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A Comparison Between Fuzzy Type-1 and Type-2 Systems in Medical Decision Making: A Systematic Review

Azam Orooji[1], Mostafa Langarizadeh[1*], Maryam Hassanzad[2], Mohamad Reza Zarkesh[3]

Abstract

Objectives: Fuzzy logic is considered a powerful instrument for dealing with uncertainty and is implemented in both type-1 and type-2 ways. The expert systems (ESs) and decision support systems (DSSs) are applied based on type-1 and type-2 fuzzy logic since medical decision-making has always been associated with various uncertainties. The present study reviewed different types of fuzzy ES/DSS in the medical domain in order to investigate whether the fuzzy type-2 performance was better compared to that of type-1.

Materials and Methods: A systematic review was conducted on PubMed, Web of sciences, Scopus, Embase, Medline, and Science Direct databases. The title, abstract, and full text of the articles, published during 2007-2017, were independently evaluated by two reviewers. The cases of disagreement were solved in a pair-work discussion. Finally, based on inclusion criteria, 12 articles were included in the study and were investigated in terms of the purpose and application, architecture and structural details, as well as the method of evaluation and the findings.

Results: Type-2 expert systems were found to have a better diagnostic function compared to Type-1 systems and other different machine learning methods. Increasing the accuracy, precision, and resistance to noise was an issue that was achieved in such systems using type-2 fuzzy logic.

Conclusions: In general, medical expert systems based on type-2 fuzzy logic are considered more appropriate for model uncertainty and ambiguity, therefore, they could be used in different medical domains that need to make decisions under uncertain circumstances.

Keywords: Expert systems, Clinical decision support systems, Medical diagnosis, Type-2 fuzzy logic

Introduction

Clinical decision-making, diagnosis, and treatment are complicated issues and in some cases, even experts fail to have an agreement in this regard. Thus, intelligent systems could be in account as a great help for physicians (1). Intercommunication of medical experts and computer engineers is an interdisciplinary domain which has developed decision support instruments (2). Expert systems (ESs) and decision support systems (DSSs) are software applications used for helping health professionals or physicians to make clinical decisions (3,4). ESs and DSSs have been widely used in the past decade due to their successful application in medical diagnosis (5-7).

A physician, usually, gets to know the health state of a patient through enquiring his/her history, physical examination, laboratory tests, and the like, though the information collected from each of these sources contains some degree of uncertainty. The diagnosis of a disease is dealt with uncertainty and imprecision which is inevitable in medical sciences (8). Thus, soft computing techniques which are capable of handling ambiguous conditions are extensively utilized in medical decision making (9). Fuzzy logic is one of the soft computation techniques, which was introduced by Lotfi Zadeh in 1965 (10) and used as an effective method for diagnosing diseases in different DSSs. In addition, this technique is closer to the human way of thinking compared to systems which are based on classic logic and does not have the restrictive rules of the classical logic (11).

As shown in Figure 1, a fuzzy system encompasses four parts (12,13):

Fuzzifier: It maps the numeric input vector $x = (x_1 \ldots. xp)^{\Gamma} \varepsilon X_1 \times X_2 \times \ldots. X_p$ on the fuzzy sets defined for different linguistic variables on x. Further, fuzzy sets are described using the membership functions (MFs) which mainly contain five types including Triangular, Trapezoidal, Γ-Membership, S-Membership, and Gaussian and Exponential-like (14);

Rule base: The rules are the heart of a fuzzy logic system (FLS) and form a mapping of input on the output.

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[1]Department of Health Information Management, School of Health Management and Information Sciences, Iran University of Medical Sciences, Tehran, Iran. [2]Pediatric Respiratory Diseases Research Center, National Research Institute of Tuberculosis and Lung Diseases, Masih Daneshvari Hospital, Shahid Beheshti University of Medical Sciences, Tehran, Iran. [3]Department of Neonatology, School of Medicine, Tehran University of Medical Sciences, Tehran, Iran.
*Corresponding Author: Mostafa Langarizadeh, Tel: +982188794301, Email: Langarizadeh.m@iums.ac.ir

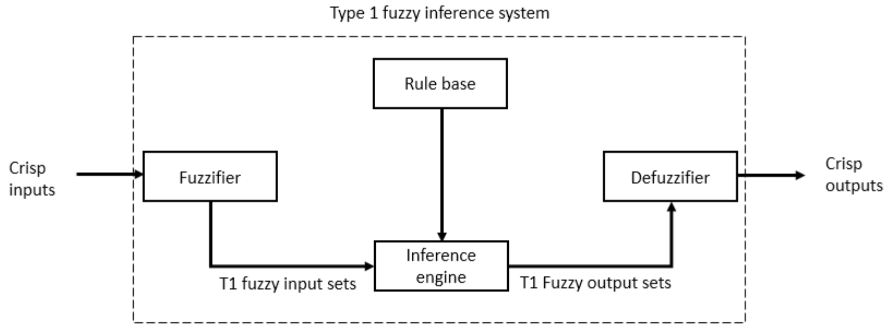

Figure 1. Type-1 Fuzzy System.

Furthermore, they may be defined by a domain expert or derived from a set of numeric data. Each linguistic variable discussed in the antecedent/consequent parts of the rule is defined using MF, which can be represented by type-1 fuzzy set (T1FS) or type-2 fuzzy set (T2FS).

Inference Engine: It combines the input and rules in a fuzzy system and yields the output which is a fuzzy set. Different types of inferences in fuzzy systems include Mamdani, Takagi-Sugeno-Kang (TSK), and Tsukamoto (15).

Defuzzifier: It is used to convert the output of the inference engine to a non-fuzzy value $\overline{Y}$. It can be implemented in several ways including the mean of maxima, the smallest of maxima, the largest of maxima, as well as centroid and bisector (16-18).

As mentioned earlier, medical knowledge is inherently associated with uncertainties (9). Although type-1 fuzzy logic is widely applied to handle uncertainty in medical domain such as screening, diagnosis, and prevention (9,19, 20) while different meanings of the words to different people, the inconsistency of the experts' knowledge, as well as the imprecise and noisy measurements cause uncertainties in the parameters of fuzzy sets which are perfectly modelled by type-2 fuzzy logic (21,22).

The concept and computations of a type-2 FLS (T2FLS) were introduced by Lotfi Zadeh in 1975 (23). However, Mendel considered the development and implementation of T2FS (24) in which a T1FS represented the membership degree of each element (12). T2FS added a new dimension to T1FS in order to demonstrate the uncertainty of membership degree. The footprint of uncertainty is the third dimension of T2FS that provides an additional degree of freedom for managing the uncertainties (25, 26). However, T2FLS is unsuitable for the real world applications since it implementation is expensive in terms of time and computation complexity. Therefore, according to Sprunk and Garcia (27), a particular type of T2FS is often used in T2FLs designing instead of T2FS, which is known as the interval type-2 fuzzy set (IT2FS) and has less computational overheads (26). There is a high similarity between interval type-2 FLS (IT2FLS) and T1FLS. However, their key difference is that at least one MF should be IT2FS in the rule base of IT2FLS. Thus, the output of the inference engine is regarded as an IT2FS which should be converted to T1FS by type-reducer (28). Karnik-Mendel (KM) algorithm is the most common type reduction algorithm. However, KM algorithm has high computational complexity due to its iterative procedure. As a result, some researchers optimized and improved this algorithm (28).

Moreover, various researchers sought to decrease the complexity of general type-2 fuzzy logic. Geometric representation of GT2FS was introduced by Coupland and John (29) while Mendel (30) and Liu (31) suggested the alpha-plane representation. Z-slices representation was proposed by Wagner and Hagras as well (32).

Unfortunately, no systematic and comprehensive review is found regarding investigating whether fuzzy type-2 performance is better than type-1 in order to design clinical ESs and DSSs. However, no evidence is available to confirm whether there is enough improvement and completely legitimized considering that the substantial computational overhead is associated with the design of T2FSs (Figure 2).

Accordingly, the present study aimed to review different types of ES and DSS based on type-2 fuzzy logic in medicine in order to investigate if type-2 fuzzy logic functioned better than type-1 in medical decision making. The paper search and selection procedure are explained in Section 2. Additionally, Section 3 discusses the findings in terms of the purpose and application, the architecture and structural details, along with the method of evaluation and the results. Finally, Sections 4 and 5deal with the discussion and conclusion, respectively.

Materials and Methods

Literature Review

Based on the guideline of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), a systematic review was performed to ensure the accuracy and adequacy of the sample in the search process. To this aim, articles indexed in PubMed, Medline, Embase, Scopus, Web of science, and ScienceDirect databases, published in 2007-2017, were searched using a

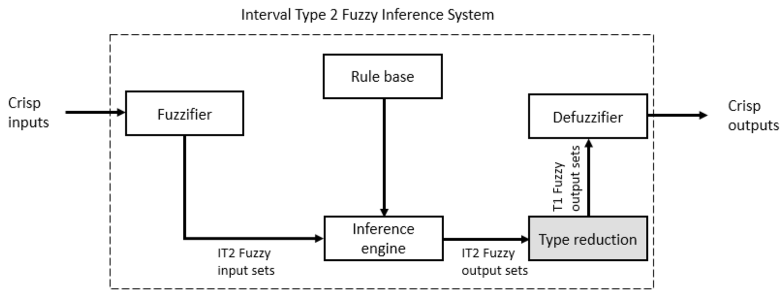

Figure 2. Interval Type 2 Fuzzy System.

combination of different key words. Table 1 represents the search query for identifying potentially eligible journal papers of interest. A total of 858 articles were found and organized in EndNote and then duplicated articles were discarded.

Inclusion and Exclusion Criteria

English-language articles which were published during 2007-2017, academic journal, original research, and full text were scrutinized in the present study. The excluded criteria were based on publication type and encompassed non-English papers, literature with no access to the full-text, and articles with non-medical aims. In addition, articles were excluded if they failed to apply type-2 fuzzy sets for decision making or compare type-1 and type-2 fuzzy. To avoid redundancy, only one article was included in the review if more than one article was written reporting a particular study.

Study Selection

The related studies were independently reviewed by two reviewers respecting with respect to their title, abstract, and full text. Finally, 7 articles were investigated in the present study based on inclusion/exclusion criteria (Figure 3). The reason for excluding the articles when reviewing their full text is explained in Table S1. Controversial cases were discussed and solved in a meeting between the reviewers and the kappa agreement rate between the two reviewers was k=0.76.

Data Extraction

A data extraction form was developed as a data collection instrument. Further, the extracted data elements were organized in four sections including the general items (i.e., author, publication year, country, and journal name), application purpose (i.e., application domain, the type of disease, and the used dataset), structural details (i.e., the type of MF and fuzzy sets, inference approach, the number of rules, the method of rule extraction, parameter tuning, and output processing), and evaluation items (i.e., the results regarding altering the system structure and resilience to noise, performance measurements, and the findings), which are provided in Table S6.

Results

Based on the review, a number of seven related papers were included in this study, the results of which were presented in 3 major categories containing application purpose,

Table 1. The Search Query

Database	Query	Item found
WoS	(TS= ((expert system OR decision support system OR rule based system) AND (fuzzy type 2 OR fuzzy interval type 2))) AND LANGUAGE: (English) AND DOCUMENT TYPES: (Article) Timespan: 2007-2017.	355
Scopus	(TITLE-ABS-KEY (fuzzy type 2)OR TITLE-ABS-KEY (fuzzy interval type 2))AND (TITLE-ABS-KEY (expert system)OR TITLE-ABS-KEY (decision support system)OR TITLE-ABS-KEY (rule-based system)) AND (LIMIT-TO (LANGUAGE , "English")) AND ((LIMIT-TO (DOCTYPE , "ar")OR LIMIT-TO (DOCTYPE , "re")OR LIMIT-TO (DOCTYPE , "ip")) AND PUBYEAR > 2007	229
Embase and Medline	('fuzzy type 2':ti,ab,kw OR 'fuzzy interval type 2':ti,ab,kw) AND ('expert systems': ti,ab,kw OR 'decision support system':ti,ab,kw OR 'rule-based system':ti,ab,kw) AND [2007-2017]/py	0
PubMed	((fuzzy type 2[Title/Abstract]) OR fuzzy interval type 2[Title/Abstract]) AND (expert systems[Title/Abstract] OR decision support system[Title/Abstract] OR rule-based system[Title/Abstract]) AND ("2007/08/04"[PDat] : "2017/07/31"[PDat])	4
Science Direct	pub-date > 2006 and (TITLE-ABSTR-KEY(fuzzy type 2) or TITLE-ABSTR-KEY(fuzzy interval type 2)) and (TITLE-ABSTR-KEY(expert system) or TITLE-ABSTR-KEY(decision support system) or TITLE-ABSTR-KEY(rule-based system))	270

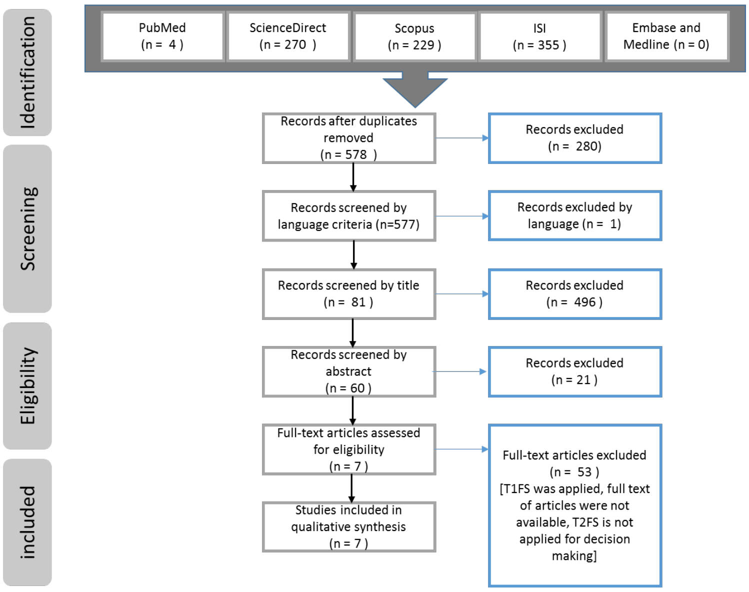

Figure 3. Review Process Based on PRISMA.

structural details, and evaluation results as described in following subsections.

Application Purpose

Fuzzy systems were mostly used for diagnostic (33-36) while less for treatment (37, 38) and prediction (39) purposes. A wide range of data type such as the signal (33, 34), image (36), and gene (39) were employed. Furthermore, 6 out of 7 articles were published after 2010, showing an increasing use of T2FS in the field of medicine. This is further true for the other domains such as intelligent control (12) and pattern recognition (40). Application purposes of the entered studies are summarized in Table S1 (Supplementary file 1).

Structural Details

Gaussian MFs (33-35,38,39) and trapezoidal MFs (37) are used to represent linguistic variables in this domain. The results of the study by Helmy et al (35) demonstrated that Gaussian MFs were more efficient compared to the triangular MFs. The number of rules varied from 3 to 80 and were extracted in three ways including using the dataset (34, 35, 39), expert knowledge (33, 36), and a combination of the two above-mentioned ways (38). However, Lee et al. (37) used fuzzy ontology instead of fuzzy rule base. The T2FLS contained more parameters compared to T1FLS, which further complicated their design. Therefore, some researchers utilized different algorithms to adjust the parameters such as genetic algorithm (36, 39) and Fuzzy C-Means (34). The developed systems mostly used IT2FS (33, 34, 36-39) while Liu (38) showed that the precision and noise-resistance of Zslice were higher compared to IT2FLS. The inference engine of all systems (if mentioned) was either Mamdani (33-36) or TSK (39) and the most common reduction methods were Karnik-Mendel (34, 39) and height (34, 35). The structural details of fuzzy systems developed in the literature are shown in Table S2 (Supplementary file 1) as well.

Evaluation Results

Table 2 demonstrates the comparisons between T1FLS and T2FLS performance in medical decision making. The performance of the system was evaluated based on different criteria in the body of literature among which accuracy was found to be the most common (33-35), the details of which are presented in Tables S3 and S4 (Supplementary file 1). Some studies evaluated the noise resistance of the systems as well (34,35,38). In addition, four articles (34-36,38) made structural modifications and investigated the effect of these changes on system performance.

Discussion

The present systematic review was implemented to investigate whether the (expert system) ES and DSS based on type-2 fuzzy logic acted more appropriately compared to type-1systems in medical decision making. Totally, seven articles were included and examined from different aspects containing the application purpose, structural details, as well as the evaluation results and findings. Based onto the data presented in Tables S3-S5 (Supplementary file 1), type-2 FLSs (T2FLSs) achieved better results than type-1 FLSs in all cases regardless of the data type and application purpose. However, several articles applied structural modifications and evaluated the effect of the changes on system performance. For instance, Helmy et al (35) assessed the effect of different MFs and defuzzification methods on T2FLS performance

Table 2. The Evaluation Details of the Literature

First Author	Modified Structures	Resilience to Noise	Major Findings
Chua (34)	Type-2 uncertain standard deviations (T2-US) classifier, type-2 uncertain means (T2-UM) classifier, type-2 uncertain standard deviations and means (T2-USUM), and base-line type-1 (BS-T1)	Yes	The noise-resistance and classification accuracy of T2FLS was better than those of T1FLS. There was no statistical difference between T2-US, T2-UM, and T2-USUM. Moreover, T1MFs had no effect on classification accuracy by using fuzzy C-means instead of the mean and standard deviation of the data to define.
Lee (37)	-	No	The experts and users were more satisfied with T2FLS performance rather than that of the T1FLS.
Helmy (35)	The impact of Gaussian or triangular MFs, height or modified height defuzzification and different training algorithm (i.e., steepest descent and heuristic on classification framework).	Yes	T2FLS was more successful in classifying and handling the uncertainties, imprecision data, and missing values compared to T1FLS. The steepest descent training algorithm was more effective than the heuristic one. Gaussian MFs were found to be more efficient than the triangular ones. The modified height defuzzifier was more effective than the height defuzzifier.
Hosseini (36)	The two different approaches for learning MFs and their footprint of uncertainty were based on the training dataset and the experts' experiences.	No	T2FLS demonstrated more efficiency in classification compared to T1FLS. Tuning T2FS parameters using the experts' opinion yielded the best results.
Chourasia (33)	-	No	T2FLS was more effective in classification than T1FLS.
Liu (38)	Two differently derived rule-bases (41) included the rule-base derived from the expert experience and an extracted rule-base based on the self-organizing fuzzy logic controller (SOFLC). Two implementations of T2FS (i.e., IT2FS and zSlice)	Yes	The extracted rule-based SOFLC showed better stability rather than the expert-derived rule-based SOFLC. Moreover, the precision and noise-resistance of Zslice associated with SOFLC were higher compared to T1 and IT2.
Mahmoodian (39)	-	No	T2FLS was more efficient than T1FLS in prediction. As for the number of rules, it was further better than T1FLS.

and found that Gaussian MFs were more efficient than the triangular ones and the modified height defuzzifier was more effective than the height defuzzifier. Further, some other studies investigated the effect of rule extraction methods and different T2FLS implementations (i.e., IT2FLS, IT2-US, IT2-UM, IT2USUM, and zslice) (34, 38) and reported that the extracted rule base was more efficient while different T2FLS implementations produced a comparable performance.

Therefore, answering the question regarding identifying the best method for optimizing type-2 fuzzy set (T2FS) would not be easy. Based on the results of some studies, parameter tuning by using the genetic algorithm (36) and fuzzy C-means (34) failed to improve the T2FLS performance. Furthermore, in another study conducted by Castillo and Melin (12), the use of genetic algorithm decreased.

"Uncertainty is regarded as an attribute of information" (42). The reason for uncertainties can be different such as various meanings of the words to different people, noisy training data, and noisy measurements (22). As a result, some studies (34, 35, 38) focused on the noise resistance and concluded that T2FLSs remain robust and consistent compared to T1FLS under any type of perturbations.

Nowadays, machine learning techniques are commonly used in the field of medicine and many clinical DSSs and ESs are built based on these techniques for detecting or diagnosing the disease (43-45). Accordingly, some researchers compared the performance of such systems with T2FLS and indicated that T2FLS was more efficient in classifying uncertain and impressed datasets (35,46,47).

The results of all the included papers revealed that even a simpler structure such as IT2FS and basic-type reduction algorithms could improve the diagnosis power in different medical domains. These findings are in consistency with the results presented in (40) which demonstrated that the superiority of type-2 over type-1 fuzzy logic was significant in classifying, clustering, and applying the pattern recognition.

Studies regarding T2FLS were rare and later employed in medical diagnosis compared to other areas such as data mining (40) and control (12). This could be due to the lack and complexity of well-prepared toolboxes or open-coded packages which further complicated the design of such systems. Therefore, the design of such tools facilitates the use of T2FLS in medical domains.

Conclusions

In general, medical decision making has always accompanied many uncertainties. That is why the fuzzy-based ES and DSSs are often used to help medical decision-making. The present research conducted a systematic review of different types of medical ES and DSS based on type-1 and type-2 fuzzy logic to investigate which one was more beneficial in medical diagnosis. The results revealed that the T2FLS outperformed T1FLS. The more effective performance of T2FLS confirmed their potential for modeling uncertainty and ambiguity. Considering the advantages of these systems, using T2FLS in diagnostic domains and various fields of medicine help to make decisions under uncertainty.

Conflict of Interests
Authors have no conflict of interests.

Ethical Issues
Not applicable.

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Supplementary Data
Supplementary file 1 contains Tables S1-S6.

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