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Big data driven graphical information based fuzzy multi criteria decision making

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ABSTRACT

Graphical information (visualized data, information, and knowledge generated from different investigations and experimentations) is a useful form of decision-relevant information in all fields of study. The usages of such information are expected to increase exponentially due to the advent of big data. Unfortunately, there are no formal methods available for directly computing the graphical information generated from big data while making a decision. This study fills this gap and presents a fuzzy logic based method, as well as a decision support tool, to perform multiple criteria decision making by directly computing the graphical information generated from big data. The effectiveness of the proposed method and tool is demonstrated by conducting a case study. Further study can be carried out to see the implication of this study in making formal decisions aided by the big data.

1. Introduction

Decision making can be classified into two broad classes, namely, naturalistic and rational decision making. In naturalistic decision making, a human decision maker (or an expert) makes decisions using mental simulation (referred to as recognition-primed process) under incomplete and unreliable information, time pressure, and ill-defined goals [1]. The plausible goals, cues to monitor, expectancies, and sequential action evaluation are the steps of naturalistic decision making. These steps can be controlled by the skill-based spontaneous act, ruled-based conscious attention and selection of relatively familiar action, and knowledge-based conscious attention and selection of relatively unfamiliar action. The naturalistic decision making helps train professionals such as firefighters, pilots, rescue workers, and soldiers who make critical decisions while being in operations without going through any formal computations.

On the contrary, rational decision making requires formal computation. It traces back to the game theory of Neumann and Morgenstern. It can be loosely divided into two categories. One of the categories is inclined more toward the traditional settings of game theory and seeks decisions from the pairwise relations between some concepts represented by a directed graph (i.e., a network). For example, consider the papers of Fang et al. [2], Inohara and Hipel [3] and the references therein where the coalition or conflict analysis based on the graph theory is used to make a decision. The other category has taken the form of the multiple criteria utility analysis [4,5] where a set of alternatives are evaluated based on a set of criteria and their relative weights or importance. The goal here is to select the optimal alternative corresponding to the maximal utility.

Though this approach (utility analysis) of making rational decisions has great impacts, numerous studies have been undertaken to see its efficacy from the viewpoint of real-life settings. For example, consider the paper of Kujawski [6] where it is described that a decision maker often seeks a balanced alternative rather than an optimal alternative. At the same time, it is important to visualize the state of an alternative rather than to automate the decision making process. Some authors [7] have found that the mental biases of decision makers affect the utility-based tradeoff analysis. This requires measures to reduce the biases regarding all aspects of decision formulation (i.e., problem statement, the importance of the criteria, evaluation data, scoring function, and combining function). As described by Briggs and Little [8], sometimes the sequence of acts (i.e., bring the necessary parties together, determining the needs, analyzing the data, and implementing a decision) is more important than the calculation process (i.e., utility based tradeoff analysis). Sometimes, determining the relevant set of criteria and their weights is a cumbersome task because of the involve-

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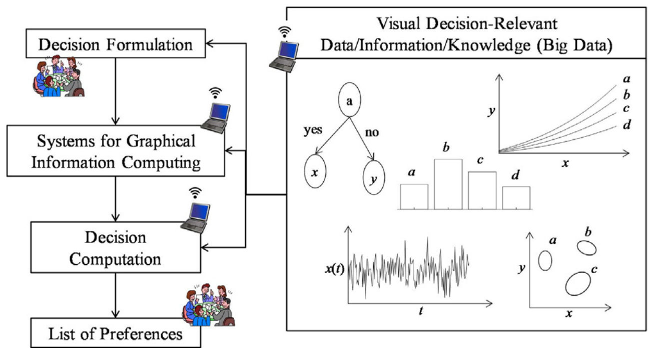

Fig. 1. The scenario of decision making using graphical information.

ment of the multiple stakeholders [9]. Thus, from the viewpoint of real-life settings, it is not an easy task to execute the utility-based rational decision making approaches. This means that to make a rational decision making approach more robust from the viewpoint of real-life settings, it must have the capability to deal with the issues of naturalistic decision making – it must work even though the decision-relevant information is incomplete and unreliable, there is a time pressure, and/or the goals are ill-defined. This has created a new direction of rational decision making, which is hereinafter referred to as pragmatic decision making. In pragmatic decision making, one tries to identify a balanced alternative rather than an optimal alternative using a set of criteria and their relative weights (similar to rational decision making) but under the incomplete and unreliable information. One of the answers pursued by many is how to identify a balanced alternative by using not simply the measurement-based information but also by using human-perception based information. This answer has incorporated in fuzzy logic [10] (a form of multi-valued logic) contextualized by the fuzzy set theory of [11]. In particular, the fuzzy logic deals with the classes of having unsharped boundaries. As a result, the degrees of belongingness of an object to unsharped classes are not a just unit (true) or zero (false) but are expressed by the numbers in the interval [0,1]. This gives an opportunity to deals with the propositions that are not only absolutely true and false but also partially true or false (i.e., incomplete and unreliable information). As a result, using fuzzy logic, one can formally compute the linguistic expressions or words, giving birth to a notion called computing with words (hereinafter referred to as CW) [10,12–20]. Numerous researchers have implemented the CW, while developing algorithms, methodology, and tools for the pragmatic decision making [21–31].

However, it is customary to consult data, information, and knowledge gathered from different investigations and experimentations while solving problems (including making decisions). As such, one of the forms of decision-relevant information has always been the results of data visualization, as schematically illustrated in Fig. 1. This type of information is hereinafter referred to as graphical or visual (decision-relevant) information. Since graphical information helps store a large amount of data, information, and knowledge in a convenient way for reuse (e.g., visualization, sharing, discussion, decision making, accountability, and so on), its usages have been increasing and will increase exponentially in the near future due to the advent of Big Data (BD) – a large amount of heterogeneous data, information, and knowledge generated by integrating various data-generating sources available on the Internet [31–41]. Therefore, the BD driven graphical information gradually becomes the primary source of decision-relevant information, affecting the all aspects of decision making from decision formulation to decision computing [32,33,37–41] as schematically illustrated in Fig. 1. One of the remarkable features of BD based computing is the application of soft computing. Some of the selected works are briefly described, as follows. For making the BD sources useful enough in solving real-life multi-objective decision making problems, new meta-heuristic algorithms have been suggested and tested [42,43]. For parameter estimation from the viewpoint of BD, new fuzzy rule formulation approach has been introduced [44]. This solves some of the learning problems that neuro-fuzzy approach faces under the BD settings. A BD based intelligent transportation system has been proposed where genetic algorithms have been integrated with the fuzzy logic based control [45]. For overcoming the bottleneck between the management of big data and the index limitation of computers, a type-2 fuzzy number based approach has been integrated with the statistical inference based approach [46]. A fuzzy logic based approach has been introduced to identify the useful nodes when BD is presented in visual forms using networks [47].

Nonetheless, for keeping the efficacy of a pragmatic decision making approach in relation to BD, not only the CW but also the Computing with Graphical Information (CGI) will be needed. This necessitates systems for performing CGI and CW in an integrated manner as far as the pragmatic decision making is concerned. The systems must work under a given decision formulation to produce the essential inputs for the next step, i.e., decision computation. Finally, the decision computation creates a list of preferences (the final decision), as schematically illustrated in Fig. 1. This article is written based on this contemplation. In particular, it describes a methodology, decision support tool, and a case study for making a pragmatic decision by integrating CGI and CW.

The remainder of this article is organized, as follows. Section 2 describes the fundamental consideration for integrating CGI and CW. Section 3 describes the mathematical settings needed to perform CGI and CW in a formal manner leading to a decision (i.e., producing a list of preferences of some given alternatives under a given decision formulation). Section 4 describes the framework needed to make a pragmatic decision integrating CGI and CW. Section 5 describes the computing tool developed to perform CGI and CW in an integrated manner. Section 6 describes a case study showing the performance of the proposed decision making approach. Section 7 provides the concluding remarks of this study.

2. Fundamental consideration

As mentioned before, CGI and CW must be integrated to make a pragmatic decision using BD driven graphical information. An immediate question is how to achieve this integration? There are many answers to this question per se, but this paper seeks an answer based on a two-faceted consideration, as follows. The first consideration is that there are various forms of information, and one form of information can be transformed into another using formal computations. The other consideration is that the decision computation must explicitly shows the contribution of the graphical information generated from BD while creating a list of preferences. The description of these two facets is as follow:

Zadeh has classified information into two broad categories, namely, *crisp* and *granular information* [16–19,48,49]. In particular, crisp information refers to measurement-based sharp numbers, e.g., the temperature is 100 °C. On the other hand, granular information refers to perception-based information or the pieces of information consisting of multiple pieces of crisp information (i.e., a collection of sharp numbers given by a well or ill-defined boundary). For example, the piece of information “temperature is 100 °C to 140 °C”, is a piece of crisp or *c*-granular information, consisting of all numerical values of temperature in the interval [100 °C, 140 °C]. In addition, consider the piece of information “temperature is about 100 °C” or “temperature is somewhat high.” The expression “about 100 °C” or “somewhat high” can be put into formal computation using fuzzy numbers [12–20]. Thus, these