International Journal of Database Theory and Application
Vol.8, No.1 (2015), pp.289-296
http://dx.doi.org/10.14257/ijdta.2015.8.1.28

A Method for Aggregating Intuitionistic Linguistic Information under Confidence Levels

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Abstract

In this paper we study a new method base on confidence levels for aggregating intuitionistic linguistic information. A new intuitionistic linguistic aggregation operator called the confidence intuitionistic linguistic ordered weighted averaging (CILOWA) operator is developed. Some of the CILOWA's main properties and different families are also studied. Moreover, a practical method based on the CILOWA operator for multi-criteria decision making with intuitionistic linguistic information is presented. Finally, an illustrative example demonstrates the practicality and effectiveness of the proposed method.

Keywords: *Intuitionistic linguistic, multi-criteria decision making, confidence levels, aggregation operator*

1. Introduction

As a generalization of Zadeh's fuzzy set (Zadeh, 196), the intuitionistic fuzzy set (IFS) proposed by Atanassov (1986), is a useful tool to describe and deal with vagueness. A prominent characteristic of IFS is that it assigns to each element a membership degree and a non-membership degree, and thus, it is more powerful to deal with uncertainty and vagueness in real applications than fuzzy set which is only assigns to each element a membership degree. The IFS has received more and more attention since its appearance (Boran *et al.*, 2009; Tan and Chen, 2010; Xu and Wang, 2012; Xu, 2011; ye, 2013; Zeng, 2013; Zhao *et al.*, 2010). However, sometimes it is difficult for decision makers to provide exact numbers for the membership and non-membership degrees of an intuitionistic fuzzy set while it is easy to provide linguistic assessment values in real decision making. In order to model this uncertain information, Wang and Li (2010) proposed the concept of intuitionistic linguistic set (ILS), whose basic elements are intuitionistic linguistic numbers (ILNs). The ILS can overcome the defects for intuitionistic fuzzy set which can only roughly represent criteria's membership and nonmember ship to a particular concept, such as ''good'' and ''bad'', *etc.*, and for linguistic variables which usually implies that membership degree is 1, and the non-membership degree and hesitation degree of decision makers can not be expressed. Wang and Li (2010) also proposed a series of operational laws for the intuitionistic linguistic set.

How to deal with these given ILNs by using a proper aggregation operator is an importance step of the decision making. Many intuitionistic linguistic aggregation operators have been studied, such as the intuitionistic linguistic generalized dependent ordered weighted average (ILGDOWA) operator (Liu, 2013), the intuitionistic linguistic power generalized weighted average (ILPGWA) (Liu and Wang, 2014), Intuitionistic fuzzy linguistic numbers geometric aggregation operators (Liu *et al.*, 2014)

ISSN: 2005-4270 IJDTA

and the intuitionistic linguistic environment and presented the intuitionistic linguistic OWA distance (ILOWAD) operator (Su *et al.*, 2014). However, it seems that there is no investigation on intuitionistic linguistic information aggregation under belief levels in the existing literature, which is an interesting and important issue. To achieve this, in this paper, we develop a new intuitionistic linguistic aggregation operator considering the confidence levels of the aggregated arguments, called the confidence intuitionistic linguistic ordered weighted averaging (CILOWA) operator. We also apply the developed operator to decision making with intuitionistic linguistic information.

The remainder of this paper is organized as follows. First, we briefly review some basic concepts of the intuitionistic linguistic in Section 2. In Second 3, we present the CILOWA operator and study some of its desirable properties. Based on the developed operator, Section 4 gives a method for decision-making under intuitionistic fuzzy environment and an illustrative example is given to show the developed method in this Section. The concluding remarks of the whole article were shown in Section 5.

2. Preliminaries

This Section briefly reviews the some concept of the ILS. Wang and Li (2010) first proposed the ILS and gave the definition of ILS.

2.1. The Linguistic Set

The linguistic approach is an approximate technique, which represents qualitative aspects as linguistic values by means of linguistic variables. For computational convenience, let $S = \{s_\alpha | \alpha = 0,1,\ldots,l-1\}$ be a finite and totally ordered discrete term set, where l the odd value is and s_α represents a possible value for a linguistic variable. For example, when $l = 9$, a set S could be given as $S = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8\}$ = {extremely poor, very poor, poor, slightly poor, fair, slightly good, good, very good, and extremely good}. In these cases, it is usually required that there exist the following (Herrera and Herrera-Viedma, 2000; Xu, 2005):

1) A negation operator: $Neg(s_i) = s_{2t-i}$;

2) The set is ordered: $s_i \le s_j$ if and only if $i \le j$;

3) Maximum operator: $\max(s_i, s_j) = s_i$, if $i \ge j$;

4) Minimum operator: $\min(s_i, s_j) = s_i$, if $i \le j$.

In order to preserve all the given information, Xu (2005) extended the discrete term set S to a continuous term set $\bar{S} = \{s_\alpha | \alpha \in [0, l]\}$, where, if $s_\alpha \in S$, then we call s_α the original term, otherwise, we call s_α the virtual term. In general, the decision maker uses the original linguistic terms to evaluate alternatives, and the virtual linguistic terms can only appear in the actual calculation (Xu, 2005).

2.2. The Intuitionistic Linguistic Set

Definition1. (Wang and Li, 2010). An ILS A in X is defined as

$$A = \left\{ \left\langle x \left[h_{\theta(x)}, \left(\mu_A(x), v_A(x) \right) \right] \right\rangle \middle| x \in X \right\} \quad (1)$$

Here $h_{\theta(x)} \in \overline{S}$, and numbers $\mu_A(x)$ and $v_A(x)$ represent, respectively, the membership degree and non-membership degree of the element x to linguistic index $h_{\theta(x)}$, $0 \le \mu_A(x) + v_A(x) \le 1$, for all $x \in X$.

For each ILS A in X, if

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x), \forall x \in X \tag{2}$$

Then $\pi_A(x)$ is called the indeterminacy degree or hesitation degree of x to linguistic index $h_{\theta(x)}$. For simplicity, we denote Ω as the all ILSs.

Definition2. (Wang and Li, 2010). Let $A = \left\{ \left\langle x \left[h_{\theta(x)}, (\mu_A(x), v_A(x)) \right] \right\rangle \middle| x \in X \right\}$ be ILS, the ternary group $\left\langle h_{\theta(x)}, (\mu_A(x), v_A(x)) \right\rangle$ is called an intuitionistic linguistic number (ILN), and A can also be viewed as a collection of the ILN. So, it can also be expressed as $A = \left\{ \left\langle h_{\theta(x)}, (\mu_A(x), v_A(x)) \right\rangle \middle| x \in X \right\}$. In addition, $\pi_A(x) = 1 - \mu_A(x) - v_A(x)$ represents the hesitancy degree, and it can also be called the intuitionistic linguistic fuzzy degree. For convenience, denote an ILN by $\tilde{a} = \left\langle s_{\theta(a)}, (\mu(a), v(a)) \right\rangle$, where $\mu(a), v(a) \ge 0$, $\mu(a) + v(a) \le 1$.

Let $\tilde{a}_1 = \left\langle s_{\theta(a_1)}, (\mu(a_1), v(a_1)) \right\rangle$ and $\tilde{a}_2 = \left\langle s_{\theta(a_2)}, (\mu(a_2), v(a_2)) \right\rangle$ be two ILNs and $\lambda \ge 0$, then the operations of ILNs are defined as follows (Wang and Li, 2010; Liu, 2013):

1) $\tilde{a}_1 + \tilde{a}_2 = \left\langle s_{\theta(a_1)+\theta(a_2)}, \left(1 - (1 - \mu(a_1))(1 - \mu(a_2)), v(a_1)v(a_2)\right) \right\rangle$;

2) $\tilde{a}_1 \otimes \tilde{a}_2 = \left\langle s_{\theta(a_1)\times\theta(a_2)}, \left(\mu(a_1)\mu(a_2), v(a_1) + v(a_2) - v(a_1)v(a_2)\right) \right\rangle$;

3) $\lambda \tilde{a}_1 = \left\langle s_{\lambda\otimes\theta(a_1)}, \left(1 - (1 - \mu(a_1))^{\lambda}, (v(a_1))^{\lambda}\right) \right\rangle$;

4) $\tilde{a}_1^{\lambda} = \left\langle s_{(\theta(a_1))^{\lambda}}, \left((\mu(a_1))^{\lambda}, 1 - (1 - v(a_1))^{\lambda}\right) \right\rangle$.

Wang and Li (2010) defined the expected value, score function and the accuracy function of ILN as following:

Definition 3. Let $\tilde{a}_1 = \left\langle s_{\theta(a_1)}, (\mu(a_1), v(a_1)) \right\rangle$ be an ILN, the expected value $E(\tilde{a}_1)$ and score function $S(\tilde{a}_1)$ of an ILN $\tilde{a}_1$ can be represented as follows:

$$E(\tilde{a}_1) = s_{\theta(a_1)\times[\mu(a_1)+\frac{1}{2}(1-\mu(a_1)-v(a_1))]} \tag{3}$$

$$S(\tilde{a}_1) = \frac{\theta(a_1)}{l-1} \times \left[\mu(a_1) + \frac{1}{2}(1 - \mu(a_1) - v(a_1)) \right] \tag{4}$$

Definition4. Let $\tilde{a}_1 = \left\langle s_{\theta(a_1)}, (\mu(a_1), v(a_1)) \right\rangle$ be an ILN, an accuracy function $H(\tilde{a}_1)$ of an ILN $\tilde{a}_1$ can be represented as follows:

$$H(\tilde{a}_1) = \frac{\theta(a_1)}{l-1} \times (\mu(a_1) + v(a_1)) \tag{5}$$

Definition5. If $\tilde{a}_1 = \langle s_{\theta(a_1)}, (\mu(a_1), v(a_1)) \rangle$ and $\tilde{a}_2 = \langle s_{\theta(a_2)}, (\mu(a_2), v(a_2)) \rangle$ are any two ILNs, then:

1) If $S(\tilde{a}_1) > S(\tilde{a}_2)$, then, $\tilde{a}_1 > \tilde{a}_2$;

2) If $S(\tilde{a}_1) = S(\tilde{a}_2)$, then

If $H(\tilde{a}_1) > H(\tilde{a}_2)$, then, $\tilde{a}_1 > \tilde{a}_2$;

If $H(\tilde{a}_1) = H(\tilde{a}_2)$, then, $\tilde{a}_1 = \tilde{a}_2$.

3. Intuitionistic Linguistic Information Aggregation Operator under Confidence Levels

In some real decision making problems, the evaluation experts are requested to provide two types of information such as the performance of the evaluation objects and the familiarity with the evaluation areas (called confidence levels) (Xia *et al.*, 2011; Yu, 2014). In this Section, we investigate the intuitionistic linguistic information aggregation method under confidence levels and introduce the CILOWA operator.

Definition6. Let $(\tilde{\alpha}_1, \tilde{\alpha}_2, ..., \tilde{\alpha}_n)$ be a collection of ILNs, l_i ($0 \le l_i \le 1$) be the confidence levels linguistic variable $\tilde{\alpha}_i$. A CILOWA operator of dimension n is a mapping CILOWA: $R^n \times \Omega^n \to \Omega$, which has an associated weighting vector W with wj $\in$ [0, 1] and $\sum_{j=1}^{n} w_j = 1$, such that:

$$CILOWA(< l_1, \tilde{\alpha}_1 >, < l_2, \tilde{\alpha}_2 >, ..., < l_n, \tilde{\alpha}_n >) = \sum_{j=1}^{n} w_j (l_j \tilde{\alpha}_j), \tag{6}$$

Where $l_j \tilde{\alpha}_j$ is the jth largest of the $l_i \tilde{\alpha}_i$. Especially, if $l_1 = l_2 = ... = l_n = 1$, then the CILOWA operator reduces to the ILOWA operator (Wang and Li, 2010).

Example1. Assume the following arguments in an aggregation process: $A = (\tilde{\alpha}_1, \tilde{\alpha}_2, \tilde{\alpha}_3, \tilde{\alpha}_4) = (\langle s_5, (0.6, 0.3) \rangle, \langle s_6, (0.8, 0.1) \rangle, \langle s_4, (0.4, 0.3) \rangle, \langle s_2, (0.5, 0.5) \rangle)$ with the following confidence levels vector is $(0.6, 0.5, 0.9, 0.6)$, and the following weighting vector $W = (0.3, 0.2, 0.1, 0.4)$, then

$$CILOWA = (\langle 0.6, \tilde{\alpha}_1 \rangle, \langle 0.5, \tilde{\alpha}_2 \rangle, \langle 0.9, \tilde{\alpha}_3 \rangle, \langle 0.6, \tilde{\alpha}_4 \rangle) = \langle s_{2.34}, (0.434, 0.467) \rangle$$

The CILOWA operator is a mean or averaging operator. This is a reflection of the fact that the operator is monotonic, idempotent, bounded and commutative. These properties are proven in the following theorems:

Theorem1. (Monotonicity): Let f be the CILOWA operator, if $\tilde{\alpha}_i \le \tilde{\beta}_i$ for all i, then

$$f(< l_1, \tilde{\alpha}_1 >, < l_2, \tilde{\alpha}_2 >, ..., < l_n, \tilde{\alpha}_n >) \le f(< l_1, \tilde{\beta}_1 >, < l_2, \tilde{\beta}_2 >, ..., < l_n, \tilde{\beta}_n >)$$

Theorem2. (Impotency): Let f be the CILOWA operator, $\tilde{\alpha}_i = \tilde{\alpha}$ for all i, then

$$f(<l_1,\tilde{\alpha}_1>,<l_2,\tilde{\alpha}_2>,\ldots,<l_n,\tilde{\alpha}_n>)=\tilde{\alpha}$$

Theorem3. (Bounded): Let f be the CILOWA operator, then

$$\min_i(l_i\tilde{\alpha}_i)\le CILOWA(<l_1,\tilde{\alpha}_1>,<l_2,\tilde{\alpha}_2>,\ldots,<l_n,\tilde{\alpha}_n>)\le\max_i(l_i\tilde{\alpha}_i)$$

Theorem4. (Commutativity): Let f be the CILOWA operator. Then

$$f(<l_1,\tilde{\alpha}_1>,<l_2,\tilde{\alpha}_2>,\ldots,<l_n,\tilde{\alpha}_n>)=f(<l_1',\tilde{\alpha}_1'>,<l_2',\tilde{\alpha}_2'>,\ldots,<l_n',\tilde{\alpha}_n'>)$$

Where $(<l_1',\tilde{\alpha}_1'>,<l_2',\tilde{\alpha}_2'>,\ldots,<l_n',\tilde{\alpha}_n'>)$ is any permutation of the arguments $(<l_1,\tilde{\alpha}_1>,<l_2,\tilde{\alpha}_2>,\ldots,<l_n,\tilde{\alpha}_n>)$.

4. An Approach Based on the CILOWA to Multi-Criteria Decision-Making

In the following, we are going to develop a decision making method about the use of the CILOWA in a multi-criteria decision-making problem. For a multi-criteria decision-making problem, let $A=\{A_1,A_2,\ldots,A_m\}$ be a discrete set of alternatives, and let $G=\{G_1,G_2,\ldots,G_n\}$ be the set of criteria. The main steps of the decision-making methods are as follows.

Step1. The decision makers provide their evaluations and belief levels about the alternative A_i under the attribute G_j, forming the decision matrix $A=\left(\tilde{\alpha}_{ij}\right)_{m\times n}$, where $\tilde{\alpha}_{ij}$ is a preference value, which takes the form of ILNs.

Step2. The decision makers provide their belief levels of the evaluations expressed by $l_{ij}(i=1,2,\ldots,m;\ j=1,2,\ldots,n)$, where l_{ij} is the belief levels of ILN $\tilde{\alpha}_{ij}$, $i=1,2,\ldots,m$; $j=1,2,\ldots,n$.

Step3. Utilize the CILOWA operator to aggregate the evaluations $\tilde{\alpha}_{ij}$ for each alternative A_i.

$$\tilde{\alpha}_i=CILOWA\left(<l_{i1},\tilde{\alpha}_{i1}>,\ldots,<l_{in},\tilde{\alpha}_{in}>\right),i=1,2,\ldots,m\ , \quad (7)$$

Step4. Rank all the alternatives A_i ($i=1,2,\ldots,m$) and identify the optimal one(s) in accordance with $\tilde{\alpha}_i$ ($i=1,2,\ldots,m$).

Next we consider a decision-making problem that concerns the evaluation of doctoral dissertation to illustrate the proposed approach and conduct a comparison analysis.

Example1. Let us consider a blind peer review of doctoral dissertation evaluation problem in China's university (adapted from (Yu, 2014)). In many Chinese universities, the doctoral dissertation will be reviewed by several experts anonymously. And they will review dissertation according to five criteria, including topic selection and literature review (G_1), innovation (G_2), theory basis and special knowledge (G_3), capacity of scientific research (G_4) and theses writing (G_5). Unlike many existing evaluation methods, the experts not only required to provide the evaluation results of the doctoral dissertation but also asked to give the degrees that they are familiar with the research topics (called belief levels). Suppose there are five declaration need to be reviewed by expert, the degree of familiarity of the five declaration provided by expert is $l_j = (0.6, 0.8, 0.7, 0.6, 0.9)$. Suppose the experts give the intuitionistic linguistic decision matrix under a linguistic framework of nine linguistic terms in the set, listed in Table 1.

Table 1. Intuitionistic Fuzzy Decision Making Metric

	S_1	S_2	S_3	S_4	S_5
A_1	$\langle s_2,(0.5,0.4)\rangle$	$\langle s_4,(0.8,0.2)\rangle$	$\langle s_4,(0.4,0.4)\rangle$	$\langle s_6,(0.7,0.1)\rangle$	$\langle s_5,(0.5,0.2)\rangle$
A_2	$\langle s_2,(0.6,0.2)\rangle$	$\langle s_4,(0.9,0.1)\rangle$	$\langle s_6,(0.7,0.2)\rangle$	$\langle s_5,(0.3,0.5)\rangle$	$\langle s_2,(0.4,0.5)\rangle$
A_3	$\langle s_4,(0.6,0.4)\rangle$	$\langle s_7,(0.6,0.3)\rangle$	$\langle s_8,(0.8,0.1)\rangle$	$\langle s_2,(0.5,0.4)\rangle$	$\langle s_4,(0.6,0.3)\rangle$
A_4	$\langle s_6,(0.7,0.2)\rangle$	$\langle s_1,(0.4,0.6)\rangle$	$\langle s_2,(0.5,0.3)\rangle$	$\langle s_2,(0.4,0.4)\rangle$	$\langle s_5,(0.7,0.3)\rangle$
A_5	$\langle s_7,(0.8,0.2)\rangle$	$\langle s_5,(0.5,0.3)\rangle$	$\langle s_5,(0.6,0.2)\rangle$	$\langle s_3,(0.6,0.4)\rangle$	$\langle s_2,(0.4,0.5)\rangle$

Suppose that the weighting vector associating with the CILOWA operator is $W = (0.11, 0.24, 0.30, 0.24, 0.11)$, which is derived by using the normal distribution based method (Xu, 2005b). With this information, it is possible to aggregate the available information in order to take a decision. Utilize the CILOWA operator (Eq. (77)) to aggregate all the preference values $\tilde{\alpha}_{ij}$ ($i = 1,2,3,4,5$) in the i th line of A, and get the overall preference values $\tilde{\alpha}_i$:

$\tilde{\alpha}_1 = \langle s_{3.15},(0.47,0.33)\rangle$, $\tilde{\alpha}_2 = \langle s_{2.52},(0.49,0.38)\rangle$, $\tilde{\alpha}_3 = \langle s_{3.20},(0.49,0.42)\rangle$, $\tilde{\alpha}_4 = \langle s_{2.26},(0.44,0.46)\rangle$, $\tilde{\alpha}_5 = \langle s_{2.54},(0.46,0.43)\rangle$

Then Calculate the scores of $\tilde{\alpha}_i$ ($i = 1,2,3,4,5$), respectively:

$S(\tilde{\alpha}_1) = 0.224$, $S(\tilde{\alpha}_2) = 0.175$, $S(\tilde{\alpha}_3) = 0.213$, $S(\tilde{\alpha}_4) = 0.138$, $S(\tilde{\alpha}_5) = 0.165$

Since $S(\tilde{\alpha}_1) > S(\tilde{\alpha}_3) > S(\tilde{\alpha}_2) > S(\tilde{\alpha}_5) > S(\tilde{\alpha}_4)$, we have $A_1 \succ A_3 \succ A_2 \succ A_5 \succ A_4$. Therefore,

The best one is the A_1.

If we do not consider the confidence levels factor, in other words, all the criteria of the evaluated objects are treated with sure familiar by the decision maker, then our proposed CILOWA operator is reduced to the existing intuitionistic linguistic aggregation operator. However, the t experts may not be familiar with the doctoral dissertation absolutely. To deal with such situations, the CILOWA proposed in this paper is useful tool. From the above analysis, the main advantages over the traditional intuitionistic linguistic operators are not only due to the fact that the CILOWA operator accommodates the intuitionistic linguistic environment but also due to the consideration of the confidence levels among the decision makers, which makes it more feasible and practical.

5. Concluding Remarks

In this paper, we have developed a new intuitionistic linguistic aggregation operator by introducing the belief levels, named the confidence intuitionistic linguistic ordered weighted averaging (CILOWA) operator. We have studied some of its main properties. We have also introduced a method based on the CILOWA operator to a multi-criteria decision making problem concerning the dissertation evaluation problem. The example shows that the CILOWA is very useful because it represents very well the uncertain information by using intuitionistic linguistic labels, as well as considering the belief levels of the decision-makers. In future research, we expect to develop further extensions by adding new characteristics in the problem such as the use of distance measures or probabilistic aggregations.

Acknowledgements

This paper is supported by the MOE Project of Humanities and Social Sciences (No.14YJC910006), Zhejiang Province Natural Science Foundation (No. LQ14G010002), Statistical Scientific Key Research Project of China (No.2013LZ48).

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