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Decision support system for dementia patients using intuitionistic fuzzy similarity measure

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ABSTRACT

Similarity measure confirms the proximity of two objects to each other. This concept can be applied as fuzzy or intuitionistic fuzzy. There are lots of fuzzy similarity measures which had been extended to intuitionistic fuzzy similarity measure, with application in different domain. There is need to investigate these methods based on their application for further modification. Thus, the aim of this research is to modify existing fuzzy and intuitionistic fuzzy similarity measures, and apply it to cognitive domain for better performance.

Existing intuitionistic fuzzy similarity methods were extended and modified. These research showed that the existing methods had been applied to various domains, and researchers had improved and extended most fuzzy similarity measure to intuitionistic fuzzy similarity measure for optimal performance. Experiment showed that the proposed methods gives higher similarity value and lower processing time.

1. Introduction

Similarity is such that if all substrings from one argument of comparison are found in the other, the final similarity degree is evaluated as '1' which is interpreted as the identity of the two strings [19]. It plays a great role in problem solving including real life problems. Similarity measure is a scientific measure for determining the degree of similarity between two objects. In the same way distance measure is an important tool which describes the difference between two sets, and it is considered as a dual concept of similarity measure. Several approaches had been scientifically opined for evaluating similarity measure These measures are as many as the broad significance and applicability of similarity measure, whose suitability depends on the application areas like pattern recognition, hierarchical cluster analysis, approximate analogical reasoning, rule matching in fuzzy control, neural networks, query processing with different fuzzy semantics. Similarity measures are based on set operations like union, intersection, maximum difference, symmetric difference etc. Similarity measure may not be effective in some cases, especially where classification is paramount.

Sets represents elements or group of elements that has common properties [22]. A set is a tool that can be used to model real life problems. Set can be represented in various forms like crisp set, fuzzy set, and intuitionistic fuzzy set among others. A crisp set evaluates to either 0 or 1. It does not depict the degree of membership. Fuzzy set is preferred to crisp set because it represents how human mind perceives and manipulates information. Human mind process hedges like weak, moderate, strong, good, very good, tall, very tall, brilliant, more brilliant to mention but few. These hedges are modelled as linguistic property, for instance type-1 linguistic fuzzy set gives overlapping partition which leads from one set to another such as small, medium and big. Fuzzy considers only membership function, to improve this it is extended to intuitionistic fuzzy set which considers membership and vagueness of a set with respect to the universal set. Intuitionistic fuzzy sets make descriptions of the objective world become more realistic, practical, accurate and promising. It has diverse application to fields like data processing, identification of functional dependency relationship between concepts in data mining systems, approximate reasoning, pattern recognition, decision making, medical diagnosis, logic programming, sale analysis and new product marketing. Other diverse application include financial services, negotiation process, psychological investigations, machine learning, image processing, fuzzy risk analysis, fault tree analysis etc.

Measures of similarity between sets is an important tool for decision making, pattern recognition, machine learning etc. [33]. Intuitionistic fuzzy set similarity measure entails comparing the information carried by intuitionistic fuzzy set. Many similarity measures had been proposed in this context but a few of them comes from the well-known distance measures. Intuitionistic fuzzy similarity measure bridges the gap of similarity measures by classifying data based on linguistic variable quintuple.

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An area of psychology popularly known as cognition is an area that needs more attention, due to its relevance to keeping track of working memory capacity. Anagram and word cognition are not exempted in this context. It has to do with evaluating user's response to anagram or word scrabble task. Application of intuitionistic fuzzy set to this area is not common. Application of intuitionistic fuzzy similarity measure on anagram or word permutation would permit to test patient's sick situation. It would detect weather patient's response is okay or otherwise. The use of ply card for scrambling and unscrambling cards moved to storing set of words of a user's register in the database such that words are presented to users in scrambled form on the computer screen, users supplies the correct anagram. Researches had applied methods like brute-force, sorting, neighbourhood frequency i.e. the use of histogram or counting for verifying if supplied anagram or word are correct or not.

Thus, previous researches that modelled anagram cognition using crisp set, stated the membership or non-membership of word supplied by user without specifying the degree of membership. Previous model analysed anagram with respect to character entailment, whereby syllabic complexity is left out. This research seeks this further to model this problem using intuitionistic fuzzy set, which can depict the membership degree of words supplied, and also putting into consideration the vagueness of the anagram or word. The degree of membership would thus be based on type-1 linguistic fuzzy terms. Other characteristics such as character length, character entailment and syllabic complexity were used as characteristic variable to model anagram or word cognition. The degree of membership is measured by intuitionistic fuzzy similarity measure. The aim of this research is to test the estimated values of common existing similarity and distance measures in psychology domain, specifically cognition assessment, and come up with accurate similarity or distance measures of high values for the context.

2. Literature review

2.1. Similarity measures and applications

Similarity and distance functions are inter-related and recent researches have combined them to improve the performances of string processing for different applications [20]. Distance measures represent similarity measure as the proximity of observations to one another across the variable in cross variant. Distance measure is a measure of dissimilarity for continuous variables, where a larger value denotes less similarity, and is converted into a similarity measure by using an inverse relationship. The distance measure best represent the concept of proximity. It focuses on the magnitude of the values and portray similar cases of the objects that are closer together as the characteristics measured by metric variables are used, distance measure is the best method to assess similarity in clusters [5].

Shun Li and Jin Wen used pattern matching method to locate periods of operation from a historical data set. This was achieved by calculating the degree of similarity between historical data window and current snapshot data in order to locate periods of historical operation that are similar to current operating conditions. This enhanced the fault detection strategy [40].

An empirical study was done to reveal the behaviour of similarity measures when dealing with high dimensional data sets. A technical frame work was proposed to analyse, compare and bench mark the influence of different similarity measures on the result of distance based clustering algorithm. The relevance of this is to be able to identify suitable distance measures for data sets, and also facilitate a comparison and evaluation of newly proposed similarity or distance measures with traditional ones.

Aahul B. Diwate et al. did a systemic review on pattern matching. They stated that pattern matching concept was used in applications like: parser, spam filters, digital libraries, computational molecular biology, natural language processing, word processors [1].

Adio Akinwale and Adam Newiadomski explored the grammatical properties of generalized n-gram matching technique of similarity measures to find exact text in electronic computer applications. The authors proposed new similarity measures of improved generalized n-gram matching, which were tested and found to be universal. It was useful in words that could be derived from the word list as a group, and retrieve relevant medical terms from data base. One of the methods achieved best correlation of values for the evaluation of subjective examination. The authors proposed best similarity measures for closeness measurement of a particular domain [3].

Grigori, Alexander, Helena and David worked on soft similarity and soft cosine measure, they generalize the well-known cosine similarity measure in vector space model by introducing soft cosine measure. Authors proposed various formulas for exact or approximate calculation of soft cosine measure. Experiments shows that soft cosine measure gives better performance in case study entrance exam question answering task. One of the proposed measures is distance weighed cosine measure, it is calculated by averaging cosine similarity measure with hamming distance. Hamming distance counts how many features two vectors do not share, it decrease the similarity value of two vectors that share less features. This is because authors claim that cosine similarity is overly biased by features with higher values and does not care about how many features two vectors share [21].

2.2. Dissimilarity measures and applications

Dissimilarity coefficients, $d(S_1, S_2)$assess the degree to which patterns differ, S_1 and S_2 are string of character. Smaller values indicates closer or higher resemblance. Distances, differences, reciprocal of similarities, all constitute examples of dissimilarity measures.

Globally, similarity and dissimilarity are referred to as proximity measures $prox(S_1, S_2)$. Proximity values are positive numbers, its range being either bounded, such as the interval [0,1] or right unbounded: $prox(S_1, S_2) \in [0; +\infty]$. Similarity and dissimilarity measures have an inverse relationship [42].

Divergence measure has to do with discrimination and inferences. A new exponential divergence measure for intuitionistic fuzzy sets was proposed by Rajesh and Satish, [23], and applied to medical investigation and pattern recognition [26].

Rajesh and Satish, [24] proposed a divergence measure called intuitionistic fuzzy Jensen-Tsalli divergence measure, the essence of this is to measure the vagueness and underlying intuitionistic fuzzy sets. It was applied to pattern recognition problem and in diagnosis of some diseases.

Authors Rajesh and others proposed a new dissimilarity measure based on Jensen inequality and α-nominal divergence measure. This method was proposed to solve multi-attribute decision making (MADM), its performance is better than other well known MADM method [25].

Rajesh and Satish proposed a new suitable divergence measure for discrimination of two probability distributions. The proposed dissimilarity measure was applied to pattern recognition [27].

A suitable divergence measure was introduced to find the distance between two probability distributions, which is very relevant in problems based on discrimination and inferences. The divergence measure is based on Shanon entropy. Proposed measure was applied to pattern recognition, and performed better than existing divergence measures. Proposed measure was extended to intuitionistic fuzzy dissimilarity measure [28].

2.3. Intuitionistic fuzzy set

Fuzziness is a concept of human thinking and speaking [11], which deals with subjectivity and vague concept. This is in contrast to crisp set which gives a true or false concept Fuzzy sets expresses the imprecision of human thinking and behaviour by appropriate mathematical tools. A fuzzy set is built from a reference set called universe of discourse.

Let X be the universe of discourse

$X = \{x1, x2, ..., xn\}$

Fuzzy set A is in $X(A \subset X)$

$\{(xi, \mu(xi))\}$

Where $xi \in x\, and\, \mu A\colon x \rightarrow [0, 1]$ is the membership function of A.

$VA\colon x \rightarrow [0, 1]$ is a non-membership function of A.

Intuitionistic fuzzy set [IFS] is a tool for modelling real life problems like sale analysis, new product marketing, financial services, negotiation process, psychological investigation etc. [7].

One of the most important fact of human thinking is its ability to summarize information into fuzzy set that bear an approximation relation to the primary data. In fuzzy sets, a membership function assigns to each element of the universe of discourse a number from the unit interval to indicate the degree of belongingness to the set under consideration. In most cases, when the degree of membership is expressed, the degree of non-membership is not expressed. Atanassov introduced the concept of IFS to resolve this. Intuitionistic fuzzy set expresses the degree of membership and non-membership with a degree of hesitancy [11].

IFS within the same universe of discourse can be evaluated for similarity. Lots of researches had been conducted on review of intuitionistic similarity and distance measures, and also extension and generation of new measures for enhancement. Intuitionistic fuzzy set similarity measure had been applied extensively to decision making [34,38], pattern recognition [12,35] and linguistic summaries [6,38,39].

2.4. Related works on existing intuitionistic fuzzy similarity measures and application

A new similarity measure was generated from the distance. It was proven from the research that the new similarity measure is simpler and more easily interpreted than the existing methods, and is well suited to be used with linguistic variables. Proposed similarity measures were used to characterize the similarity between linguistic variables. The proposed similarity measures are reliable in applications with compound linguistic variables. Existing measures are not that friendly with fuzzy queries, and defining the degree of similarity between fuzzy sets. [10]

Xu Zeshui and J Chen reviewed distance and similarity measures of intuitionistic fuzzy set comprehensively. This shows that distance and similarity measures of IFSs are based on geometric distance model, and set theoretic approach. Their review indicates that the most widely used tools are Hamming distance, Euclidean distance and Hausdourff distance. The authors defined distance measures between interval valued intuitionistic fuzzy set based on extension of hamming distance, Normalized Hamming distance, weighted Hamming distance, Euclidean distance Normalized Euclidean Distance, Weighted Euclidean distance to interval value intuitionistic fuzzy set. Two other measures were defined by combining Hausdorff metric with weight Hamming distance and weight Euclidean distance. There were non-extended methods and new proposed methods that satisfied the conditions of the metric. These methods have some good geometric properties, that are not as fit as proposed ones [11].

Jun Ye considered the information carried by membership and non-membership degree in IFSs as a vector representation with two elements. The author proposed a cosine similarity measure and a weighted cosine similarity measure between intuitionistic fuzzy similarity based on the concept of cosine similarity measure for fuzzy sets. The proposed measures were compared with the existing measures to test for efficiency. Research revealed that cosine similarity measure is the most reasonable. This was demonstrated with application to pattern recognition and medical diagnosis. Existing similarity measures cannot carry out pattern recognition in some cases [36].

Jun Ye developed a decision making method with optimism, neutralism and pessimism by use of the Dice similarity measure based on the reduct IFSs of interval valued intuitionistic fuzzy set [IVIFS]. The author addressed the issue of decision making method using the dice similarity measure between the reduct IFSs of IVIFS to treat the influences of optimism neutralism and persimism on the multicriteria decision making problem. The author also proposed Jacccard, Dice and cosine similarity measures between intutionistic trapezoidal fuzzy numbers that are treated as continuous and applied to multicriteria group decision making problems. In fuzzy environment, information available is imprecise/uncertain, which is a torment for decision maker in the decision making process. Dice is preferred to Jaccard and cosine because it gives better result when second vector is undefined. Result of Dice similarity measure based on expected interval of trapezoidal fuzzy numbers was compared with Zeng's single expected value method with known criteria weight. This proposed method is simple and effective in the decision making problem with completely unknown criteria weights [37].

Chandresegar and Seithikurmer applied intuitionistic fuzzy network for Customer to Business decision making. The method attained intuitionistic fuzzy optimization for customer to business, and resolved multi decision making problem. The method reduced the complexity of the customers to take best decision with less effort. The method minimized the decision making criteria by means of assigning the range of sets with the contribution of similarity degree measures. The method optimized customer to business decision making, and optimize decision making problem. Its application to customer to business has not received much attention over the internet [34].

Dimitris and Elpikini proposed a novel approach to the construction of cognitive map based on intuitionistic fuzzy logic. The new model called intuitionistic fuzzy cognitive map extends fuzzy cognitive map by considering expert hesitancy in determination of causal relation between the concept of a domain. It's advantage over fuzzy cognitive map model is that it can incorporate additional information regarding the hesitancy of the experts in the definition of the cause-effect relations between the concepts involved in a domain. Intuitionistic fuzzy cognitive map is capable of modelling real world medical decision making tasks closer to the way human perceive them. Existing methods lack ability to perform approximate reasoning and handle incomplete information [13].

Boran and other authors proposed intuitionistic fuzzy TOPSIS method for evaluation of supplier's multi-criteria group decision. Intuitionistic fuzzy weighted averaging operator was utilized to aggregate individual opinions of decision making for rating the important criteria and alternative. The weight of each criteria was given as linguistic terms characterized by intuitionistic fuzzy numbers. Intuitionistic fuzzy operator was utilized to aggregate opinions of decision makers. Ideal solutions were calculated based on Euclidean distance. This approach created a huge success for multi-criteria decision making problems because of vague perception of decision maker's opinions. Proposed method is more suitable in this context because criteria provided by decision makers are difficult to precisely express by crisp data in the selection of supplier problem [4].

Chao-Ming et al. proposed a new similarity measure formula for intuitionistic fuzzy set induced by Sugeno integral. This was compared with other existing similarity measures for intuitionistic fuzzy set and Sugeno performs better than existing ones, because it provides an operation similar to expected value. The proposed similarity measure uses a robust clustering method to recognize the pattern of intuitionistic fuzzy set. There was no existing method that considered Sugeno integral technique [12]

Ejagwa et al. authors showed a novel application of intuitionistic fuzzy set to model the uncertainty and vagueness in career determining using normalized Euclidean distance method to measure the distance between each student and each career respectively. Career was prescribed based on smallest distance between each student and each career. Existing career determination tool lacked the vagueness and hesitancy factor. Career determination using intuitionistic fuzzy set gave accurate and proper career choice based on academic performance [7].

Table 1
Intuitionistic Fuzzy similarity values for pattern/text with unequal length.

S/No.	Pattern/Text	IFV [jaccard, modified canbera, modified bigram]	IFV [jaccard, modified canbera, dice]
1	NAILS/NAIL	[0.8, 0.2] [0.8, 0.2] [0.25, 0.75]	[0.8, 0.2] [0.8, 0.2] [0.14, 0.86]
2	Gallery/Real	[0.57, 0.43] [0.667, 0.333] [0.833, 0.167]	[0.57, 0.43] [0.667, 0.333] [0.78, 0.22]
3	ANTLER/LATER	[0.83, 0.167] [0.83, 0.167] [0.8, 0.2]	[0.83, 0.167] [0.83, 0.167] [0.78, 0.22]
4	ANTLER/RENT	[0.667, 0.333] [0.667, 0.333] [0.8, 0.2]	[0.667, 0.333] [0.667, 0.333] [0.75, 0.25]
5	RENTAL/TEN	[0.5, 0.5] [0.5, 0.5] [0.8, 0.2]	[0.5, 0.5] [0.5, 0.5] [0.714, 0.286]
6	RENTAL/NET	[0.5, 0.5] [0.5, 0.5] [1.0, 0.0]	[0.5, 0.5] [0.5, 0.5] [1.0, 0.0]
7	RENTAL/RENT	[0.67, 0.33] [0.67, 0.33] [0.4, 0.6]	[0.67, 0.33] [0.67, 0.33] [0.25, 0.75]
8	GALLERY/GALL	[0.57, 0.43] [0.5, 0.5] [0.5, 0.5]	[0.57, 0.43] [0.5, 0.5] [0.33, 0.67]
9	GALLERY/ALL	[0.43, 0.57] [0.33, 0.67] [0.67, 0.33]	[0.43, 0.57] [0.33, 0.67] [0.50, 0.50]
10	BROAD/ROAD	[0.80, 0.20] [0.80, 0.20] [0.25 , 0.75]	[0.80, 0.20] [0.80, 0.20] [0.75, 0.25]
11	LARGELY/LAY	[0.43, 0.57] [0.50, 0.50] [0.83 , 0.17]	[0.43, 0.57] [0.50, 0.50] [0.75, 0.25]
12	LARGELY/GEAR	[0.57, 0.43] [0.67, 0.33] [0.67 , 0.33]	[0.57, 0.43] [0.67, 0.33] [0.56, 0.44]
13	ACRE/ACE	[0.75, 0.25] [0.75, 0.25] [0.67 , 0.33]	[0.75, 0.25] [0.75, 0.25] [0.60, 0.40]
14	ACRE/ARE	[0.75, 0.25] [0.75, 0.25] [0.67 , 0.33]	[0.75, 0.25] [0.75, 0.25] [0.60, 0.40]
15	Alter/Tar	[0.6, 0.4] [0.6, 0.4] [1.0, 0.0]	[0.6, 0.4] [0.6, 0.4] [1.0, 0.0]
16	Alter/Tear	[0.8, 0.2] [0.8, 0.2] [0.75, 0.25]	[0.8, 0.2] [0.8, 0.2] [0.71, 0.29]
17	Wean/An	[0.5, 0.5] [0.5, 0.5] [0.667, 0.333]	[0.5, 0.5] [0.5, 0.5] [0.5, 0.5]
18	SLAIN/SIN	[0.60, 0.40] [0.60, 0.40] [0.75, 0.25]	[0.60, 0.40] [0.60, 0.40] [0.67, 0.33]
19	SLAIN/AN	[0.40, 0.60] [0.40, 0.60] [1.0 , 0.0]	[0.40, 0.60] [0.40, 0.60] [1.0 , 0.0]
20	SLAIN/IN	[0.40, 0.60] [0.40, 0.60] [0.75 , 0.25]	[0.40, 0.60] [0.40, 0.60] [0.60 , 0.40]
21	ACRITICAL/CRITIC	[0.67, 0.33] [0.67, 0.33] [0.38 , 0.63]	[0.67, 0.33] [0.67, 0.33] [0.30 , 0.70]

2.5. Effect of cognition task on dementia patients

One of the tools used in psychology to investigate cognitive processes is anagram task. Adam et al. made a useful contribution to measurement models of human cognitive problem solving [2]. Robert, [29] worked on anagram software for cognitive research, the software provides different modes of operation: interactive and automatic. All possible anagrams are identified using sorting technique, and the lemma frequency information for all orthographically identical word forms is summed and printed. The research did not consider bi-gram frequency in anagrams.

Ktori presents series of orthographic measures for psycholinguistic research. Orthographic measure factors are word length, word-form frequency, lemma frequency, neighbourhood density, neighbourhood frequency, transposition neighbours [15]. Anagram tasks are frequently used in behavioural research to investigate a wide array of cognitive phenomena. Most prominently, they are used to study the cognitive stages involved in problem solving, specifically insight [29]. Researches on anagram had explored different methods for detecting orthographic similarity between anagrams. Methods like Brute force [18], Sorting [29], Bubble sort [9], Neighbourhood frequency of counting and histogram [14,16,17], have been used to detect anagram.

In previous researches on the use of anagram task for cognition there are drawbacks such as restriction of anagram letters to five [30,32]. There is no standard software for anagram detection, and statistical analysis tool was only used. [14,16]. Oral conduction of anagram test, no standard software was developed [31].

The existing cognitive software does not incorporate bigram orthographic structure. It only uses sorting detection technique, and there was no syllabic structure relationship detection [29]. It makes use of bigram frequency with bubble sort anagram detection without consideration of position of characters [9]. The processing time of Anagram detection is very high [9,18]

3. Method

3.1. Metrics and dissimilarity property

A distance or metric, d, is a real valued function of two points that obeys the following properties:

$$1.\ Positivity: \quad d(S_1,S_2) \geq 0\ and\ d(S_1,S_2)=0 \Leftrightarrow S_1 = S_2 \tag{1}$$

$$2.\ Symmetryproperty: \quad d(S_1,S_2) = d(S_2,S_1) \tag{2}$$

$$3.\ Triangleinequity: \quad d(S_1,S_3) \leq d(S_1,S_2) + d(S_2,S_3) \tag{3}$$

$Thepositivitysubsumesthefollowingtwodistanceaxioms:$

$$1.\ Consistenceofself-similarity: \quad d(S_1,S_1) = d(S_2,S_2) \tag{4}$$

$$2.\ Minimalityofself-similarity: \quad d(S_1,S_2) \leq d(S_2,S_1) \tag{5}$$

3.2. Similarity as a relation

$$AsimilarityrelationonasetUisafuzzybinaryrelation \quad R: U \times R \to [0,1]\ Holdingthefollowingproperties: \quad Reflexive: \quad R(x,x) = 1\ for\ any\ x \in U \tag{6}$$

$$Symmetric: \quad R(x,y) = R(y,x)\ for\ any\ x,y \in U \tag{7}$$

$$Transitive: \quad R(x,z) \geq R(x,y) \Delta R(y,z) for\ any\ x,y,z \in U \tag{8}$$

$W here\ the\ operator\ is\ an\ arbitrary\ t-norm: [0,1] \times [0,1] \to [0,1]$

It is a binary operator which is commutative, associative, monotone in both arguments and$1 \Delta x = x$. Hence it subsumes the classical two valued conjuction operator. A relation of similarity x_1 *and* x_2 is written as $x_1 \sim x_2$ [3].

3.3. Concept of intuitionistic fuzzy similarity measure

Let X be a nonempty set. An intuitionistic fuzzy set A in X is an object having the form:

$$A = \{(x, \mu_A(x), V_A(x)) : x \in X\}$$

Where $\mu_A(x)$, $V_A(x)$: $x \to [0, 1]$ define respectively the degree of membership and nonmembership of the element $x \in X$to the set A, which is the subset of X.

Also, for every element $x \in X$, $0 \leq \mu_A(x), V_A(x) \leq 1$.

Thus, $\pi_A(x) = 1 - \mu_A(x) - V_A(x)$ is called the intuitionistic fuzzy set index or is called hesitation margin of $x$in A. $\pi_A(x)$ is the degree of indeterminacy of $x \in X$ to the IFS A and $\pi_A(x) \in [0, 1]$ i.e. $\pi_A(x)$: $x \to [0, 1]$ and $0 \leq \pi_A(x) \leq 1$ for every $x \in X$ [41].

Table 2
Intuitionistic Fuzzy similarity measure [IFSM] of pattern/text with unequal lengths.

Pattern/Text	Linguistic Variable (anagram)	Euc. New Bigram	Euc. Dice	Can. New Bigram	Can. Dice	Ham. New Bigram	Ham. Dice
NAILS/NAIL	Simple	0.710	0.680	0.728	0.703	0.387	0.347
	Moderate	0.816	0.749	0.896	0.751	0.720	0.424
	Hard	0.739	0.649	0.833	0.803	0.577	0.518
Gallery/Real	Weak	0.73	0.77	0.748	0.762	0.419	0.442
	Moderate	0.91	0.94	0.896	0.913	0.720	0.760
	Hard	0.93	0.93	0.876	0.880	0.674	0.681
ANTLER/LATER	Simple	0.586	0.596	0.656	0.660	0.282	0.288
	Moderate	0.862	0.869	0.801	0.807	0.514	0.525
	Hard	0.998	0.997	0.978	0.971	0.936	0.916
ANTLER/RENT	Weak	0.733	0.76	0.731	0.74	0.393	0.413
	Moderate	0.95	0.97	0.904	0.913	0.716	0.753
	Hard	0.95	0.95	0.895	0.89	0.766	0.729
RENTAL/TEN	Weak	0.835	0.888	0.819	0.843	0.549	0.598
	Moderate	0.942	0.835	0.875	0.819	0.670	0.549
	Hard	0.835	0.803	0.819	0.766	0.549	0.449
RENTAL/NET	Weak	0.684	0.684	0.766	0.766	0.449	0.449
	Moderate	0.835	0.835	0.819	0.819	0.549	0.549
	Hard	0.803	0.803	0.766	0.766	0.449	0.449
RENTAL/RENT	Weak	0.867	0.848	0.837	0.796	0.586	0.505
	Moderate	0.952	0.877	0.895	0.851	0.716	0.616
	Hard	0.823	0.713	0.801	0.762	0.514	0.442
GALLERY/GALL	Weak	0.952	0.957	0.883	0.893	0.690	0.713
	Moderate	0.979	0.921	0.927	0.876	0.795	0.673
	Hard	0.793	0.697	0.759	0.717	0.436	0.369
GALLERY/ALL	Weak	0.926	0.985	0.886	0.937	0.696	0.822
	Moderate	0.900	0.895	0.845	0.836	0.604	0.584
	Hard	0.689	0.640	0.723	0.685	0.379	0.320
BROAD/ROAD	Weak	0.710	0.680	0.728	0.703	0.387	0.347
	Moderate	0.816	0.749	0.779	0.751	0.472	0.424
	Hard	0.739	0.649	0.833	0.803	0.577	0.518
LARGELY/LAY	Weak	0.820	0.875	0.829	0.852	0.570	0.619
	Moderate	0.910	0.940	0.845	0.869	0.604	0.656
	Hard	0.795	0.795	0.791	0.787	0.495	0.486
LARGELY/GEAR	Weak	0.842	0.882	0.791	0.820	0.495	0.486
	Moderate	0.990	0.993	0.947	0.954	0.494	0.552
	Hard	0.916	0.878	0.848	0.817	0.850	0.869
ACRE/ACE	Weak	0.729	0.752	0.725	0.741	0.380	0.407
	Moderate	0.952	0.956	0.885	0.905	0.693	0.741
	Hard	0.977	0.956	0.925	0.905	0.972	0.741
ACRE/ARE	Weak	0.729	0.752	0.725	0.741	0.380	0.407
	Moderate	0.952	0.956	0.885	0.905	0.693	0.741
	Hard	0.977	0.956	0.925	0.905	0.972	0.741
SLAIN/SIN	Weak	0.816	0.860	0.779	0.801	0.472	0.513
	Moderate	0.978	0.996	0.951	0.978	0.861	0.935
	Hard	0.921	0.907	0.861	0.837	0.638	0.587
SLAIN/AN	Weak	0.698	0.698	0.819	0.819	0.549	0.549
	Moderate	0.787	0.787	0.766	0.766	0.449	0.449
	Hard	0.698	0.698	0.717	0.717	0.368	0.368
SLAIN/IN	Weak	0.884	0.961	0.890	0.935	0.705	0.819
	Moderate	0.902	0.923	0.833	0.875	0.577	0.670
	Hard	0.724	0.698	0.754	0.717	0.427	0.368
ACRITICAL/CRITIC	Weak	0.867	0.843	0.830	0.791	0.572	0.495
	Moderate	0.942	0.865	0.887	0.845	0.698	0.605
	Hard	0.806	0.698	0.795	0.757	0.501	0.434
	Sum	45.606	44.94	44.71	44.22	31.59	30.41
	Average	0.84456	0.8323	0.8278	0.8189	0.5849	0.5631

3.3.1. *Conditions for intuitionistic fuzzy similarity measure*

A mapping S: $IFS \times IFS \rightarrow [0, 1], S(A, B)$ is said to be the degree of similarity between $A \in IFSs(x)\, and\, B \in IFSs(x)$, if $S(A, B)$ satisfies the following condition:

Let S be real function S such that:

$IFS \times IFS \rightarrow R^{+}.S$ is called a similarity measure if it satisfies the following conditions [11]:

$$IS1 - 0 \leq S(A,B) \leq 1$$
$$IS2 - S(A,B) = 1\ if\ and\ only\ if\ A = B$$
$$IS3 - S(A,B) = S(B,A)$$
$$IS4 - S(A,C) \leq S(A,B)\, and\, S(A,C)$$
$$if\ A \subseteq B \subseteq C,\ C \in IFSs(X)$$

3.3.2. *Properties of intuitionistic fuzzy relation*

Reflexive:

An intuitionistic fuzzy relation $R(x_1 \times x_2)$ is said to be reflexive if

$$R(x_1 \times x_2)$$
$$\forall x_1, x_2 \in X, \mu R(x_1, x_1) = 1$$

Symmetric: if $x_1, x_2 \in X$

$$\mu R(x_1, x_2) = \mu R(x_2, x_1)\, and$$
$$VR(x_1, x_2) = VR(x_2, x_1)$$

Transitive:

If R^2 is a subset of R where

$$R^2 = R\, o\, R$$

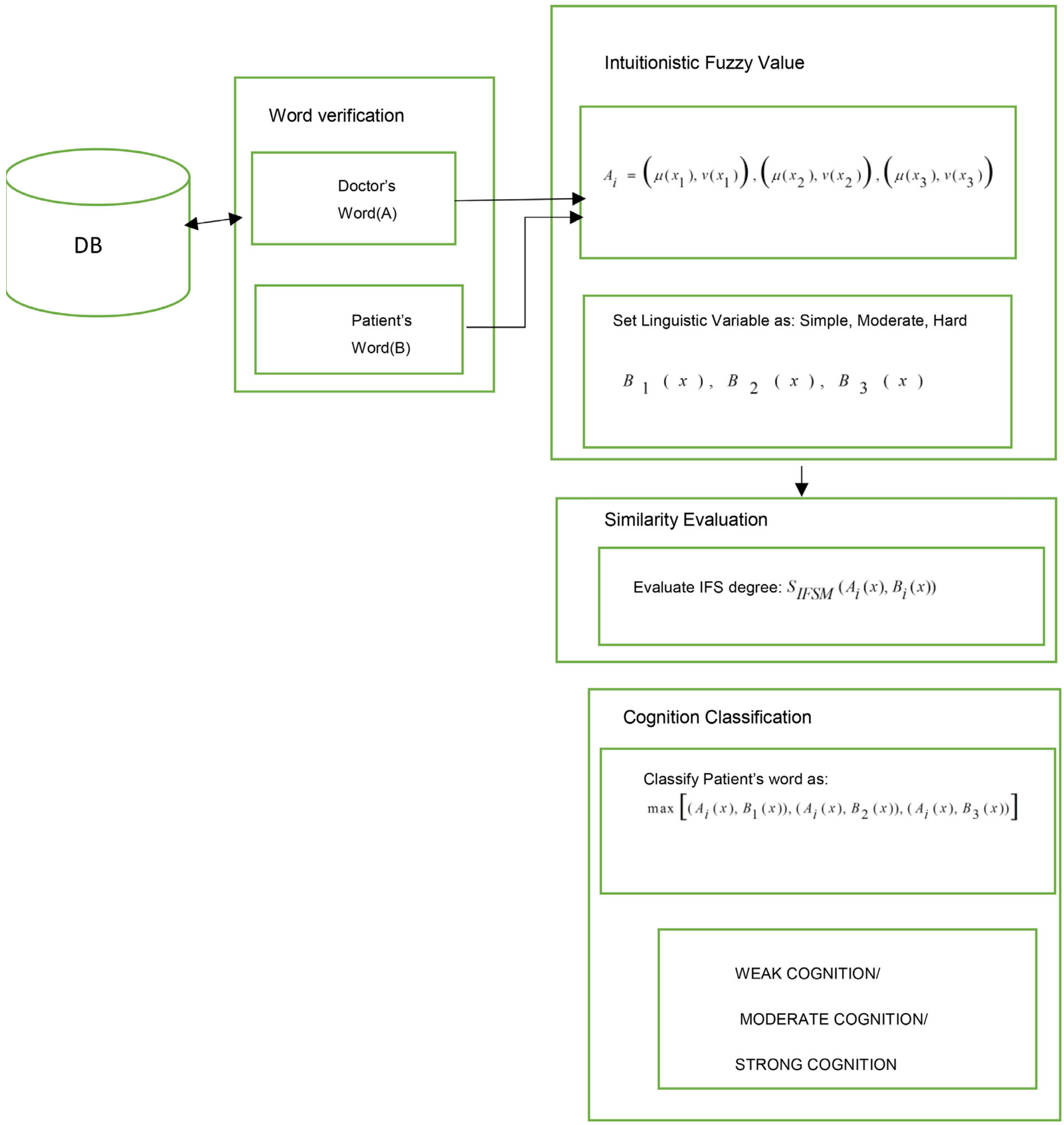

Fig. 1. Representation of the working principle of Cognition Assessment Decision Making.

3.4. Algorithm for intuitionistic fuzzy cognition assessment decision making

1 Calculate the system word and patient's word for characteristic featurex_1: character length using modified Canberra similarity and distance measures for determination of membership and non-membership μ, v respectively.

$$\mu(x_1) = 1 - \frac{|A| - |B|}{|A|} \tag{9}$$

$$v(x_1) = \frac{|A| - |B|}{|A|} \tag{10}$$

2 Calculate the system word and patient's word for characteristic featurex_2: character entailment using Jaccard similarity and distance measures for determination of membership and non-membership μ, v respectively.

$$\mu(x_2) = \frac{|A \cap B|}{|A \cup B|} \tag{11}$$

$$v(x_2) = 1 - \frac{|A \cap B|}{|A \cup B|} \tag{12}$$

3 Calculate the system word and patient's word for characteristic featurex_3: character entailment using modified Bigram (proposed method) distance and similarity measures for determination of membership and non-membership μ, v respectively.

$$\mu(x_3) = 1 - \frac{bigram(|A \cap B|)}{\max(|bigramA|, |bigramB|)} \tag{13}$$

$$v(x_3) = \frac{bigram(|A \cap B|)}{\max(|bigramA|, |bigramB|)} \tag{14}$$

Table 3
Processing Time of IFSM with modified bigram and IFSM dice for selected text and pattern.

S/No.	Euclidean Dice(ms)	Euclidean Bigram (ms)	Canberra Dice (ms)	Canberra Bigram (ms)	Hamming Dice (ms)	Hamming Bigram (ms)
1	1.00	0.992	1.00	1.00	0.999	1.00
2	1.00	0.999	1.00	1.00	0.999	0.999
3	1.00	0.995	0.999	1.00	1.00	1.00
4	1.00	0.999	1.015	0.999	1.00	1.00
5	0.999	0.997	1.00	0.999	1.00	0.999
6	0.999	0.998	1.000	1.00	1.00	1.00
7	1.00	0.999	1.000	0.999	1.00	1.00
8	1.00	1.015	0.999	1.00	1.015	1.00
9	1.015	1.015	1.000	1.00	1.00	1.015
10	0.999	0.999	1.000	1.00	1.00	0.999
11	1.00	0.999	1.000	1.001	1.00	1.015
12	1.00	0.999	1.000	0.999	1.015	1.00
13	1.00	1.013	1.015	1.015	1.00	0.999
14	1.00	0.997	1.00	1.015	1.015	1.00
15	1.00	0.997	1.015	1.00	1.00	1.015
Sum	15.012	15.003	15.043	15.027	15.043	15.031
Avg	1.8765	1.8754	1.8804	1.8784	1.8804	1.8789
Cost	0.450072	0.443805	0.44026	0.435067	0.311071	0.299727

4 Intuitionistic fuzzy value is generated as:

$$A_i(x) = \left(\mu(x_1), \upsilon(x_1)\right), \left(\mu(x_2), \upsilon(x_2)\right), \left(\mu(x_3), \upsilon(x_3)\right)$$

5 Set the linguistic variables as:

$$\begin{aligned} &Simple\ :\ [0.4,\ 0.6]\,[0.4,\ 0.6]\,[0.4, 0.6]\ =\ B_1(x) \\ &Moderate\ :\ [0.6,\ 0.4]\,[0.6,\ 0.4]\,[0.6, 0.4]\ =\ B_2(x) \\ &Hard\ :\ [0.8,\ 0.2]\,[0.8,\ 0.2]\,[0.8, 0.2]\ =\ B_3(x) \end{aligned}$$

6 Intuitionistic fuzzy degree is evaluated between the set IFV and generated IFV for linguistic variables:

$$S_{IFSM}(A_i(x), B_i(x))$$

7 The patient's input is classified as IFV and linguistic variable with highest intuitionistic fuzzy similarity value:

$$\max\left[(A_i(x), B_1(x)), (A_i(x), B_2(x)), (A_i(x), B_3(x))\right]$$

Equations 9 – 14 are for converting Doctor's and Patient's Words to IFV. Eqs. (10) and (14) are modified Canberra and Dice respectively. The modified methods gives higher IFV values, emphasis is more on the modified method in Eq. (14) i.e. modified bigram because it is used to measure the characteristic word permutation. This characteristic is added to character entailment and length measure, to improve word cognition measure. Step 5 shows the threshold for classifying IFSMs, this is based on Evan's calibration. Steps 6 and 7 indicates how IFV are converted to IFSM and classified to simple, moderate and hard.

3.5. Modified and extended intuitionistic fuzzy distance measures for classification of intuitionistic fuzzy values of text and pattern

The formulas for conversion of strings into intuitionistic fuzzy values above in Eqs. (9)-14 will be adapted into IFSM.Anagram detection will be broadened by improving detection from [True/False] to Type-1 Anagram Detection i.e. using the linguistic terms A1- Not Anagram, A2- weak Anagram, A3- Average Anagram and A4- Hard Anagram. The IFV obtained from Eq. (9)-14 will be classified to type-1 anagram using modified and extended methods in Eqs. (18)–(20).

The similarity measure between IFS A and B as follows:

$$\begin{aligned} &S(A,B) = \frac{f(d_H(A,B)) - f(1)}{f(0) - f(1)} \\ &S(A,B)\ satisfies\ the\ properties\ of\ similarity\ measure \\ &The\ simplest\ f\ that\ can\ be\ chosen\ is\ : \\ &f(x)\ =\ 1 - x \end{aligned} \tag{15}$$

Similarity measure between A and B is denoted as follows:

$$\begin{aligned} &S(A,B)\ =\ 1 -\ d_H(A,B) \\ &d_H(A,B)\ =\ \left[\sum_{i=1}^{n} \left|a_i - b_i\right|^H\right]^{1/H} \\ &This\ denotes\ distance\ function,\ it\ represents\ the\ Hth \\ &order\ between\ points\ a\ and\ b. \\ &When\ H\ =\ 1\ and\ H\ =\ \infty \\ &d_1(A,B)\ =\ \left[\sum_{i=1}^{n} \left|a_i - b_i\right|^H\right] \\ &d_\infty(A,B)\ =\ \max_i\ \left|a_i - b_i\right| \end{aligned} \tag{16}$$

Also an exponential operation is highly useful in dealing with a similarity relation. Thus

$$f(x) = e^{-x} \tag{17}$$

3.5.1. Modified Euclidean intuitionistic fuzzy similarity measure based on exponential function

$$\begin{aligned} &E_{IFS}(A,B) = \sum_{i=1}^{n} \frac{\left|\mu_A(x_i) - \mu_B(x_i)\right|^2 + \left|V_A(x_i) - V_B(x_i)\right|^2}{2(\left|\mu_A(x_i) + \mu_B(x_i)\right| + \left|V_A(x_i) + V_B(x_i)\right|)} \\ &S_{new1}(A,B) = e^{-E_{IFS}(A,B)} \end{aligned} \tag{18}$$

3.5.2. Modified Canberra intuitionistic fuzzy similarity measure based on exponential function

$$\begin{aligned} &CA_{IFS}(A,B) = \sum_{i=1}^{n} \frac{\left|\mu_A(x_i) - \mu_B(x_i)\right| +\ \left|V_A(x_i) - V_B(x_i)\right|}{\left|\mu_A(x_i) + \mu_B(x_i)\right|\ +\ \left|V_A(x_i) + V_B(x_i)\right|} \\ &CA_{IFS}(A,B)\ -\ represent\ Canberra\ Intuitionistic\ Fuzzy\ distance\ measure \\ &S_{new2}\ =\ e^{-CA_{IFS}(A,B)} \end{aligned} \tag{19}$$

3.5.3. 3.11.3 modified hamming intuitionistic fuzzy similarity measure based on exponential function

$$\begin{aligned} &H_{IFS}(A,B) = \frac{\sum_{i=1}^{n} \left|\mu_A(x_i) - \mu_B(x_i)\right| + \left|V_A(x_i) - V_B(x_i)\right|}{2} \\ &S_{new3} = e^{-H_{IFS}(A,B)} \\ &H_{IFS}(A,B) -\ Hamming\ intuitionistic\ fuzzy\ similarity\ measure \end{aligned} \tag{20}$$

4. Result

Previous researches explored the use of anagram detection techniques like brute force, sorting, counting and histogram with

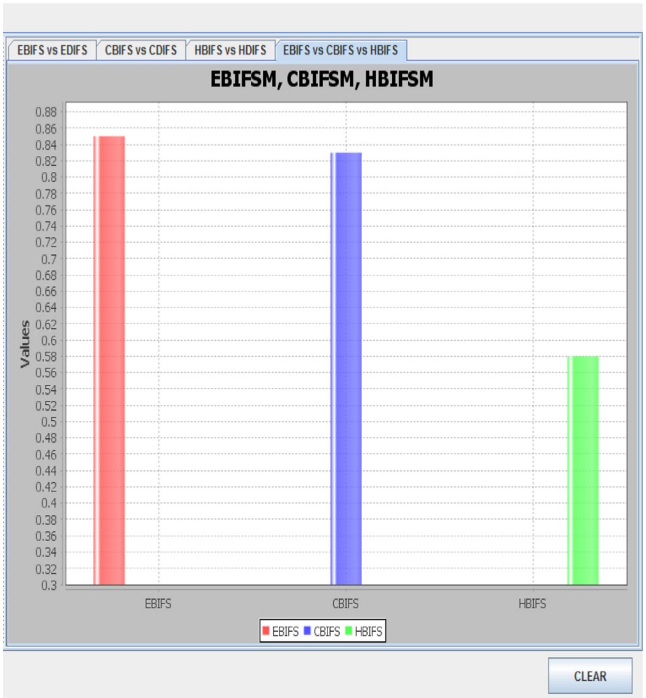

Fig. 2. EBIFSM, CBIFSM, HBIFSM.

complexitiesO(n!),O(n^2),O(n), O(n)respectively. They all returns crisp values i.e. gives information on the pattern and text been anagram or not anagram. The only difference is their processing time. Old methods compares pattern and text, to return crisp value i.e. 0 or 1, it returns true or false without giving any idea about the level of membership/ non-membership. The existing algorithms for anagram detection method such as sorting, counting, neighbourhood frequency considers character length and character entailment. These characteristics cannot reveal the degree of anagram membership i.e. strong/moderate/simple. The best existing anagram detection technique is counting, it gives the same crisp value like other techniques but runs at a faster processing time.

Similarity values for existing and proposed methods:

Experiment was performed using 250 words, some of these were represented on Tables 1 and 2. The IFV generated for character length, entailment and permutation of character using modified Canberra, Jaccard, Dice (old method for permutation of characters) and Modified bigram (modified dice proposed method for permutation of characters) as stated in algorithm 3.4 steps 1–3, Table 1 depicts generated IFV for some data set. IFVs were passed for classification to proposed IFSMs Exponential base Euclidean, Canberra and Hamming in steps 4–7, Table 2 depicts this. All these steps are depicted in Fig. 1. Similarity values of existing methods are lower than that of proposed methods, the same goes with the cost which is determined by similarity value with respect to processing time, Table 3 depicts processing time. The proposed method IFSMs Exponential base Euclidean with modified bigram gives the highest similarity value and cost, hence the most effective value, followed by Canberra and Hamming with modified bigram. Fig. 2 depicts these, Table 6 shows the processing time of the existing and proposed methods respectively .

$$cost = \frac{value}{time} \tag{21}$$

5. Conclusion

The measure of patient's word cognition is dependent on the text supplied by the patient. The character length, entailment and syllabic complexity relationship between the text/ pattern of patient/doctor's randomly generated word is measured by selected and modified similarity measures of the text. These measures gives the intuitionistic fuzzy value of text supplied by patient. The generated IFV is classified using type-1 intuitionistic fuzzy threshold by author in [8] This classifies into simple, moderate and hard.

The tool intuitionistic fuzzy similarity measures gives a better word cognition measure compared to existing crisp measure. This is to enhance classification to type-1 technique in contrast to Boolean method. Also the Boolean/ crisp method is restricted to character length and entailment in feature. Thus it is not easy to determine the relationship between pattern/ text.

Previous approaches to orthographic similarity of anagrams were based on Brute force, Sorting, Orthographic neighbourhood frequency. User defined vocabularies and orthographic parameters were used for orthographic verification. Experiment revealed that the measures has the capacity to test for orthographic similarity of anagram through character entailment verification only. The drawback thus, lies in lack of character position verification and syllabic relationship test which are very vital while testing user's working memory capacity i.e. the wellness of the state of mind. These draw backs can be adapted into an enhanced anagram/scrabble measure through intuitionistic fuzzy set similarity measures, existing and modified IFSM measures were tested with numerical examples. These shows that a more accurate detection and classification can be derived through IFSM of anagrams/scrabble words.

References

[1] Aahul B. Diwate, Satish J. Alaspurkar, Systemic review on pattern matching, in: Proceedings of the International Journal of Advanced Research in Computer Science and Software Engineering, 2013.
[2] J.W. Adams, M. Stone, R.D. Vincent, S.J. Muncer, "The role of syllables in anagram solution: a Rasch analysis, J. Gen. Psychol. 138 (2) (2011) 94–109.
[3] Adio Akinwale, Nieweiadomski Adam, Efficient similarity measure for text matching, J. Appl. Comput. Sci. 23 (1) (2015) 21.
[4] F.E. Boran, S. Genç, M. Kurt, D. Akay, A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method, Expert Syst. Appl. 36 (8) (2009) 11363–11368.
[5] S. Dahal, Effect of different measures in result of cluster analysis, Aalto University School of Engineering, 2015.
[6] M. Dziedzic, S. Zadrożny, J. Kacprzyk, Towards bipolar linguistic summaries: a novel fuzzy bipolar querying based approach, in: Proceedings of the IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2012.
[7] P.A. Ejagwa, A.J. Kubo, O.M. Joshua, Intuitionistic fuzzy set and it' s application in career determination via normalized euclidean distance method, Eur. Sci. J. 10 (15) (2014).
[8] J.D. Evan, Straight Forward Statistics For Behavioral Sciences, Brooks 1 Cole Publishing, Pacific Groove, CA, 1996.
[9] J. Henin, E. Accorsi, P. Cho, W. Tabor, Extraordinary natural ability: anagram solution as an extension of normal reading ability, in: Proceedings of the 31st Annual Meeting of the Cognitive Science Society, 2009.
[10] Wen-Liang Hung, Miin-Shen Yang, Similarity measures of intuitionistic fuzzy sets based on Hausdorff distance, Pattern Recognit. Lett. 25 (14) (2004) 1603–1611.
[11] W.L. Hung, M.S. Yang, On similarity measures between intuitionistic fuzzy sets, Int. J. Intell. Syst. 23 (3) (2008) 364–383.
[12] Chao-Ming Hwang, Miin-Shen Yang, Wen-Liang Hung, Ming-Gay Lee, A similarity measure of intuitionistic fuzzy sets based on the Sugeno integral with its application to pattern recognition, Inf. Sci. (Ny) 189 (2012) 93–109.
[13] D.K. Lakovidis, E. Papageorgiou, Intuitionistic fuzzy cognitive maps for medical decision making, IEEE Trans. Inf. Technol. Biomed. 15 (1) (2011) 100–107.
[14] Lequex, C.P.a. (2004). anagram effect in visual word recognition, https://archives-onverts.fr/hat0042984.
[15] Ktori Maria, J.B. Walter, Nicola Van Heuven, J. Ptchford, Greek Lex: a lexical database of modern greek, Behav. Res. Methods 40 (3) (2008) 773–783.
[16] A.F. Mary, J.F. Hugh, W. Alice, R. Leslie, Anagram solving: does effort have an effect, Memory Cognit. 17 (6) (1989) 755–758.
[17] E.S. Menelaos, T.P. Chris, Linguistic effect on anagram solution: the case of transparent language, World Class J. Educ. 3 (4) (2013) 41–51.
[18] Timothy R. Jordan, Axel Monteiro, Generating anagrams from multiple core strings employing user defined vocabularies and orthographic parameters, Behav. Res. Methods, Instrum. Comput. 35 (1) (2003) 129–135.
[19] A. Niewiadomski, J. Ochelska, P. Szczepaniak, "Interval-valued linguistic summaries of databases, Control Cybern 35 (2006) 415–443.
[20] Akinwale Adio, Niewiadomski Adam, Effective similarity measure in electronic testing at programming languages, J. Appl. Comput. Sci. (2012).
[21] Sidrov Grigori, Gelbukh Alexander, Gomez-Adorno Helena, Pinto David, Soft similarity and soft cosine measure: similarity of features in vector space model, Comput. Syst. 18 (3) (2014) 14.

[22] Laijun Luo, Haiping Ren, "A new similarity measure for intuitionistic fuzzy set and application in MADM problem, AMSE J. -Ser. Adv. A 59 (1) (2016) 20.
[23] Rajesh Joshi, Satish Kumar, Exponential Jensen intuitionistic fuzzy divergence measure with applications in medical investigation and pattern recognition, Soft Computing 23 (18) (2018) 8995–9008, doi:10.1007/s00500-018-3505-2.
[24] Rajesh Joshi, Satish Kumar, "Jensen-Tsalli's intuitionistic fuzzy divergence measure and its applications in medical analysis and pattern recognition, International J. Uncertaint. Fuzziness Knowl. Based Syst. 27 (1) (2019) 145–169, doi:10.1142/S0218488519500077.
[25] Rajesh Joshi, Satish Kumar, Deepak Gupta, Hans Kaur, A Jensen-α-norm dissimilarity measure for intuitionistic fuzzy sets and its applications in multiple attribute decision making, Int. J. Fuzzy Syst. 20 (4) (2017) 1188–1202, doi:10.1007/s40815-017-0389-8.
[26] Rajesh Joshi, Satish Kumar, An exponential Jesen fuzzy divergence measure with applications in multiple attribute decision making, Hindawi, Math. Probl. Eng. (2018), doi:10.1155/2018/4342098.
[27] Rajesh Joshi, Satish Kumar, A dissimilarity jensen-shannon divergence measure for intuitionistic fuzzy sets, Int. J. Intell. Syst. 33 (11) (2018) 2216–2235, doi:10.1002/int.22026.
[28] Rajesh Joshi, Satish Kumar, A dissimilarity measure based on jensen-shannon divergence measure, Int. J. Gen. Syst. 48 (3) (2018) 280–301, doi:10.1080/03081079.2018.1552685.
[29] D.V. Robert, K.G. Yael, A.T. Debra, "Anagram software for cognitive research that enables specification of Pscholinguistic variables, Behav. Res. Methods, Instrum. Comput. (2006), doi:10.3758/BF0319558738(2).
[30] L.R. Norvick, S...J. Sharman, Type based bigram frequencies for five letter words, Behav. Res. Methods, Instrum. Comput. (2004), doi:10.3758/BF0319558736(3):397-401.
[31] W. Sandra, M. M.-Marse, W. Christina, R. Alfred, J.R. Emily, K.T. Cynthia, "The Northerwestern Test: measuring sentence production in primary progressive Aphasia, Am. J. Alzhheinder's Dis. Other Dementias (2009).
[32] P. Sergio, O. A., E.T. Juan, P. Pedro, Randomized Anagram revisited." Cosec Laboratory, Elsevier, 2014.
[33] Y. Song, X. Wang, L. Lei, A. Xue, A novel similarity measure on intuitionistic fuzzy sets with its applications, Appl. Intell. 42 (2) (2015) 252–261.
[34] C. Thirumalai, M. Senthilkumar, An assessment framework of intuitionistic fuzzy network for C2B decision making, in: Proceedings of the 4th International Conference on Electronics and Communication Systems (ICECS), 2017.
[35] A.P. Wibawa, A. Nafalski, A.E. Kadarisman, W.F. Mahmudy, Indonesian-to-Javanese machine translation, Int. J. Innov. Manag. Technol. 4 (4) (2013) 451.
[36] J. Ye, Cosine similarity measures for intuitionistic fuzzy sets and their applications, Math. Comput. Model. 53 (1) (2011) 91–97.
[37] J. Ye, Multicriteria group decision-making method using vector similarity measures for trapezoidal intuitionistic fuzzy numbers, Group Decis. Negotiat. (2012).
[38] S. Zadrożny, J. Kacprzyk, Z. Raś, Supporting consensus reaching processes under fuzzy preferences and a fuzzy majority via linguistic summaries and action rules, Consensual Processes 289-314 (2011).
[39] S. Zadrozny, J. Kacprzyk, G. Sobota, Avoiding duplicate records in a /database using a linguistic quantifier based aggregation-a practical approach. Fuzzy Systems, 2008, in: Proceedings of the IEEE International Conference on FUZZ-IEEE (IEEE World Congress on Computational Intelligence), 2008.
[40] S. Li, J. Wen, Application of pattern matching method for detecting faults in air handling unit system, Automation in Construction, Elsevier 43 (2014) 49–59.
[41] K.T. Atanassov, Intuitionistic fuzzy sets: theory and application, Springer (1999).
[42] D Chen, X Chang, Similarity measure and clustering of pattern, Pattern Recognition and String Matching (2002).