# Fuzzy Speech Recognition: A Review

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## ABSTRACT
The area of speech recognition is one of the interesting field in speech signal processing. Achieving accuracy and robustness is a very difficult constraint to various environmental factors. Progressive work and reviews in the speech recognition application has been adopted using fuzzy, as one of the technique to improve the recognition accuracies. This review paper reviews the various concepts of fuzzy technique and its applications to speech signal processing area. Since the nature of speech signal is vague, it does not pocess uniformity at all time intervals. To deal with this vagueness and uncertainties, many researchers have suggested fuzzy is one of the better technique to analyze the speech signals. This paper presents the literature work available related to speech recognition using fuzzy techniques.

## Keywords
Classification, Feature Extraction, Fuzzy Database, Fuzzy logic (FL),probability, Fuzzy membership function, fuzzy modeling, Speech Recognition[SR].

## 1. INTRODUCTION
Research in automatic speech recognition by machine has been conducted for more than ten decades. With the advancement of the computer technologies the artificial or machine intelligence techniques are applied in the field of speech signal processing. Speech recognition is one of the dominant field in speech signal processing. Currently, fuzzy logic has drawn the attention of researchers for fine tuning the speech signal applications in improving the robustness and accuracies of the speech signals. Probabilistic and fuzzy formulation approaches are basically applied in the field of speech signal processing. Application of fuzzy at the front end and at the classification level are highlighted in this review paper.

Fuzzy logic was introduced by Zadeh in 1965 for handling the uncertainties present in the data [1]. The theory of fuzzy logic provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning. The conventional approaches for knowledge representation lack the meaning but it can be increased by fuzzy concepts. Fuzzy logic provides an inference morphology that enables the approximate human reasoning capabilities to the knowledge-based systems. This paper is organized as follows: section 2 discusses about speech recognition system architectures. Section 3 discusses about Fuzzy system design. Section 4 presents related review using fuzzy to speech extraction, feature selection and at classification level. Section 5 and 6 presents logical and reasoning systems with the advantages and disadvantages of fuzzy systems with the open challenges that can be addressed by fuzzy technique. Lastly computation intelligence vs. Artificial intelligence paradigms is discussed with conclusions.

## 2. SPEECH RECOGNITION SYSTEM ARCHITECTURE
Generally the Speech Recognition [2] systems are mainly classified as conventional, probabilistic and fuzzy model as shown in figure 1

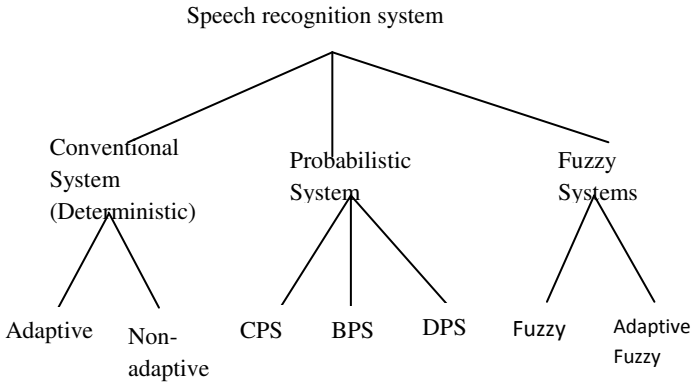


**Figure 1: Types of systems**

### 2.1 Conventional Speech Recognition System
Speech recognition [2] is the process of automatically recognizing the linguistic content in a spoken utterance. Figure 2 depicts the general speech recognition block diagram with various phases. It consists of feature extraction (parameterization) and signal modeling phase. These are the two major phases of recognition system as shown below.

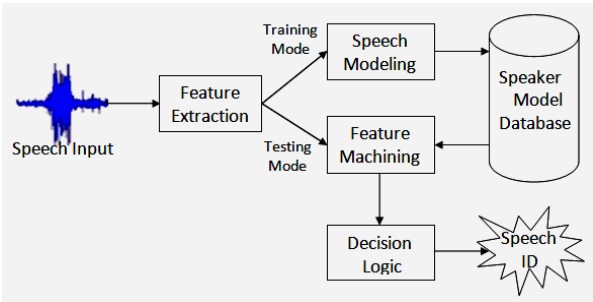


**Figure 2: Conventional Speech Recognition system**

During feature extraction the speech signal are converted to more discriminative and reliable form of parametric representation help to analyze the signal .In the literature various types of feature extraction methods in literature namely linear predictive coding(LPC), Mel-frequency cepstrum coefficients (MFCC) and *perceptual linear prediction (PLP)*. For modeling the speech signal clustering and classification techniques can be adopted to compute the recognition and error rate.

### 2.1.1 Deterministic Systems

A system is said to be deterministic if its outputs are certain. In this the relationships between various components are fully known and certain. The output is fully predictable and determined with certainty for a given input which can of two types namely:

i) **Adaptive:** A system is said to be adaptive if it modifies itself with the changes in its environment.

ii) **Non-adaptive Systems** A non-adaptive system does not react to changes in its environment.

## 2.2 Probabilistic systems

A system is said to be probabilistic, if the output of the system behaves probabilistically. The output of the system is predicted according to probability values. A probabilistic system is one, where events and occurrences cannot be predicted with precise accuracy. A probabilistic system must be analyzed according to the various possible outcomes and their relative probability of occurrence. In the literature two types of probabilistic systems[103] are discussed using HMM models i.e. Discrete Probability system (DPS), continuous Probability system (CPS) and Bayesian Probability system(BPS)

a) Bayesian Probability: It gives a mathematical framework for performing inference using probability. It is used to judge the relative validity of hypotheses in for noisy, sparse and uncertain data.

b) Discrete probabilistic systems: Transition systems on discrete state spaces comes in different flavors like: fully probabilistic (Markov chains), labeled (wither active or generative labels), or combining on-determinism and probability. Probabilities in DPS appear as labels on transitions between states. For example, in a Markov chain a transition from one state to another is taken with a given probability

c) Continuous probabilistic system: These are transition systems modeling probabilistic behavior on continuous state spaces. The basic model of a Markov process is adopted in Hidden Markov models. In CPS probability measure is considered as a measurable space.

Since this paper is towards the application of fuzzy for speech recognition, it highlights and reviews on fuzzy concepts to the various levels of Speech recognition process system design.

## 2.3 Fuzzy Systems

Fuzzy systems are those that transforms (or map) fuzzy sets to fuzzy sets. This uses fuzzy reasoning techniques as a basic feature for transforming or mapping. The systems with crisp input and/or output are called fuzzy systems. The approaches of fuzzy systems are based on first order logic and classical probability theory. Conventional system does not provide an appropriate conceptual framework for dealing with the representation of commonsense knowledge. It lacks both lexically imprecise and non categorical forms of data. The development of fuzzy logic was motivated in large measure to address the issue of uncertainty and lexical imprecision [5]. Fuzzy logic treats everything as a matter of degree and Knowledge is interpreted as a collection of elastic variables. Inference is viewed as a process of propagation of elastic constraints.

### 2.2.1 Fuzzy Speech Recognition

Fuzzy speech recognition model is similar to conventional speech recognition. In this, the fuzzy concepts are applied for different stages of speech recognition system i.e. feature extraction and classification**.** The general fuzzy block diagram is as shown in figure 3.

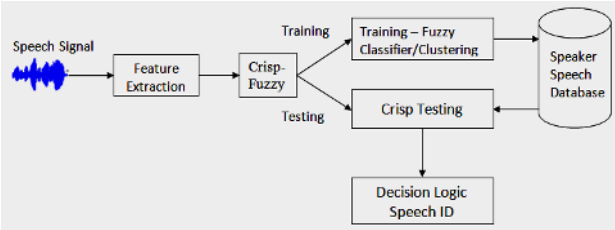


**Figure 3: Fuzzy Speech recognition**

- **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.
- **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. FUZZY SYSTEM DESIGN

Fuzzy logic system (FLS) is designed as the nonlinear mapping of an input data set to a scalar output data [8,9].The implementation of fuzzy systems in real time considers the input as crisp and converts to fuzzy to process the output in fuzzy. Since the fuzzy membership values are not understandable, the information needs to be converted back to Crisp. Fuzzy system can be of following types i)Crisp CC: Crisp input / Crisp output ii)CF: Crisp input / Fuzzy output iii)FC: Fuzzy input / Crisp output iv)FF: Fuzzy input / Fuzzy output.

The fuzzification process [8,9] of FLS consists of three main parts:

i) Fuzzifier

ii) Rules inference engine

iii) Defuzzifier.

Using the above three steps the fuzzy model can be modeled as shown in the figure 5

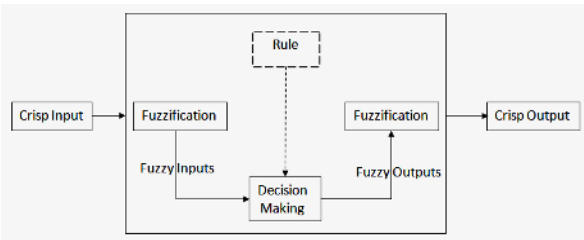


**Figure 5 Fuzzy Inference System**

## 3.1 Fuzzifier

Fuzzification: It is the first step in the fuzzy inference mechanism. The process of mapping the crisp (numerical) value into its degrees, to which the input belong to the respective fuzzy sets. The fuzzification step takes the crisp

inputs and converts it to linguistic variables by using the membership functions that are stored in the knowledge base.

- **Linguistic Variables**: Linguistic variables are the input or the output variables of the system whose values are words or sentences from a natural language, instead of numerical values. A linguistic variable is generally decomposed into a set of linguistic terms like high, medium, low, large, very large etc.
- **Membership Functions**: Membership functions are used in the fuzzification and defuzzification steps of a FLS, to map the non-fuzzy input values to fuzzy linguistic terms and vice versa. There are different forms of fuzzy membership functions to represent a fuzzy set graphically. The predominantly used membership function are Gaussian, Triangular and Trapezoidal that are explained in the below.

a) Triangular Membership Function.

b) Trapezoidal Membership Function.

c) Piecewise linear Membership Function.

d) Gaussian Membership Function.

e) Singleton Membership Function

Figure 6 shows the parts of the constraints and terms used to express Fuzzy Membership Functions:

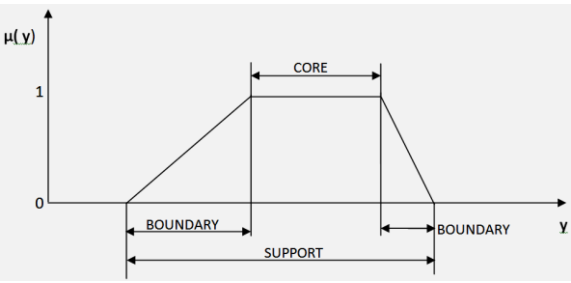


**Figure 6 Fuzzy Membership Functions**

i) Support : Z is the set of all point y ∈ Y such that μA(y) > 0

ii) Core: y ∈ Y such that μA(y) = 1

iii) Crossover (Z) = {y ∈ Y | μA(y) = 0.5}

iv) Normality (Z) =1 if μA(y) =1, for all yϵY and

v) (y, μA(y)) ∈ Z

vi) Fuzzy singleton: |=| {(y, μA(y))| μA(y) =1}|

vii) α - cut: Zα = {y ∈ Y | μA(y)≥α}

viii) Strong α - cut: Aα = {y ∈ Y | μA(y) >α}.

**a) Triangular Fuzzy Membership:** The triangular MFs are formed using straight lines and hence it is easy to use. The fuzzy membership value represents the linguistic term. It is defined by a lower limit a, an upper limit b, and a value m, where a < m < b defined as follows.

$$\mu_A(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{m-a}, & a<x\le m \\ \dfrac{b-x}{b-m}, & m<x<b \\ 0, & x\ge b \end{cases}$$

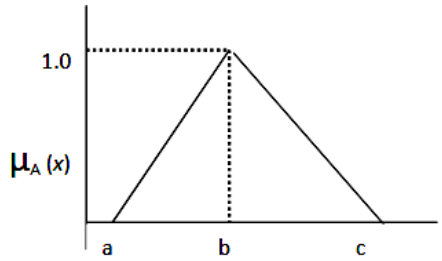


Figure 7: Triangular Membership function

Where a, b and c represent the x coordinates of the three vertices of μA (x) in a fuzzy set A. a: lower boundary c: upper boundary where membership degree is zero, b: the centre where membership degree is 1.

Where b,c > 0, otherwise 0

Triangular shapes represent fuzzy numbers as shown in figure 7. From the literature it is identified that, the triangular membership function is opted for computational efficiency.

**b) Trapezoidal function**: Trapezoid shapes represent fuzzy intervals as shown from figure 8. This function is described using the following equation:

$$\text{Trapézoïdal } (x;a,b,c,d) \begin{cases} 0 & x < a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{d-x}{d-c} & c \le x \le d \\ 0 & d \le x \end{cases}$$

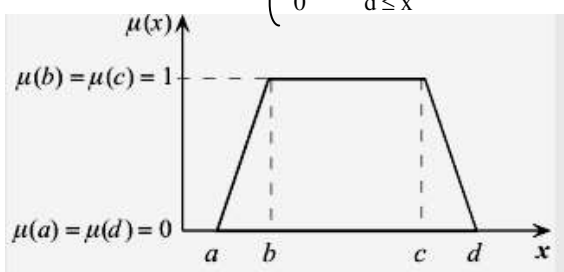


**Figure 8: Trapezoidal Membership Function**

x: represents real value (Crisp Value)

a, b, c, d represent a x- coordinates of the four heads of the trapezoidal and values should validate the following condition:

a < b < c < d

i)Real values which lies between b and c is the degree of

membership 1,ii) If the values lies between a and b, then the degree of membership increases closer to b.iii) If the values lies between c and d , then the degree of membership is gradually closer to the element of d otherwise membership degree is zero

**c)Gaussian Membership Function:** Gaussian fuzzy membership function is quite popular function applied in the fuzzy logic literature, as they are for the basis for the connection between fuzzy systems, radial basis function (RBF) and neural network . Gaussian membership function is given by:

$$\text{gaussian}(x; c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2}.$$

c: centre and width of the $i^{th}$ fuzzy set $x_i$,

σ: width of the $i^{th}$ fuzzy set $x_i$

The following advantages make its usage more

- Smoothness for handling continuous values.
- It is easy to apply since it does not include options and multiple conditions are compared to the previous functions.
- All values are non-zero.

## 3.2 Rule Inference engine

In the inference engine design, the IF–THEN rules stored in the knowledge base are used to compute the fuzzy output from the fuzzy input. In rule based fuzzy systems, the fuzzy sets and fuzzy logic are used as tools for representing different forms of knowledge about the problem and to model the interactions and relationships between its variables using membership function.

Rule Based system are characterized by i) completeness, ii) iii) consistency iii) continuity and iv) Interaction. Their rules are defined in table1 with their advantages and disadvantages.

**Table 1: Rule Based System characteristics.**

| | |
|---|---|
| Completeness | If any combination of input values result in an appropriate output value then a set of IF-THEN rules is complete |
| Consistency | If there are two rules with the same rules-antecedent but different consequent rules then, a set of IF–THEN rules is inconsistent. |
| Continuity | A set of IF–THEN rules is continuous, if it does not have neighboring rules with output fuzzy sets that have empty intersection |
| Interaction | In the interaction property, "IF x is A THEN y is B," this meaning i.e if no proper interaction between the variables then the result B is not obtained |

**Advantages of Rule Based System**

- Rules are written to represent the natural knowledge
- It has uniform structure
- Separation of Knowledge can be handled using rules
- Deals with incomplete and uncertain knowledge

**Disadvantages**

- Opaque relations between rules exists
- Ineffective search strategy

## 3.3 Defuzzification

It is the process of converting a fuzzified output into a single crisp value. The following are the methods for defuzzification

i) Center of Sums Method (COS)

ii) Center of gravity (COG) / Centroid of Area (COA) Method

iii) Center of Area / Bisector of Area Method (BOA)

iv) Weighted Average Method

v) Maxima Methods

a. First of Maxima Method (FOM)

b. Last of Maxima Method (LOM)

c. Mean of Maxima Method (MOM)

- **Center of Sums (COS) Method:** This is the most simple and common method. Defuzzification is carried out by identifying the overlapping area twice.
- **Center of gravity (COG) / Centroid of Area (COA) Method:** In this method the output depends on the center of gravity. The total represented area of the membership function is divided into sub-parts. For each area, center of gravity is calculated and total sum of all the sub parts is taken to find the output.
- **Center of Area / Bisector of Area Method (BOA):**This method identifies the partition in such a way that the area under membership is divided into two equal partitions.
- **Weighted Average method** is suitable for membership functions that are symmetrical in nature. This method is very much similar to center of area defuzzification method. In this method the output value is by its maximum membership value. The following are the various maxima methods that determine the smallest value of the domain with maximum membership value.

**Maxima methods**

**a) Last of Maxima Method (LOM):** In this method defuzzification value will be the largest value of the domain with maximum membership value.

**b) Mean of Maxima Method (MOM):** In this method the output will be the value with highest membership values. The maximum values are more than one membership function and its average is considered.

**c) First of maxima (last of maxima):** This method uses the overall output or union of all individual output fuzzy membership value is used for determining the smallest value of the domain maximized membership.

## 3.4 Fuzzy Inference Models [14]:

There are several types of FIS model. The commonly used are the Mamdani Fuzzy model and Takagi Sugeno Fuzzy model. The difference between these comes from the consequents of their fuzzy rules. The aggregation and defuzzification

procedures are different in each model for computing consequent values.

**a) Mamdani Fuzzy Model:**
This system was proposed in 1975 by Ebhasim Mamdani as shown in figure7. Basically, it was anticipated to control a steam engine and it is having more intuitive and understandable rules. Hence these are well-suited to expert system applications. The general rule for Mamdani Fuzzy Model is as follows.
Mamdani: If M is X1, and N is X2, then C is X3.

Where M and N are input variables ,

X1 ,X2 and X3 are Linguistic Variables

C is Output

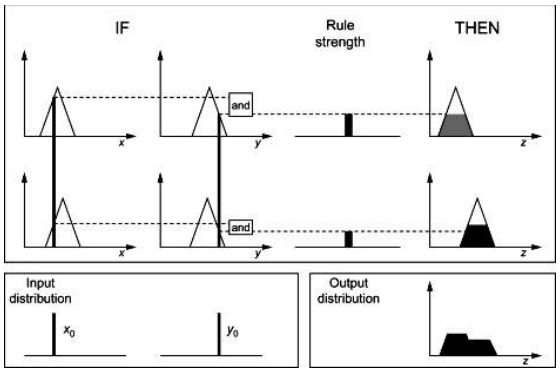


**Fig 7 Mamdani fuzzy interface system [33].**

**b) Takagi-Sugeno Model [15].**This model was presented in 1985 by Takagi and Sugeno as shown in figure 8. It is very similar to the Mamdani method except the consequent of the rule is changed. Fuzzification and defuzzification is used for the input variable instead of fuzzy set. However mathematical rules exist for the Sugeno rule than the Mamdani rule. The Sugeno controller has more adjustable parameters than the Mamdani controller. The general rule for the Sugeno fuzzy model is as follows.
If M is X1 and N is X2 then C = ax1 + bx2 + c

(linear expression)

Where M and N are input variables ,

X1 ,X2 are Linguistic Variables

C is Output

a,b and c are constants

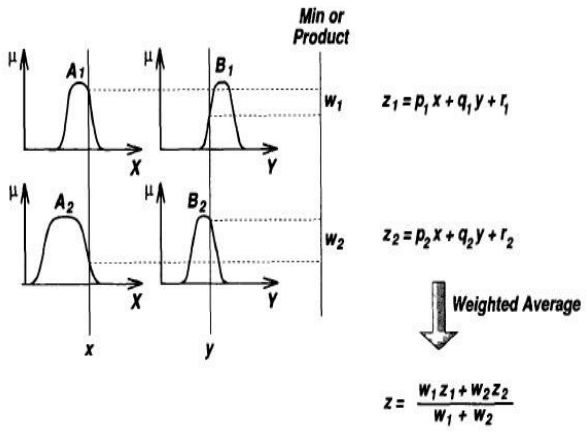


**Figure 8: 1st order Sugeno Fuzzy Model**

The general procedure used in fuzzy inference Mamdani/Takagi-Sugeno Fuzzy Inference System

Step 1: Identify the number of fuzzy rules

Step 2: Convert crisp inputs to the fuzzy outputs by using the membership function.

Step 3: The fuzzified inputs must be aggregated based on the fuzzy rules.

Step 4: Consequent is identified by joining the rule strength and the output membership function.

4 a) If the model is Sugeno, output membership functions are either linear or constant.

4 b) If model is mamdani, output membership functions is constant

Step 5: All the consequents must be combined to get the output

Step 6: output distribution is defuzzied.

# 4. RELATED LITERATURE ON FUZZY TO SPEECH RECOGNITION.

This section discusses the literature review to the various phases of speech recognition system where the fuzzy have been applied. Figure 9 presents the fuzzy at various levels of speech recognition systems in the literature.

**Table 2: 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 | 0dB to 20dB<br>30 to 90 %<br>87 to 90 %<br>80 to 94 %<br>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. | S.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, F., Parcham, E., Pournazary, M., & Borzue, N. | Classification | 97% Accuracy for clean Speech signals | 5 layer Fuzzy Neural network is developed and classified using Fire fly algorithm | Phoneme Level |

| | | | | | |
|---|---|---|---|---|---|
| | (2012) | | | | |
| 18. | Fooad Jalili(2016) | Classification | 96.7% accuracy for 15dB 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 L.V., Savchenko A.V. (2013) | Classification | 95% | Fuzzy for phoneme classification | Phoneme level |
| 25. | Daniaraghsanavard, 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, P., & Castillo, O. (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. (2008). | Classification | 87% to 94% | Improved algorithm of T-S fuzzy neural network. | Phoneme Level |
| 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 |

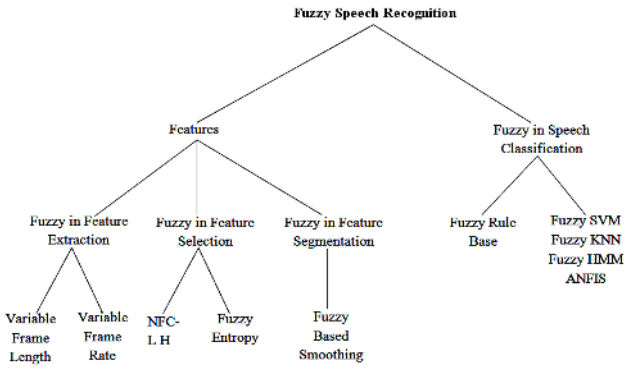


**Figure 9: Fuzzy at various phases**

## 4.1 At Front End

**Feature Extraction\Selection Level:**

The fuzzy technique is applied in the front phase i.e. within and after the Feature extraction by adopting fuzzy variable length and fuzzy entropy techniques. In the FE, the fuzzy is applied to fixed frame length [16]. Whereas Fuzzy entropy is applied to select optimal features obtained from the FE phase [17]

Fuzzy is applied in designing fuzzy logic control [16] system to select number of frames automatically over the conventional system. FLC selects frames depending on energy coefficients of the words. They identify the length of the frames to be varied from each other, which in turn depends on the length and the energy parameter present during the word utterances. Hence fuzzy is adopted to calculate variable frame length for words .In the conventional method the frame length is constant irrespective of type of the signal. FLC is used to compute variable frames. Once variable frame lengths are calculated,feature extraction process is continued as normal. Further FLC is used to calculate and validate the residual error by applying LPC residual error and PCRE index.

Fuzzy feature selection [17] process is carried out by selecting relevant, discriminative and complementary features. These features are calculated by using conflicting objective function for measuring the goodness of the selected features. The fuzzy formulation and fuzzy aggregation objectives are used to address uncertainties involved in the problem. This reduces the dimensionality without compromising for speech recognition rate.

Paper [18] discusses the fuzzy application for the identification of the speaker's age. Outputs of the classifiers are collected to measure the confidence of each decision made by the classifier. To aggregate the fuzzy sets, various combinations of operators are used. Operators like conjunctive combination, disjunctive combination, compromise combinations are used with its own unique properties. Fuzzy entropy [19] is adopted for feature selection to remove the noise present in the signal. Fuzzy Entropy is computed for all the frames and these feature values are used by the SVM classifier. Extra frames obtained during the noisy signal processing are treated as noise frames and are removed.

**b) Linguistic Hedges**

Paper [18] discusses the new approach for feature selection. The method is also applied to character recognition, disease diagnosis. The results of the reduced features helps in reducing computation time. The feature selection depends on dilation and concentration threshold. The obtained LH values are used to show the importance of fuzzy set degree. The features are filtered depending upon the closeness to the concentration. If they are close, the features are selected else dropped. According to the LHs feature values, the redundant, noisy features can be eliminated by retaining the selected significant features.

## 4.2 Clustering level

In Paper [20] Fuzzy is applied to cluster the different parameters of fatigueness such as the largest Lyapunov exponent, fractal dimension and approximate entropy for the degree of human fatigue changes. The fuzzy membership degrees are used to train speech samples to compute membership function by fuzzy SVM method.Multi-feature fusion classifier is suggested for fatigue recognition classification. HMM uses Fuzzy vector quantization [21] to generate fuzzy codebooks for various speakers that make a soft decision about which codeword (mean vector) is closest to the input vector. It generates an output vector component that indicates the relative closeness of each codeword to the input.

## 4.3 Classifier level:

**Fuzzy HMM [21-23]**

A Fuzzy approach to the hidden Markov model (HMM) called fuzzy HMM for speech and speaker recognition applications are proposed. Fuzzy has been applied to expectation maximizing algorithm of HMM. The fuzzy Gaussian mixture models were created to estimate the states using discrete and continuous HMM parameters. The performance comparison over conventional and fuzzy HMM are discussed and is proposed for HMM better recognition performance.

A novel method using continuous-density hidden Markov model (CDHMM) for speech recognition based on the principle of maximizing the minimum multi-class separation margin is presented [22] i.e. large margin HMM. It discusses large margin HMM estimation problem formulation considering constrained mini-max optimization problem with penalized gradient descent algorithm, where the original objective function, i.e., minimum margin, is approximated by a differentiable function by considering penalty terms in the objective function. Paper presents large margin training methods yields significant reduction in error rate over some popular discriminative training methods

**Fuzzy SVM** Fuzzy approach to SVM for emotion detection [24-29] is applied for the input values to calculate the membership values. The method is applied for each sample to determine the belongingness of each class. This method works with approximate reasoning rather than fixed reasoning with good classification accuracy. The radial basis kernel function (RBKF) is adapted to increase the recognition accuracy. One-Against-All concept is proposed for fuzzy output multi classification. The fuzzy memberships are encoded for labels to have fuzzy classification. The experimental results of Fuzzy SVM shows better performances compared to fuzzy MLP and fuzzy K-NN architectures.

**Fuzzy KNN [30-35]** Fuzzy is applied to KNN for speech recognition application. The theory of fuzzy sets is introduced into the AT-nearest neighbour technique to develop a fuzzy version of the algorithm. The labels are assigned using fuzzy memberships function to reduce the error rate and to improve the confidence measure of the classification. Paper [32] proposes fuzzy KNN, as an alternative to standard k-NN algorithm for Timit phoneme recognition. FkNN computes the fuzzy distances between the data phonemes, that defines the cluster fuzziness with the Mel Frequency Cepstral Coefficients (MFCC) associated with their first and second

derivative energy coefficients. It is also applied for emotion recognition [33 34] to extract and model emotion depression features by calculating weighted Euclidean distance.

**Hybrid system using Fuzzy and ANN [36, 37]**
ANFIS is designed to differentiate between various emotions for speech signals. Parameters like pitch, first and second formant frequencies, energy, speaking rate are collected to build the hybrid system with Fuzzy and ANN. ANFIS is also applied for speech recognition[37] using two Stage Fuzzy Decision Classifier (TSFDC)]. It is applied for post processing the classes that are not recognised by ANN classifier. In [37] fuzzy also applied for vowel recognition in tone language using fundamental frequency (F0), first and second formant (F1 and F2) frequencies of the phonemes. A detailed survey table 8.

# 5. LOGICAL AND REASONING SYSTEMS: [38, 39]

Fuzzy systems are designed with logical and reasoning of system that are explained as follows.

## 5.1 Logical Systems [40-43]

Logical systems are simple, very powerful, effective and efficient means to represent and handle imprecise (vague) information. Fuzzy set is a mathematical model of vague qualitative or quantitative data, frequently generated by means of the natural language. The model is based on the generalization of the classical concepts of set and its characteristic function. The following are the different types of fuzzy system. First two systems are widely used in building fuzzy models hence these two are explained in brief.

i) Type-1 fuzzy logic systems

ii) Interval type-2 fuzzy logic systems

**iii)** Generalized type-2 fuzzy logic systems

**iv)** Type-2 logic hesitant fuzzy sets

**a) Type 1 Fuzzy Logic Systems**: A type-1 fuzzy set is characterized by a membership function μA (x) within the interval [0,1].

**b) Type 2 Fuzzy:**Type-2 fuzzy sets are finding very wide applicability in rule-based fuzzy logic systems (FLSs) because they let uncertainties to be modelled which cannot be modelled by type-1 fuzzy sets. It is referred as a function approximation application of fuzzy sets because it minimizes the error function.

## 5.2 Characteristics of Fuzzy Logic systems [43]

- Flexible and easy to implement machine learning techniques.
- Helps to mimic the logic of human thought.
- It views inference as a process of propagating elastic constraints
- It allows to build nonlinear functions of arbitrary complexity.
- It should be built with the complete guidance of experts or inference systems
- They are suitable for uncertain or approximate reasoning, especially for the system with a mathematical model which is difficult to derive
- They allow decision making with estimated values under incomplete or uncertain information.

Differences in Type1 and Type2 :

**Table 3: Differences in Type1 and Type2**

| Sl . No | Type-1 fuzzy | Type-2 fuzzy |
|---|---|---|
| 1. | No interval fuzzy set is supported . | At least one membership function of interval type 2 fuzzy set is supported |
| 2. | Not supported before defuzzification. | Supports before de fuzzification. |
| 3. | Less tolerant to noise | Sustain more noise compare to Type1 fuzzy. |
| 4. | The computation cost is less. | The computation cost is more. |
| 5. | Comparatively less efficient in handling the uncertainties. | More efficient in handling the uncertainties because their member ship functions are fuzzy. |

## 5.3 Reasoning Systems

Logic seeks tangible, visible or audible proof of a sound thought process by reasoning. There are four types of reasoning: 1.Inductive 2. Deductive 3. Causal 4. Abductive

i) **Inductive Reasoning:** In this reasoning a decision is made, depending on observations. i.e. the decisions are from precise to generic. It is a type of proportional logic or bottom up reasoning which uses historical data to generate generic rule. There are two subtypes of inductive reasoning

a. Formal Inductive reasoning

b. Informal Inductive reasoning

ii) **Deductive reasoning:** Deductive reasoning begins with general or guess and it moves in the direction of conclusion depending upon the proof.

iii) **Causal Reasoning:** Casual reasoning is an active area of research in the field of artificial intelligence. It is the process of identifying causality i.e. relationship between cause and its effect.

iv) **Abductive reasoning** Abductive reasoning is used to get the best explanation from an incomplete set of preconditions.

Differences between Logical and Reasoning systems is tabulated in table 4.

**Table 4 Logical vs Reasoning Systems**

| Logical Systems | Reasoning Systems |
|---|---|
| Logic is an actual science that follows clearly defined rules and tests for critical thinking. | Reasoning is subjected to personal opinion and is designed using AI and Knowledge based system. |
| The output depends on knowledge availability and logical techniques | The output depends on cognitive activity and a formal model |
| Logical systems are designed for analyzing the concept of deduction and induction. | Reasoning system are used for analyzing and reasoning systems |
| Logical models are structures used to provide better interpretation of symbolism used in formal systems | Reasoning system is used to address things which do not fall within descriptive model. |

## 6. FUZZY SPEECH DATABASE [45-48]

A fuzzy database is as an extended version of relational database. The database consists of fuzzy attribute and fuzzy truth values represented with fuzzy sets. The fuzzy data base consists of uncertain or imprecise data. Fuzzy databases are based on fuzzy logic (FL) and fuzzy set theory (FST) with. Membership value range between the values 0 and 1.The imprecise data stored in FDB are accessed through queries using FL and FST present during the life cycle of FDB.

Example of Fuzzy data base models are Distribution-fuzzy-relational model and Generalized Fuzzy Relational Database (GEFRED)

## 7. DIFFERENCES AND SIMILARITIES [49,50]

### a. Fuzzy Logic and Probability

**Table 5: Fuzzy logic vs Probability**

| Fuzzy Logic | Probability |
|---|---|
| The values are represented in degree of membership | The values are represented in terms of percentage |
| Fuzzy logic takes truth degrees as a mathematical basis on the model of the vagueness phenomenon | Probability is a mathematical model of ignorance |
| It tries to represent the vagueness | It tries to represent the chance to occur an event |
| The meaning of partial truth is captured by Fuzzy Logic | The meaning of partial knowledge is captured by probability theory |

### b. Multi valued vs. Fuzzy Logic [51]

**Table 6: Multi valued vs. FL**

| Slno | Multi-valued | Fuzzy Logic |
|---|---|---|
| 1 | Multi Valued Logic proposed by Jan Lukasiewicz in 1920's. | Fuzzy Logic Proposed by Zadeh in 1965 |
| 2 | Multi valued Logic can have values from some set, for instance {0,1,2}, or {0,1,2,3} | Fuzzy logic allows multi-valued values between [ 0-1] |
| 3 | Multi valued Logic Supports values from fuzzy membership to a given set | Fuzzy Supports values from fuzzy membership to a given set using defuzzification. |

## 8. ADVANTAGES AND DISADVANTAGES OF FUZZY SYSTEMS[52]

**Advantages**

- The structure of Fuzzy Logic Systems is easy and understandable
- It helps us to deal with the uncertainties exists in engineering problems.
- It is robust even though no precise inputs are required
- It can be easily modified to improve the performance of the system.
- It provides a most effective solution to complex issues.

**Disadvantages**

- Setting exact fuzzy rules and membership functions is a difficult task
- Validation and Verification of a fuzzy knowledge-based system needs extensive testing process.
- In fuzzy logic, exact reasoning is viewed as a limiting case of approximate reasoning.

## 9. APPLICATION OF FUZZY IN SPEECH RECOGNITIONS SYSTEMS:[53]

- Spontaneous and emotional speech recognition
- Spontaneous speech search in dialogues
- Automatic subtitling
- Speech synthesis
- Multimodal speech synthesis
- Voice adaptation, transformation and conversion
- Speaker indexing/diarization
- Analysis and extraction of emotional and expressive features
- Speech and voice quality assessment and

categorization

- Spectral analysis
- Robust speech signal representation and coding
- Intelligent human-machine interaction
- Singing speech synthesis

## 10. EXISTING OPEN CHALLENGES ADDRESSABLE BY FUZZY TECHNIQUE FOR SPEECH APPLICATIONS:

There exists few open challenges that can be addressed by fuzzy. Few of them are mentioned below

- Noise ( background ,environmental noise, Channel variability )
- Accuracy and Fault Tolerance
- Unnatural speech pattern matching and Ambiguity
- Human Language-(speech type spontaneous or freestyle)
- Sample size and data search space

## 11. COMPUTATIONAL INTELLIGENCE VS ARTIFICIAL INTELLIGENCE[54]

Computational Intelligence is a subset of Artificial Intelligence. It is the theory, design, application and development of biologically and linguistically motivated computational paradigm. Traditionally the three main pillars of CI are Neural Networks, Fuzzy Systems and Evolutionary Computation. CI is an evolving field and at present in addition to the three main constituents, it encompasses computing paradigms like ambient intelligence, artificial life, cultural learning, artificial endocrine networks, social reasoning, and artificial hormone networks etc.

The following table presents the differences between CI and AI

**Table 7: CI vs AI**

| Sl. No | Computational Intelligence | Artificial Intelligence |
|---|---|---|
| 1 | It is a branch of Computer Science involved in studying problems for which no effective algorithms exists. | AI techniques prefer theoretical guarantees and focus on deductive reasoning with effective algorithms. |
| 2 | CI-rooted techniques handle specific problems. | AI-rooted techniques handles general problems |
| 3 | Characterized by bottom-up data i.e. from numbers to symbol | Characterized by top-down approach |
| 4 | Examples Like :<br>1. Fuzzy Logic<br>2. Neural Networks<br>Evolutionar computation<br>Learning theory | Examples Like :<br>1.Genetic Algorithms<br>2.Tabu search<br>3.Minimum description length<br>4.Heuristic Greedy Search<br>5.Constraint Satisfaction 6.Expert Syste<br>7.Formal Logics |

## 12. CONCLUSION

This paper presents the fundamental of fuzzy speech recognition system with the application of fuzzy concepts at the various levels. The detailed literature available on fuzzy for speech signal processing is discussed in detail for the various approaches like feature extraction ,feature selection, segmentation, clustering and a detailed literature survey table presents the detail insights into the fuzzy inference system design procedure that can be adopted for any classifier using fuzzy logic. Application for fuzzy speech recognition , similarities and differences of probability, fuzzy-type-1, type2 fuzzy logic, logical and reasoning systems, multi-valued and fuzzy logic, Computational and Artificial Intelligence are also discussed. It also highlights few of the existing open challenges that can be addressable using fuzzy logic. Hence this paper presents the requirements to design the complete Fuzzy system.

## 13. AACKNOWLEDGMENT

Our thanks to the experts who have contributed towards development of the template.

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