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Adaptive Activation Function for Isolated Digit Recognition Based on Speaker Dependent System

Ummu Salmah, M.H
Department of Information Technology,
Kolej Universiti Islam Sultan Azlan Shah,
33000 Kuala Kangsar, Perak, Malaysia.

Saira Banu, O.K.
Computing Department
Universiti Pendidikan Sultan Idris
35000 Tg. Malim, Perak, Malaysia.

Siti Mariyam, S.
Department of Computer Graphics and Multimedia,
Universiti Teknologi Malaysia,
81300 Skudai, Johor, Malaysia.

Nor Azah,
Center of Language for Foundational Studies (CELFOS),
Kolej Universiti Islam Sultan Azlan Shah,
33000 Kuala Kangsar, Perak, Malaysia.

Abstract— An automatic speech recognition (ASR) system has been the goal in speech research for more than 6 decades. This study focuses on developing the robustness of the MLP neural network for the Malay isolated digit recognition system by proposing a simple novel approach. An adaptive sigmoid function is implemented to achieve this objective. A typical or fixed sigmoid function method is used in the learning phase. In the recognition phase, an adaptive sigmoid function is employed. In this sense, the slope of the activation function is adjusted to gain highest recognition rate. The outcome of the simulation reveals that adaptive sigmoidal function offers a number of advantages over traditional fixed sigmoid function, resulting in better generalization performance. The proposed approach implicates ASR is applicable for the task on Malay language continuous speech and the speaker independent task to fulfill the ultimate goal in speech technology, towards natural ASR.

Keywords- Automatic Speech Recognition; Multilayer Perceptron; Endpoint Detection; Artificial Neural Network.

I. INTRODUCTION

An automatic speech recognition (ASR) system has been a goal in speech research for more than 6 decades [1]. The ASR research began in the 1900's and has attracted much interest in the market recently because of the advancements in its methods, algorithm, and related technology [2]. The ultimate goal in ASR is to establish a natural spoken language with an independent spoken style in all environments. However, achieving such a goal is not free from obstacles. Such obstacles can be handled easily by impressive human speech production. A similar approach with biological nerve cells in the human brain is a promising way to overcome those problems [3]. One of the more effective methods associated with the human brain is a neural network (NN). A neural network consists of interconnected nerve cells [4].

The Neural network is capable of classifying noisy data, various patterned data, variable data streams, multiple data and overlapping, interacting and incomplete cues. Neural networks have made great progress in isolated word recognition and other ASR fields [5] but the main obstacles that are faced by the NN model is the long training duration which increases with the data set. Besides that, the robustness of isolated digit recognition is not trivial because it has been widely used for many applications [6]. These applications include recognizing telephone numbers, spelled names and addresses, zip codes, and as a spelling mode for use with difficult words and out-of-vocabulary items in a continuous speech recognizer, mobile equipment and voice command-based consumer electronic products.

II. ACTIVATION FUNCTIONS

The activation function is also known as a transfer function. Activation function is a nonlinear function. This function is used to determine the relationship between inputs and output of neurons by applying to the net input of a neuron. Generally, its domain must be real numbers as there is no theoretical limit to what the net input can be [7]. Normally, the range of an activation function is limited to 0 to 1 or –1 to 1. Even though any differentiable function can qualify as an activation function in theory, but in practice, only a small number of "well-behaved" (bounded, monotonically increasing, and differentiable) activation functions are used. There are 4 activation functions that are frequently used in NN model, namely [8], identity function, linear function, threshold function and sigmoid function.

The threshold function is activated if the weighted sum of input is less than of the threshold, then the neuron's output is 0 otherwise the output is 1. The two common functions used for threshold function are:

$$f(x) = \begin{cases} 0, & x < \mathrm{P} \\ 1, & x \geq \mathrm{P} \end{cases} \qquad \text{or} \qquad f(x) = \begin{cases} 0, & x < \mathrm{P} \\ x, & x \geq \mathrm{P} \end{cases}$$

A sigmoid function is defined as a continuous real value function with real domain. Its derivative is always positive and the sigmoid is a bell-shaped curve with large values in the middle range and small values toward both extremes [9]. This shape avoids large changes in weights, when the sum of the back-propagated errors approaches a very large or a very small value. In this study the activation of hidden and output neuron is computed by using sigmoid (S-shaped) function as described in Figure 1 and defined as

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

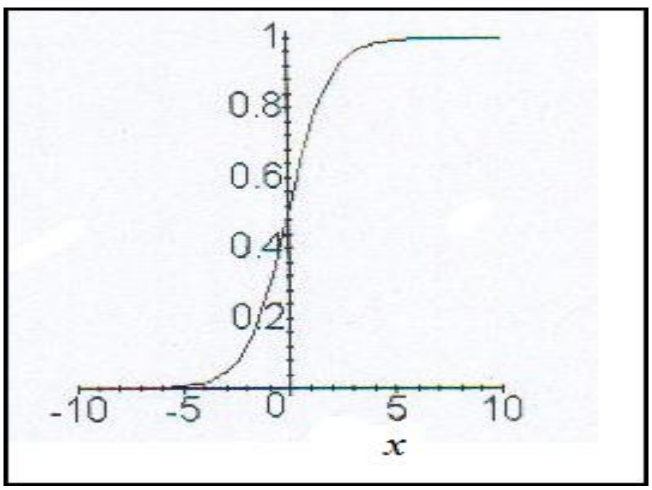

Figure 1. Logistic Function

The most commonly employed sigmoid function is the logistic function. The advantage of this function is that its derivative is easily found [9] as follows:

$$f^{'}(x) = f(x)(1 - f(x)) \tag{1}$$

The identity, linear and threshold functions are relatively simple in computation. Meanwhile the computation of sigmoid function, which is a non-linear function, is relatively complex. However most current NN models use sigmoid function to solve real-world task.

Adaptive sigmoid function

Interest in adaptive activation function has arisen recently. This strategy seems to produce better fitting properties than fixed activation function [10]. Basically, adaptive sigmoid function is an activation that consisting of one or more adjustable parameter. Consider examples of the equation below,

$$f(net) = \frac{1}{1+\exp(-\beta net)} \tag{2}$$

where net is, the summing product of the connection weights and the corresponding neuron output, β represents the slope parameter of the activation function f(net) in the region and an adjustable parameter.

Several researchers study this area to improve the learning time and recognition rate in NN field. Chen and Chang [3] proposed a novel shape tunable hyperbolic tangent activation function to accelerate the learning time and get better learning ability. Vecci et al. [10] adapted the spline activation function by varying the control points of a Catmull-Rom cubic spline. This method successfully reduced learning time, improved the generalization process, and reduced hardware complexity. Campolucci et al. [12] proposed new neural network architecture based on adaptive spline activation function. This activation function is built as a piecewise approximation with suitable cubic splines. An arbitrary shape can be obtained and the learning time can be reduced. Liang [13] proposed an adaptive function to maximize multiresolution learning. They introduced a new concept and method to adapt the slope of neural logistic activation function to the learning data at different resolution during multiresolution learning process. The performance of recognition rate and the learning time was improved by using this method, which was tested on real-world sunspot series predictions. Xu and Zhang [14] proposed a similar works as Liang but their logistic activation function has 6 free parameters. These parameters are adjustable during learning process and produced faster learning time compared to fixed activation function. Karma and Chandra [15] did a study on cascady neural networks utilizing adaptive sigmoid function (CNNASS) to build a dynamic cascading architecture.

This study is important, as no researcher has investigated this approach in speech recognition field. In this study, an adaptive function is proposed to increase the recognition rate for speech data. Most of the researchers focused on learning phase only. Our adaptive activation function approach is performed in a different way where it emphasizes in the recognition phase.

In this phase the backpropagation (BP) used the weight information to generalize the speech data (learning data and testing data). The results can be categorized into two possibilities, either a recognized word or unrecognized word. The input pattern is recognized if the output neuron produces value that greater than 0.5 threshold. In other words, if the value of the output neuron is greater than 0.5 then it will consider as 1 and if it is less than 0.5, consider as 0, which means the input pattern is unrecognized. The threshold value of 0.5 is sufficient to MLP capable for recognized any patterns

[16]. The process for the recognition procedure is described below.

Step 0. Restore weights that are obtained from learning process.
Step 1. For each input patterns, do steps 2.
Step 2. Perform the Feedforward (refer to previous standard learning algorithm for standard BP)

In conventional NN, the output computed by the neuron during learning and generalization is performed by fixed activation function. In this study, a new approach to generalize the speech data in recognition phase is introduced. In this sense, the fixed activation function was used only in learning process while in the recognition phase, the adaptive sigmoid function was employed.

The fixed sigmoid function is defined as:

$$f(net) = \frac{1}{1+\exp(-net)} \quad (3)$$

The Adaptive Sigmoid Function is defined as:

$$f(net) = \frac{1}{1+\exp(-\beta net)} \quad (4)$$

where β is a slope parameter of the sigmoid function in the region.

Throughout this study, the steepness of the slope of sigmoid function was adjusted in the generalization process to get the best fitting properties. Therefore, the highest recognition accuracy will be produced. Figure 2 shows the sigmoid activation function with different slope. This slope is control by β parameter. The higher the β is, the steeper will be the slope. In this study the β was tested between 1.0 to 2.0. Other than this value made the recognition rate is low. From the experiment, the value 2.0 contributes to the highest recognition for most of the experiments. The algorithm to perform the adaptive sigmoid function is given below.

Step 0. Restore weights that are obtained from learning process.
Step 1. Define the value for slope of parameter of sigmoid function.
Step 2. For each input patterns, do step 3.
Step 3. Perform the feed forward (refer to previous standard learning algorithm for standard BP).
Step 4. Select the highest recognition accuracy (according to the best value of the slope of parameter of sigmoid function).
Step 5. Repeat the step 1 for other value of parameter of sigmoid function

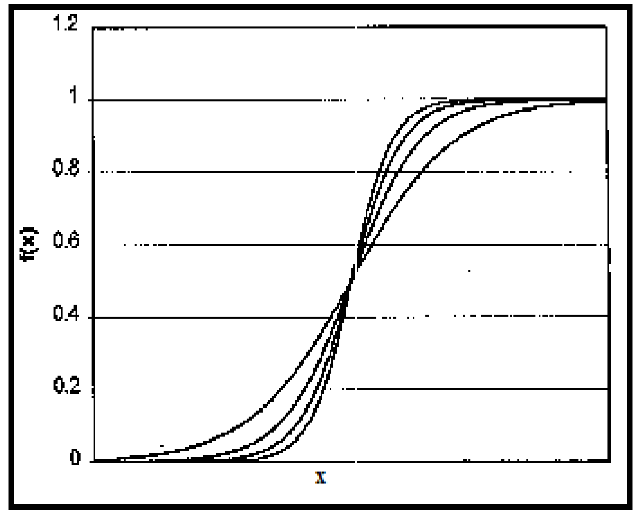

Figure 2. Activation Function with Different Slope

Therefore in this study the main objective is to do an enhancement to improve the robustness of the Multilayer Perceptron (MLP) NN for the Malay isolated digit recognition. The enhancement emphasizes on the recognition phase, particularly on activation function.

III. RESULTS AND DISCUSSION

The preprocessing module prepared the speech signal in a digitized form before being processed by the NN module. This phase comprised of five stages: recording, endpoint detection, time axis normalization, feature extraction, and normalization. These stages are explained accordingly. The recording session is carried out to develop the Malay language corpus for the purpose of this study. Endpoint detection is used to separate the speech segments from non-speech segments. Time-axis normalization is implemented to normalize the speech length to get a fixed number of neurons in order to cope with the NN structure. The Linear Predictive Code (LPC) method is used to represent the speech model. The normalization stage is the final stage in preprocessing before the speech data is fed into the NN module. In this study, we used 2 sets of data; Malay dataset and TI46 dataset.

Malay Data Set

The Malay data set is a speaker-dependent corpus, comprising of isolated speech words from a single male speaker. The speech samples acquired at a 10kHz sampling rate were digitized into 8-bit resolutions. The speaker uttered numbers “sifar” to “sembilan” (0 to 9) at least 100 times and the total number of datasets taken was 1000 samples. The first 400 speech samples were used as the training set and the remaining 600 speech samples were used for data testing.

TI46 Data Set

The TI46 data set is a benchmark corpus for English text-dependent speaker recognition (Chen et al., 2002). It contains isolated speech words from 16 speakers, eight males and eight females. They were divided into 2 sets: TI20 and TI_Alpha. The TI20 was used in this study that comprised of digits from “0” to “9”. This dataset had been captured at a 12,500Hz sampling rate and digitized to 16-bit resolution. Each speaker uttered number "0" to "9" 10 times. The first 5 repetitions were used as the training set while the remaining 5 as the testing set. The recording was done in a high signal-to-noise ratio condition (SNR). The TI46 data set was split into male and female data sets. Thus, the total number of samples in the training set was 400 and the number of samples in the test data set was 400 for both males and females respectively. The male and female datasets were trained separately in this study.

IV. ADAPTIVE SIGMOID FUNCTION EXPERIMENT

This section discusses the experiments of endpoint detection method and normalization method using adaptive sigmoid function. The percentage improvement of recognition rate is selected after testing an adaptive sigmoid function on three best performed hidden neurons.

Endpoint detections experiments

The following experiments describe the results using the adaptive sigmoid function for Malay and TI46 data sets. Table 1 shows the percentage improvement of recognition rate gained by various endpoint detection methods after using adaptive sigmoid function in generalization process.

TABLE 1: THE HIGHEST RECOGNITION RATE PRODUCED BY ADAPTIVE ACTIVATION FUNCTION ON VARIOUS ENDPOINT DETECTION METHODS (MALAY DATA SET)

Endpoint Detection Method	Fixed Sigmoid Function (%)	Adaptive Sigmoid Function (%)	Percentage Improvement
Energy	94.80	95.66	1.76
Variance	98.50	99.16	0.66
Energy and Zero Crossing	92.60	94.50	1.90

Figure 3 describes the results graphically. It shows that energy and zero crossing method gain the highest percentage improvement of recognition rate, which is 1.9%. In other words, the adaptive sigmoid function method is able to correctly recognize 12 speech tokens more compared to conventional method. Then, the performance of the adaptive sigmoid function is further investigated on TI46 data set.

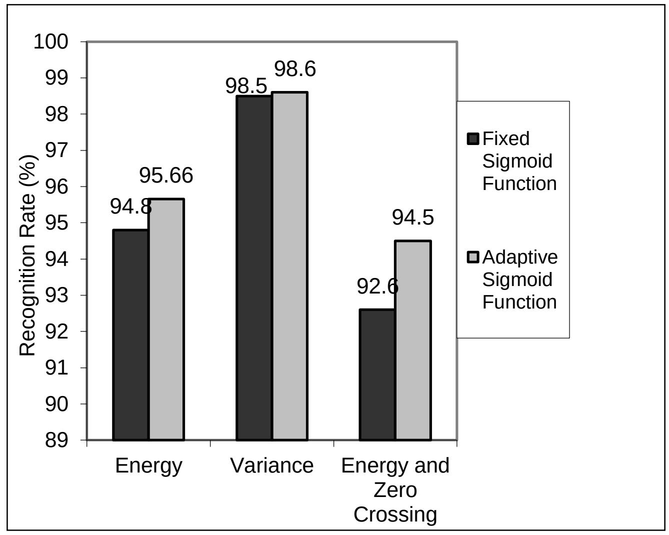

Figure 3. The Comparison Of Recognition Rate Between Fixed Adaptive Function And Adaptive Sigmoid Function For Various Endpoint Detections Method (Malay Data Set)

Table 2 and 3 shows the percentage improvement of recognition rate for male and female data set. Energy and zero crossing method with 1.75% as shown in Figure 4 and 5 achieve the highest percentage improvement of recognition rate for male data set. Meanwhile, for female data set, the highest percentage improvement of recognition rate was produced by variance method with 2.5%. Therefore the adaptive sigmoid function successfully recognized 7 speech tokens and 10 speech tokens more for male and female data sets respectively

TABLE 2: THE HIGHEST RECOGNITION RATE PRODUCED BY ADAPTIVE ACTIVATION FUNCTION ON VARIOUS ENDPOINT DETECTION METHODS (MALE DATA SET)

Endpoint Detection Method	Fixed Sigmoid Function (%)	Adaptive Sigmoid Function (%)	Percentage of Improvement
Variance	92.25	93.75	1.50
Energy	93.75	94.75	1.00
Energy and Zero Crossing	85.25	87.00	1.75

TABLE 3: THE HIGHEST RECOGNITION RATE PRODUCED BY ADAPTIVE ACTIVATION FUNCTION ON VARIOUS ENDPOINT DETECTION METHODS (FEMALE DATA SET)

Endpoint Detection Method	Fixed Sigmoid Function (%)	Adaptive Sigmoid Function (%)	Percentage of Improvement
Variance	94.00	96.50	2.50
Energy	91.50	92.25	0.75
Energy and Zero Crossing	83.50	85.00	1.50

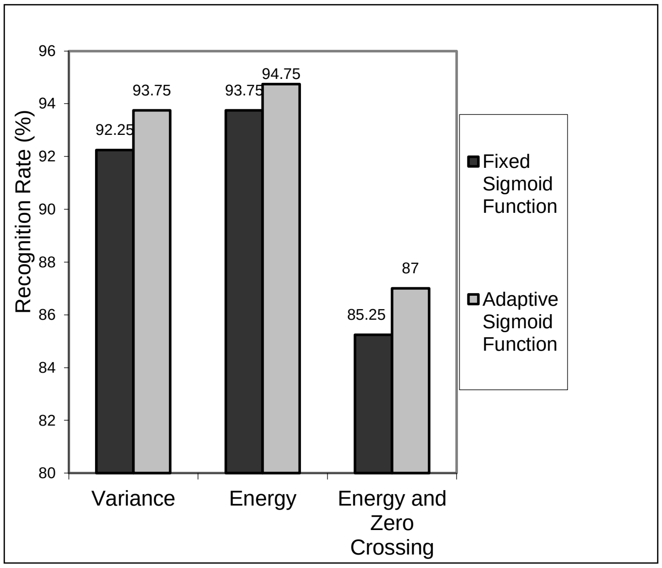

Figure 4. The Comparison of Recognition Rate Between Fixed Adaptive Function and Adaptive Sigmoid Function for Various Endpoint Detections Method (Male Data Set)

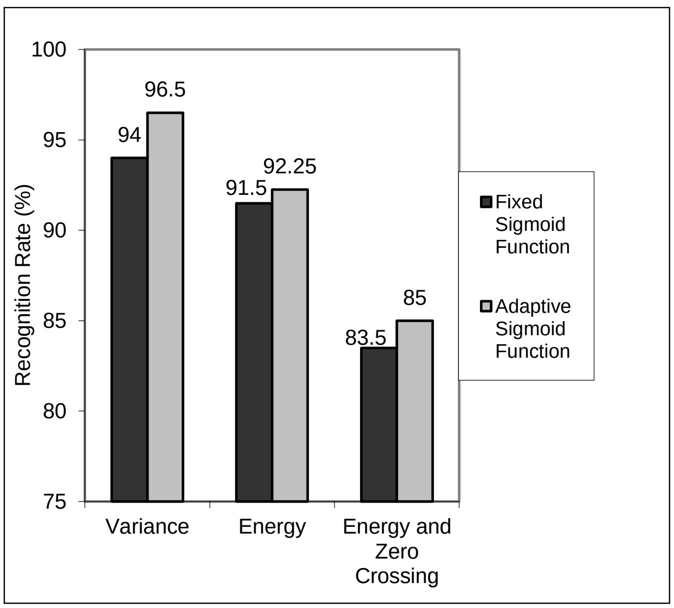

Figure 5. The Comparison of Recognition Rate Between Fixed Adaptive Function and Adaptive Sigmoid Function for Various Endpoint Detections Method (Female Data Set)

Malay data set experiments

The experiments were further extended on normalization methods for Malay and TI46 data set. Table 4 and Figure 6 shows the percentage improvement of recognition rate achieved by various normalization methods after using adaptive sigmoid function in generalization process. The highest percentage improvement of recognition rate is achieved by variance method, which is 1.37% and correctly recognizes 9 speech tokens more for Malay data set.

TABLE 4: THE HIGHEST RECOGNITION RATE PRODUCED BY ADAPTIVE ACTIVATION FUNCTION ON VARIOUS NORMALIZATION METHODS (MALAY DATA SET)

Normalization Method	**Fixed Sigmoid Function (%)**	**Adaptive Sigmoid Function (%)**	**Percentage of Improvement**
Variance	98.33	99.70	1.37
Range I	98.33	99.33	1.00
Range II	98.83	99.70	0.87
Simple	98.6	99.50	0.90
Exponent	98.66	99.16	0.50
Hybrid I	99.00	99.50	0.50
Hybrid II	99.00	99.83	0.83

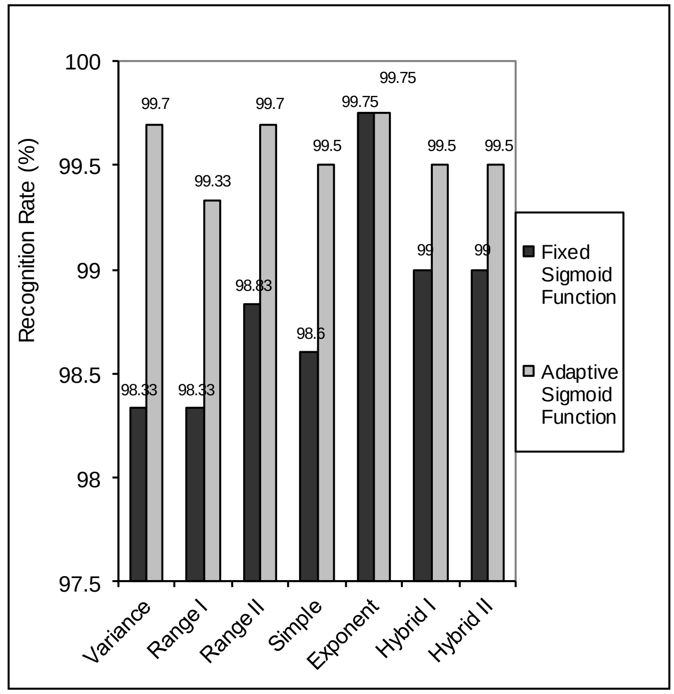

Figure 6. The Comparison of Recognition Rate Between Fixed Adaptive Function and Adaptive Sigmoid Function for Various Normalization Method (Malay Data Set)

TI46 data sets experiments

The adaptive sigmoid function successfully has increased the recognition rate for male data set using various normalization methods as shown in Table 5. From Figure 7 shows that the hybrid I gained the highest percentage improvement of recognition rate with 2%. Hence, the hybrid I successfully increases the recognition rate of male data set by recognizing 8 speech tokens more using the adaptive sigmoid function.

TABLE 5: THE HIGHEST RECOGNITION RATE PRODUCED BY ADAPTIVE ACTIVATION FUNCTION ON VARIOUS NORMALIZATION METHODS (MALE DATA SET)

Normalization Method	**Fixed Sigmoid Function (%)**	**Adaptive Sigmoid Function (%)**	**Percentage of Improvement**
Variance	88.75	89.25	0.50
Range I	87.75	87.75	None
Range II	90.25	91.75	1.50
Simple	91.50	91.50	None
Exponent	93.75	94.75	1.00
Hybrid I	91.25	93.25	2.00
Hybrid II	91.75	93.00	1.25

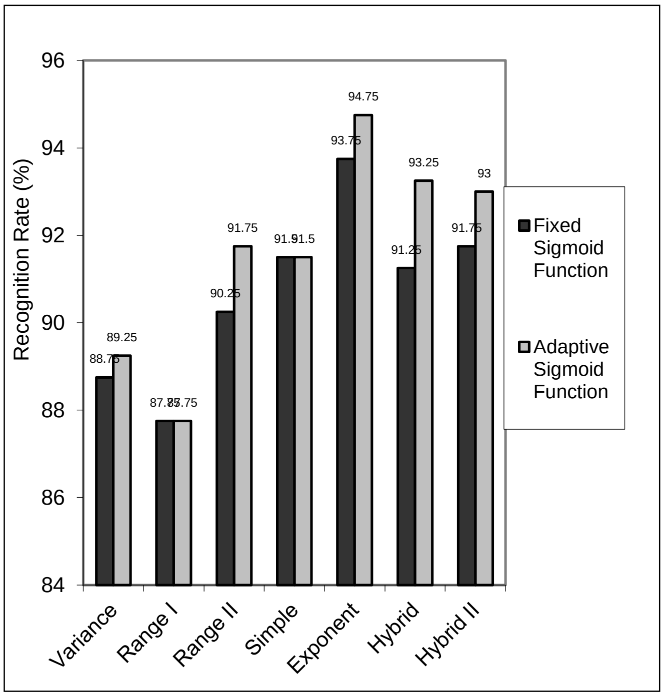

Figure 7. The Comparison of Recognition Rate Between Fixed Adaptive Function and Adaptive Sigmoid Function for Various Normalization Method (Male Data Set)

Experiments further carried out for female data set. In these experiments, the adaptive sigmoid function was evaluated in 2 conditions with 0.02 and 0.05 minimum error rate. Table 6 shows the percentage improvement of recognition rate gained by various normalization methods after using adaptive sigmoid function. Figure 8 shows the improvement in recognition rate for female data sets. It shows that exponent and hybrid II method gain the highest percentage improvement of recognition rate, which are 2.5%. This indicates that the adaptive sigmoid function is capable to recognize 10 tokens more for female data sets in both normalization methods.

TABLE 6: THE HIGHEST RECOGNITION RATE PRODUCED BY ADAPTIVE ACTIVATION FUNCTION ON VARIOUS NORMALIZATION METHODS (FEMALE DATA SET- ERROR - RATE 0.02)

Normalization Method	**Standard Sigmoid Function (%)**	**Adaptive Sigmoid Function (%)**	**Percentage of Improvement**
Variance	93.75	93.75	None
Range I	92.25	92.50	0.50
Range II	93.25	94.50	1.25
Simple	94.50	95.75	1.25
Exponent	94.00	96.50	2.50
Hybrid I	94.75	96.25	1.50
Hybrid II	91.50	94.00	2.50

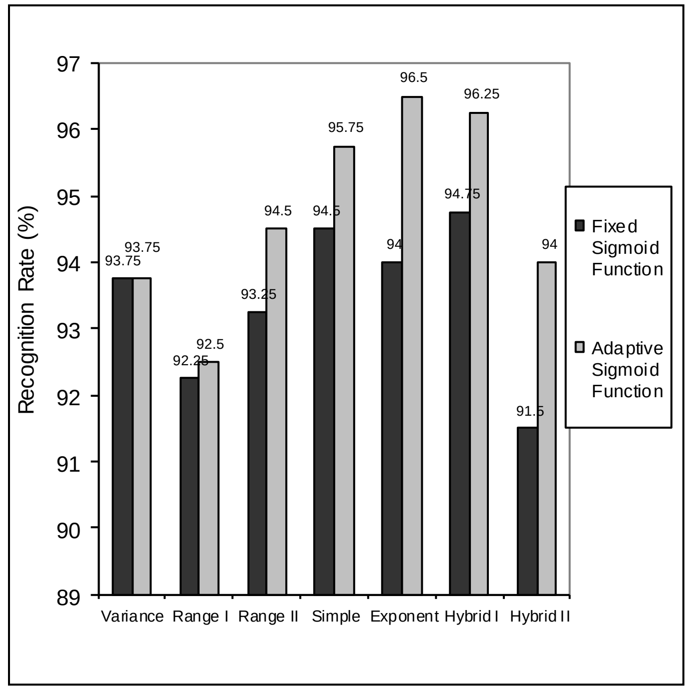

Figure 8. The Comparison of Recognition Rate Between Fixed Adaptive Function and Adaptive Sigmoid Function for Various Normalization Method (Female Data Set- Error Rate 0.02)

Experiments were further investigated for female data sets using minimum error rate 0.05. Table 7 lists the percentage improvement of recognition rate achieved by each method. Figure 9 shows graphically the results from Table 7. It seems that hybrid I and hybrid II obtained highest percentage improvement of recognition rate with 3% by using the adaptive sigmoid function method. In this sense, the adaptive sigmoid function had successfully increased 12 tokens more for female data set using both normalization methods. Therefore, it is clearly shown that the adaptive sigmoid function is capable to enhance the recognition rate for Malay and TI46 data set respectively.

TABLE 7: THE HIGHEST RECOGNITION RATE PRODUCED BY ADAPTIVE ACTIVATION FUNCTION ON VARIOUS NORMALIZATION METHODS (FEMALE DATA SET- ERROR RATE 0.05)

Normalization Method	Fixed Sigmoid Function (%)	Adaptive Sigmoid Function (%)	Percentage Improvement
Variance	92.25	93.50	1.25
Range I	92.00	92.75	0.75
Range II	93.00	94.75	1.75
Simple	94.00	94.50	2.50
Exponent	93.75	96.75	3.00
Hybrid	92.75	95.25	2.50
Hybrid II	91.00	94.00	3.00

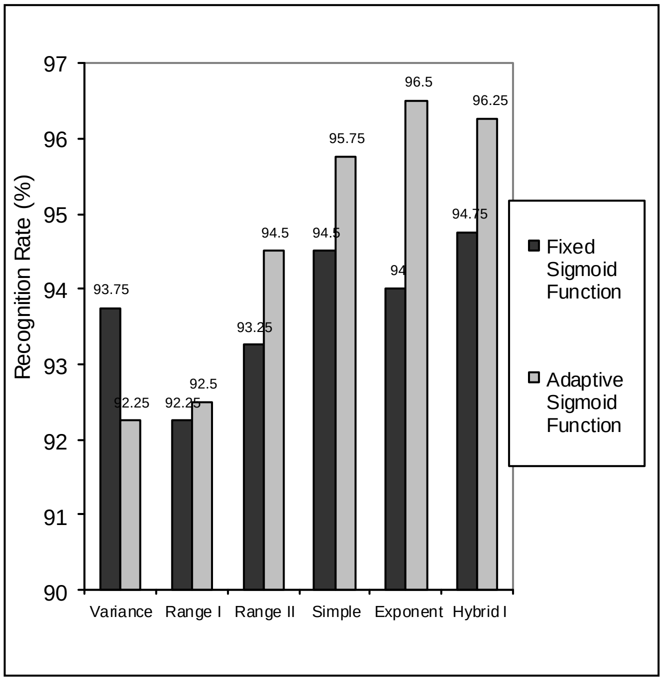

Figure 9. The Comparison of Recognition Rate Between Fixed Adaptive Function and Adaptive Sigmoid Function for Various Normalization Method (Female Data Set-Error Rate 0.05)

The adaptive sigmoid function method has successfully increased the recognition rate for most of the experiments. This is because some of the desired output values are below threshold, which is 0.5 when it sends fixed activation function $f(x)=\frac{1}{1+e^{-x}}$, x is desired output or undesired output. However, this value is propagated to adaptive activation function ($f(x)=\frac{1}{1+e^{-\beta x}}$) and the value of desired output is increased by this function to be greater than threshold due to multiplication with β value. Hence, it leads to the increment in recognition rate. To increase the desired output greater than 0.5 (the fixed threshold in this study), the β and x value must be positive. This is because the activation function will approach 1, when the exponent is powered with any small number. For instance, consider the equations below:

$$f(x)=\frac{1}{1+\left(e^{-(\beta\times x)}\right)}=0.6883, \tag{5}$$

where $\beta=3.1$ and $x=0.255549$

and

$$f(x)=\frac{1}{1+\left(e^{-(\beta\times x)}\right)}=0.3116, \tag{6}$$

where β = -3.1 and $x=0.255549$

The Equation 5 produces 0.69 that is nearer to 1; meanwhile the Equation 6 yielded 0.31 outputs that is nearer to 0. These results proves that some of the desired output produced that are below 0.5 after using fixed activation function could be greater than 0.5 by using the adaptive activation function. The value of adaptive sigmoid function is selected from 1.0 to 2.0. It is based on the condition that if the β value is too small or greater than 2.0, the recognition will decrease. For example, if the β value is small such as –10.00, the desired output produced will be less than or equal to 0.5. If the β value is too large, the undesired output also will compete with desired output to be greater than 0.5. Thus these two situations will drop the recognition rate. For example, consider the equation below :

$$f(x)=\frac{1}{1+\left(e^{-(\beta\times x)}\right)}=0.0758, \tag{7}$$

where β = -10.0 and $x=0.255549$

where x is desired output, and

$$f(x)=\frac{1}{1+\left(e^{-(\beta\times x)}\right)}=0.578, \tag{8}$$

where $\beta=10.0$ and $x=0.578$

where x is undesired output.

The β value is set to 10 and –10 for both equations. In the Equation 7, the β value is small and the produced desired output is equal to 0.0758. Meanwhile in the Equation 8, the produced undesired output is greater than 0.5 when the β value is quite large. Therefore, an appropriate β value for gained highest percentage improvement of recognition rate is 1.0 to 2.0.

V. CONCLUSION

A new approach to generalize the speech data in recognition phase is introduced. The adaptive sigmoid function ensures that the performance of recognition is increased for speaker dependent system. This concludes that the approach achieves better performance as compared to the traditional fixed sigmoid function.

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AUTHORS PROFILE

Ummu Salmah Mohamad Hussin received her Bachelor in Computer Science from Universiti Putra Malaysia (UPM), Master degree and PhD, in Speech Recognition & Artificial Intelligence from Universiti Putra Malaysia (UPM), MALAYSIA. Currently, she is a senior lecturer of Faculty Information Technology, Kolej Islam Darul Ridzuan (KISDAR). Her research interests include Speech Recognition and Pattern Recognition.

Saira Banu Omar Khan received her Bachelor in Computer Science from Universiti Putra Malaysia (UPM), Master degree in Computer Science from Universiti Sains Malaysia (USM), MALAYSIA. Currently, she is a lecturer in Faculty of Art, Computing and Creative Industry, Universiti Pendidikan Sultan Idris (UPSI), Malaysia. Her research interests include Operational Research, Data Structure and Algorithms.

Siti Mariyam Shamsuddin received her Bachelor and Master degree in Mathematics from New Jersey USA, and Phd in Pattern Recognition & Artificial Intelligence from Universiti Putra Malaysia (UPM), MALAYSIA. Currently, she is a Head of Soft Computing Research Group, k-Economy Research Alliance, Universiti Teknologi Malaysia (UTM), Johor MALAYSIA. Her research interests include the Fundamental Aspects of Soft Computing and its Application, Pattern Recognition, Forensic Document Analysis, and Geometric Modeling.

Nor Azah received her Bachelor of TESL from MARA University of Technology MAlaysia (UiTM). She is now in her final semester of completing her Master of TESL in University Pendidikan Sultan Idris Malaysia, (UPSI). Her research interest include applied linguistics and bilingualism.