Adaptive Decision-level Fusion for Fongbe Phoneme Classification using Fuzzy Logic and Deep Belief Networks

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Abstract: In this paper, we compare three approaches for decision fusion in a phoneme classification problem. We especially deal with decision-level fusion from Naive Bayes and Learning Vector Quantization (LVQ) classifiers that were trained and tested by three speech analysis techniques: Mel-frequency Cepstral Coefficients (MFCC), Relative Spectral Transform - Perceptual Linear Prediction (Rasta-PLP) and Perceptual Linear Prediction (PLP). Optimal decision making is performed with the non-parametric and parametric methods. We investigated the performance of both decision methods with a third proposed approach using fuzzy logic. The work discusses the classification of an African language phoneme namely Fongbe language and all experiments were performed on its dataset. After classification and the decision fusion, the overall decision fusion performance is obtained on test data with the proposed approach using fuzzy logic whose classification accuracies are $95,54\%$ for consonants and $83,97\%$ for vowels despite the lower execution time of Deep Belief Networks.

1 INTRODUCTION

One of the most exciting and difficult open problem of automatic speech recognition is enabling a recognizer machine to perform the phoneme classification task and to recognize the phoneme segments in a speech signal. Phoneme classification is an integrated process to the phoneme recognition and the first and important step in automatic speech recognition. Since the 60s, very significant research progress and related to the development of statistical methods and artificial intelligence techniques, tried to overcome the problems of analysis and characterization of the speech signal. Among the problems, there is still the acoustic and linguistic specificity of each language. Considering the number of languages that exists, there were some good reasons to approach the phoneme recognition problems.

The aim of the speech recognition is to convert the acoustic signal to generate a set of words from a phonemic or syllabic segmentation of the sentence contained in the signal. Phoneme classification is the process of finding the phonetic identity of a short section of a spoken signal (Genussov et al., 2010). To obtain good recognition, phoneme classification step must be well achieved in order to provide acoustic knowledge of phonemes of the given language. Like this, phoneme classification is applied in various applications such as speech and speaker recognition, speaker indexing, synthesis etc. and it is a difficult and challenging problem.

In this paper, we placed the phoneme recognition problems in a classification context from multiple classifiers. We have dealt with the decision-level fusion from two different classifiers namely: Naive Bayes and Learning Vector Quantization (LVQ). Since the 90s, the combination of classifiers has been one of the most sustained research directions in the area of pattern recognition. Methods of decision-level fusion have been successfully applied in various areas as the recognition and verification of signatures, identification and recognition of faces or the medical image analysis. In automatic speech recognition, decision-level fusion was introduced to recognize phoneme, speech, speaker age and gender and to identify language with the best performance. The work we present in this paper deals with the phoneme

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recognition of Fongbe language which is an unressourced language. Fongbe is an African language spoken especially in Benin, Togo and Nigeria. It is a poorly endowed language which is characterized by a series of vowels (oral and nasal) and consonants (oral and nasal). Its writing recently created consists of a number of Latin characters and the International Phonetic Alphabet. Scientific studies on the Fongbe started in 1963. In 2010, there was the first publication of Fongbe-French dictionary (Akoha., 2010). Since 1976, several linguists have worked on the language and many papers are published on the linguistic aspects of Fongbe. Until today, these works have been aimed at the linguistic description of the language, but less work has approached the automatic processing with a computing perspective.

The idea behind this work is to build a robust discriminatory system of consonants and vowels based on decision-level fusion from independent decisions of two classifiers. To do this, we investigated both methods of decision fusion namely the non-parametric method using weighted combination and parametric method using deep neural networks and a proposed adaptive approach based on fuzzy logic. To perform classification, we extracted from the speech signals the popular speech features as Mel Frequency Cepstral Coefficents (MFCCs), Perceptual linear prediction coefficients (PLP) and Relative Spectral Transform - Perceptual Linear Prediction Coefficients (RASTA-PLP). These speech analysis techniques were combined to produce coefficients as input variables to the classifiers. Experiments were performed on our Fongbe phoneme dataset and showed better performance with the proposed fuzzy logic approach. The rest of the paper is organized as follows. In section 2, we briefly present the related work in phoneme recognition and decision fusion. Section 3 presents an overview of our classification system. In section 4, we describe the classifiers methods and their algorithms. In section 5, the proposed Fongbe phoneme classification is detailed and explained. Experimental results are reported in section 6. In the same section we show a detailed analysis of the used performance parameters to evaluate the decision fusion methods. We conclude in section 7.

2 RELATED WORK

This work deals with two different issues: decision-level fusion from multiple classifiers and phoneme classification of a West Africa local language (Fongbe).

2.1 Phoneme Classification

Some of the recent research works related to phoneme classification applied to the world's languages is discussed as follows.

In (Lung et al., 2014), the authors have proposed an approach of phoneme classification which performed better on TIMIT speech corpus, with warp factor value greater than 1. They have worked on compensating inter-speaker variability through Vocal tract length normalization multi-speaker frequency warping alternative approach. Finally, they compare each phoneme recognition results from warping factor between 0.74 and 1.54 with 0.02 increments on nine different ranges of frequency warping boundary. Their results obtained show that performance in phoneme recognition and spoken word recognition have been respectively improved by 0.7% and 0.5% using warp factor of 1.40 on frequency range of 300 – 5000 Hz.

Phoneme classification is investigated for linear feature domains with the aim of improving robustness to additive noise (Ager et al., 2013). In this paper, the authors performed their experiments on all phonemes from the TIMIT database in order to study some of the potential benefits of phoneme classification in linear feature domains directly related to the acoustic waveform, with the aim of implementing exact noise adaptation of the resulting density model. Their conclusion was that they obtain the best practical classifiers paper by using the combination of acoustic waveforms with PLP$+\triangle + \triangle + \triangle$.

In (Genussov et al., 2010), the authors integrated into the phoneme classification a non-linear manifold learning technique, namely "Diffusion maps" that is to build a graph from the feature vectors and maps the connections in the graph to Euclidean distances, so using Euclidean distances for classification after the non-linear mapping is optimal. The experiments performed on more than 1100 isolated phonemes, excerpted from the TIMIT speech database, of both male and female speakers show that Diffusion maps allows dimensionality reduction and improves the classification results.

The work presented in (Palaz et al., 2013) successfully investigates a convolutional neural network approach for raw speech signal with the experiments performed on the TIMIT and Wall Street Journal corpus datasets. Always on the TIMIT datasets, the authors in (Yousafzai et al., 2009) focused their work on the robustness of phoneme classification to additive noise in the acoustic waveform domain using support vector machines (SVMs). The authors in (Esposito et al., 1998) used a preprocessing technique based on a modified Rasta-plp algorithm and a classification algorithm based on a simplified Time Delay Neural Network (TDNN) architecture to propose an automatic system for classifying the English stops [b,d,g,p,t,k]. And in (Esposito et al., 1996), they proposed an artificial Neural Network architecture to detect and classify correctly the acoustic features in speech signals.

Several works have been achieved on the TIMIT dataset which is the reference speech dataset but other works were performed on other languages than those included in the TIMIT dataset. We can cite, for example the following papers (Le and L, 2009; Niesler and Louw, 2004; Schlippe and Edy Guevara Komgang Djomgang, 2012; Mugler et al., 2014), where the authors have worked respectively on Vietnamese, Afrikaans, English, Xhosa, Hausa language and all American English phonemes.

A state of the art on the works related to Fongbe language present the work that has been done in the linguistic area as most Gbe dialects. In (Agoli-Agbo and Bernard, 2009), the authors have studied how six Fon enunciative particles work : the six emphatic particles h...n ”hence”, sin ”but”, m ”in”, l ”I insist”, lo ”I am warning you”, and n ”there”. Their work aimed at showing the various and specific of these enunciative particles. In these works (Lefebvre and Brousseau., 2001; Akoha., 2010) listed in the Fongbe language processing, the authors introduced and studied grammar, syntax and lexicology of Fongbe.

In (LALEYE et al., 2014), the authors addressed the Fongbe automatic processing by proposing a classification system based on a weighted combination of two different classifiers. Because of the uncertainty of obtained opinions of each classifier due to the imbalance per class of training data, the authors used the weighted voting to recognize the consonants and vowels.

2.2 Decision-level Fusion Methods

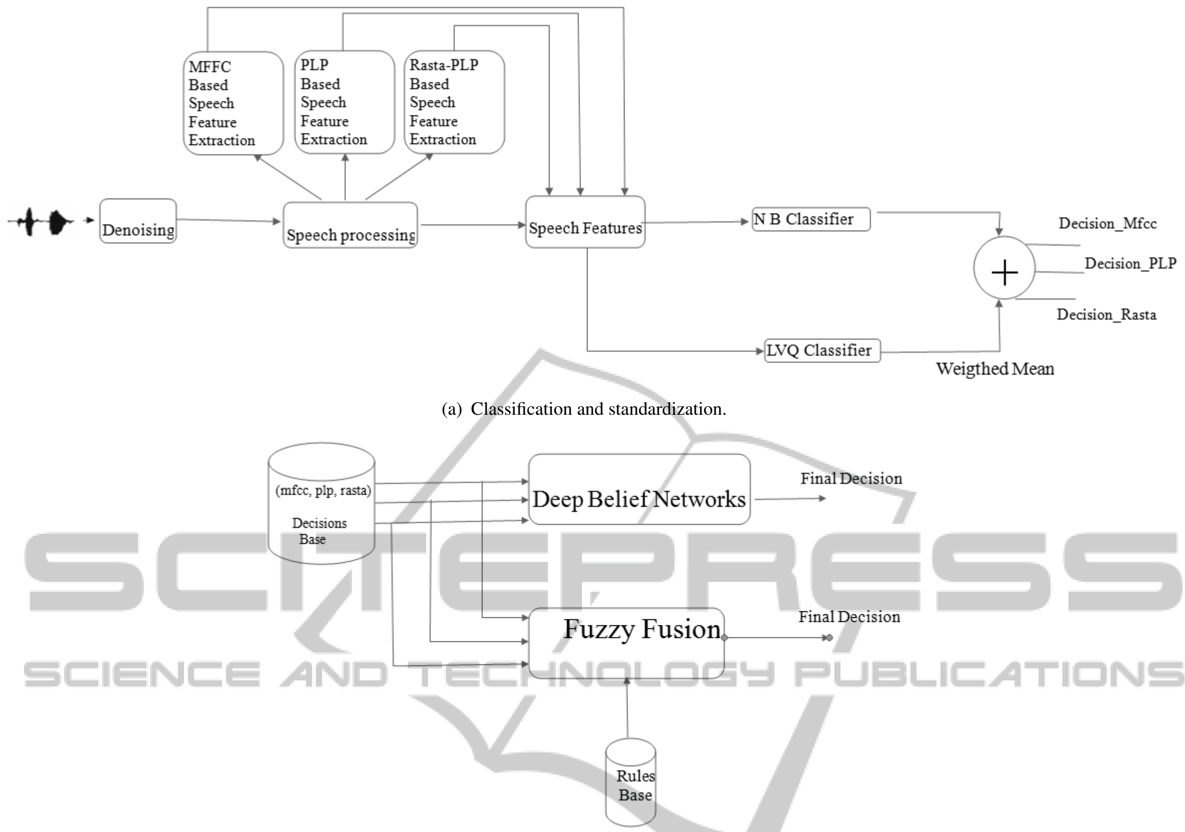
The second issue dealt with in this work is the decision fusion for optimal Fongbe phoneme classification. Combining decisions from classifiers to achieve an optimal decision and higher accuracy became an important research topic. In the literature, there are researchers who decided to combine multiple classifiers (Rogova., 1994; Cho and Kim., 1995; Kittler et al., 1998). Some researchers worked on mixture of experts (Jacobs., 1995; Jacobs et al., 1991)

In decision fusion methods, there are so-called non-parametric methods (classifiers outputs are combined in a scheme whose parameters are invariant) and the methods with learning that seek to learn and adapt on the available data, the necessary parameters to the fusion. In speech recognition, several researchers have successfully adopted the decision level fusion to recognize phoneme, speech, speaker age and gender and to identify language. For example, the authors in (A. Metallinou and Narayanan., 2010) performed decision level combination of multiple modalities for the recognition and the analysis of emotional expression. Some authors have adopted non-parametric methods as weighted mean (Lewis and Powers., 2001; Iyengar et al., 2003; Neti et al., 2000) and majority voting (Corradini et al., 2003; Pfleger., 2004). Others have adopted parametric methods as Bayesian inference (Pitsikalis et al., 2006; Meyer et al., 2004; Xu and Chua., 2006) and Dempster-Shafer method (Foucher et al., 2006).

In this work we adopted both methods to compare their performance in decision fusion of classifiers for an optimal phoneme classification of Fongbe language. First, we performed a weighted mean, which is a non-parametric method, to combine decisions. This method needs a threshold value chosen judiciously by experiment in the training stage. The second method we used is a parametric method with learning based on deep belief networks. Deep Belief Networks (DBNs) have recently shown impressive performance in decision fusion and classification problems (O'Connor et al., 2013). Other than these both methods we also used an adaptive approach based on fuzzy logic. Fuzzy logic is often used for classification problems and recently has shown a good performance in speech recognition (Malcangi et al., 2013). Indeed, the limitations of the use of threshold value that requires weighted mean is that the value is fixed and does not provide flexibility to counter any variations in the input data. In order to overcome the limitations of the threshold based weighted mean which gives a hard output decision of which either “True” or “false” and the time that can be taken a training process of deep belief networks, we proposed a third approach based on fuzzy logic which can imitate the decision of humans by encoding their knowledge in the form of linguistic rules. Fuzzy logic requires the use of expert knowledge and it is able to emulate human thinking capabilities in dealing with uncertainties.

3 OVERVIEW OF OUR PHONEME CLASSIFICATION SYSTEM

The phoneme classification system consist of three modules which are each subdivided into submodules.



(a) Classification and standardization.

(b) Decision fusion using fuzzy logic and Deep Belief Networks.

Figure 1: Paradigm of our classification system.

The first module performs classification with Naive Bayes and LVQ classifier and produces outputs with the coefficients applied as input. It contains the submodules which are (i) signal denoising, (ii) feature extraction (MFCC, PLP, and Rasta-PLP), (iii) classification with Naive Bayes and LVQ. The second module performs weighted mean calculation of classifiers outputs and contains the submodule which is (iv) standardization for classifiers decisions database. The last module performs in parallel the decisions fusion with fuzzy approach that we proposed and the method with learning based on Deep Belief Networks. Figure 1 shows the various steps of classification.

4 CLASSIFICATION METHODS AND ALGORITHMS

4.1 Naive Bayes Classifier

Naive Bayes is a probabilistic learning method based on the Bayes theorem of Thomas Bayes with independence assumptions between predictors. It appeared in the speech recognition to solve the multi-class classification problems. It calculates explicitly the probabilities for hypothesis and it is robust to noise in input data. Despite its simplicity, the Naive Bayesian classifier often does surprisingly well and is widely used because it often outperforms more sophisticated classification methods. The Bayes classifier decides the class $c(x)$ of the input data x based on the Bayes rule:

$$p(c|x) = \frac{p(c,x)}{p(x)} \quad (1)$$

$$= \frac{p(c)p(x|c)}{\sum_{c'} p(c')p(x|c')} \quad (2)$$

where $p(c)$ is the prior probability of class c, and $p(x|c)$ is the class c-conditional probability of x.

Consider an example $X = \{x_1, x_2, ..., x_n\}$

X is classified as the class $C = +$ if and only if,

$$F(X) = \frac{p(C = +|X)}{p(C = -|X)} \geq 1 \quad (3)$$

$F(X)$ is a Bayesian classifier.

Naive Bayes is the simplest form of Bayesian network, in which we assume that all attributes are independent given the class (Zhang., 2005).

$$p(X|c) = p(x_1, x_2, ..., x_n|c) = \prod_{i=1}^{n} p(x_i|c) \tag{4}$$

The naive Bayesian classifier is obtained by :

$$F_{nb}(X) = \frac{p(C=+|X)}{p(C=-|X)} \prod_{i=1}^{n} \frac{p(x_i|C=+)}{p(x_i|C=-)} \tag{5}$$

4.2 Learning Vector Quantization Classifier

Learning Vector Quantization (LVQ) is a supervised version of vector quantization. Networks LVQ were proposed by Kohonen (Kohonen., 1988) and are hybrid networks which use a partially supervised learning (Borne et al., 2007). Figure 2 shows a representation of LVQ network which presents two layers.

Algorithm:

LVQ method algorithm can be summarized as follows:

1. Initialize the weights $w_{ij}^{(1)}$ to random values between 0 and 1.
2. Adjust the learning coefficient $\eta(t)$
3. For each prototype p_i, find the neuron of the index i^* which has the weight vector $w_{i^*}^{(1)}$ closest to the p_i.
4. If the specified class at the network output for the neuron of the index i^* corresponds to the prototype of the index i, then do:

$$w_{i^*}^{(1)}(t+1) = w_{i^*}^{(1)}(t) + \eta(t)(p(t) - w_{i^*}^{(1)}(t)) \tag{6}$$

else

$$w_{i^*}^{(1)}(t+1) = w_{i^*}^{(1)}(t) - \eta(k)(p(t) - w_{i^*}^{(1)}(t)) \tag{7}$$

5. If the algorithm has converged with the desired accuracy, then stop otherwise go to the step 2 by changing the prototype.

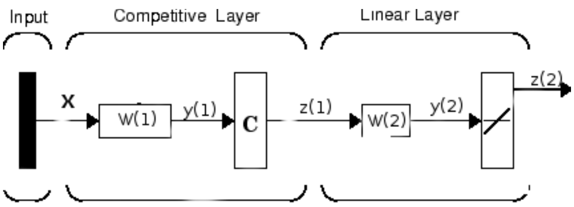


Figure 2: Representation of a network LVQ.

5 OUR FONGBE PHONEME CLASSIFICATION

To compare the optimal decisions obtained with each fusion approach, in a first step, we extract speech signals that are then classified into two classes (consonants and vowels) by the Naive Bayes and LVQ classifiers. The outputs are then combined in the second step to produce a single decision that is applied to the modules of fuzzy fusion and neuronal fusion.

5.1 Speech Feature Extraction

From phoneme signals we extracted MFCC, PLP and Rasta-PLP coefficients to perform the proposed adaptive decision fusion using Fuzzy approach and deep belief networks. The benefit of using these three types of coefficients is to expand the variation scale from input data of classification system. This enabled to our system to learn more acoustic information of Fongbe phonemes. These three speech analysis techniques were initially allowed to train two classifiers and then put together to build the set of input variables to the decision fusion. Phoneme signals were split into frame segments of length 32ms and the first 13 cepstral values were taken.

5.2 Decision Fusion using Simple Weighted Mean

An intermediate step between the two steps was the normalization of output data of the first step. First, we calculated the weighted mean value of the two classifier outputs for each coefficient using the expression (8).

$$input_1 = \frac{S^{naivebayes} \times \tau^{naivebayes} + S^{lvq} \times \tau^{lvq}}{\tau^{naivebayes} + \tau^{lvq}} \tag{8}$$

S^A represents the output of classifier A whereas τ^A represents the recognition rate of classifier A. Before applying fuzzy logic and neuronal technique to fuse the decisions of each classifier, we performed the output combination based on the simple weighted sums method using the threshold value obtained and given by the equation 9.

$$\tau = -1,2\sum_i C_i + 2,75(\sum_k w_k^1 \lambda_1 + \sum_k w_k^2 \lambda_2) \tag{9}$$

C_i : is the number of class i, w_k^1 : weight of classifier k related to the class 1, w_k^2 : weight of classifier k related to the class 2, λ_1 and λ_2 are values that are 0 or 1 depending on the class. For example, for the consonant class: $\lambda_1 = 1$ and $\lambda_2 = 0$. The results are compared with fuzzy logic method and neuronal method to evaluate the performance of our phoneme classification system.

5.3 Fuzzy Logic Based Fusion

5.3.1 Fuzzy Logic

Fuzzy logic is a mathematical-linguistic approach introduced by L.A. Zadeh in 1965 to generalize Boolean logic which has some drawbacks. Fuzzy logic provides a simple way to arrive at a definite conclusion based upon vagueness, ambiguous, imprecise, noisy, or missing input information. Fuzzy logic models consist of a number of conditional "*if-then*" rules. The fuzzy systems convert these rules to their mathematical equivalents.

5.3.2 Decision of Fuzzy Fusion

Nature of the results obtained in the first step allows us to apply fuzzy logic on four membership functions. The inputs to our fuzzy logic system are MFCC, PLP and Rasta-PLP and the output obtained is the membership degree of a phoneme to consonant or vowel class. The input variables are fuzzified into four complementary sets namely: *low, medium, high and very high* and the output variable is fuzzified into two sets namely: consonant and vowel. Table 1 shows the fuzzy rules which were generated after fuzzification. First, the input data is arranged in an interval as [Xmin .. Xmax]. The different membership functions were obtained by examining the local distribution of samples of both classes. Local distribution has induced four subsets according to the variation of the input data and the output is obtained depending on the nature of the data. For example, if we give MFCC, PLP and Rasta as input to the system, the consonant or vowel output is obtained according to the subsets of the input data. Because of the linearity of values in the subsets, a simple triangle curve (*trimf*) is used for low and medium membership functions and a trapeze curve (*trapmf*) is used for high and very high membership functions.

5.4 DBN Based Fusion

In this section, we describe the second method used for decision fusion to adapt the final classification decision. This method based on the use of deep belief networks requires a learning step for a good adaptation of the decisions to the system input.

5.4.1 Deep Belief Networks

DBNs are multilayered probabilistic generative models which are constructed as hierarchies of recurrently connected simpler probabilistic graphical models, so called Restricted Boltzmann Machines (RBMs) (Bengio et al., 2006; Hinton et al., 2006). Every RBM consists of two layers of neurons, a hidden and a visible layer. Using unsupervised learning, each RBM is trained to encode in its weight matrix a probability distribution that predicts the activity of the visible layer from the activity of the hidden layer (O'Connor et al., 2013).

Table 1: Generated fuzzy rules.

Rules No	Input			Output
	mfcc	rasta	plp	
1	low	low	low	consonant
2	low	low	medium	vowel
3	low	low	high	consonant
4	low	medium	low	vowel
5	low	high	low	consonant
6	low	high	high	consonant
7	low	very high	low	vowel
8	low	very high	very high	vowel
9	medium	low	low	vowel
10	medium	low	very high	vowel
11	medium	very high	low	vowel
12	medium	very high	very high	vowel
13	high	low	low	consonant
14	high	low	high	consonant
15	high	high	low	consonant
16	high	high	high	consonant
17	very high	low	low	vowel
18	very high	low	medium	vowel
19	very high	low	high	consonant
20	very high	low	very high	vowel
21	very high	medium	low	vowel
22	very high	medium	very high	vowel
23	very high	high	high	consonant
24	very high	very high	low	vowel
25	very high	very high	medium	vowel
26	very high	very high	very high	vowel

5.4.2 Decision of Deep Belief Networks

To perform the classifier for making of decision we used the DBN parameters showed in Table 2.

Table 2: DBN parameters.

RBM Layer 1	200 units
RBM Layer 2	200 units
Learning rate	0.01
Training Epochs	100
Batch size	8

5.5 Classification Algorithms

Algorithms 1 and 2 summarize the different parts of our classifier implemented with Matlab.

In the algorithms description, function names give the idea about the operation they perform and sentences beginning with // represent comments. For example, final_decision_2 $\leftarrow dbnfusion(all\_input)$ means that the optimal decision given by DBN fusion is stored in final_decision_2.

Algorithm 1: Classification with Naive Bayes and LVQ.

Data: Phoneme signals
Result: Decision of each classifier for each extraction technique.

signal denoising;
for $signal \in phoneme_database$ **do**
  signal←denoising(signal);
  base←put(signal)
end
Feature extraction;
for $signal \in base$ **do**
  m←mfcc_calculation(signal);
  p←plp_calculation(signal);
  r←rasta_calculation(signal);
  base_mfcc←put(m);
  base_plp←put(p);
  base_rasta←put(r);
end
training←put(m,p,r);
//Classification with Naive Bayes and LVQ;
for $i \leftarrow 1$ **to** $size(training)$ **do**
  if $i <= size(base\_mfcc)$ **then**
    $bayes\_mfcc\_decision \leftarrow bayes(training(i))$;
    lvq_mfcc_decision←lvq(training(i));
  end
  if $i > size(base\_mfcc)$ **and** $i <= size(base\_mfcc) + size(base\_plp)$ **then**
    $bayes\_plp\_decision \leftarrow bayes(training(i))$;
    lvq_plp_decision←lvq(training(i));
  end
  if $i > size(base\_mfcc) + size(base\_plp)$ **and** $i <= size(base\_mfcc) + size(base\_plp) + size(base\_rasta)$ **then**
    $bayes\_rasta\_decision \leftarrow bayes(training(i))$;
    lvq_rasta_decision←lvq(training(i));
  end
end

Algorithm 2: Decision fusion with Fuzzy logic and Deep belief networks.

Data: Decision of each classifier for each extraction technique.
Result: Final Decision

//calculation of recognition rate;
for $j \leftarrow 1$ **to** $size(classes)$ **and** $k \leftarrow 1$ **to** $size(classifiers)$ **do**
  $\tau \leftarrow -1,2\sum_i C_i + 2,75(\sum_k w_k^1 \lambda_1 + \sum_k w_k^2 \lambda_2)$;
end
//calculation of weighted mean values as input of fuzzy system;
for $l \leftarrow 1$ **to** 3 **do**
  $input_i \leftarrow \frac{S^{naivebayes} * \tau^{naivebayes} + S^{lvq} * \tau^{lvq}}{\tau^{naivebayes} + \tau^{lvq}}$;
  $all\_input \leftarrow put(input_i)$;
end
final_decision_1 $\leftarrow fuzzylogicsystem(all\_input)$;
final_decision_2 $\leftarrow dbnfusion(all\_input)$;

6 EXPERIMENTAL RESULTS AND ANALYSIS

we present different results obtained after training and testing with two classifiers and results of decision fusion with fuzzy logic approach and deep belief networks. Experiments were performed on phonemes of the Fongbe language that we describe in the next subsection. Programming was done with Matlab in an environment which is Intel Core i7 CPU L 640 @ 2.13GHz × 4 processor with 4GB memory.

6.1 Speech Data Structure

The used speech dataset were obtained by recording different phonemes pronounced by foreigners and natives speakers with a recorder in various environments of real life. It contains 174 speakers whose ages are between 9 and 45 years, including 53 women (children and adults) and 119 men (children and adults). It is an audio corpus of around 4 hours of pronounced phonemes which includes 4929 speech signals for all 32 phonemes. 80% of speech signals in dataset is used to construct the training data and 20% for the testing data.

6.2 Experimental Results

6.2.1 Classification Results

LVQ parameters:

- number of hidden neurons: 60
- first class and second class percentage: 0.6 and 0.4
- learning rate: 0.005
- number of epochs: 750

Normal distribution is used for Naive Bayes classification. Table 3 shows the training results and the testing recognition rate..

Table 3: Training and Testing results. Values are estimated in percentage.

Classifier	MFCC		RASTA-PLP		PLP	
	C_1	C_2	C_1	C_2	C_1	C_2
Training results						
Naive Bayes	88,66	51,53	90,43	59,17	88,2	68,25
LVQ	98,09	47,44	97,32	40,65	97,35	51,53
Testing results						
Naive Bayes	92,29	38,34	91,48	46,04	93,10	60,24
LVQ	98,78	24,95	98,58	21,70	97,97	20,89

6.2.2 Decision Fusion Results of Classifiers

We presented in Table 4 the fusion results of used methods.

Table 4: Results of decision fusion using fuzzy logic.

Fusion methods	Consonant	Vowel
Weighted mean	99,73%	54,02%
Fuzzy logic	95,54%	83,97%
Deep Belief Networks	88,84%	84,79

6.3 Performance Analysis

Several measures have been developed to deal with the classification problem (Wang and Yao., 2009). The values of True Positive (TP), True Negative (TN), False Positive and False Negative were calculated after decision fusion with the different used methods. These values are used to compute performance parameters like sensitivity (SE), specificity (SP), Likelihood Ratio Positive (LRP), Accuracy (Ac) and Precision (Pr). Three other important measures are used as evaluation metrics: F-measure, G-measure and execution time. F-mesure considers both the precision Pr and the sensitivity SE to compute the score which represents the weighted harmonic mean (precision&sensitivity). G-mean is defined by sensitivity and specificity and measures the balanced performance of a learning between the positive class and the negative class. Execution time measures the computation time of each fusion methods in the testing step.

We used the same dataset to evaluate the performance of Naive Bayes, LVQ and the decision fusion methods on consonants and vowels of Fongbe phoneme. Table 4 shows that by considering the balance of phoneme classes, decision fusion of classifiers based on fuzzy logic has achieved better performance even if the approaches based on the weighted mean and deep belief networks classify respectively consonants and vowels better than fuzzy logic. We find that fuzzy logic approach combines efficiently the decisions and gets the optimal decision but with an execution time increased by sixty percent compared to DBN. The results in Table 5 show the highest performances of Fuzzy logic approach on Accuracy, F-measure and G-measure parameters which are the chosen metrics to evaluate the performance of compared methods. The best performances obtained with fuzzy logic confirm that adding extra expert knowledge improves decision making after decision combination made by multiple classifiers.

Table 5: Performance analysis. Values in bold are emphasized for the performance comparison.

Parameters	Naive Bayes	LVQ	Using weighted mean	Using Fuzzy logic	Using Deep Belief Nets
SE	0.93	0.99	0.99	0.95	0.88
SP	0.60	0.25	0.38	0.84	0.86
LRP	2.36	1.32	1.60	5.94	6.28
LRN	0.12	0.04	0.03	0.06	0.14
Ac	0.77	0.62	**0.69**	**0.90**	**0.87**
Pr	0.70	0.57	0.62	0.86	0.88
F-measure	0.80	0.72	**0.76**	**0.90**	**0.88**
G-measure	0.75	0.50	**0.61**	**0.89**	**0.87**
Execution time (seconds)	-	-	**0.10**	**0.7**	**0.04**

7 CONCLUSIONS

In this paper, we have compared three decision-level fusion methods in a classification problem with multiple classifiers. The performance evaluation of decision fusion module has been achieved with the methods as weighted mean, deep belief networks and fuzzy logic. After classification with the classifiers namely Naive Bayes and LVQ, we combined their outputs for making an optimal decision. The results of the accuracy, F-measure and G-measure parameters achieved in Table 5, show the best performance with the proposed decision fusion using fuzzy logic which uses human reasoning. So, this paper highlights two main results which are performance comparison of three decisions fusion methods in a phoneme classification problem with multiple classifiers and the proposal of a robust Fongbe phoneme classification system which incorporates a fusion of Naive Bayes and LVQ classifiers using fuzzy logic approach. This proposal builds on the performance achieved by our fuzzy logic based approach compared to DBN based approach and especially because of the limitations of the fixed threshold value in weighted combination. The future of this work is an automatic continuous speech recognition from phonetic segmentation in Fongbe language.

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