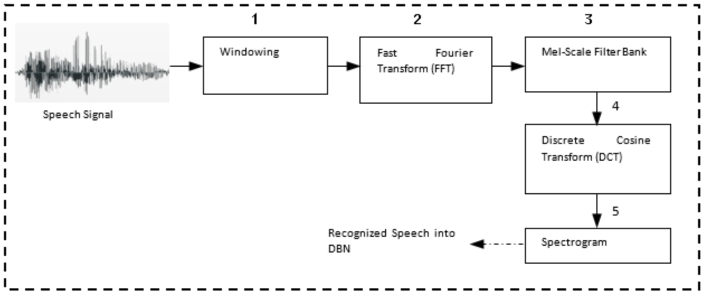

1
2
3
Speech Signal
Windowing
Fast Fourier Transform (FFT)
Mel-Scale Filter Bank
4
Discrete Cosine Transform (DCT)
5
Spectrogram
Recognized Speech into DBN

Figure 2. Proposed Model in Speech Recognition

3.1.1 Pre-Processing for Speech Recognition

In speech recognition there are so many techniques to store in traditionally of voices signal such as .mp3, .wav, .mid, etc. Despite of that in the pre-processing we traditionally chose the voices signal into .wav files for more comfortability. Then, in the feature extraction stage signal speech scripts converted into vector then combine it with MFCC feature of the signal as audio script to perform the input for the classifier.

Next process after we know the feature of audio script the machine learns to classify the recognized speech data. Our proposed method consists of several steps to extract the analog signal and digitalized the feature. The several steps extracted feature of the signal from proposed model in Figure 2 can be introduced as shown below:

1. Windowing

Speech is commonly dynamic time series signal in which the composition of properties changes very quickly over time. Before extracting the speech signal from analog to digital, at this stage we do frame blocking, the speech signal is divided into several frames with a general length of 20-30 ms containing N samples of each frame separated by M (M < N) where M is the number of shifts between frames. The first frame contains the first N sample. The second frame begins the sample M after the start of the first frame, so this second frame overlaps the first frame as much as the N-M sample. Frame blocking is necessary because the voice signal changes over a period of time. The N-M frames blocking can be illustrated as Figure 3.

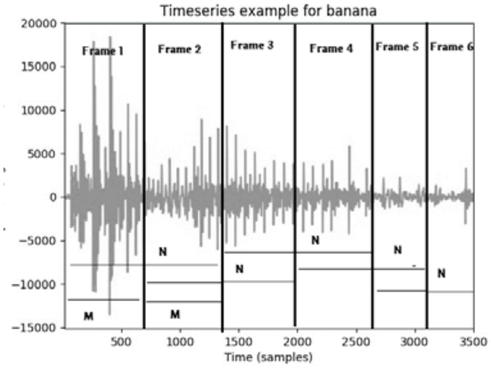


Figure 3 Frame Blocking Process

In the windowing process to minimize the discontinuity that occurs in the signal, which is caused by spectral leakage when the frame blocking process is done where the new signal, has a different frequency with the original signal. The concept of windowing is to taper the end of the signal to zero at the beginning and end of each frame. By using windowing functions, the ability of an FFT to extract spectral data from signals can further enhance. Windowing functions act on raw data to reduce the effects of the leakage that occurs during an FFT of the data. The windowing process is multiplying each frame from the type of window used.

By designing the analog signal with hamming windows, the spectral analysis can be better for FFT processing. We use hamming windows to detect the peak of signal characteristic. The Hamming window has the lowest first side lobe level of all three types of windows. The slow decay means that leakage two or three bins away from a signal's center frequency are lower for the Hamming window.

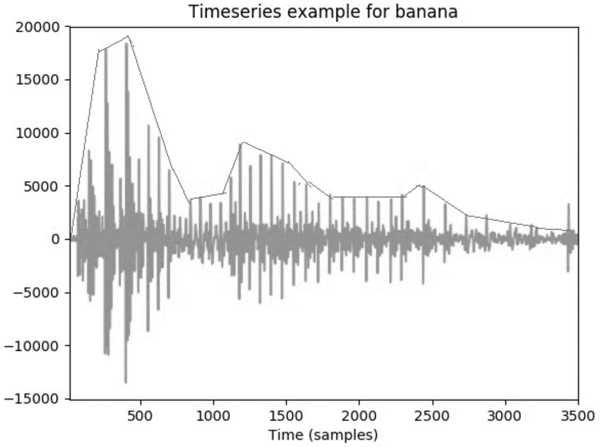


Figure 4 Hamming Window Process Example from Analog Signal

2. Fast Fourier Transform (FFT)

For better understanding, we choose the FFT due to the potential characteristic of signal waveform when detects the pattern in voices. Fast Fourier Transform algorithm serves as a signal modifier from time domain to frequency domain. The frequency values obtained from this process will be used in the filtering stage to obtain vector coefficients. Fast Fourier Transform (FFT) is a step to change each frame consisting of N samples from time domain into frequency domain. FFT is done to get the frequency of each frame. The output of this FFT process is a spectrum or periodogram.

One of the most popular FFT algorithms is radix-2. As a comparison with the DFT, for a large number of N samples such as N = 512, using DFT calculations requires a calculation of 114 times more than is required by FFT calculations. The larger the number of N samples, the more complex the calculation is if using DFT. The first step to interpret FFT is to calculate the frequency value of each middle sample of the FFT. If the sample time received by FFT is in real form, then only the output $X(m)$ from $m = 2$ to $m = N/2$ as independent. In this research, we calculate the FFT frequency value for $0 \leq m \leq N/2$ if the time sample received is complex, we must calculate all FFT frequency values of m from $0 \leq m \leq N - 1$.

3. Mel-Scale Filter

Mel-Frequency Wrapping uses Filter bank to filter the sound signals that have been converted into frequency domain form. Filter bank is a system that divides the signal input into a set of signal analysis, each corresponding to a different region spectrum. The performance of the MFCC is also influenced by one being the number of filters, in a study conducted by Vibha Tiwari in 2010 [58], the researchers used a filter count of 32 filters, and resulted in better accuracy. The number of filters that are too many or too little will produce poor accuracy.

At this stage we will filter the signal for each frame. The filter used at this stage using filter bank mel. To make a filter bank mel, first set the upper and lower limits of the frequency. For the specified lower limit is 300 Hz and the upper limit is Sampling Frequency / 2 which is 8000 Hz.

4. Discrete Cosine Transform (DCT)

In this last stage, the value of mel will be converted back into time domain, the result is called Mel Frequency Ceptral Coefficient. This conversion is done using Discrete Cosine Transform (DCT). The average value in dB that can be used to estimate the energy coming from the filter bank. The DCT coefficient is the amplitude value of the resulting spectrum. At this stage the number of ceptrum taken is as much as 13 pieces per frame.

5. Spectrogram

After all process is completed the analog signal will be converted into spectrogram. A sound spectrograph (or sonogram) is a visual representation of an acoustic signal. To simplify things with a reasonable amount, the Fast Fourier transform is applied to electronically recorded sounds. Basically, this analysis separates the frequency and amplitudes of the simplex wave components. The results can be visually displayed from this spectrograph, we can see with the amplitude level (represented light to dark, like white = no energy, black = lots of energy), at various frequencies (usually on the vertical axis) by time (horizontal). For overall process in this research could be determined by figure 5.

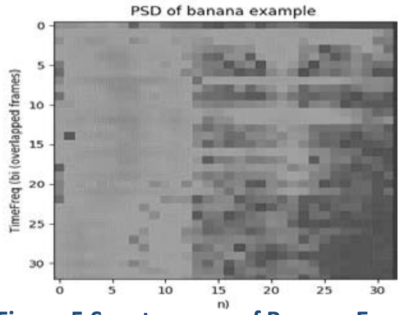


Figure 5 Spectrogram of Banana Example

3.1.2 Data Classification

The final step in our purposed model was classified and search the final accuracy of speech. A deep belief network is obtained by stacked several layers in RBM on top each other. The input of hidden layer at layer '*j*' in our system becomes the input of the RBM layer at '*j+1*'. The first layer in RBM as an input of network then the last of hidden layer in RBM represented the output. When used in classification, the DBN treated as Multi-Layer Perceptron (MLP). We used logistic regression as projecting data points onto a set of a hyperplane and calculated the distance to which is used to determine a class of membership probability.

3.2 Experimental Design

In our experimental design the simple dataset was traditionally recorded from Google Code Archive [17], this data set is consisting of 105 audio files in .wav formatted and each files containing utterance of one fruit name spoken by a single speaker. These audio files are divided into seven class categories of fruit names i.e (apple, banana, kiwi, lime, orange, peach and pineapple) one category consists of 15 audio files.

The whole dataset is separated into training (91 samples of audio) and testing (14 samples of audio). The detailed information shown in Table 2.

Table 1. Number of Data

Dataset	Apple	Banana	Kiwi	Lime	Orange	Peach	Pineapple
Number of train	14	14	14	14	14	14	14
Total Training	91						
Validation	105						

We randomly chose the data for training, validation and testing sets with ratio of 2:1:1 and did the observation of MFCC as well as for feature learned to test our system performances. After that, the voice signal analyzed with processing in windowing and fixed frame rate. Then processed to Fourier transform based on the log filter bank and the energy was disturbed in a Mel-scale, from this process the signal transformed into Discrete Cosine Transform (DCT) derived into MFCC features. Then, data were normalized so that each coefficient had zero mean and unit variance across the training into RBM unit layers.

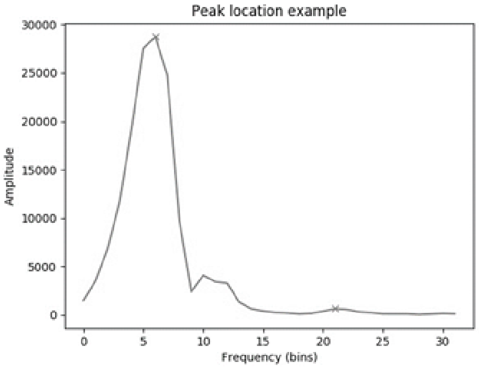
4 Experiment and Discussion

4.1 Experiment Result

4.1.1 Pre-Processing for Speech Recognition Result

This section describes the experimental design in speech audio files. First step we are conducted the signal it could be read in our system, defined the signal voice with maximum size of 32 KHz then processed the signal into short-time Fourier transform (STFT) by windowing process using hamming-window (change the figure become time vs freq) as shown as figure 5 to reduce spectral leakage caused by the framing of the signal. After that signal waveform will be extracted into a single data matrix, and a label vector with the correct label for each data file is created.

Once of data has been inputted into a system and converted into a data matrix. The next step extracted the feature selection from the raw data, when it is done we have conducted the signal into Mel Frequency Cepstral Coefficient (MFCC). In this research, we used Short Time Fourier Transform (STFT) to approach the signal peak for processing into signal digital then converted it into the spectrogram.



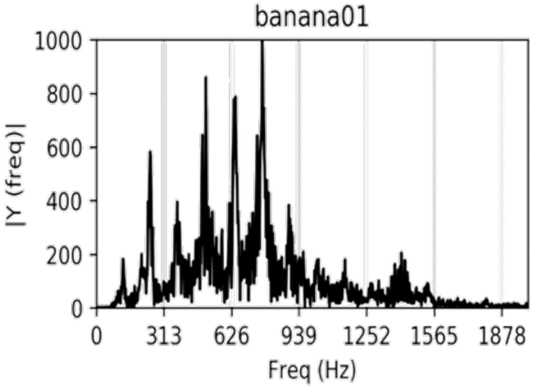


Figure 6. Spoken Word of Banana Time series

Figure 7. Peak Detection Spoken Word of Banana

Once we found the peak of the signal as seems like figure 6, the signal converted to "mfcc" vector and having six features. These mfcc features represented applying Gaussian Mixture Model (GMM). Feature extraction provides a complexity representation of digitalizing from speech. This digitalize perform Figure 7. indicates that spectral look of voice from sample speaks about ("apple") utterance. This signal has characteristic recorded in 3.5 second and the frequency domain of speech is 16 KHz.

4.1.2 Data Classification Using DBN Result

In this section our dataset in speech recognition contains 367.5 seconds of speech. This number comes from in each single speaker the datasets consists of 3,5 second length of time then we time this with 105 total of dataset. The acoustic model training set was also used to train only single language for these experiments. Once the data has been inputted and turned into an input matrix, the next step is to extract feature from the raw data, then extracts the raw data into matrix the information of data input describe the sound over both frequency and time.

After that's, we prepare the speech analyses using hamming window with fixed frames rate. In the Mel Frequency Cepstral Coefficient we normally use Cepstral mean normalization over each utterance. These are generated by applying a truncated discrete cosine transformation (DCT) to a log spectral estimate computed by smoothing a Fast Fourier Transforms (FFT) with around 20 frequency bins distributed across the speech spectrum to find peaks in frequency. Typically, we use 13 mfcc coefficients in our experiment.

The spectrogram in Figure. 7 has 30x30 dimensional matrix. This dimensional is advantageous for us to process in DBN through to RBM layer as binary data. For the first layer we used binary data to the RBMs input layer. We normalize the data so it has the zero mean and unit variance. Before processing into RBM the MFCC features attempt to eliminate the information of speech data when it is not having relevancies for recognition purpose. MFCC itself offered the alternative model as individual component to be independent so they are much easier to model using a mixture of diagonal covariance Gaussians.

We carried out the classification with a matrix to show that our system works well predicting the accuracy of each class in speech. This matrix result is obtained from the process of waveform in MFCC procedure then converted into RBM, from RBM the feature of MFCC combined onto multi-layer perceptron that processed in DBN. In Figure 6 indicates that the diagonally blocks our systems can predict the single word in 100% accuracy. As we can see each "block" from the figure shows the example predictive word "ap" means an apple, "ba" has a meaning of banana, also "ki" means kiwi and so forth.

4.2 Enhancing Result

In our experiment the signal is sampled in a range 8000 Hz and quantized with 16 bits. The signal is splits up in short frames of 80 samples corresponding to 10 ms of speech. That's range was choosing by relatively limited flexibility of the throat. When process into deep belief network we pick put the features from frequency domain and taking it with fast Fourier transform multiply by a hamming window to reduce the spectral leakage caused by framing of the signal. The input in DBN forming a total of 216 (6x36). So after we gets the binary data through to RBM, the structure of RBM has a weakness such as repeating learning could be consuming the time of structure of evaluation and leads to inefficiency in the structure optimization, so by the modularization structure of optimization is performed efficiently by shortening calculation time. By optimized the structure of DBN, we were able to find appropriate structure.

We consider using taboo search in partially of solution space and divided it into multiple subspaces first then the promising regions performed the search procedure. We conducted the experiment with 10 trial of each experiment with different modularization. In each trial, number of units hidden layers are similar to each other. Also we conduct of experiment with the number of hidden layer using different parameter setting, it's like 500-1000 and 2000 in single run of epochs.

Table 3. Performance Accuracy

Test Data	DBN (%)	DBN Structure Opt (%)
Speech	99.38	100

In this experiment we believe, using more number of unit in DBN, the feature is not good enough to generate the classifier. Due to the simple speech that we have conducted the performance is quite well enough. In the table 4, we tried to figure it out about the effect of varying size number of unit in initial space search solution. The main trend in table 4 is that adding more initial number of unit gives the better performance. Although, this research does not try the bigger size of dataset. In other hand, we tried an experimental design in HMM theorem for benchmarking algorithm, we got the accuracy of classification 80 % also with the same data set.

5 Conclusion and Future Work

This study review of the work in DBN and DBN improvement with RBM modularization as better as predicted the simplest speech audio signal files in better way accuracy. The modularization of hidden layer using taboo search is almost the same performance as DBN as without modularization. Even we set the minimum parameter setting of hidden layer size in 500, the performance is optimized well. Otherwise the speed of running the model much be increased when we were running the big data of speech.

The larger the number of solution dimensions the execution time will be shortened and made the effective of modularization. Then, the larger number of input dimensions the smaller of calculations amount in solution search. However, when comparing the structure optimized DBN without using DBN structurally optimized using modularization the performance is almost same.

In the future work, we will conduct some kind of the experiments on different voices dataset for benchmarking. Also, we will consider about different processing procedure in signal audio to improve the accuracy. Also we considered about speech in Parkinson diseases would be interested area.

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