NOVEL APPROACH FOR SPEECH RECOGNITION BY USING SELF – ORGANIZED MAPS

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ABSTRACT

The method of self-organizing maps (SOM) is a method of exploratory data analysis used for clustering and projecting multi-dimensional data into a lower-dimensional space to reveal hidden structure of the data. The Self-Organizing Feature Maps (SOFMs) [11] is a class of neural networks capable of recognizing the main features of the data they are trained on. There is extensive literature on its biological and mathematical concepts and even more on its implementation in a variety of areas including medicine, finance, chaos and data mining in general [4,2]. The aim of this research is to implement a self-organizing neural network based technique for speech recognition. The Mean-SOM performance for the feature Intensity is obtained maximum as 98.17%. The Median-SOM performance for the feature Intensity is obtained maximum as 98.54%.

KEYWORDS: *Self-organized map, Artificial Neural Networks, Feature, Mean-SOM performance, Median-SOM performance, LPCC, MFCC, Pitch, Intensity, Hits, Cycles, Iterations.*

1. INTRODUCTION

The SOMs are usually defined in metric vector spaces. In SOMs of symbol strings or other nonvectorial representations, the relative locations of the images of the strings on the SOM ought to reflect [10,8]. The self-organizing feature map (SOFM) is primarily used to map high-dimensional data into low-dimensional spaces for pattern classification applications [1]. Some well known theoretical results concerning the universal approximation property of MLP neural networks with one hidden layer have shown that for any function f from [0, 1]n to R, only the output layer weights depend on f. This result is used to propose a network architecture called the predictive Kohonen map allowing to design a new speech features extractor. The SOMs are usually defined in metric vector spaces [7].

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1.1 SOM Network Architecture

The hidden layer of an ANN is one of the most complex parts to design in an artificial neural network. This section proposes a Supervised SOM Based Architecture, which consists of Input layer, Competitive layer and Output layer.

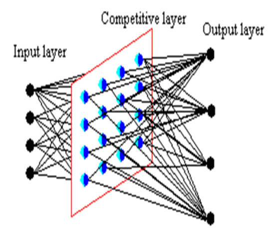


Fig.1 SOM Network Architecture

Input Layer

Accepts multidimensional input pattern from the environment. An input pattern is represented by a vector. Each neurode in the input layer represents one dimension of the input pattern. An input neurode distributes its assigned element of the input vector to the competitive layer.

Competitive layer

Each neurode in the competitive layer receives a sum of weighted inputs from the input layer. Every neurode in the competitive layer is associated with a collection of other neurodes which make up its 'neighbourhood’. We can organize Competitive layer on any dimension. Upon receipt of a given input, some of the neurodes will be sufficiently excited to fire. This event can have either an inhibitory, or an excitatory effect on its neighborhood. The model has been copied from biological systems, and is known as 'on-center, off-surround' architecture, also known as lateral feedback / inhibition.

Output layer

Organization of the output layer is application-dependent. Strictly speaking, not necessary for proper functioning of a Kohonen network. The "output" of the network is the way we choose to view the interconnections between nodes in the competitive layer. If nodes are arranged along a single dimension, output can be seen as a continuum:

A self-organizing map (newsom) consists of a competitive layer which can classify a dataset of vectors with any number of dimensions into as many classes as the layer has neurons. The neurons are arranged in a 2D topology, which allows the layer to form a representation of the distribution and a two-dimensional approximation of the topology of the dataset. The network is trained with the SOM batch algorithm.

1.2 SELF ORGANIZATION MAP

The principal goal of the SOM is to transform an incoming signal pattern of arbitrary dimension into one or two dimensional discrete map, and to perform this transformation adaptively in a topologically order fashion.

There are three essential processes involved in the formation of the SOM.

Competition: For each input pattern, the neurons in the network compute their respective values of a discriminant function. This discriminant function provides the basis for competition among the neurons. The particular neuron with the largest value of discriminant function is declared winner of the competition.

Cooperation: The winning neuron determines the spatial location of a topological neighborhood excited neurons, thereby providing the basis for cooperation among such neighborhood neurons.

Synaptic Adaptation: This last mechanism enables the excited neurons to increase their individual values of the discriminant function in relation to the input pattern through suitable adjustments applied to their synaptic weights. The adjustments made are such that the response of the winning neuron to the subsequent application of a similar input pattern is enhanced.

Self-organizing feature maps (SOFM) learn to classify input vectors according to how they are grouped in the input space. They differ from competitive layers in that neighboring neurons in the self-organizing map learn to recognize neighboring sections of the input space. Thus, self-organizing maps learn both the distribution and topology of the input vectors they are trained on.

1.3 SOM ALGORITHM

Kohonen's Self Organizing Feature Map: The self organizing feature map developed by Kohonen which groups the input data into clusters. Self-Organizing Map (SOM), with its variants, is the most popular artificial neural network algorithm in the unsupervised learning category [3]. The Kohonen learning algorithm is controlled by two learning parameters, which have to be chosen empirically because there exists neither rules nor a method for their calculation [5].

The Kohonen algorithm is

Step1. Initialization:

Set neighborhood parameter h and learning rate α.

Initialize the weight vectors: w1, w2, w3,…….,wm of m computing units are selected at a random.

Step2. Sampling: Draw sample input vector X from input space.
Step3. Matching: Find the best-matching for winning neuron winner = I(X) = minimum of dj.

Where dj is the squared Euclidean distance.

$$d_j = \sum (x_i - w_{ij})^2 \; i = 1 \; to \; m \; and \; j = 1 \; to \; n$$

Euclidean distance square: Generally Euclidean norm length of an n-tuple vector X is denoted as $\|X\|$ and $\|X\| = (X^T X)^{1/2}$

Note that the Euclidean norm can be computed by using matrix multiplication. Indeed, for an n-component vector X can be written in the form

$$\| X \| = \left([x_1 \ x_2 .... x_n] \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \right)^{1/2} \quad = \left[\sum_{i=1}^{n} x_i^2 \right]^{1/2}$$

Similarly we can write

$$\| X_i - W_{ij} \| = \left[\sum_{i=1}^{n} \| x_i - w_{ij} \|^2 \right]^{1/2}$$

Therefore square of the Euclidean norm = $\left[\sum_{i=1}^{n} \| x_i - w_{ij} \|^2 \right]$

Step4. Updating: Update the weights which are connected with the winner.

$$w_{ij}(k+1) = w_{ij}(k) + \alpha.h \, [x_i - w_{ij}(k)]$$

or, $w_{ij}(new) = w_{ij}(old) + \alpha.h \, [x_i - w_{ij}(old)]$

Where h is the neighborhood of the winning neuron I(X).
Which applied to all the neurons in the lattice that lie inside the topological neighborhood h of winning neuron i.
Change the learning rate.
Reduce the radius.

Step5. Continuation: Return to step-2 until some changes in the feature map are observed.

$$w_{ij}(k+1) = w_{ij}(k) + \alpha.h \, [x_i - w_{ij}(k)]$$

2. SYSTEM CONCEPT

2.1 Dataset

Speech dictation of the word “Jaundice” is given and spelt as “Jaundice”, “Zaundice”, “Zaundis”, “Jaundis”, Johndis”, Johndice”, “Jhondis”, “Jaandis”, “Zaundees”, Jaundees”, “Jandice”, “Jowndis” depending on the understanding capabilities (of the speakers). These words are then pronounced in a quite environment and uttered by five speakers (3Male, 2Female).

2.2 Preprocessing

The speech signals are recorded in a low noise environment with good quality recording equipment. The signals are samples at 11kHz. Reasonable results can be achieved in isolated word recognition when the input data is surrounded by silence.

2.3 Sampling Rate

150 samples are chosen with sampling rate 11kHz, which is adequate to represent all speech sounds.

2.4 Windowing

Inorder to avoid discontinuties at the end of speech segments the signal should be tapered to zero or near zero and hence reduce the mismatch. To the given 12 Mel-Frequency coefficients, and for time 0.005 seconds, a window length of 0.015 is selected by the Praat Object software tool.

2.5 Features Extraction

2.5.1 Linear Predictive Cepstral Coefficients

The goal of feature extraction is to represent speech signal by a finite number of measures of the signal. This is because the entirety of the information in the acoustic signal is too much to process, and not all of the information is relevant for specific tasks. In present Speech Recognition systems, the approach of feature extraction has generally been to find a representation that is relatively stable for different examples of the same speech sound, despite differences in the speaker or various environmental characteristics, while keeping the part that represents the message in the speech signal relatively intact.

Linear predictive coding (LPC) is a tool used mostly in audio signal processing and speech processing for representing the spectral envelope of a digital signal of speech in compressed form, using the information of a linear predictive mode. It is one of the most powerful speech analysis techniques, and one of the most useful methods for encoding good quality speech at a low bit rate and provides extremely accurate estimates of speech parameters.

LPC analyzes the speech signal by estimating the formats, removing their effects from the speech signal, and estimating the Intensity and frequency of the remaining buzz. The process of removing the formants is called inverse filtering, and the remaining signal after the subtraction of the filtered modeled signal is called the reside.

The number which describe the Intensity and frequency of the buzz, the formants, and the reside signal, can be stored or transmitted somewhere else. LPC synthesizes the speech signal by reversing the process: use the buzz parameters and the residue to create a source signal. Use the formants to create a filter (which represents the tube), and run the sources through the filter, resulting in speech.

Because speech signals vary with time, this process is done on short chunks of the speech signal, which are called frames; generally 30 to 50 frames per second give intelligible speech with good compression.

LPC is frequently used for transmitting spectral envelope information, and as such it has to be tolerant of transmission errors. Transmission of the filter coefficients directly is undesirable, since they are very sensitive to errors. In other words, a very small error can distort the whole spectrum, or worse, a small error might make the prediction filter unstable.

LPC is generally used for speech analysis and resynthesis. It is used as a form of voice compression by phone companies, for example in the GSM standard. It is also used for secure wireless, where voice must be digitized, encrypted and sent over a narrow voice channel.

In the LPC analysis one tries to predict x_n on the basis of the p previous samples,

$$x_n^{'} = \sum a_k \, x_{n-k}$$

then $\{a_1, a_2, ..., a_p\}$ can be chosen to minimize the prediction power Q_p where

$$Q_p = E\left[\; \left| x_n - x_n^{'} \right|^2 \; \right]$$

Linear Predictive Coding is used to extract the LPCC coefficients from the speech tokens. The LPCC coefficients are then converted to cepstral coefficients. The cepstral coefficients are normalized in between 1 and -1. The speech is blocked into overlapping frames of 20ms every 10ms using Hamming window. LPCC was implemented using the autocorrelation method. A drawback of LPCC estimates is their high sensitivity to quantization noise. Convert LPCC coefficients into cepstral coefficients where the cepstral order is the LPCC order and to decrease the sensitivity of high and low-order cepstral coefficients to noise, the obtained cepstral coefficients are then weighted. 16 Linear Predictive Cepstral Coefficients are considered for windowing. Linear Predictive Coding analysis of speech is based on human perception experiments. Sample the signal with 11 kHz. Frames are obtained for each utterance of the speaker form Linear Predicitve Cepstral Coefficients.

2.5.2 Mel-Frequency Cepstral Coefficients

Feature extraction consists of computing representations of the speech signal that are robust to acoustic variation but sensitive to linguistic content. The Mel-filter is used to find band filtering in the frequency domain with a bank of filters. The filter functions used are triangular in shape on a curvear frequency scale. The filter function depends on three parameters: the lower frequency, the central frequency and higher frequency. On a Mel scale the distances between the lower and the central frequencies and that of the higher and the central frequencies are equal. The filter functions are

$$H(f)=0 \ \ for\ f \le f_l \ \ and\ \ f \ge f_h$$

$$H(f)=(f-f_l)/(f_c-f_l) \ \ for\ f_l \le f \le f_c$$

$$H(f)=(f_h-f)/(f_h-f_c) \ \ for\ f_c \le f \le f_h$$

Mel - Frequency cepstral coefficients are found from the Discrete Cosine Transform of the Filter bank spectrum by using the formula given by Davis and Mermelstein[1980].

$$c_i=\sum_{j=1}^{N} P_j \cos(i\pi / N(j-0.5))),$$

Pj denotes the power in dB in the jth filter and N denotes number of samples.

12 Mel- Frequency coefficients are considered for windowing. Mel-Frequency analysis of speech is based on human perception experiments. Sample the signal with 11 kHz, apply the sample speech data to the mel-filter and the filtered signal is trained. Frames are obtained for each utterance of the speaker form Mel-Frequency Cepstral Coefficients.

2.5.3 PITCH

Pitch, in speech, the relative highness or lowness of a tone as perceived by the ear, which depends on the number of vibrations per second produced by the vocal cords. Pitch is the main acoustic correlate of tone and intonation.

Pitch is the property of voice and is determined by the rate of vibration of the vocal cords. The greater the number of vibrations per second, the higher the Pitch. The rate of vibration, in turn, is determined by the length and thickness of the vocal cords and by the tightening or relaxation of these cords.

The voice control is dependent largely upon emotional control. When human get excited or frightened, unconsciously the muscles around your voice box or larynx are tightened. The resulting tension in the vocal cords, according to the science of sound, produces a greater frequency of vibration and consequently a higher Pitch. It is an indication of lack of mental poise if you habitually speak in a voice Pitched too high. Frames are obtained for each utterance of the speaker form Intensity.

2.5.4 INTENSITY

Vocal Intensity, the major vocal attribute, depends primarily on the amplitude of vocal cord vibrations and thus on the pressure of the subglottic airstream. The greater the expiratory effort, the greater the vocal volume. Another component of vocal Intensity is the radiating efficiency of the sound generator and its superimposed resonator. The larynx has been compared to the physical shape of a horn. The Intensity (or energy flow) of a sound wave is the power (in energy/sec) transmitted through an area of $1m^2$ oriented perpendicular to (normal to) the propagation direction of the wave. Almost everyone knows that if they move away from a constant sound source, they perceive a decrease in loudness. Consider the following example:

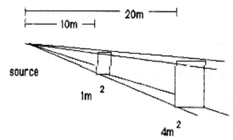


Fig2 Decrease in loudness over distance

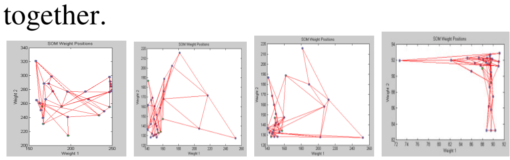
Assume that a sound from a source propagates through $1m^2$ of air at 10m from the source. Looking at the diagram we can see that the power that is concentrated over $1m^2$ at 10m from the source, is spread over a larger area at the distance of 20m. The same amount of energy is spread over a larger area, so the Intensity has decreased. Specifically, the area at 20m is $4m^2$ which is 4 times the area at 10m ($1m^2$), making the energy at 20m 1/4 the Intensity that it was at 10m. That is:

$$I = \frac{1}{\gamma^2}$$

where r is the distance from the source.
The sensation of loudness is determined by the Intensity. The greater the Intensity the greater is the perceived loudness. It is usual to symbolise Intensity as I expressed in watt/m^2.

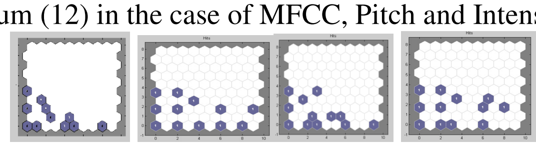
3 COMPUTER SIMULATIONS

The self-organizing maps are drawn for features LPCC, MFCC, Pitch and Intensity respectively and the same are shown in Fig.3. It is found that each map is found with different cycle patterns. The weight vectors, shown with the circles, are almost randomly placed. From the Fig.3, it is found that, even after presentation cycles, neighboring neurons, connected by lines, have weight vectors close together.

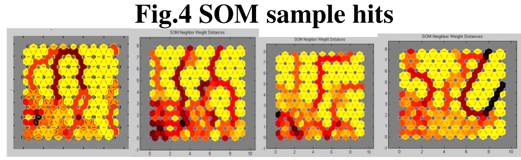


LPCC MFCC Pitch Intensity
Fig.3 Self-Organized Maps

The association of the training data with each of the neurons(cluster centers) for the features LPCC, MFCC, Pitch and Intensity are presented in the Fig.4. The topology is a 10X10 grid with 100 neurons. The maximum number of hits associated with any neuron is 1. It is found that the number of hits is maximum (12) in the case of MFCC, Pitch and Intensity features.

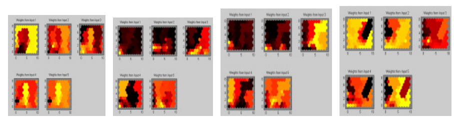


LPCC MFCC Pitch Intensity
Fig.4 SOM sample hits



LPCC MFCC Pitch Intensity
Fig.5 SOM neighbor weight distances

The weight planes for each speaker of the input vector is found against features LPCC, MFCC, Pitch and Intensity. The inputs are assumed to be highly correlated when the connection patterns of inputs were very similar.



LPCC MFCC Pitch Intensity

Fig.6 SOM weight planes

In a bubble chart the data are displayed as a collection of bubbles, each linking the value of the cell in a first selected column to the position of the points on the X (horizontal) axis and the value of the same cell in a second column to the position on the Y (vertical) axis. A bubble chart can highlight various kinds of relationships between data contained in different columns (different dimensions). Clusters can be visually identified as in the Fig.6 and linear or nonlinear relationships between data points can be identified.

4. PERFORMANCE

The set of records available for developing classification methods is generally divided into two disjoint subsets – a training set and a test set. The former is used for deriving the classifier, while the latter is used to measure the accuracy of the classifier. The accuracy of the classifier is determined by the percentage of the test examples that are correctly classified.

There are five speakers and four features. Each speaker is trained and tested with remaining speakers in each case of the features respectively LPCC, MFCC, Pitch and Intensity. Performances are evaluated for each speaker against each feature and presented in the table.

Table 1: Performance of speakers

Feature	LPCC		MFCC		Pitch		Intensity	
Speaker number	Performance (%)	Iteration no	Performance (%)	Iteration no	Performance (%)	Iteration no	Performance (%)	Iteration no
Speaker1	88.05	36	89.58	1	88.56	5	97.50	66
Speaker2	84.90	34	89.19	1	82.70	40	97.40	24
Speaker3	86.04	48	89.27	1	98.22	1	98.54	53
Speaker4	96.18	27	89.56	1	95.34	13	98.72	8
Speaker5	93.92	23	86.58	44	80.23	2	98.69	8

The performances of each speaker against the features LPCC, MFCC, Pitch and Intensity are depicted in the Fig.7 – 11. All speaker performances except speaker 3 are non- monotonic line graphs where as speaker 3 performance is monotonic one. The speaker 1 performance for Intensity is 90.30% times that of LPCC, 91.87% of MFCC and 90.83% of Pitch. The speaker 2 performance for Intensity is 87.16% times that of LPCC, 91.57% of MFCC and 84.90% of Pitch. The speaker 3 performance for Intensity is 87.31% times that of LPCC, 90.59% of MFCC and 99.67% of Pitch. The speaker 4 performance for Intensity is 97.42% times that of LPCC, 90.72% of MFCC and 96.57% of Pitch. The speaker 5 performance for Intensity is 95.16% times that of LPCC, 87.72% of MFCC and 81.29% of Pitch.

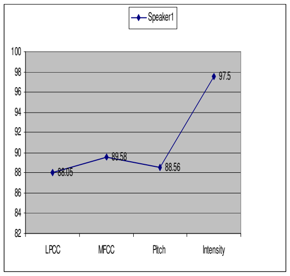


Fig.7 Line graph for speaker1 performance

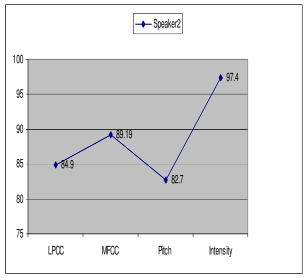


Fig.8 Line graph for speaker2 performance

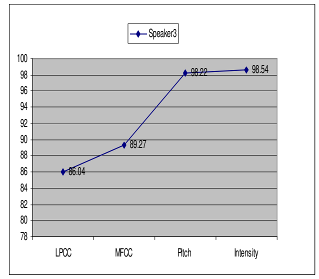


Fig.9 Line graph for speaker3 performance

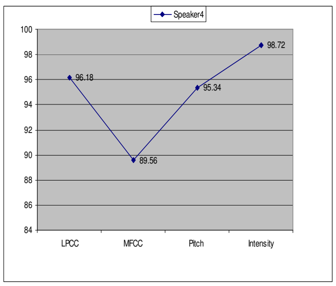


Fig.10 Line graph for speaker4 performance

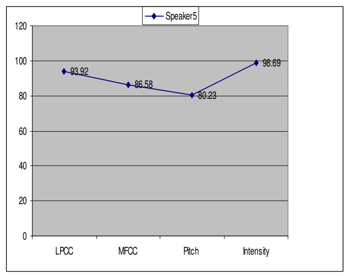


Fig.11 Line graph for speaker5 performance

The mean SOM performance and median SOM performance for each feature is estimated and presented in table.

Table 2: Mean and Median SOM performance

Feature	Mean- SOM Performance	Median-SOM Performance
LPCC	89.81	88.05
MFCC	88.83	89.27
Pitch	89.01	88.56
Intensity	98.17	98.54

The Mean SOM performance is compared with Median SOM performance in Fig.12. The Mean SOM performance is decreasing from LPCC to MFCC and increasing from MFCC to Intensity. The Median SOM performance is increasing from LPCC to MFCC and decreasing from MFCC to Pitch and then increasing from Pitch to Intensity. Both Mean and Median SOM performances are steadily increasing from Pitch to Intensity.

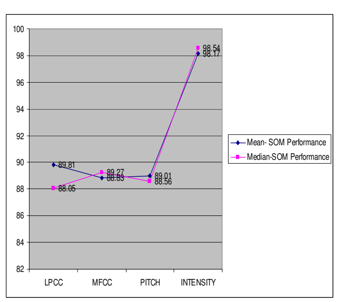


Fig.12 Mean SOM performance Vs Median SOM performances

The Mean-SOM Performance is a increasing when the speech feature changes from LPCC to MFCC and performance decreases from MFCC to Pitch and the performance rapidly increasing from Pitch to Intensity. The Median – SOM Performance is decreasing from the speech feature LPCC to MFCC and slowly increasing from MFCC to Pitch and rapidly increasing from Pitch to Intensity.

It is found that difference of two central tendency SOM – Performances is least for the Intensity feature.

Analysis of Convergence

The speech data is trained and tested to find out the analysis of convergence of Kohenen's learning algorithms. The SOM performance of Speakers for feature Intensity is convergent within iteration numbers 66, 24, 53, 8 and 8 respectively. The convergence is decreasing from Speaker 1 to Speaker 5.

CONCLUSION

It is found that SOM classifier is apt for the dataset that is chosen to find each speaker performance. In terns of type of classification used, syllable classification has the better performance, having the highest recognition accuracy. This is because scope of vocabulary size becomes smaller when syllable is used as classification unit. In this paper a new approach based on Self-organized maps which is applied to speech recognition is presented. MFCC, LPCC, Pitch and Intensity are taken as cepstral features, these features taken for each speaker for the corresponding 12 words. The obtained frames are trained and tested for SOM. Promising results are obtained. The performance of each speaker varies significantly within the number of iterations. It has shown that SOM classifier has a good rate in both training and testing. It is found that for the speech feature Intensity, SOM speaker performance is best for speakers 1-5 as 99.97%, 99.99%, 99.96%, 99.97% and 99.69%. It is found that Speaker 2 has attained maximum SOM Performance.

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