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Speech recognition using HMM and Soft Computing

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ABSTRACT

The region of speech acknowledgment is one of the fascinating fields with regard to speech signal handling. Accomplishing precision and strength is an extremely troublesome limitation to different natural elements. Reformist work and audits in the speech acknowledgment application have been received utilizing fuzzy HMM, as one of the procedures to improve the acknowledgment exactness. This survey paper audits the different ideas of fuzzy HMM strategy and its applications to speech signal handling territory. Since the idea of a speech signal is dubious, it doesn't handle consistency at untouched stretches. To manage this dubiousness and vulnerabilities, numerous scientists have proposed fuzzy HMM is one of the better strategy to break down the speech signals. This paper presents the writing work accessible identified with speech acknowledgment utilizing fuzzy HMM procedures.

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1. ıntroduction

Examination in programmed speech acknowledgment by machine has been led for over ten decades. With the headway of the PC innovations the counterfeit or machine insight methods are applied in the field of speech signal handling. Speech acknowledgment is one of the prevailing field in speech signal preparing. As of now, fuzzy rationale has drawn the consideration of scientists for adjusting the speech signal applications in improving the strength and correct nesses of the speech signals. Probabilistic and fuzzy HMM plan approaches are fundamentally applied in the field of speech signal handling. Use of fuzzy at the front end and at the order level are featured in this review paper.

Fuzzy rationale was presented by Zadeh in 1965 for dealing with the vulnerabilities present in the information [1]. The hypothesis of fuzzy rationale gives a numerical solidarity to catch the vulnerabilities related with human psychological cycles, like reasoning and thinking. The regular methodologies for information portrayal do not have the importance yet it very well may be expanded by fuzzy ideas. Fuzzy rationale gives a derivation morphology that empowers the estimated human thinking abilities to the information based frameworks. This paper is coordinated as follows: segment 2 examines about speech acknowledgment framework structures. Area 3 examines about Fuzzy framework plan. Area 4 presents related survey utilizing fuzzy HMM to speech extraction, include choice and at grouping level. Area 5 and 6 presents coherent and HMM thinking frameworks with the open difficulties that can be tended to by fuzzy strategy. Ultimately calculation insight versus computerized reasoning ideal models is talked about with ends.

2. system architecture of speech recognition

Generally the Speech Recognition [2] systems are mainly classified as conventional, probabilistic and fuzzy model as shown in Fig. 1

2.1. Conventional speech recognition system

Speech acknowledgment [2] is the cycle of consequently perceiving the semantic substance in an expressed expression. Fig. 2 portrays the overall speech acknowledgment block outline with different stages. It comprises of highlight extraction (definition) and sign demonstrating stage. These are the two significant periods of acknowledgment framework as demonstrated underneath.

During highlight extraction the speech signal are changed over to more discriminative and dependable type of parametric portrayal help to examine the sign. In the writing different kinds of highlight extraction strategies in writing.

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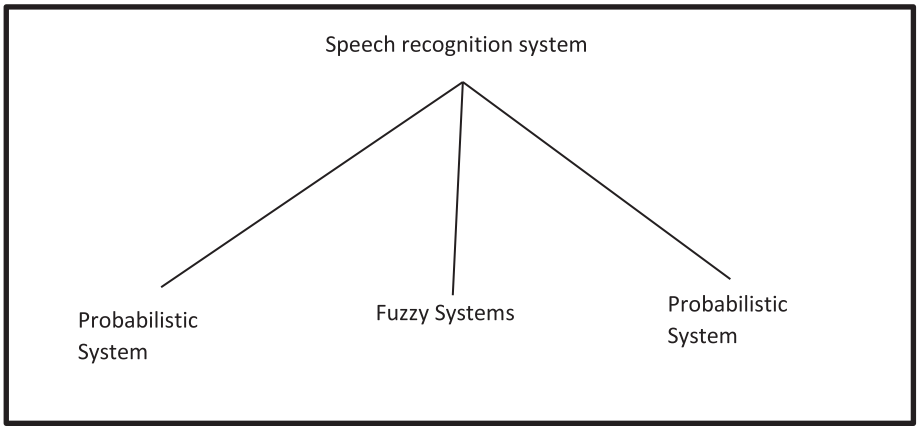

Fig. 1. Types of systems.

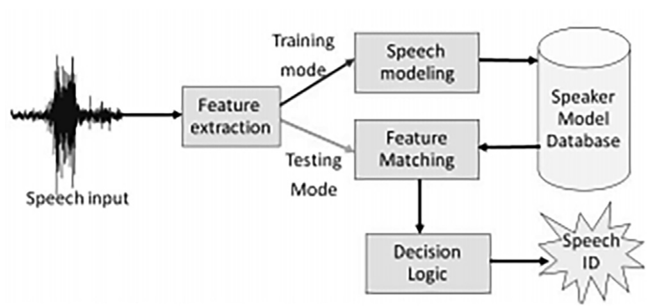

Fig. 2. Conventional Speech Recognition system.

2.2. B. Deterministic systems

A framework is supposed to be deterministic if its yields are sure. In this the connections between different parts are completely known and certain. The yield is completely unsurprising and decided with assurance for a given information which container of two sorts in particular:

i) **Non-adaptive Systems** A non-adaptive system does not react to changes in its environment.
ii) **Adaptive:** A system is said to be adaptive if it modifies itself with the changes in its environment.

2.3. C. Probabilistic systems

A framework is supposed to be probabilistic, if the yield of the framework acts probabilistically. The yield of the framework is anticipated by likelihood esteems. A probabilistic framework is one, where occasions and events can't be anticipated with exact exactness. A probabilistic framework should be investigated by the different potential results and their overall likelihood of event. In the writing two kinds of probabilistic systems [103] are examined utilizing

Well models for example Discrete Probability framework (DPS), ceaseless Probability framework (CPS) and Bayesian Probability system (BPS)

a) Bayesian Probability: It gives a numerical structure for performing surmising utilizing likelihood. It is utilized to pass judgment on the overall legitimacy of speculations in for loud, meager and unsure information.
b) Discrete probabilistic frameworks: Transition frameworks on discrete state spaces comes in various flavors like: completely probabilistic (Markov chains), named (wilt dynamic or generative names), or consolidating on-determinism and likelihood. Probabilities in DPS show up as marks on changes between states. For instance, in a Markov chain a progress starting with one state then onto the next is taken with a given likelihood.
c) Continuous probabilistic framework: These are progress frameworks displaying probabilistic conduct on persistent state spaces. The fundamental model of a Markov interaction is received in Hidden Markov models. In CPS likelihood measure is considered as a quantifiable space.

Since this paper is towards the utilization of technique of speech acknowledgment, it features and audits on fluffy ideas to the different degrees of Speech acknowledgment measure framework plan.

3. Fuzzy systems

Fuzzy frameworks are those that changes (or guide) fuzzy sets to fuzzy sets. This uses fuzzy thinking methods as a fundamental component for changing or planning. The frameworks with fresh information as well as yield are called fuzzy frameworks. The methodologies of fuzzy frameworks depend on first request rationale and traditional likelihood hypothesis. Ordinary framework doesn't give a proper calculated system to managing the portrayal of conventional information. It needs both lexically loose and non-clear cut types of information. The improvement of fuzzy rationale was spurred in enormous measure to address the issue of vulnerability and lexical imprecision [5]. Fluffy rationale regards everything as an issue of degree and Knowledge is deciphered as an assortment of versatile factors. Deduction is seen as an interaction of engendering of flexible imperatives.

3.1. A. Fuzzy speech recognition

Fuzzy speech acknowledgment model is like customary speech acknowledgment. In this, the fuzzy ideas are applied for various phases of speech acknowledgment framework for example highlight extraction and arrangement. The overall fuzzy square outline is as demonstrated in Fig. 3.

- **Feature Extraction** [10]: During feature extraction the fuzzy is applied for selecting, extracting and segmenting the features by varying the frame rate and frame length.
- **Feature selection**: The optimal and discriminative MFCC [6] features are selected by removing the noise values by applying Fuzzy Entropy concept.

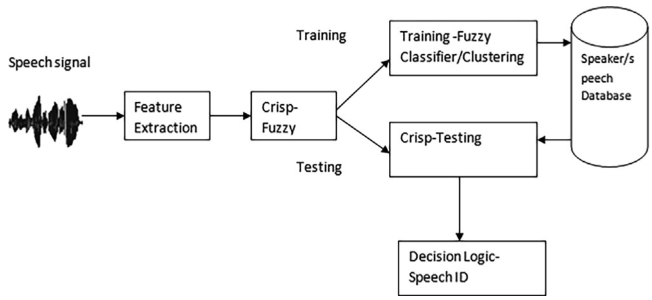

Fig. 3. Fuzzy Speech recognition.

- **Classification** [7]**:** In classification the features are classified with conventional methods by converting crisp to fuzzy values using membership functions either for the labels or for the input model training. The testing procedure same procedure is applied to identify the belongingness of the data.

3.2. B. Fuzzy system design

Fuzzy rationale framework (FLS) is planned as the nonlinear planning of an info informational collection to a scalar yield information [8,9].The execution of fuzzy frameworks continuously thinks about the contribution as fresh and converts to fuzzy to deal with the yield in fuzzy. Since the fluffy enrollment esteems are not justifiable, the data should be changed over back to Crisp. Fluffy framework can be of following sorts i) Crisp CC: Crisp info/Crisp yield ii) CF: Crisp information/Fuzzy yield iii) FC: Fuzzy info/Crisp yield iv) FF: Fuzzy information/Fuzzy yield. The fuzzification process [8,9] of FLS consists of three main parts:

i) Rules inference engine
ii) Fuzzifier
iii) Defuzzifier.

Using the above three steps the fuzzy model can be modeled as shown in the Fig. 4

4. Fuzzifier

Fuzzification: It is the initial phase in the fuzzy induction instrument. The way toward planning the fresh (mathematical) esteem into its degrees, to which the information have a place with the particular fuzzy sets. The fuzzification step takes the fresh data sources and converts it to phonetic factors by utilizing the enrollment capacities that are put away in the information base.

- Linguistic Variables: Linguistic factors are the info or the yield factors of the framework whose qualities are words or sentences from a characteristic language, rather than mathematical qualities. A phonetic variable is for the most part decayed into a bunch of etymological terms like high, medium, and low, enormous, extremely huge and so on.
- Membership Functions: Membership capacities are utilized in the fuzzification and defuzzification steps of a FLS, to plan the non-fuzzy information esteems to fuzzy etymological terms and the other way around. There are various types of fuzzy participation capacities to address a fuzzy set graphically. The overwhelmingly utilized participation work is Gaussian, Triangular and Trapezoidal that are clarified in the underneath.
  a) Triangular Membership Function.
  b) Trapezoidal Membership Function.
  c) Piecewise linear Membership Function.
  d) Gaussian Membership Function.
  e) Singleton Membership Function

Fig. 5 shows the parts of the constraints and terms used to express Fuzzy Membership Functions:

5. Literature review on speech recognition

This part examines the writing audit to the different periods of speech acknowledgment framework where the fuzzy have been applied. Presents the fuzzy at different degrees of speech acknowledgment frameworks in the writing. Table 1

6. Classifier

6.1. Fuzzy HMM

A Fuzzy way to deal with the secret Markov model (HMM) called fuzzy HMM for speech and speaker acknowledgment applications are proposed. Fuzzy has been applied to assumption augmenting calculation of HMM. The fuzzy Gaussian combination models were made to gauge the states utilizing discrete and constant HMM boundaries. The exhibition correlation over ordinary and fuzzy HMM are talked about and is proposed for HMM better acknowledgment execution.

An epic strategy utilizing constant thickness covered up Markov model (CDHMM) for speech acknowledgment dependent on the guideline of amplifying the base multi-class partition edge is introduced [21] for example huge edge HMM. It talks about huge edge HMM assessment issue definition considering compelled scaled down max enhancement issue with punished inclination drop calculation, where the first target work, i.e., least edge, is approxi-

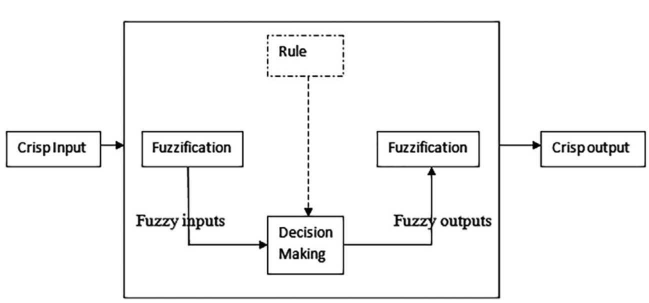

Fig. 4. Fuzzy Inference System.

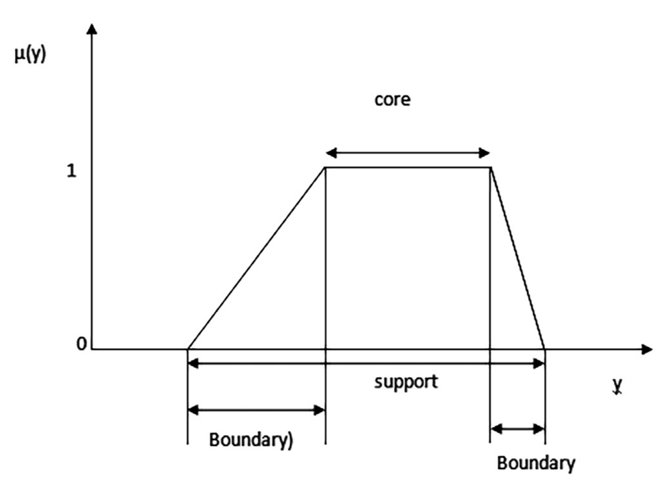

Fig. 5. Fuzzy Membership Functions.

Table 1
Literature review for application of fuzzy at various levels.

Sl. No.	Authors	Fuzzy Usage	Performance (%)	Purpose	Data set used
1.	Casacuberta, F., Vidal, E., & Benedi, J. M. (1987)	Feature selection at the lexical level	94–99	A formal representation of data by fuzzy sets	Phoneme level
2.	Beritelli, F., & Casale, S. (n.d.). (1997)	Feature Selection	0 dB to 20 dB 30 to 90 % 87 to 90 % 80 to 94 % 75 to 95 %	Fuzzy approach to the problem of voicing decision for Babble white, car, traffic noise.	Phrase Level
3.	Yin Win Chit Soe Soe Khaing 2018	Time domain feature extraction	Base method proposed	Fuzzy for time domain features	Continuous sentence
4.	Kunjithapatham Meena1 (2013)	Time domain features using triangular membership	Naïve base classifier	Fuzzy rules to determine voice of male or female	Word Level
5.	Catherine J Nereveetti (2007)	Feature selection (Gaussian membership functions)	Sugeno model is compared to mamdani model and 17.7% to 45.3% smoothness is improved by Sugeno Model.	MFCC features are Reduced by FIS rules	Word level
6.	Seyed Mostafa Mirhassani⁎, Hua-Nong Tin (2014)	Feature selection	Improvement up to 53.33% age estimation accuracy	MFCC features are filtered using fuzzy approach	Word level
7.	Ing-Jr Ding (2013)	Feature Selection	Fuzzy variable frame length	Frames are varied depending on the length of the word using fuzzy	Phoneme level
8.	Shahnawazuddin (2019)	Feature extraction	Reduced Error Rate -relative improvements is up to 17–31% over the baseline approaches	Frames are varied according to speaking-rate using fuzzy	Word Level
9.	Deividas Eringis (2004)	Feature Extraction	Improved 2.5 % recognition rate	window length and frame shift are varied	Word level
10.	Hui Ping (1999)	Feature extraction and classification	73.5% to 90.5%	Fuzzy pattern matching using FCM with LPC and MFCC features	Word Level
11.	Mohammed Algabri (2015)	Feature Extraction and Classification	2.5 % error between human classification and automatic classification	For gender classification using fuzzy rules	Word Level
12.	N Kasabov (1997)	Feature extraction and classification	68.4%	Classification using Neural network and Recognition using SOM	Phoneme level
13.	Lee (2004)	Feature selection	96 % for Speaker identification	Dimensionality reduction	Word level
14.	Yao CC., Tsai MH. (2010)	Feature Extraction	95%	An adaptive fuzzy filter for speech signal enhancement and speech recognition	Word level
15.	Sachin Lakra (2012)	Feature Extraction	87%	comparison of various soft computing techniques for filtering and enhancing speech signal	Word level
16.	M. Malcangi (2009)	Segmentation	96%	Fuzzy logic inference engine for segmentation and classification	Phoneme Level
17.	Hoseinkhani et al. (2012)	Classification	97% Accuracy for clean Speech signals	5 layer Fuzzy Neural network is developed and classified using Fire fly algorithm	Phoneme Level
18.	Fooad Jalili (2016)	Classification	96.7% accuracy for 15 dB Noisy signal	Fuzzy classification using FNN and Recognition using Ant colony optimization	Word level
19.	D. Torre Toledano (1998)	Fuzzy speech Rules for Segmentation	97%	Simulation of human segmentation and labeling of the speech	Phoneme level
20.	R. Halavati (2004)	Fuzzy rules for Recognition	85% to 98%	Fuzzy for spectrogram analysis interpretation	Phoneme level
21.	Brancalioni, Ana Rita Karine (2012)	Fuzzy rules for classifying the severity	Kappa statistics is used, with a significance level of $p < 0.05$	To classify Phonological disorder based on MICT.	Word Level
22.	Lubna Eljawad (2019)	Classification	72%	Convert wavelet features to fuzzy features	Word level
23.	Arjuwan M. (2009)	Classification	(Males) True % 80% 73.3% False True 20% False % 26.7%	energy, signal, power spectrum features are used for vowel sound classification	Word level
24.	Savchenko and Savchenko (2013)	Classification	95%	Fuzzy for phoneme classification	Phoneme level
25.	Daniar aghsanavard, et al (2016)	Classification	94% to 98% for various noise level of dB	Classification using FIS and optimization using Firefly algorithm	Word Level
26.	Yong Qian Ying (1999)	Recognition	95%	Fuzzy is better compared conventional algorithm	Word Level
27.	Paulraj, M. P et al (2010)	Classification	92.13% to 92.76%	To segment the voiced and unvoiced portions of a speech signal	Word Level
28.	Melin and Castillo (2005)	classification	96% recognition rate on over 100 words	Type-2 fuzzy rules is used for decision making	Word Level
29.	Sachin Lakra et al (2012)	Literature Survey	Various methodologies for speech recognition including Fuzzy and Neuro Fuzzy Techniques	Discuss the problems on accent, speed of pronunciation and emphasis in speech recognition	Word Level
30.	Mustaquim M.M. (2011)	Classification	Operations for playing a game	Fuzzy logic based controller to detect user's emotion from their voice command for controlling the game	Word Level
31.	Zhang, X., Wang, P., Li, G., & Hou, W.	Classification	87% to 94%	Improved algorithm of T-S fuzzy neural network.	Phoneme Level

(*continued on next page*)

Table 1 (*continued*)

Sl. No.	Authors	Fuzzy Usage	Performance (%)	Purpose	Data set used
	(2008).				
32.	Francesco Beritelli (1997)	Classification	96%	Classification using fuzzy rules	Phoneme
33.	V. Prabhu and G. Gunasekaran (2016)	Classification	96%	speech recognition of Tamil words	Phoneme Level
34.	Salam Hamdan (2016)	Classification	98% accuracy	Fuzzy inference system (FIS) to choose the optimum weight for Feed Forward neural network.	Word Level
35.	Mario Malcangi Philip Grew (2015)	Classification	95%	Multimodal evolutionary neuro-fuzzy approach	Word Level
36.	Jiping Sun (2002)	Speech recognition	81.76%	Fuzzy rules to recognize sentence	Continuous sentences
37.	Guillermo Cueva-Fernandez (2016)	Speech Recognition	95 %	Adaptive speech interface to allow users to create applications by using their voice	Word Level
38.	Horia-Nicolai L. Teodorescu (2015)	a Neuro-fuzzy segmentation voice activity detection	Survey	Discusses current applications of fuzzy logic	Word level
39.	Mingchun Liu (2004)	Classification	87%	Content-Based Audio Classification	Word level
40.	Ines Ben Fredj (2013)	Classification	98,85%, with MFCC and Fuzzy logic	MFCC features are classified using fuzzy rules	Phonemes
41.	Zhen Xing Zhang (2016)	Classification	83.5%	Emotion Detection	Word level
42.	Ing-Jr Ding and Chih-Ta Yen (2013)	Recognition	84%to 98%	Various Eigen space fuzzy models are discussed	Word level
43.	Sachin Lakra (2012)	Classification	96.55 %.	Gender detection using adaptive FIS	Word level
44.	Waardenburg, T (1989)	Classification	89.7% for narrow band 76.2% for the wideband	Fuzzy logic for classifying fricatives	Phoneme
45.	Amano (1989)	Classification	92% –96%	Neural networks for acoustic feature detection and fuzzy logic for the decision procedure.	Phoneme
46.	Mayora-Ibarra, O., & Curatelli, F. (2002).	Segmentation	95%	To identify Inter syllabic boundary placements using Fuzzy Rules	Word level
47.	Uvais Qidwai (2010)	Command Recognition	95%	The design of speech controlled wheel chair using fuzzy	Word level
48.	Laleye, F. A. A., Ezin, E. C., & Motamed, C (2017)	Segmentation	92.7% (correct detection)	Time domain features are analysed using Fuzzy	continuous speech
49.	Amane TALEB (2012)	Classification	72.43% For Noisy Data	ANFIS is improved by GA	Phoneme
50	Nona Helmi (2008)	Recognition	ANFIS-96%	Kohonen and LVQ networks are used for compaction and learning the data and neuro fuzzy system for classifying.	Word Level

mated by a differentiable capacity by considering punishment terms in the goal work. Paper presents huge edge preparing techniques yields critical decrease in mistake rate over some mainstream discriminative preparing strategies.

7. conclusion

In this review paper, we have talked about the procedure created in each phase of speech acknowledgment framework. We additionally introduced the rundown of strategy with their properties for Feature extraction. Through this audit it is discovered that MFCC is utilized generally for highlight extraction of speech and GHM and HMM is best among all demonstrating procedure.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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