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Systematic literature review of fuzzy logic based text summarization

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Abstract

'Information Overload'is not a new term but with the massive development in technology which enables anytime, anywhere, easy and unlimited access; participation & publishing of information has consequently escalated its impact. Assisting users'informational searches with reduced reading surfing time by extracting and evaluating accurate, authentic & relevant information are the primary concerns in the present milieu. Automatic text summarization is the process of condensing an original document into shorter form to create smaller, compact version from the abundant information that is available, preserving the content & meaning such that it meets the needs of the user. Though many summarization techniques have been proposed but there are no 'silver bullets'to achieve the superlative results as of human generated summaries. Thus, the domain of text summarization is an active and dynamic field of study, practice & research with the continuous need to expound novel techniques for achieving comparable & effectual results. Fuzzy logic has appeared as a powerful theoretical framework for studying human reasoning and its application has been explored within the domain of text summarization in the past few years. This paper is a systematic literature review to gather, analyze, and report the trends, gaps and prospects of using fuzzy logic for automatic text summarization on the basis of the findings in original studies.

Keywords: Automatic text summarization, fuzzy logic, systematic literature review.

1 Introduction

According to worldwidewebsize.com, the indexed Web contains at least 4.5 billion pages (Monday, 20 March, 2017). With the massive proliferation in the velocity, volume and variety of information accessible online and the consequent need to develop viable paradigms which facilitate better techniques to access this information, there has been a strong resurgence of interest in Web Information Retrieval (Web IR) research in recent years. The ultimate challenge of Web IR research is to provide improved systems that retrieve the most relevant information available on the web to better satisfy a users information need [9, 8]. A simple keyword search on the Internet results in hundreds of result in less than a second, some of which are not even relevant to the users query and finding the pertinent information is a difficult and time consuming task.

Summarization has been identified as an effective Web IR task, which helps users to locate the right information at the right time thus facilitating timely decisions.Human summarization can be biased, context-dependent and may vary with human cognition. Thus, suitable techniques & tools are needed to extort pertinent and imperative sections such that critical information in the form of summary is acquired; providing a machine generated summary free from bias. The following real-world analogy helps us understand the meaning and need of summary: A person wants to decide his/her visit to an exhibition at a Local Art Gallery; the display list suggests the highlights of the exhibition giving an insight to what is the theme of the exhibition, though nothing really can be said about the quality of art-work presented but the visitation decision can surely be made depending on the person's interest to the summarized highlights.

Automatic Text Summarization (ATS) [35, 36] is defined as the process of creating a compact, coherent version of the original document by selecting, filtering, and extracting only relevant information and presenting it in a human-understandable manner. Applications of text summarization tools reportedly range from facilitating document selection

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& literature searches to generation of customised summaries for question-answering systems. No matter what the intent, type or context of summary generated is, the primary objective is to assist users'informational searches with reduced reading/surfing time and also improve the document indexing efficiency at the same time. Work on Automatic Text Summarization was first reported in late 1950s and there has been a continuous interest in this domain with pertinent literature reporting various studies on proposed paradigms and tools. But there are no 'silver bullets'to achieve the superlative results as of human generated summaries. Thus, the domain of text summarization is an active and dynamic field of study, practice & research with the continuous need to expound novel techniques for achieving comparable & effectual results.

Fuzzy logic has appeared as a powerful theoretical framework for studying human reasoning. It formalizes human reasoning by setting rules in natural language used to explain decisions from human reasoning [15]. It reinforces exibility for reasoning, which makes it possible to take into account inaccuracies and uncertainties. Use of fuzzy logic in WebIR has been amply investigated with valuable findings to ease the process of Information Retrieval, for example fuzzy logic has been used to extract key phrases from news articles [38] and from other web articles. The use of fuzzy logic in text summarization was first testified in 2003 by Witte & Bergler [51].Thus this survey includes all the papers which demonstrate the use of fuzzy logic for automatic text summarization from the first reported study till date. We identified and compared various automatic extractive text summarization techniques which use fuzzy logic on the basis of the results given in the original studies. The objective of this SLR is to gather empirical evidence and interpret results from existing research to proffer concluded information systematically and critically analyzed in order to summarize the existing trends in available research, identify gaps in current search and provide future prospects in the area by means of answering the established research questions.

The paper is organised as follows: In the next section, the basics pertaining to the process and types of text summarization techniques are explained followed by the brief introduction to fuzzy logic. The section 3 elaborates the review methodology enlisting the Research Questions identified to conduct this study review. Section 4 overviews the literature survey of the selected studies concisely. Finally section 5 provides the results and discussion followed by the conclusion.

2 Automatic text summarization

Automatic Text Summarization is the process of finding a summary of a document available on the Web by a computer without changing the meaning of the original document for retrieving the useful information like the structure of document [44].Text summarizers have demonstrated their use in various application domains that range from stock market prediction to keyword extraction for search optimization. More recently, automatic Email summary generation using cue words has also been suggested by Carenini et al [13]. This categorization of text summarization techniques is depicted in the figure 1 below [16].

Primary categorization of text summarization techniques is on the basis of the type of summary generated. It can either be of extractive or abstractive type. Generating abstractive summary is cumbersome as it gives summary with sentences different from the original document, though the meaning of information is preserved. On the other hand, Extractive text summarization uses sentences from the document to provide condensed form of the document that is in simple terms, it is the subset of the actual document. Most of the studies on text summarization are on extractive techniques [28]. Other categorizations can be on the basis of the purpose, that is, the summary generated can be either

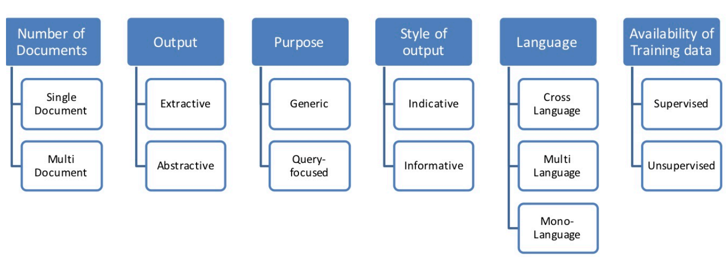

Figure 1: Categories of text summarization based on different characteristics.

generic, for everyone like summary of a news article, or it can be query-specific/ topic specific, only for a particular user or group of users, generated on the request. Moreover, the document can be a single document or a set of documents and the techniques which are applicable to single document may not necessarily be applicable on multi-documents.

Further, on the basis of the style of the output, the summaries can be indicative or informative. The former tells what the document is about, and the later gives information on the topic of the document [16].

Summarization techniques can also be categorized on the basis of whether the training data is available or not, that is if its available they are referred to as supervised. If training data is not provided the techniques are known as unsupervised learning. Another categorization of summarization is on the basis of language. If the language of the document and the summary is same, it is known as monolingual summary. If the document to be summarized is available in various languages, it is called as multi-lingual. If the language of summary and the document is different, it is referred to as cross-lingual summarization [16].

The following sub-section describes the various summarization methods available across literature followed by an overview of a typical fuzzylogic based ATS.

2.1 Summarization methods:

Due to the inherent complexity of generating abstractive summary, extractive summaries have been more frequently generated and used in practical applications [16]. Significant literature studies establish that various types of methods can be used to generate extractive summaries[28]. These methods with their techniques are shown in the Figure 2.We briefly explicate these methods.

- *Statistical Based Methods:* The methods generate summaries using statistical features of the document like sentence position, centrality of the sentence, sentence length, numeric data in sentence, title similarity etc.[8]. These techniques are language independent and do not require much storage or fast processors.
- *Graph Based Methods:* In this method, the words or sentences are represented by nodes of the graph and edges between these node represents the similarity value between these nodes. The sentences to be taken in extractive summary are found by traversing the graph and selecting the sentences which have similarity index above the defined threshold. Some of the recognised graph based methods are Text Rank and LexRank [16].
- *Discourse Based Methods:* These methods require understanding the textual structure and are complex to use as they take into account the connections between sentences and parts in a text. The Inter-paragraph & Intra-paragraph analysis is also done. Three levels of discourse structure may be identified based on cohesion, coherence, and cross-document relations [16].
- *Topic Based Methods:* In this method the summary is generated by firstly identifying the subject or theme of the document. Then this is used to extract the sentences which are related to the subject [16].
- *Machine Learning Based Methods:* These include approaches which learn from the data provided to the machine for summarization. They can either be supervised where the training data is provided with the summaries of the document such that the machine can learn how to summarize the data or unsupervised where only the documents are provided and the machine learns by analyzing the documents.
- *Optimization techniques:* The techniques use nature inspired or swarm algorithms for finding summaries or features for summaries employing optimization algorithms like particle swarm optimization, artificial bee colony. These techniques are usually used in combination with other techniques [28].

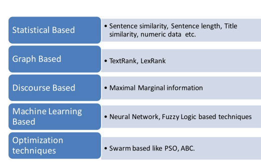

Figure 2: Summarization Methods.

A great deal of work has been done in these areas and the recent techniques proposed have mostly been machine learning based, swarm intelligence based or the hybrid of two or more types of summarization techniques.

2.2 Text summarization using fuzzy logic:

Fuzzy logic model intends to offer linguistic representation for handling uncertainties. Research on fuzzy logic started in 1965 by Zadeh [53] and since the inception it has been widely accepted and used in various application domains owing to the underlying primary notion which replicates a typical human inference process. Fuzzy logic handles uncertainties in the input better than other models, and no another method performs better in computing with words [53] and thus is preferably used for linguistic summarization [12]. A typical fuzzy logic based model for ATS takes as input eight

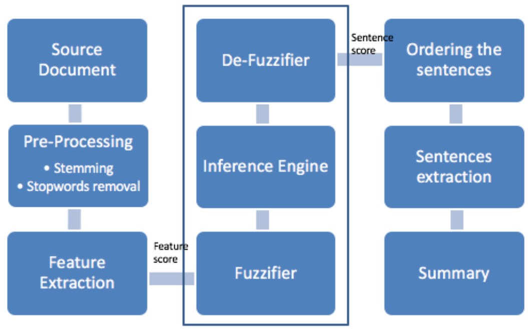

Figure 3: Text summarization using fuzzy logic.

features for each sentence (Title word, Sentence length, Sentence position, Numerical data, Thematic words, Sentence to sentence similarity, Term weight, Proper noun) to calculate its importance. Once the value of these eight features has been extracted, it is passed to a Fuzzy Inference System(FIS). Also, research has substantiated that a summary length is nearly 10% of the actual document length and the resultant summary consists of sentences extracted with the original order maintained. Figure 3 depicts this architecture. Main components of FIS are: *Fuzzification*- In this step the crisp values are converted into fuzzy value using membership function. Various types of membership functions like triangular, trapezoidal, ball, Gaussian distribution function, are available for mapping. For example, if a trapezoidal function is used, then each inputs'membership degree into a fuzzy set usually having three values low, medium or high. The generalized trapezoidal membership function depends upon four parameters p,q,r and s as given by the following equation.

$$f(x,p,q,r,s) = max\left(min\left(\frac{x-p}{q-p}, 1, \frac{s-x}{s-r}\right), 0\right)$$

Where p and s represent the feet of the trapezoid and q and r represent the shoulders [53].

Inference Logic- A knowledge base is created with IF-THEN rules and the inference engine derives the output based on these rules taking the input value generated in the first step. IF-THEN rules are used to balance the weights of key and non-key factors.An IF-THEN rule is stated in following format:

If (title similarity is medium) and (sentence length is medium) and (sentence location is medium) and (numerical data is low or medium or high) and (sentence centrality is low) then (output is key)

Defuzzification : - In this final step, the results generated in second step are mapped to crisp values using membership function, i.e. it converts the linguistic result from inference engine into a numeric value. The output membership function could be taken same trapezoidal or any other depending on the situation. The centroid method is used to find the crisp value.

3 Review process

Systematic reviews intends to identify, critically evaluate and integrate the findings of all relevant, high-quality primary studies addressing specific research questions pertaining to the research domain [23]. This review was conducted based on the format of Systematic Literature Review (SLR) defined by Ketchenham and Charters [23]. The review process was divided into six phases, namely, Research Question Formulation, Search Strategy Design, Study Selection, Quality Assessment, Data Extraction and Data Synthesis as shown in the following figure 4. This phase-wise process supported the study to be conducted in a well-structured manner. The goal of the first phase was to ascertain & formulate the research questions within the domain recognized for survey. Then in the next phase, a Search strategy was designed

Figure 4: Review process.

& adopted to ascertain how the search would be conducted. This was primarily done to find and locate the relevant research studies addressing one or more research questions. The scope of the study was narrowed in the Study Selection phase by using a selection criterion known as inclusion-exclusion criteria. The worthiness of the papers was then calculated using weighted parameters in the Quality assessment phase. The purpose of the Study Selection & Quality Assessment phase was to ensure the quality and similarity of included studies, and clearly define the boundaries of the review. Post this screening and eligibility decisions on the articles, in the next phase, the data was extracted to answer the research questions to finally critically analyze the research domain.

3.1 Research question formulation:

This SLR was planned to identify, appraise and synthesize research evidence from individual studies using Fuzzy logic for Automatic Text Summarization. For this purpose the following three research questions were formulated:

1. ***RQ1: What is the need of using Fuzzy Logic in Automatic Text Summarization?*** RQ1 aims to identify the motivation behind the use of fuzzy logic in ATS. The limitations of conventional techniques used for ATS advocating the need to explore novel paradigms.

2. ***RQ2 : What are the different techniques of fuzzy logic used in ATS till date?*** RQ2 identifies different techniques which have been proposed across literature studies on ATS using fuzzy logic. This question intends to explore the scope and extent of use of fuzzy logic in ATS including hybrid studies.

3. ***RQ3 : What is the accuracy of different Fuzzy Logic Techniques on Automatic Text Summarization?*** RQ3 targets to quantify the best techniques by comparing them on the basis of performance accuracy and data set.

3.2 Search strategy:

A strategy for exhaustive search of all studies that have been conducted on the topic was set up to find as many potentially relevant articles as possible. Specifically in this phase, the research questions were broken into individual concepts to create search terms and databases, additional sources to be searched.
Thus, the following search terms were extracted from the research questions : text summarization using fuzzy logic, text summarization using ML techniques, document summarization and fuzzy logic. These search terms defined the initial search string which was enhanced using alternative search terms, such as synonyms and different spellings. In this SLR, six electronic databases namely IEEE Xplore, ACM Digital Library, Science Direct, Google Scholar, Springer and Wiley Digital Online were used for selecting the relevant literature that cover the research questions. The search terms identified were then used to discover the conference and journals articles within these six electronic databases. The search indices were limited to the title, abstract, and keywords, except in google scholar where only the title was considered. The reference section of the relevant studies were also examined to extract cross-citations. Some secondary studies (existing literature surveys) were also obtained.

3.3 Study selection:

The primary and secondary studies which were identified from the search phase were then subject to a selection criteria known as the inclusionexclusion criteria. The goal was to limit the scope of search and also weed out the non- pertinent work. The following Inclusion-Exclusion criteria was considered for this SLR:

Inclusion Criteria: Articles with information restricted to following terms were only considered

- Empirical studies on text summarization using fuzzy logic.
- Studies proposing fuzzy inference system for document summarization (single or multiple)
- Survey of text summarization using machine learning or optimization techniques.
- Studies combining the fuzzy logic with other summarization technique

Quality Level	Number of studies	Percentage
$Outstanding(9.5 < score <= 1)$	3	6.8%
$Excellent(8 < score <= 9.5)$	7	15.9%
$Good(7 < score <= 8)$	11	25.0%
$Average(5.5 < score <= 7)$	12	27.27%
$BelowAverage(4 < score <= 5.5)$	6	13.63%
$Poor(score <= 4)$	5	11.36%

Table 1: Quality Assessment

- Extensive literature studies of text summarization.
- Empirical studies comparing the fuzzy logic based text summarization system with other text summarization systems.

Exclusion Criteria: The following studies were omitted to narrow the search

- Studies having linguistic summarization using fuzzy logic.
- Studying without text summarization i.e. containing video, audio summarization.
- Studies of text summarization using ML techniques other than Fuzzy logic.
- Studies of manual or human summarization.
- Individual survey studies on either fuzzy logic or text summarization.

3.4 Quality assessment:

A systematic review requires investigators to identify studies of sufficient quality to include in the analysis; because, if the raw material is flawed, then the conclusions of systematic reviews cannot be trusted [21]. Hence, in this phase, the selected studies were evaluated for their significance and strength based on various weighted parameters.The following parameters were identified for quality assessment:

- *Novelty:* Is the technique proposed new or just an enhancement/improvement to an existing technique?
- *Technically content:* Is the motivation behind the proposed method clearly indicated? Is the scope and limitation of the proposed models evident and un-ambiguous.
- *Result & Analysis:* Is the testing of the model has been on a standard benchmark data set or any random data set, with proper evaluation of performance measures and comparison with existing models?
- *Publication:* Does the study belong to a higher indexed journal or is from a conference? How many citations does the study have? Although we haven't given it much weight-age because a recent study may not have citations.

Thus, each article was given a score out of 10. The score was split as per the following values: 2 for novelty, 1.5 for publisher, 5 for Results & Analysis in which 2 was for data set, 2 for evaluation criteria used and 1 for the comparison with any of the existing technique and the rest 1.5 for technical writing.

3.5 Data extraction:

The aim of this phase was to summarize the information extracted from the studies with respect to the research questions. The idea was to map the studies to the research questions, that is, which study addressed which research question. Thus, data which was extracted from all the papers were details about author, year of publication, techniques used, dataset used for evaluation, the performance metrics used, the motivation and pros-cons of the method proposed. This information was then stored in a table to further synthesise it for the review.

3.6 Data synthesis:

The aim of the data synthesis phase was to summarize and interpret the information obtained from the data extraction phase. Different visualization techniques (tables, graphs, charts) were also used for interpretation of the resultant data. Thus to summarize, the research process adopted for this SLR generated the following information for critical analysis and review. To enhance the research review and filter the most significant and qualitative work, the search process and study selection was done twice; one with initial & expanded (alternatives and boolean expressions) search string and then re-run using cross-references from the initial studies retrieved. Consequently, 51 studies were initially extracted from the six selected electronic databases. Out of these 60, 52 studies (49 primary and 3 secondary) were considered as these were exclusive and did not contain any redundant information (extended versions or similar versions of work published). Based on the inclusion-exclusion criteria from these 52 only 45 were pertinent to our topic of interest (42 primary papers and 3 secondary papers). The search and selection phase was then repeated on the extracted studies based on cross-referencing. 4 papers were found to be relevant, but only 2 satisfied the inclusion-exclusion criteria.

The secondary studies did not propose any novel technique but reviewed the existing work, so though they were evaluated for final SLR discussions but were not subject to quality assessment. Hence a total of 44 papers (42 primary papers+2 cross-referenced) were subject to the qualitative assessment. All the studies with quality level greater than 4 were considered and we were left only with 39 primary studies out of 44 which eventually shaped the core of this review paper. In the final data extraction and synthesis phases the information retrieved from both primary (39) and secondary studies (3) [total 42] are coalesced to describe the existing findings, their extent and progress in the domain. The final output is a summarized critique to evaluate, extend, or establish implications for practice, identify gaps and inconsistencies, if any and provide directions for future research. The following paper depicts this summary.

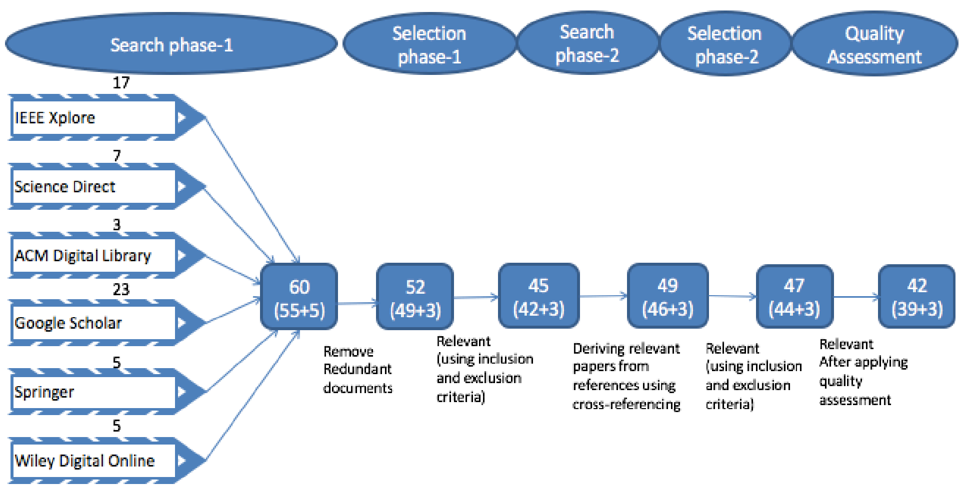

Figure 5: Systematic Literature Review Process.

4 Literature survey

In this section, a brief idea about all the selected studies has been given in reverse chronological order in the form of a table. The table 2 contains the state-of-art of this fuzzy logic based ATS where all the primary studies are briefly reviewed based on publication year, author, dataset used, evaluation metrics, motivation of their work and lastly details and scope of the work. Motivation discusses the reason why the authors have proposed this method, and what were the limitation of the existing techniques that lead to this work. Details and scope section contains the basic overview of the technique and its pros and cons of the proposed technique. The Accuracy is given as per the original studies, whether they are evaluated using Precision (P), Recall (R), Fitness (F), ROUGUE -1 , ROUGE-2.

Sr. No.	Year	Author	Technique	Data s0et	Accuracy	Description
S-1	2017	A. Guran, M. Uysal, Y. Ekinci, C. B. Guran	Fuzzy Analytical Hierarchy Process (FAHP) [17]	Two different Turkish datasets (130 & 20 documents)	Fitness: 0.552	A hierarchy is generated of the features after calculating their weights. Genetic Algorithm is used as heuristic algorithm as it can handle inherent uncertainty and allows the human involvement. They used 15 features which are classified under 5 main features. The features are pair wisely compared to the main feature to calculate the weights.

Table 2: Summary of the Primary Studies

S-2	2017	Muha- mmad Azhari, Y. J. Kumar	Adaptive Neuro-Fuzzy Inference System [4]	DUC 2002	Precision: 0.79, Recall: 0.77, Fitness: 0.78	Utilizing the benefits of both fuzzy logic and neural network, as fuzzy logic is knowledge-driven, whereas neural network is data-driven. It Performs better than Fuzzy logic and neural network. Evaluation was not done using ROUGE. LM backpropagation method is used in combination with Least-square Estimate model to estimate the parameters of membership function. It compares the model with Neural Network, Fuzzy Logic and optimized Fuzzy Logic and shows that ANFIS performs better than these models.
S-3	2017	Y. J. Kumar, F. J. Kang, O. S. Goh, A. Khan	Adaptive Neuro-Fuzzy Inference System [26]	DUC 2002	P :- 71.28, R :- 69.82, F :- 70.54	Utilizing the benefits of both fuzzy logic and neural network, as fuzzy logic is knowledge-driven, whereas neural network is data-driven. Performs better than Fuzzy logic and neural network. Evaluation should be done using ROUGE. LM backpropagation method is used in combination with Least-square Estimate model to estimate the parameters of membership function.
S-4	2016	R. Abbasi-ghalehtaki, H. Khotanlou, M.E. Eilpour	Artificial Bee Colony, Cellular Automata, PSO, GA, FL[1]	DUC 2002	ROUGE-1: 0.48685, ROUGE-2 : 0.22910	A hybrid technique which outperform other similar summarization techniques. Uses combination of CA and ABC for finding best diversity sentences. PSO and GA are used for assigning weights to features extracted. FL is used to score the Sentences.
S-5	2016	Jyoti Yadav, Dr. Yogesh Kumar Meena	Fuzzy Logic, Bushy Path, WordNet Synonyms [52]	DUC 2002	ROUGE1 (R): 0.4682, ROUGE1 (P): 0.4341, ROUGE2 (R) : 0.2449, ROUGE2 (P): 0.2255	Summary from three techniques are generated simultaneously. The sentences which come in all three are considered most important and then put into the summary, after that according to the length of the summary defined, the top scorer from all the three summaries are selected. Provides better result than individually used. Should be tested for long data set and for multi-document.
S-6	2016	Mehdi Jafari, A. M. Shabhabi, J. Wang, Y. Qin, X. Tao, M. Gheisari	Fuzzy Logic using both syntactic and semantic parameters [20]	50 random articles	F :- 0.59, P :- 0.6, R :- 0.58	A technique taking into consideration both the syntactic and semantic parameters for achieving high quality summary. Compared with MS word, Copernic, and Huang, the purposed method performed better than others. Not tested on the standard dataset, so cannot generalize the result.
S-7	2016	S. Chintaluri, R. P. Reddy, K. Nara.	Fuzzy Logic with Genetic Algorithm [1]	Documents related to Earth, Nature, Forest and Metadata	P :- 0.67, R :- 0.57, F :- 0.56	Genetic fuzzy systems are fuzzy systems constructed by using genetic algorithms, which mirrors the process of evolution to identify its structure and parameter. The main idea is to maintain a population of candidate solutions to the concrete problem being solved. It is being compared with Basic Fuzzy logic based model and the proposed method performed better than basic model.
S-8	2015	R. P. Reddy, K. Nara.	Fuzzy Logic with Genetic Algorithm [43]	Documents related to Earth, Nature, Forest and Meta data	Exact values are not given	Genetic fuzzy systems are fuzzy systems constructed by using genetic algorithms, which mirrors the process of evolution to identify its structure and parameter. The main idea is to maintain a population of candidate solutions to the concrete problem being solved. It is being compared with Basic Fuzzy logic based model and General Statistical Method and the proposed method performed better than both the models.
S-9	2015	Farshad Kiyoumarsi	Fuzzy Logic, Vector approach [24]	DUC 2004 (100 Documents)	ROUGE1: 29.6, ROUGE2: 7.8, ROUGE3: 2.6, ROUGE4: 0.9, ROUGE L: 25.3, ROUGE W-1/2 :- 18.9	Analysed human summaries to understand why they perform better than automatic summaries. The cue features are taken in account also at paragraph and essay level not just on sentence level in fuzzy method. Shown that human summaries are more accurate than automated summaries. Fuzzy performs better than vector method.
S-10	2015	S. A. Babar, Pallavi D. Patil	Fuzzy Logic, Latent Semantic Analysis (LSA) [5]	10 datasets (small)	P :- 90.77572, R :- 44.36375, F :- 67.56974	A hybrid technique of LSA and Fuzzy logic. LSA is used for handling semantic relations of the text. Fuzzy logic with eight features is used for improving the summary. Result of both the techniques is combined to achieve more accurate summary using set operations. To be certain of the accuracy, system should be tested on large dataset.
S-11	2015	Pallavi D. Patil, P. M. Mane	Fuzzy Logic, Latent Semantic Analysis (LSA), Agglomerative K-means [41]	Random Dataset	P :- 89, R :- 43.6, F :- 66.3	Uses LSA and Fuzzy logic for single document summarization. For multi-document, agglomerative K-means algorithm is used. The term frequency of each cluster is assigned as the name of the cluster an given as input to LSA. 12 Overall Fitness measure of the proposed system results in slightly lesser value than LSA summary.
S-12	2014	S. A. Babar, S. A. Thorat	Fuzzy Logic, Latent Semantic Analysis (LSA) [6]	5 datasets with different length of summary	Avg Accuracy : 85.33, Time complexity: 80-94 msec	Hybrid of Fuzzy logic and LSA. Tested on 5 different datasets and compared with gold standard human generated summary. Proposed method performs better than only fuzzy-based summarization.
S-13	2014	R. Abbasighale-htaki, H. Khotanlou, M. Esmaeilpour	Fuzzy Logic, Cellular Learning Automata (CLA), Particle Swarm Optimization (PSO) [2]	DUC 2002 (100 documents)	ROUGE 1(avg-F) :-0.46622, ROUGE 2(avg F) :- 0.2075, ROUGE L (avg F) :- 0.43001	Two techniques were proposed, one using CLA for calculating similarity of sentences and the calculating the score of the sentences on the basis of statistical features. Second is a hybrid technique of CLA, PSO and fuzzy. CLA is used in feature extraction for calculating similarity. PSO is used for assigning weights to the features, and fuzzy is used for calculating the sentence score. Second method performs better than other compared methods except for H2-H1 method.
S-14	2014	Pallavi D. Patil, N. J. Kulkarni	Fuzzy Logic [40]	–	–	Uses Fuzzy method to generate Scores of sentences. Eight types of features are extracted. Triangular membership function is used. Method was not tested on any dataset.
S-15	2014	R.J. Shinde, S.H. R., S.S. J., S.R. Sagare	Fuzzy Logic [45]	Random dataset	compression ratio	Similar to the method proposed in [16]. Shows better result than Ms Word. Method was not tested compared to human generated summaries.
S-16	2014	Y. J. Kumar, N. Salim, A. Abuobieda, A. T. Albaham	Generic-Case Based Reasoning (CBR), Fuzzy Logic [27]	DUC 2002	Accuracy:- 84.47%, ROUGE 1: 0.335, ROUGE 2: 0.128, ROUGE S: 0.096, ROUGE SU: 0.1009	Presented two techniques. Generic CBR, for finding cross-document relations from un-annotated text. A fuzzy model for ATS using Generic CBR. Both the methods performed better than other similar techniques when compared.
S-17	2014	S. Santhana Megala, A. Kavitha, A. Marimuthu	Fuzzy Logic, Neural Network [37]	50 Legal Judgement Documents	P :- 0.48629, R:- 0.41269, F :- 0.46823	They used 10 features for feature extraction process to improve the results. Comparison with neural network shows that fuzzy logic behaves better than neural network when the specific vocabulary is used depending upon the input documents.
S-18	2014	G. Padmapriya, K. Duraiswamy	Fuzzy Logic with Deep Learning Algorithm [39]	DUC 2002	P:- 0.37, R :- 0.86, F :- 0.50	Used some of documents to initially train the RBM, to get the adjust the weights of neural network to get only the sentences with minimum value of feature score. Uses the feature matrix defined on the number of sentences. Initially the fuzzy logic is used to categorize each sentence into the category after that RBM is used.
S-19	2014	V. E. Balas, S. Banerjee	Seeded Auto-Text Summarization [7]	–	–	It uses intra-textual ranking mechanism. Reduce the number of words to be considered for evaluation during pre-processing phase using the seed provided by user to reduce the cost and complexity of evaluation.

Table 2: Summary of the Primary Studies

S-20	2013	A. R. Kulkarni, S. S. Apte	Fuzzy Logic [25]	2 sports news articles	Average fitness=0.71	Uses the same technique as Patil. Not tested on enough dataset to be said as good results.
S-21	2012	A. Ladekar, A. M. , P. Nipane, S. Tomar, Kavitha S.	Fuzzy Logic, Genetic Algorithm, Genetic Programming [32]	–	–	Proposes an optimized membership function and rule based fuzzy system with GA and GP. Fuzzy logic is given unstructured features of the text as input. The Membership function is optimized using GA. Rule sets are optimized using GP. The method is not evaluated on any dataset.
S-22	2012	R. S. Dixit, S. S. Apte	Fuzzy Logic [14]	30 documents from news based URL	Accuracy :- 81%, Position similarity :- 79%	Uses Fuzzy logic for calculating relevance score of each sentence on the basis of the values of eight features. Provides more intelligent summaries as compared to Ms Word and Copernic summarizer. Need to test on standard dataset of multiple domains.
S-23	2011	L. Suanmali, N. Salim, M. S. Binwahlan	Fuzzy Logic, Genetic Algorithm (GA), Semantic Role Labelling (SLR) [49]	DUC 2002 (100 documents)	ROUGE 1(P): 49.95%, ROUGE 1(R): 45.19%, ROUGE 1(F): 47.04%	Proposes a hybrid model for ATS using Fuzzy logic, GA, and SLR. GA is used for optimizing feature selection process and for also calculating the weights of each feature during training time. Fuzzy logic is used to handle uncertainties in the data and balance thee weight between more relevant and less relevant features. SLR captures the semantic data in the text and includes those in the summary. The score of each sentence by both fuzzy logic and SLR is added up to find the final score, on basis of which the sentences are extracted for automated summary.
S-24	2010	M. S. Binwahlan, N. Salim, L. Suanmali	Maximal Marginal Importance, Particle Swarm Optimization, Fuzzy Logic [11]	DUC 2002 (100 Documents)	1st: ROUGE1: 44.94%, ROUGE2: 20.07%, ROUGE-L: 41.38%, 2nd: ROUGE1: 45.87%, ROUGE2: 20.42%, ROUGE-L 42.29%	Two models were proposed, one dominating the diversity measure, second not. In first the scores are calculated by three different methods: diversity, swarm diversity, and fuzzy swarm based. Different weights are assigned to all the three components to find the appropriate sentences from all the components. Second also takes three components, but in place of swarm diversity, it uses fuzzy swarm base instead of swarm diversity, and third component is replaced by swarm based. While the first is handling redundancy better than second, but the overall more accurate summary is being generated by the second method.
S-25	2010	S. Alzahrami, N. Salim, C.K. Kent	Fuzzy Swarm based Technique [3]	–	–	Text summarization solves multiple issues, it can handle cross language documents very easily. The redundancy in data can also be found with the use of TS. Improves the plagiarism detection process.
S-26	2010	F. Kyoomarsi, H. Khosravi, E. E., M. Davoudi	Fuzzy Logic, Word Net [29]	DUC 2003 (50 Documents)	ROUGE 1 :- 0.6124	Five features are taken in account including Word-net. Shown that fuzzy model with word net performs better than existing market tools for generating automated summary. Tested the model in two different scenarios.
S-27	2009	F. Kyoomarsi, H. K., E. E., P. K. D., A. Tajoddin	Fuzzy Logic [30]	10 Documents only	Tested by 5 humans. Avg accuracy :58%	They compared vector approach based methods with fuzzy logic. They first calculate the features scores and then used the MATLABs Fuzzy tool to calculate the final score on their basis.
S-28	2009	HH Hunag, HC Yang, YH kuo	Fuzzy logic, Rough Set [19]	DUC 2006	ROUGE-1 :0.40636, ROUGE 2:-0.08245	Proposed a hybrid approach of rough set and fuzzy logic for multi-document summarization. Tested with other 35 techniques. Performance comes in first one third techniques.
S-29	2009	L. Suanmali, N. S., M.S. Binwahlan	Fuzzy Logic [47]	30 documents	F:- 0.47873	To use human reasoning system. They used both single and multi-document summary generation.
S-30	2009	L. Suanmali , N. Salim, M. S. Binwahlan	Fuzzy Logic [48]	DUC 2002 (125 Documents)	F:- 0.47181	Same technique as above. Use triangular membership function. Tested on DUC to make results trustworthy.
S-31	2009	L. Suanmali, N. Salim, M.S. Binwahlan	Fuzzy Logic [46]	DUC 2002 (30 Documents)	F :- 0.47019	9 Features were selected instead of 8 in the above model. Gaussian Membership function has been used. Results do not improve.
S-32	2009	L. Suanmali, N. S., M. S. Binwahlan	Fuzzy Logic, PSO [10]	DUC 2002	ROUGE 1(F):- 0.45524, ROUGE 2(F):- 0.20847	Not every feature is of same importance, so to treat them accordingly, the PSO is used. PSO assigns the weights to each feature and then calculate the score of each token with its feature value and weight and pass it to FIS. Performs better than other models, but still only fuzzy also performed the same.
S-33	2008	L. Suanmali, N. S., M. S. Binwahlan	Fuzzy Logic [50]	DUC 2002 (6 documents)	F :- 0.50433	It was the first basic model of the techniques proposed in their rest five papers. It uses eight features and Bell membership function.
S-34	2008	F. Kyoomarsi, H. K., E. E., P. K. D., A. Tajoddin	Fuzzy Logic [31]	Random 10 documents	Tested by Humans. Avg accuracy :77%	They compared vector approach based methods with fuzzy logic. They first calculate the features scores and then used the MATLABs Fuzzy tool to calculate the final score on their basis.
S-35	2006	Arman Kiani-B, M.-R. Akbarzadeh-T., M.H. Moeinzadeh	Fuzzy Logic [22]	3 news articles	Average F:-0.752	A novel technique for summarization to handle uncertainties. They proposed the use of fuzzy logic with triangular membership function on the six features. This was one of the basic method, whose limitations has been covered by the above models.
S-36	2006	Hsun-Hui Hunag, Horng-Chang Yang, Yau-Hwang kuo.	Fuzzy Logic, Rough sets, Semantic patterns [18]	8 articles from JAIR	Average ROUGE-1(F) :- 0.4620391	To remove the redundancy and uncertainty. Semantic of the words are taken to reduce the similar sentences with synonym words. Fuzzy set and rough set improves the process of removing uncertainty in the feature values extracted. The final score of the redundancy removed articles are calculated by FIS.
S-37	2006	Arman Kiani-B, M.-R. Akbarzadeh -T	Fuzzy Logic, Genetic Algorithm, Genetic Programming	3 news articles	F1 :- 0.728, F :- 0.961	GA improves the membership function of the FIS. GP improves the rule set according to the training data. The accuracy of a fuzzy machine depends only on three thing its input, which we are pre-processing to improve better results, rest of the two have been improved in this method. Performs better than other ATS techniques.
S-38	2005	Chang-Shing Lee, ZW Jian, LK Huang	Fuzzy Logic [33]	News articles	compression ratio was used for evaluation	Enhanced the FIS. Instead of the five layer standard fuzzy system, a new seven layer fuzzy system was proposed. Havent been used by any researcher again, not tested for accuracy of the summary.
S-39	2003	R. Witte, S. Bergler	Fuzzy Logic, ERSS [51]	DUC 2003	Not evaluated using standard measures	To resolve the co-reference resolution of the text words by reducing the uncertainty using Fuzzy logic. Used a POS tagger along with fuzzy logic and WordNet to handle the uncertainties in the co-reference text. Results are not that satisfactory and need complex heuristics.

Table 2: Summary of the Primary Studies

5 Results and discussion

In this section, we analyse the studies to attain the solutions of the research questions defined during the course of SLR. To comprehend the status of research in this field, we examined year-wise qualitative studies. Although the research in ATS started in late 1950s, but usage of fuzzy logic in ATS was first reported in twenty-first century. Rather more significant work in this field has been accounted for in the last 14 years. The following chart depicts the numbers of papers that have been published annually in this domain and indicate a positive trend and gained momentum due to promising results & increased applications.

Figure 6 represents only the 30 primary studies selected in the SLR process. 3 Secondary studies were also taken into account to apprehend other summarization techniques which used fuzzy logic for improving performance. According to the quality criteria defined in section 3.4, the percentage distribution of studies with respect to quality is shown in Fig.7. Now we discuss the findings and conclusions of the review, mapping them to respective research questions.

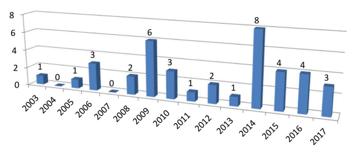

Figure 6: Year wise distribution of studies.

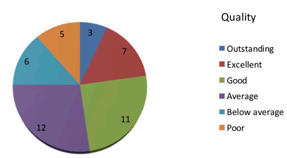

Figure 7: Distribution of studies according to the quality.

RQ1 was presented to establish the need of using Fuzzy Logic in Automatic Text Summarization. The basic model and implementation of Fuzzy logic in ATS has been illustrated in Section 2, whereas the section 4 covers the summary of pertinent studies, their motivation and benefits. The advantages of using fuzzy logic in ATS endorsed by the literature can thus be enlisted as:

- It handles the uncertainties in the input.
- It resembles the human reasoning system.
- Not everything in world can be defined in terms of zero and one, so provides more efficient ways to represent the feature values of sentences.
- It provides better way to calculate the sentence score using various types of membership functions.
- It handles the words better than other statistical techniques.

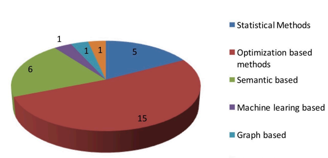

Figure 8: Classification of Hybrid models.

RQ2 intended to uncover the variety of fuzzy logic based techniques used in ATS. The literature survey illustrated in table 2 of Section 4 offers a complete coverage on studies using fuzzy logic for text summarization. Some hybrid techniques using fuzzy logic have been explored and the following table represents the techniques which have been used in combination with fuzzy logic for enhancing the results along with the number of studies conducted.

Sr. No.	Journals	Number of Studies
1.	Swarm and Evolutionary conference (Elsevier)	1
2.	Information Processing and Management (Elsevier)	1
3.	Applied Soft Computing (Elsevier)	1
4.	International Journal of Computer science trends and technology	1
5.	International Journal of innovative research in advance engineering	2
6.	International Journal of Soft Computing and Information Technology	2
7.	International Journal of Computer Engineering	2
8.	IEEE Transactions on systems, MAN & Cybernets	1
9.	International Journal of Computer Science and Technology	1
10.	International Journal of Engineering Research & Applications	1
11.	Irarnian Journal of Fuzzy Systems	1

Table 3: Journals Covering the Studies on ATS using Fuzzy Logic

Sr. No.	Technique	Summarization Method	Number of Times
1.	Genetic Algorithm	Optimization based	6
2.	Genetic Programming	Optimization based	3
3.	Particle Swarm Optimization	Optimization based	4
4.	Artificial bee Colony	Optimization based	2
5.	Rough sets	Statistical based	2
6.	Cellular Learning Automata	Statistical based	2
7.	Agglomerative K-means	Statistical based	1
8.	Latent Semantic Analysis	Semantic based	3
9.	WordNet	Semantic based	3
10.	Maximal Marginal Information	Diversity based	1
11.	Case Based Reasoning	Machine Learning based	1
12.	Neural Network	Machine Learning Based	3
13.	Bushy Path	Graph Based	1

Table 4: Techniques used along with Fuzzy logic in ATS

Figure 8 shows that around 50% of the studies about hybrid techniques are using optimization based methods, as they enhance the performance of the summarizer as compared to other techniques. Also, most of the studies combine more than 2 techniques to describe a hybrid model. The idea is to generate finest summaries with a fuzzy based model optimized with a nature inspired technique. Moreover, it was observed that the best results were achieved by combining more than two summarization methods (as given in Fig 2) with fuzzy logic [15].

The third research question intended to compare the accuracy of different Fuzzy Logic Techniques used in Text Summarization. Not all the studies have been tested on the benchmarked dataset, rather some have been evalutated on small random data set. The distribution of these techniques according to the dataset used is shown in the following figure (Fig 9).Moreover, the techniques have not been evaluated using the same criteria and the standard evaluation tool for text summarization, ROUGE (Recall-Oriented Understudy for Gisting Evaluation), it contains different matrix for automatically evaluate the worth of a summary generated by comparing it with a human generated summary [34]. Some of the studies have been tested on other basis too, such as testing based on humans understanding, compression ratio, fitness value etc.

The DUC (Document Understanding Conference) datasets [16] are the de-facto standard data sets that the NLP community uses for evaluating summarization systems. From the 17 studies on DUC, 13 of them were using DUC 2002. Some of the studies had used other methods like Precision(P), Recall(R), and Fitness(F) for determining the quality of the summary produced by the model, So the comparision of all the models are not possible, although the

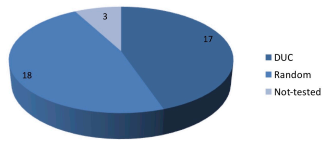

Figure 9: Studies distributed according to dataset used.

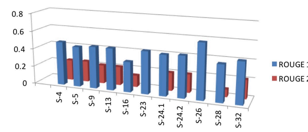

Figure 10: Comparison of Fuzzy based techniques.

comparision between these different matrices provided by Ravindra et al shows that ROUGE values except ROUGE-WLCS are equivalent to F-measure [42], but no other study has still endorsed this result, thats why we are comparing the results of only the studies evaluated using ROUGE score. The techniques proposed have been serially numbered in the summary table given at the beginning of this section. We use these serially numbers in the following bar-graph in fig 10 which represents the comparison of the techniques on the basis of ROUGE-1 & ROUGE-2. Though the techniques were tested on DUC but not all of them used the same set of documents and moreover the number of documents were also different. Thus, the comparison is not a benchmark result but still was adequate to answer the research question.

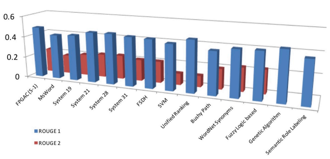

Figure 11: Comparison of Fuzzy based model with other text summarizers.

Figure 11 shows the comparison of the best fuzzy based model FPGAC with other models using their ROUGE values on DUC 2002 dataset. The latest method ANFIS is also showing superior results, but as it was evaluated using F-measure, we cannot compare it with the FPGAC. On examining figure 12 precisely, S-26 appears to give superior results with high ROUGE-1 value but it is evaluated using only 5 documents. S-4 on the whole surpasses S-32 and other summarizers as its evaluation was done using benchmark dataset with ROUGE-1 and ROUGE-2 both gives sounder result (except for S-32 for ROUGE-1) as shown in fig 11.

6 Conclusions

The evolution of Web from the Web of Documents to the Web of People (Social Web) to the Web of Data (Semantic Web) has multiplied the volume, velocity and variety of information available online. Finding useful, relevant, trending, interesting information from this garbage in-garbage out puddle has been a major focus of current research. Text summarization has emerged as one of the vital technique to handle this problem. The incredible ability of fuzzy inference systems to make logical assessment in an ambiguous and uncertain environment has made is a trending choice for practical applications such as text summarization, that involve imprecision and uncertainty. In this paper, we have reviewed various studies on fuzzy-logic based text summarization from 2003 to 2017, published in conference proceedings and journals of high repute. The purpose was to evaluate the progress made so far, identify the trends and gaps in studies to ascertain the future scope of research within the domain. The following key-points were observed:

- Fuzzy logic is an attractive choice to achieve optimal summaries due to its resemblance to human reasoning. The goal of text summarization is to achieve superlative results comparable to human generated summaries and mapping the fuzzy logic inference mechanism gives the desired brainpower.
- It is promising to see the paradigm shift from conventional summarization methods to contemporary, novel intelligence based methods. Nearly 50% studies have been done with hybrid models of fuzzy logic with optimization

methods, followed by equal number of studies done on hybrids of fuzzy-logic with statistical and semantic techniques respectively. Combinational hybrids using two or more conventional techniques with fuzzy-logic though have been reported but the sphere is an open research problem to achieve enhanced summarization results.

- Though the DUC (Document Understanding Conference) datasets are the de-facto standard data sets used for evaluating summarization systems but less than 50% studies have reportedly used it. This makes comparing the empirical results vague and non-uniform, thus identifying the need of more benchmarked studies and subsequent evaluation.

This literature review identified and compared various automatic extractive text summarization techniques which use fuzzy logic. The limitation of this work is that the techniques obtained across studies are not compared on a common dataset, though most of them have used the ROUGE-N metric for evaluation. The need of more standard studies on benchmark dataset thus exists. Moreover, no studies have been done to classify the use of type-1 and type-2 fuzzy within the domain, calling for an investigation in this direction. Also, during the search and review process we also discovered that so far no studies have been done to explore & see the impact of using fuzzy logic in abstractive text summarization, making it a significant avenue of research.

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Systematic literature review of fuzzy logic based text summarization

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بررسی متون اصولی منطق فازی براساس خلاصه سازی متن

چکیده. « زیادی اطلاعات » یک اصطلاح جدید نیست بلکه با توسعه‌ی عظیم در تکنولوژی که دسترسی آسان و بدون محدودیت را در هر زمان و هر مکان مقدور می‌سازد، اشتراک و انتشار اطلاعات نتیجتاً اثر آن را افزایش داده‌است. کمک به جستجوی اطلاعاتی کاربران با زمان صرف شده کاهش یافته جهت مطالعه، با استخراج و ارزیابی دقیق، معتبر و مرتبط اطلاعات از جمله نگرانی‌های اولیه اجتماع حاضراست. خلاصه‌سازی موضوع اتوماتیک روند متراکم‌سازی یک سند اصلی در فرم کوتاه‌تر برای خلق نسخه فشرده کوچک‌تر از اطلاعات فراوانی است که فراهم است، حفظ محتوا و مفهوم به نحوی که نیاز کاربر را برآورده کند. از این رو، بسیاری از تکنیک‌های خلاصه‌سازی پیشنهاد شده، اما نه راه حل معجزه آسایی همانند خلاصه‌سازی ساخت بشرکه نتایج عالی ببار آورد. بنابراین، حوزه خلاصه سازی متن، یک میدان مطالعه‌ی پویا و فعال، تمرین و تحقیق با نیاز مداوم به تفسیر تکنیک‌های جدید برای رسیدن به نتایج مقایسه‌پذیر و مؤثر می‌باشد. منطق فازی به عنوان یک چارچوب نظری توانمند برای مطالعه‌ی استدلال بشری و کاربرد آن در حوزه خلاصه‌سازی متن در چند ساله گذشته کشف شده‌است. این مقاله یک بررسی متون اصولی جمع‌آوری، تحلیل و گزارش گرایش‌ها، شکاف‌ها و چشم‌اندازهای بکار بردن منطق فازی برای خلاصه‌سازی متن اتوماتیک برمبنای یافته‌ها در مطالعات اصلی است.