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Speaker Verification System Based On Cartesian Genetic Programming (CGP) and Cartesian Genetic Programming Evolved ANN (CGP-E-ANN)

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***Abstract*—** Speaker Recognition is the work out obligation of authorizing a user's demanded identity using physiognomies removed from their voices. This skill is one of the supreme valuable and standard biometric recognition practices in the world chiefly linked to zones in which security is a foremost concern. It can be used for confirmation, investigation, surveillance, reconnaissance, authentication, forensic speaker recognition and a numeral of associated accomplishments. Speaker recognition can be categorized into identification and verification. Speaker identification is the technique of influencing which registered speaker delivers an assumed utterance. Speaker verification, in contrast, is the technique of accepting or discarding the identity claim of a speaker. The progression of Speaker recognition involves of two segments i.e. feature extraction and feature classifying. Feature extraction is the method in which we extract a minor expanse of data from the voice signal that can be used in future to indicate each speaker. Feature classifying is the procedure of familiarize the system with features. Our proposed work consists of feature extraction from the voices of speakers through Mel frequency Cepstral Coefficients (MFCC) and classifying them by Cartesian Genetic Programing (CGP) to get an efficient logic gates circuit and by Cartesian Genetic Programing Evolved Artificial Neural Network (CGP-E-ANN) to develop an efficient and novel system for speaker verification.

***Keywords*—** MFCC, CGP, CGP-E-ANN, Speaker verification.

I. INTRODUCTION

A. Biometric

Security is increasingly an important topic in current concerns whether in reference to the security of information, including the wider privacy implications, the security of national borders, particularly from the threat of terrorists, or security within those borders.

With this focus on security has come a wider interest in the area of biometrics, particularly for the purpose of person authentication. A biometric context is an illustration of recognition system, which brands a distinct recognizable proof by finding the credibility of a specific physiological or social qualities précised by the client. It involves techniques for extraordinarily perceiving people dependent on at least one characteristic physical or social qualities. Biometrics is utilized as a type of character get to the board and access control. It is additionally used to recognize people in bunches that are under observation.

Biometric appearances can be alienated into 2 chief modules:-

1) Physiological

It is related to the figure of the body. Instances comprise

a) Fingerprint recognition
b) Face recognition
c) D.N.A
d) Palm print
e) Hand geometry
f) Iris recognition

2) Behavioral

It is linked to behavior of the creature, Instances comprise

a) Rhythm
b) Gait
c) Voice

Carefully, voice is likewise a physiological quality on the grounds that each individual has an alternate vocal tract, however voice (speaker) recognition is chiefly founded on the investigation of the manner in which an individual talks, usually delegated conduct. Among the above mentioned, the most prominent biometric framework is the speaker (voice) acknowledgment framework in light of its simple usage and affordable equipment.

B. *The Voice Biometric*

Using the voice as a biometric which is more commonly known in the literature as speaker recognition has some desirable characteristics. Speaker recognition is a non-invasive and convenient technology that is relatively accurate as a biometric. It has the potential to be applied to a number of person authentication applications, particularly when there is a physical parting between the claimant and the biometric system[1]. Suitable applications in the security as surveillance domain include suspect identification by voice, combating terrorism by using the voice to locate and track terrorists, exposure of a speaker's existence at a remote site and explanation and indexing of speakers in acoustic data. Wired and wireless telecommunications are media of particular relevance for these applications. In the private sector, most applications can be categorized as over the phone person authentication tasks including phone banking, credit card transaction verification and other forms of customer authentication.

The convenience of interacting with businesses via the telephone has led to a massive increase in the range of services offered in this medium as well as the increased use of speech technology for providing these services. The consequential demand to verify the distinctiveness of the being on the other end of the phone line has presented a security challenge ripe for speaker recognition technology. These applications support the importance of developing and introducing the technology of automatic speaker recognition.

II. Speaker Recognition

Speaker recognition means at diagnosing the expression spoken in discourse of speaker, the intention of instinctive speaker recognition systems excerpt, illustrate and recognize the info in the speech signal assigning by speaker [4].

Through prior information of the expression to be vocalized, text-dependent recognition extracts additional information in the form of linguistic content from the spoken utterance. For instance a text-dependent scheme might require a user to recite a particular phrase to perform verification. In contrast, text-independent recognizers have no prior knowledge or requirement of this sort, typically using conversational or spontaneous speech for recognition.

Although text-dependent recognition to date delivers better performance, text-independent recognition is a more attractive technology in terms of its broad scope of possible applications. Due to the unobtrusive nature of text-independent recognition, it can be incorporated into many applications without imposing any additional requirements on a user.

For instance, the authentication of telephone transactions can be performed as a background operation while the details of the transaction are determined.

In addition, many developments in text-independent coordination can be incorporated into text-dependent systems.

Extracting and modelling the information required to characterize a speaker is a complex problem for a number of reasons. Firstly, the raw speech signal must be reduced to a customary of features that provide the required speaker info. However, the speech signal itself is the product of several factors such as the linguistic and semantic content of the signal, the emotional state and health of the speaker as well as their physical characteristics.

Speech is therefore a biometric consisting of both physiological and behavioral aspects. It is possible to use all of these factors to aid in the recognition task but most serve to obfuscate the issue if they are not modelled appropriately.

Another complexity is introduced by the conditions under which a speech sample is obtained. Unlike some further biometrics for example fingerprint analysis, speaker recognition systems typically have very limited control on the equipment used to gather samples due to the physical separation of the claimant and the system for most applications. Due to their ubiquity and familiarity for users, telephones and telephone networks are a natural choice of sampling device for many applications.

The use of telephone equipment incurs a substantial amount of environmental noise and an almost infinite variety of telephone handsets and transmission.

A. *Modes of Speaker Recognition*

The broad zone of speaker recognition shelters two additional major tasks.

- Speaker Verification
- Speaker Identification

1) *Speaker Verification*

In a speaker verification system, the client will initially give his distinctiveness to the client and subsequently the system will examine if this character is accurate by breaking down the speaker voice. For instance, on account of an ATM, the client will embed his Visa in the ATM. This Master card comprises the personality of the client.

In the event that the ATM encloses an ASR module, the ATM can check the card existence utilized by its proprietor or by an impostor by requesting that the client input specific speech. For this situation, the reader needs to see meanwhile the client will give his individuality to the system, just a yes/no choice obligation be finished.

The Auto Speaker Recognition just needs to contrast the voice contribution and the model connected to the character gave by the client. This implies the Auto Speaker Recognition will play out a solitary examination and afterward a solitary evaluation and then a sole decision centered on the result of that association.

Then again, in a speaker identification system, the client won't give his uniqueness to the system. Rather, the client will enter his speech and the system will indicate which speaker model improved competitions the speech contribution. For this situation, the system needs to execute N examinations, being N the quantity of speakers in the system catalogue. Every correlation will create a probability score so the system will choice the identity connected to the in all likelihood speaker model. This implies the sort of choice will be "Speaker I" with i=1...N.

Un mistakably the speaker identification issue is more unpredictable than speaker verification and in this way, the outcomes accomplished in speaker identification systems will be fewer fortunate than in speaker verification.

2) Speaker Identification

This is the chore of describing which one is speaking from a set of identified speakers. So the system necessity execute a 1: N sorting to recognize the speaker. Usually it is thought the strange voice which must be originate a static set of voices of acknowledged speakers, thus the duty execute by this system is often stated to as closed-set identification of speaker [7].

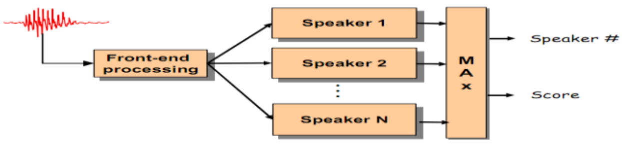


Figure 1. Block Diagram of Speaker Identification

The elementary structure of Speaker Identification system is revealed in Fig.1 We advertise that the main machineries in Identification system are the identical as in Speaker Verification System. In System Identification System, the models having M speakers are recorded in matching and the closely resemble one is described.

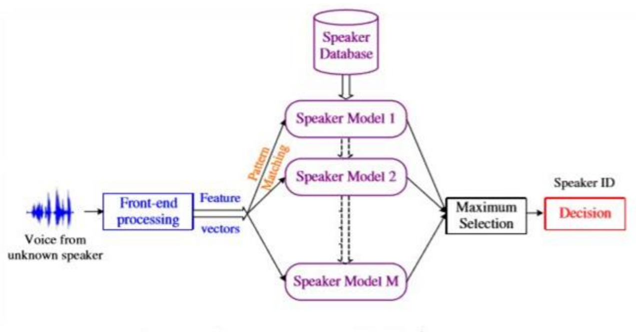


Figure 2. Simple Structure Of Speaker Identification

B. Components of Speaker Verification System

Three core mechanism exposed in this structure are: Front-end Processing, Speaker Modeling, and Pattern Matching. Front-end treating is used to climax the pertinent features and eliminate the immaterial ones.

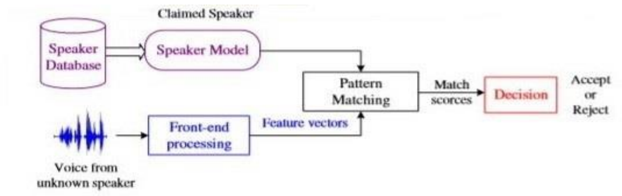


Figure 3. Basic Arrangement of Speaker Verification

In the event that the match is over a specific edge, the personality guarantee is confirmed. Utilizing a high limit, framework gets high well-being and counteracts impostors to be reputed, yet in the mean while it likewise goes for broke of dismissing the real individual, and vice versa.

Speaker Verification: the speaker exhibits a personality guarantee alongside the stream. The case is one of the preparation of the speakers definitely identified by the framework. The framework is required to confirm this case by a yes/no answer [10].

C. Evaluation of Speaker Verification

Evaluating the effectiveness of a verification system is essential for both using and researching the technology.

There are two requirements for evaluating and comparing the performance of a verification system. Firstly, a testing protocol must be in place with a well-defined set of verification trials. Secondly, methods for quantifying the performance are required based on the verification trials prescribed by the verification protocol. The protocols and supporting corpora as well as the performance measures used for their evaluation in this hypothesis are explained.

D. Phases of Speaker Recognition System

Speaker recognition systems encompass two stages namely, training and testing. Training is the procedure of acquainting the system with the voice features of the speakers registering to the system, while testing is the genuine recognition task [2].

III. PROPOSED MODEL

This section briefly describes the procedure that we have used in completing this project features extraction from voices of speakers followed by training and testing. This methodology has three main steps:

- Searching a Database from internet
- Extracting feature from the voices of the speakers using recent and most powerful feature extraction technique
- Classifying features through Cartesian Genetic Programming (CGP) and Cartesian Genetic Programming Evolved Artificial Neural Network (CGP-E-ANN) Classifier

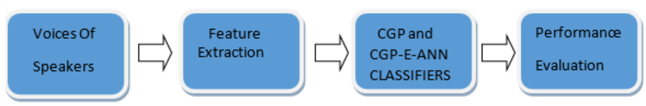


Figure 4. Block Diagram of Methodology

A. Feature Extraction

For speaker recognition, as for any classification task, extraction is necessary to extract the information required to conclude a speaker's individuality from the raw speech signal. Desirable characteristics for the extracted features are maximizing the inter-speaker variability while minimizing the intra-speaker variations and to represent the relevant information in a compact form [2]. An ideal set of features would make the modelling and classification of speakers a trivial task; it would seem however that this is an unrealizable goal and a mixture of sophisticated feature extraction and modelling methods is required for acceptable performance

B. Feature Extraction Technique Mel Frequency Cepstrum Coefficient (MFCC)

Following are the most powerful procedure which is recycled for feature extraction from voice.

The incentive behind this feature extraction technique is to variation over the speech waveform to some generous of parametric portrayal for further investigation and preparing. The speech signal is termed quasi-stationary in light of the fact that it is a gradually coordinated fluctuating sign. At the juncture when we examined over a sufficiently transitory time casing (Between 10 and 50 ms), its attributes are genuinely stationary. In any case, over significant stretches of time (1/4 seconds or additional) the signal distinguishing alteration to mirror the diverse discourse sounds being pronounced [24]. The MFCC have the following steps.

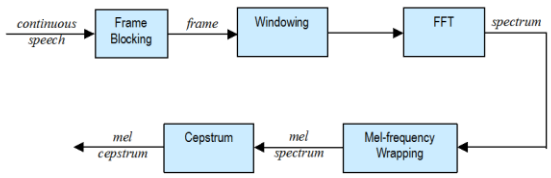


Figure 5. Block Diagram of MFCC

After collecting the features the two classiefiers CGP and CGPANN is used.

C. Cartesian Genetic Programming

Cartesian Genetic Programming (CGP) is an Evolutionary Programming Algorithm established by Miller and Thomson [18]. It is named 'Cartesian' because it consists of two-dimensional graphs of nodes. In CGP, programs are signified in the form of focused acyclic graphs. These graphs are denoted as a two-dimensional lattice of nodes which are made of genes.

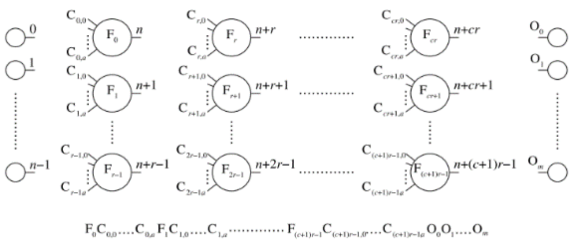


Figure 6. Cartesian Genetic Programming

CGP has three constraints that are selected by the consumer while designing CGP classifier. These are the numeral of columns, the numeral of rows and levels-back. They are indicated by nc, nr and l, respectively. The products of the first two constraints show the supreme number of calculated nodes. Ln = nc×nr. The parameter l grips the attachment of the graph encrypted.

When we choose the numeral of columns small and the numeral of rows immense resultant graph of genotype is tall and thin and when we choose the quantity of columns immense and the quantity of rows minor resultant graph of genotype is short, wide graphs.

1) Mutation

Initially we design a set of genotype and then we pass the data from it and checking it that what percentage of speaker they identify and select best one from them [25]. Then we progress the best genotypes from one generation to the resultant the $1 + \lambda$ (also $\lambda = 4$) through evolutionary approach [26]. In this tactic the parental genotype is unaffected and 4 or 9 offspring are created by mutating the parental genotype by calling mutation function.

To produce offspring the mutation operative applied in CGP which is a fact mutation operator, an allele which is arbitrarily selected gene location is altered to a different legal arbitrary value.

Also, an effective worth for a program output gene is the address of the output of any node in the genotype or the address of a program input. How numerous of genes in genotype are mutated are usually determined by mutation rate. The mutation rate, is denoted by μr. The value of μr is generally taken 5% or 10% [27].

D. Cartesian Genetic Programming Evolved Artificial Neural Network (CGPANN)

CGPANN is centered on Cartesian genetic programming [18]. In CGPANN (Cartesian genetic programming ANN) we exchange the nodes of the network with artificial neurons consuming non-linear initiation functions and slanted networks.

Contemplate that CGPANNs genotype which has m, numeral of nodes and numeral of input per node is a. Then node Ni genes must be F, I1, W1, I2, W2, I3, W3 • • • Ia, Wa. The genotype is denoted by G(m) = N1, N2, • • • , Nm, O1, O2, • • • , Op where the value of F be 0 or 1 presenting which initiation function is adopted (each sigmoid or hyperbolic tangent) and Ii indicates the input to the node.

The CGPEANN network is coupled in feed forward collier. In this miner each node can be linked to whichever a program input or a node in a column prior the column holding the existing node.

Wi shows the bulk related to Ii which is an actual-valued number in the limit of -1 to +1 and Oi signify which neurons convey the network productions. Single node (neuron) with input per node is a = 3 is showed in Figure (7).

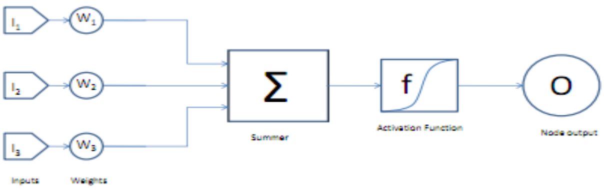
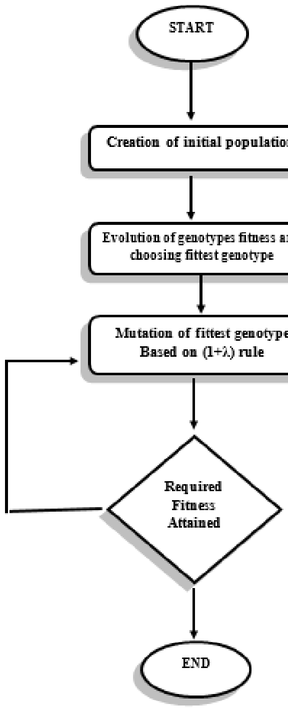
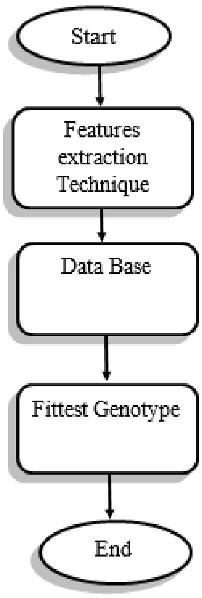


Figure 7. Node of CGPANN

1) Block Diagram of Training CGP-E-ANN



2) Block Diagram of Testing CGP-E-ANN



IV. Results and Analysis

This chapter gives overview of the experimental setups and parameters and also shows the results obtain by changing the network size of CGP and CGPE-ANN classifiers. Size of CGP and CGP-E-ANN classifiers can be diverted by fluctuating following parameters.

Statistics of nodes in network

Statistics of input per node

Statistics of program input

Statistics of output network

First we take voice data base of four speakers and take set of 100 different voice of speaker one and set of 100 voices of speaker 2, 3, 4 and extract features from these voices through MFCC and train the CGP and CGP-E-ANN classifiers to verify speaker one voice in set up 200 voices of four speakers. Then we take another set of 100 different voices of speaker one and set of 100 voices of speaker 2, 3, 4 and test CGP and CGP-E-ANN classifiers the results obtained by performing trials are given below in table no.1.

Table 1. Efficiency Compression of CGP and CGP-E-ANN classifier

SNo	No Of Nodes in Genotype	No Of Program Input	CGP		CGP-E-ANN	
			Training Efficiency	Testing Efficiency	Training Efficiency	Testing Efficiency
1	15	13	53%	53%	67.5 %	67.5 %
2	20	13	55%	54%	71%	71%
3	26	13	54%	53%	72%	72%
4	40	13	53.5%	53.5%	67.5 %	67.5 %
5	50	13	51.5%	50%	65%	65%
6	26	13	53%	53%	67.5 %	67.5 %

Now we take data base of 200 voices of two speakers in such a way speaker 1 against speaker 2, speaker 1 verses speaker no 3 and speaker 1 versus speaker 4 and also limited the output of genotype to only output of nodes which does not depend on program input. Train and test system for verification of speaker 1. The results obtained are given below in table no.2.

Table 2. Comparison of Speaker 1 vs. 2, 3, and 4 by using CGP and CGP-E-ANN classifiers

Verification Of Speakers	No Of Nodes Of Genotype	No Of Program Input	CGP		CGP-E-ANN	
			Training Efficiency	Testing Efficiency	Training Efficiency	Testing Efficiency
1 vs 2	26	13	68%	67%	79.5%	78.5%

1 vs 3	26	13	72%	71.5%	100%	96.5%
1 vs 4	26	13	72%	71%	97%	95%

After that we take another data base of 200 voices of two speakers in such a way speaker 2 versus 3, speaker 2 versus 4 and verify the speaker 2 by training and testing CGPANN. The results obtained are given below in table 3.

Table 3. Speaker Verification of Speaker 2 with Speaker 3 And 4

Verification Of Speakers	No Of Nodes Of Genotype	No Of Program Input	CGP		CGPP-E-ANN	
			Training Efficiency	Testing Efficiency	Training Efficiency	Testing Efficiency
2 vs 3	26	13	73%	72.5%	100%	99%
2 vs 4	26	13	69%	68%	91%	87.5%

And that we verify speaker 3 versus 4. The results obtained are given below in table.4.

Table 4. Verification of Speaker 3 with Speaker 4

Verification Of Speakers	No Of Nodes Of Genotype	No Of Program Input	CGP		CGPP-E-ANN	
			Training Efficiency	Testing Efficiency	Training Efficiency	Testing Efficiency
3 vs 4	26	13	69%	68%	99%	95.6%

The result obtained by limiting the output gene of genotype to the output of nodes is acceptable and satisfactory therefore we verify speaker 2 versus speaker 1, 3 and 4, speaker 3 versus 1, 2 and 4, and speaker 4 versus 1, 2, and 3 by this limited output CGP-E-ANN. The results obtained are given below in table 5.

Table 5. Verification of Speakers With All One Another

Verification Of Speakers With All	No Of Nodes Of Genotype	No Of Program Input	CGP		CGPP-E-ANN	
			Training Efficiency	Testing Efficiency	Training Efficiency	Testing Efficiency
Speaker 2 vs All	26	13	55%	53.5%	74.5%	74.5%
Speaker 3 vs All	26	13	71%	71%	100%	99%
Speaker 4 vs All	26	13	67%	67%	92%	88%

As it is clear from the comparission of results obtain by changing the network size of CGP and CGP-E-ANN classifiers, CGP has reduced results and accuracy while CGP-E-ANN has better results and accuracy. CGP the circuit of sytem become computationaly simplex while CGP-E-ANN will increase the accuracy of the regnition process as these have best performance in some other recongintion problem.

CONCLUSION

The speaker recognition systems already exist have not acceptable accuracy. For example technique introduced by Aaron. E. Rosenberg for speaker verification was 79% accurate by using DTW classifier, while using SVM classifier accuracy was 60-72%. Prosodic features set of speech signal was used by Sen, Nirmalya, T.K Basu, and Hemant.A. Patil and its average accuracy rate was 69%.

To improve the simplicity of circuit and reduce the number of logic gates CGP is used and CGP-E-ANN is used to advance the efficiency of a system. For feature extraction MFCC and for classification of features CGP and CGPANN is used. The results obtained using MFCC and CGP are quite good for the reduction of number of logic gates in circuit and made the circuit simple while the efficiency is not good and classifying the features through CGP-E-ANN is appreciable in the case of efficiency but the system is complex. Its efficiency is 100% in training for verification of speaker # 3 and speaker # 4 while in testing it reduced to 99%.

Similarly CGP-E-AANN the average efficiency of speaker#1 vs. speaker #2, 3 and 4 was above 95% for both training and testing by two fold network also for speaker 2 and speaker 3 vs. each speaker. The average efficiency of speaker 1, speaker 2 in all speakers is 74% which may be improve above 90% by mutating above 1 lac.

As it is clear from the above discussion that CGP provides a better simpler curcuit and poor efficiency while CGP-ANN system is quit complex but has appreciable efficincy. In CGP the circuit of sytem become computationaly simplex while CGP-E-ANN is increases the accuracy of the regnition process.

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