Perceptual Computing with Comparative Linguistic Expressions

Abstract

A perceptual computer provides a framework of modeling perceptions of different individuals regarding a linguistic information. Due to differences in the understanding of words or linguistic terms between individuals, and also due to difficulties in providing exact definitions for such terms through an interval, uncertainties are associated with linguistic features. These are often termed as the linguistic uncertainties. The vanilla perceptual computer deals well with such uncertainties. However, in practical scenarios, humans often hesitate while choosing amongst words that express their judgements aptly. In such scenarios, responses are comprised of linguistic expressions encompassing multiple linguistic terms. Therefore, the framework of a perceptual computer must be augmented to handle such scenarios to make the former robust enough to handle all possible linguistic responses. We have thus proposed the idea of perceptual computing with comparative linguistic expressions, wherein a perceptual computer is not just activated through single words, but also linguistic expressions. In the process, we have also proposed two different types of hesitancies that are associated with different types of information.

1. Introduction

With the growth in tendency of catering to a large group of people with highly personalized results, there has been a rapid increase in the development of models that process the choices obtained from such individuals. Such processes are aided by options that are presented to the target individual, who then responds with appropriate selections based on his/her preferences. Similarly, one must also consider the rise in computer aided models that are made available which accept the responses of individuals and produce results relevant to the end user.

Currently, also on the rise is the development of various other computer aided models that aim to simulate the behavioral aspects of a human being. One such aspect is the ability of human beings to react under the impreciseness and vagueness that words have to offer. A dominant portion of the communication that occurs between humans involves linguistic features, which includes words. Since words mostly represent qualitative aspects, their meanings vary amongst individuals. This is due to the dissimilar and diverse perceptions of individuals with respect to a context.

2. Background

To tackle this inherent impreciseness and vagueness within linguistic features, Zadeh in 1975 [1] proposed the idea of linguistic variables within the domain of computing with words (CWW) [2]. According to this proposal, linguistic variables are used to model linguistic terms within systems. These linguistic variables find their basis in fuzzy sets (FS) [3] which handle the linguistic uncertainty in words. Each linguistic variable is a quintuple conveying the name of the associated linguistic term, its syntactic and semantic definition (associated membership function (MF)), the linguistic term set (LTS) fixed a priori to which the linguistic term belongs, along with the universe of discourse.

Many existing approaches have constructed their models on CWW, such as the models based on extension principle, symbolic method, 2-tuple and the likes [4-6]. Each of these models has been widely applied to many practical domains such as supply chain, risk evaluation, information retrieval, engineering systems [7], etc. Each of the models discussed above draws linguistic terms from an LTS which is fixed a priori, often by experts.

However, this is not one of the most practical assumptions to be made when it comes to real-life applications. None of the above model discusses about the formation of the LTS. Also, since the proposal of type-2 FSs (T2 FSs) [8], they are considered to be better in modelling uncertainty than their previous counterparts, namely type-1 (T1) FSs. This is because T2 FSs assign another degree of membership to the primary membership. This holds true within the domain of CWW [9] because a linguistic term usually encapsulates two types of uncertainties namely the ¬intra-uncertainty and the inter-uncertainty which a T1 FS fails to model due to its less degrees of freedom [10]. The intra-uncertainty is faced by a person while providing an appropriate definition for the linguistic term in concern, whereas, the inter-uncertainty arises due to a disagreement amongst various individuals regarding the definition of a linguistic term. Mendel has hence, recently stated that it is scientifically correct to model a linguistic term using T2 FSs or higher representational models [11].

T2 FSs were employed in decision making problems in [12]. Also, recently IT2 FSs were used to model timing constraints in an Industry 4.0 ecosystem in [13]. Apart from this, IT2 FSs have also been utilized in improving the deep learning abilities within restricted Boltzmann machines [14] and deep belief networks [15]. In [16], uncertainty modelling in gene expression datasets was done using IT2 FSs.

A CWW framework called the perceptual computer (Per-C) [10] takes into consideration the aforementioned drawbacks of the previously existing CWW models. A Per-C when applied to an application collects end-point data for intervals that define the linguistic terms from various individuals. These data are then processed to give an interval T2 (IT2) FS based representation for the linguistic terms, which results in a codebook. Later in the context of the considered application, the decision maker selects words from the codebook for different parameters, which are aggregated together to obtain a final recommendation. To this day, the framework of Per-C has proven to possess good applicability within various domains such as health monitoring of heart failure patients [17], hierarchical decision making [18], investment judgment advising [10] and, power optimization [19-20].

Even though Per-C conquers the drawbacks of the existing CWW approaches, its framework still suffers from a drawback. Many times, humans feel hesitant while choosing or selecting the best option according to their preference. This reflects within the phrases that humans use on a regular basis, such as ‘my scores are between good and very good’ or ‘the performance of the candidate is more than average’. Such phrases are called comparative linguistic expressions (CLE) [21]. They are more complex than single linguistic terms to be handled with traditional linguistic models.

Such expressions were first handled by the hesitant fuzzy linguistic term sets (HFLTS) based linguistic model [22]. The idea of HFLTS was studied further in [23] where its authors augmented the framework for large-scale group decision making. In [24], a consensus model for multiple attribute group decision making was developed for multi-granular HFLTSs. Due to the ability of T2 FSs to handle linguistic uncertainties efficiently, T2 FS based HFLTSs were recently proposed [25]. Within this framework, linguistic terms were represented using T2 FSs, which were used for multiple criteria group decision making.

3. Our proposal, contribution and publication

Given the practicality of CLEs and the advantages of Per-C over the other existing linguistic models, it is motivating to augment the existing framework of Per-C to handle hesitancy along with the linguistic uncertainties associated with linguistic terms described above. Hence, in our published paper titled '*Perceptual computing with comparative linguistic expressions*' [26] we have proposed to introduce the idea of perceptual computing with CLEs, wherein the hesitancy of individuals are handled appropriately whenever such a situation arises throughout the Per-C framework. Moving along these lines, we have also defined two different forms of hesitancies, namely the definitive and non-definitive hesitancy. These hesitancies provided better robustness to the Per-C framework as they enable the Per-C to handle even more uncertainties associated with linguistic features. This enrich the quality of linguistic information elicited within the Per-C framework.

In summary, our contributions presented through the paper [26] are given below:

- Non-definitive and definitive hesitancy: Concept of two types of hesitancies were introduced which are associated with linguistic and numeric data respectively.
- Definitions of new hesitancies: Proper grammar rules to generate CLEs corresponding to the new hesitancies were introduced.
- New hesitant term: A new hesitant term that expresses a certain type of hesitancy amongst individuals was introduced.

- Handle CLEs in augmented Per-C framework: We handled linguistic phrases as inputs when the individual interacting with the Per-C hesitates while providing her/his input.

4. Future Work

For our future work, we plan to extend the above work by introducing formal methods of data collection for linguistic data which includes CLEs as well as single terms. We also plan to consider the underlying theories of multiple data collection models such as the interval approach (IA) [27], enhanced IA (EIA) [28] and the Hao-Mendel [29] approach and include them within our extension to observe their effects. Another plan of extension includes the utilization of general T2 FSs (GT2 FS) to model linguistic information, which we expect to be able to enhance the robustness of the current model by handling more uncertainties associated with linguistic features such as words/terms and expressions.

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