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A three-level-similarity measuring method of participant opinions in multiple-criteria group decision supports

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ABSTRACT

Measuring opinion similarity between participants is an important strategy to reduce the chance of making and applying inappropriate decisions in multi-criteria group decision making applications. Due to the small-sized opinion data and the varieties of opinion representations, measuring the similarity between opinions is difficult and has not been well-studied in developing decision support. Considering that the similarity changes with the number of concerned criteria, this paper develops a gradual aggregation algorithm and establishes a three-level-similarity measuring (TLSM) method based on it to measure the opinion similarity at the assessment level, the criterion level and the problem level. Two applications of the TLSM method on social policy selection and energy policy evaluation are conducted. The study indicates that the TLSM method can effectively measure the similarity between opinions in small-size with possibly missing values and simulate the dynamic generation of a decision.

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1. Introduction

Multiple-criteria group decision making (MCGDM) is recognized as an efficient strategy in many organizational decision problems [14,22], where a final decision is made based on the opinions of individual participants. Overly similar opinions increase the chance of putting an inappropriate decision into effect. In practice, making an appropriate decision is already a time-consuming and costly task; however, tuning an inappropriate decision will cost even more. To reduce this risk, measuring opinion similarity between participants (MOSP) in advance is an important issue in developing decision support for essential decision problems.

Opinion similarity is used in many fields such as on-line recommender systems [1,31]. However, the MOSP problem is still an unsolved and challenging issue. Difficulties in solving the MOSP problem include the effective processing of small-size opinion data and the varied opinion representations. Due to the restrictions on time, cost, private policies, and other issues, a decision is often made on small sized opinion data of a limited number of participants. Even though all participants would like to express their opinions thoroughly in an ideal situation, the small-size opinion data makes it very hard to apply methods for large-size data in solving the MOSP problem. Varied opinion representation is another difficulty in solving the MOSP problem. Participants prefer to express their opinions in their own ways based on their understandings of and experiences in a given topic. However, this is bound to difficulties for measuring the similarity between their opinions. A strategy commonly used to regulate opinion representation is providing a fixed number of choices, for example, some predefined linguistic terms or a set of ordinal numbers [9,15,22]. However, this cannot completely avoid varied opinion representations because the predefined choices may have different semantics for different persons and for different evaluation criteria.

Keeping the aforementioned difficulties in mind, this paper presents a three-level-similarity measuring (TLSM) method to solve the MOSP problem based on three assumptions: 1) Given a criterion, if the opinions of two participant are similar for the majority of options, then they are similar; 2) Given a set of criteria, if the opinions of two participants are similar for the majority of important criteria, then they are similar; and 3) Given a decision problem, if the opinions of two participants produce a similar decision, then they are similar.

The rest of the paper is organized as follows. Section 2 reviews related works in opinion analysis, similarity measurement and aggregation operations. Section 3 develops a gradual aggregation algorithm (GAA) which is used to generate an overall opinion similarity. In Section 4, we introduce the TLSM method in detail. Section 5 illustrates two case studies in social policy selection and energy policy evaluation

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problems. Section 6 summarizes the main contributions of the work and future study plans.

2. Related works

Opinion analysis is extensively studied in social psychology fields [2]; recently, requirements for effectively extracting, summarizing, and segmenting opinions of general or specific users boosted the growing research on opinion mining and sentiment analysis [13,25,27]. Many opinion mining systems have been developed and applied [7,25,28]. However, these methods are not suitable for the MOSP problem because of the aforementioned difficulties. In the MCGDM field, study of opinion analysis is conducted in two main areas. Qualitative studies analyze and simulate the behavior patterns of peoples based on their opinions of a considered affair [21,24]. Quantitative research focuses on how to represent and process opinions in a computational framework [9,26]. For instance, fuzzy sets and fuzzy logic are widely used as opinion representation and process facilities [8,10] because they can effectively interpret and model the subjective information with uncertainties. These computation-based techniques provide support to develop solutions for the MOSP problem.

Similarity measurement is widely studied in human knowledge representation, behavior analysis, and real-world problem solving [30,11,12]. Generally speaking, a similarity metric can be derived from a distance metric. The Euclidean metric, the absolute value metric, and the Chebyshev metric are commonly used. Noting that the majority of existing similarity metrics will ultimately produce a crisp numeric value, which cannot sufficiently depict the fuzziness in real cases, Chakraborty and Chakraborty [6] defined a similarity metric whose value is a fuzzy set and implemented a clustering algorithm to solve a group decision making problem.

Using aggregation to integrate evaluations of individual participants is a crucial step to develop a solution for an MCGDM problem. According to whether or not an aggregation operator explicitly considers the relevant importance (weights) of the evaluation criteria, three main types of aggregation operators are used in MCGDM research. The first type treats all evaluation criteria equally. Typical examples include the arithmetic mean, the geometric mean, and the t-norms (or t-conorms) [4,5]. The second type explicitly distinguishes the weights of the evaluation criteria either by their impacts on the decision problem, or by their processing order. The weighted mean and the ordered weighted aggregation (OWA) [29], as well as their extensions [18,19] belong to this type. A third type is defined by certain integral theories, such as the Sugeno and Choquet integrals [16,17,20]. Currently existing aggregation operators in MCGDM research often assume that the inputs are complete and simply ignore any missing values when generating an aggregation result. This assumption is not consistent with the realities of applications. How to process missing values is, therefore, a key concern when applying an aggregation operator; but this issue has not yet been solved. Although so many powerful aggregation operators have been presented, little is known about how to select an appropriate one in real applications. Beliakov [3] reported a solution by using the mathematical programming technique to adjust the parameters of a form-fixed aggregation operator.

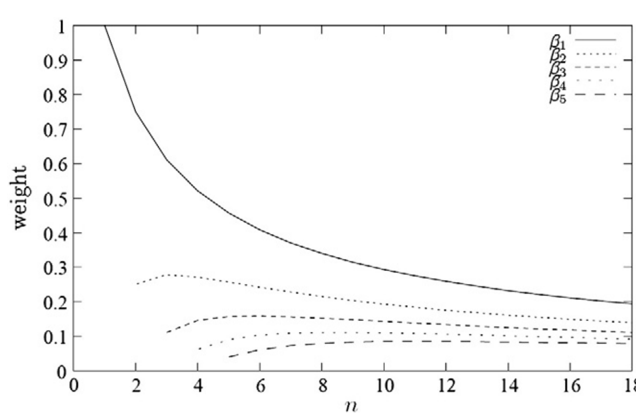

Fig. 1. Changing weights with the number of inputs.

Table 1
An example for processing a missing value.

		S1	S2		S3			
No.	Input	OGA	DM	OGA–DM	IM-0	OGA-0	IM-M	OGA-M
1	0.840	0.840	0.840	0.840	0.840	0.840	0.840	0.840
2	**0.783**	0.812	0.912	0.876	<u>0.000</u>	0.420	<u>0.549</u>	0.694
3	0.912	0.845	0.335	0.696	0.912	0.584	0.912	0.767
4	0.335	0.718	0.278	0.591	0.335	0.522	0.335	0.659
5	0.278	0.630	0.477	0.568	0.278	0.473	0.278	0.583
6	0.477	0.604	0.365	0.535	0.477	0.474	0.477	0.565
7	0.365	0.570	0.952	0.594	0.365	0.458	0.365	0.537
8	0.952	0.618	0.636	0.599	0.952	0.520	0.952	0.588
9	0.636	0.620	0.142	0.549	0.636	0.533	0.636	0.594
10	0.142	0.572			0.142	0.494	0.142	0.549
Result	**0.572**	**0.683**	**0.549**	**0.650**	**0.494**	**0.532**	**0.549**	**0.638**

Suppose the second input 0.783 (bold) is missing, the IM-o method uses 0.000 (underlined) for it and the IM-M method uses the mean (0.549, underlined) of the other nine inputs for it. Row "Result" shows the results (bold) of different methods in the three scenarios, respectively.

3. A gradual aggregation algorithm

3.1. Motivations and implementations

Two practical issues are commonly faced in an MCGDM problem. The first one is how to handle missing values. The other issue is how to generate a decision dynamically which refers to the procedure of making the final decision from a sketched one based on a few number of criteria at the initial stage and then amending it in the following stages by considering more criteria added gradually. To solve these two issues, this section develops a gradual aggregation algorithm (GAA) which is implemented in two ways, i.e., the ordinary gradual aggregation (OGA) and the weighted gradual aggregation (WGA). The difference between them is that the OGA does not explicitly process the criteria weights but leaves it to the aggregation operator; while the WGA does.

Following the notations in [5], aggregation operator $\mathscr{A}$ over a closed set X is denoted by $\mathscr{A}:\cup_{i\in\mathbb{N}^+}\left\{A_i : X^i \rightarrow X\right\}$ where A_i is called the i-ary aggregation operator in $\mathscr{A}$. For convenience, let X be a closed subset of $\mathbb{R}$.

Definition 3.1. *Let $\mathscr{A}$ and $\mathscr{B}$ be two aggregation operators. A mapping G_n from X^n to X is called an n-ary ordinary gradual aggregation (OGA) with respect to $\mathscr{A}$ and $\mathscr{B}$:*

$$G_n(x_1,\cdots,x_n) = B_n(\{A_i(x_1,\cdots,x_i), i = 1,\ldots,n\}).$$

Table 2
Outline of main processes in the TLSM method.

Process level	Main steps
Assessment	*Input*: *two experts' evaluation reports*; *evaluation term set* T_j
	Output: *the similarity about criterion* c_j
	1.1 Determine a similarity matrix for evaluation terms for criterion c_j;
	1.2 Determine a clustering algorithm;
	1.3 Generate semantic-equal groups by the clustering algorithm;
	1.4 Calculate similarity between two opinions for criterion.
Criterion	*Input*: *the similarity at the assessment level and weights of criteria*
	Output: *similarity with respect to each criterion against the criteria set*
	2.1 Identify a similarity utility function u_j of each criterion;
	2.2 Calculate similarity with respect to criterion c_j by u_j.
Problem	*Input*: similarities obtained at the criterion level
	Output: similarity between two opinions
	3.1 Construct the GAA from a pair of aggregation operators;
	3.2 Calculate the similarity between opinions using the GAA.

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