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Evaluation of user satisfaction using evidential reasoning-based methodology

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ABSTRACT

For the sake of gaining competitive advantages, it is important to evaluate the satisfaction level of a product or service from the users' perspective. This can be done by investigating the relationship among customer attributes (customer requirements) and design attributes (product configurations). However, such relationship would be highly non-linear in nature. In this regard, many approaches have been proposed over traditional linear methods. Particularly, the Adaptive Neuro-Fuzzy Inference System (ANFIS) method has been prevalently utilized in modeling such vague and complex relationship among these attributes and evaluating user satisfaction towards certain products or services. Despite the fact that the ANFIS method can explicitly model the non-linear relation among these attributes, it may be restricted if uncertain information can be observed due to subjectivity and incompleteness. To overcome these limitations, a belief rule base (BRB) approach with evidential reasoning (ER) is applied in this paper. For justification purpose, both the ANFIS and BRB methods are applied to the same case. Comparison results indicate that the BRB is capable of minimizing the human biases in evaluating user satisfaction and rectifying the inappropriateness associated with the ANFIS method. Also, the BRB method can generate more rational and informative evaluation results.

1. Introduction

With an increasing emphasis on a company's ability to produce high-quality consumer products, it is important to examine user satisfaction which has a direct influence on user retention as well as company's profitability [3,15]. According to users' needs and preferences, it is vital to find out how user satisfaction would be affected especially within a highly competitive market [11]. In this regard, user satisfaction has been evaluated with different methods such as statistical regression [8], fuzzy regression [2,16], neural networks [1,10], fuzzy rule-based modeling [5,19], etc. However, in most of the current literature, a linear relationship between customer attributes (customers' requirements) and design attributes (products' configuration) is always assumed, although such a relationship would be highly non-linear [18]. In addition, a number of models in the literature mentioned above are implicit, i.e., they are in essence a "black box" model in which a separate explanation facility is required to justify the reasoning process [32].

To overcome these shortcomings, a modified method based on an Adaptive Neuro-Fuzzy Inference System (ANFIS) [18] is proposed to evaluate user satisfaction. The advantages of such a method are (i) the non-linear relationship between customer attributes and design attributes can be modeled; (ii) the generated models are more simple and explicit than that from the original ANFIS. This method was verified through a case study about the evaluation of user satisfaction towards different notebook computers. However, both the original and the modified ANFIS methods have some limitations, which can be summarized as follows:

- Some design attributes such as the color of a product cannot be numerically measured due to their imprecise and uncertain features. Hence, advanced soft computing methods like ANFIS are not applicable for modeling such attributes [20]. In addition, due to the complexity of user perception, incompleteness may exist in the information regarding design attributes, i.e. many samples collected from survey may be incomplete, and such incompleteness cannot be properly addressed by ANFIS [17].
- Using ANFIS, the information regarding the relations among customer attributes and design attributes is represented by a fuzzy rule base which can be inferred from numerical data or

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expert knowledge [7]. Due to the complexity of user perception towards notebook computers, information regarding such relations may be uncertain because of subjectivity or incompleteness. However, ANFIS is not able to handle the uncertain information.

- The information aggregation process of ANFIS is conducted by a weighted summation method which suffers from the following limitations:
  - In the aggregation formula, different measurement units (e.g., "LCD Screen Size" in inches. and "weight" in kg of notebook computers) are summed up directly. This is inappropriate and the aggregated results may induce confusion since the physical meanings of those measures are, in fact, quite different.
  - The aggregation formula can only handle numerical information without uncertainty. As discussed before, some design attributes cannot be quantified (e.g. color of the notebook computer).
  - Using the weighted summation method, different combination of attribute values may lead to the same result. In other words, the variations among distinct sets of attributes may be ignored, which leads to significant information loss.
- Using ANFIS, a single score is computed to measure user satisfaction, but such score cannot reflect the proportion of uncertain information regarding design attributes, which are the major input to the evaluation model.
- Also, it oversimplifies the reality by describing human perception with a single value, which only indicates the overall impression but not the diverse nature of human perception towards a certain product. Thus, the strengths or weaknesses of the product cannot be truly revealed [25].

Due to the above constraints, a Belief Rule Base (BRB) method [26] is applied to evaluate user satisfaction in this study. Similar to both the modified ANFIS method in Kwong et al. [18] and the original ANFIS method [12], the BRB method is also able to explicitly model the non-linear relationship among customer attributes and design attributes. Also, it can overcome all the above constraints of ANFIS. To demonstrate the advantages of the BRB method over the ANFIS method, two case studies with the same data in [18] are conducted.

The paper is organized as follows: in Section 2, the BRB method is introduced and the advantages of the BRB method over the ANFIS method for user satisfaction evaluation are analyzed, the BRB method is then validated by two case studies in Section 3, and Section 4 concludes the paper with future research direction.

2. The proposed method

As discussed in the previous section, design attributes of a certain product may be of different inherent features, and thus should be assessed in different forms. In addition, different types of uncertainties are inevitably involved in the process of evaluating user satisfaction due to the subjectivity and incompleteness. In order to capture information of different forms and accommodate uncertainties of different types under a unified framework, belief distribution is introduced.

2.1. Belief distribution and belief rule base

A belief distribution was originally developed to model a subjective evaluation with uncertainty [27]. For example, when evaluating the performance of a product, a customer may think that its performance is classified as "Good" with 70% confidence level and "Excellent" with 30% confidence level. The above evaluation thus can be represented by a belief distribution: $E(Performance)=\{(Excellent, 0.3), (Good, 0.7)\}$, where $E(Performance)$ is the evaluation of the product's performance, and 0.3 and 0.7 are the degrees of belief in assigning the grades "Excellent" and "Good" respectively. The sum of degree of belief is 1.0 which indicates a complete evaluation. However, when evaluating user satisfaction, the incomplete judgment may be observed due to several reasons such as lack of data or evidence, or the novelty or complexity of the product. For example, incomplete judgment can be noted as $E(Performance)=\{(Excellent, 0.3), (Good, 0.5)\}$ where the sum of degree of belief is only $0.8<1.0$. Therefore, such evaluation is incomplete if the customer does not have sufficient information to assign his/her degree of belief in judging the product's performance. However, it is expected that the incompleteness will be resolved after the customer has acquired more information by experiencing the product.

Although belief distribution is originally used to model subjective judgments, it can conform to quantitative information with the transformation method proposed in [27]. Also, fuzzy numbers can be embedded by belief distribution using the max–min operator [26]. Therefore, as a unified framework, belief distribution is able to process different forms of information such as quantitative, fuzzy or qualitative, etc.

In general, a belief distribution can be expressed by (1) where $E(Attribute)$ stands for the performance evaluation in terms of a particular attribute, $H_1,\ldots,H_n$ are the grades used to classify that attribute, and $\beta_1,\ldots,\beta_n$ are the belief degrees attached to the corresponding grades.

$$E(Attribute)=\{(H_1,\beta_1),(H_2,\beta_2),\ldots,(H_n,\beta_n)\} \tag{1}$$

In (1), if $\sum_{i=1}^{n}\beta_i=1$, the evaluation is deemed as *complete*, otherwise *incomplete*. Based on the belief distribution, a Belief Rule Base (BRB) is proposed in [26], which consists of L belief rules, and the k-th ($k\in\{1,2,\ldots,L\}$) belief rule (R_k) in a BRB can be denoted by (2). In (2), $\beta_{i,k}(i=1,2,\ldots,N, 0\le\beta_{i,k}\le1)$ is the degree of D_i to which the consequence D in the k-th rule is likely to appear. If the knowledge regarding the relation among A_i and D where A_i is described by $A_{i,p_i}(p_i\in\{1,2,\ldots,M_i\})$ is complete, $\sum_{i=1}^{N}\beta_{i,k}=1$, otherwise, $\sum_{i=1}^{N}\beta_{i,k}<1$, for all $i=1,\ldots,M$. In the rule base, θ_k (rule weight) is used to reflect the relative importance of R_k and $\delta_{k,j}$ is used to denote the relative importance of the j-th antecedent (A_j) of R_k for all $j=1,\ldots,M$.

$$R_k: IF\ A_1\ is\ A^k_{1,p1}\ AND\ A_2 is A^k_{2,p2}\ \ AND\ \ \ldots AND\ \ A_M\ is\ A^k_{M,pM},$$
$$THEN\ D\ is\ \{(D_1,\beta_{1,k}),(D_2,\beta_{2,k}),\ldots,(D_N,\beta_{N,K})\} \tag{2}$$

Specifically, the details of R_k can be depicted as – there are M antecedents ($A_1,\ldots,A_M$) and the consequence is represented by D, which consists of N possible values ($D_1,\ldots,D_N$). When A_j is described by the grade of A^k_{j,p_j} for all $j=1,\ldots,N$, the consequence D can be described by D_i with the belief degree of $\beta_{i,k}$ for all $i=1,\ldots,N$.

2.2. Inference and result explanation

Before conducting the inference based on BRB, the information regarding each antecedent should be first transformed into a belief distribution using the method proposed in [27]. After the transformation, different forms of information regarding each antecedent and different types of uncertainties involved can be modeled by belief distributions in a unified way. Specifically, the information regarding antecedent A_i (for $i=1,\ldots,M$) in (2) can be represented by a belief distribution as shown in (3). In (3), A_i can be described by $A_{i,j}$ which are the referential values or grades, to the degree of $\alpha_{i,j}$ where $i=1,\ldots,M$ and $j=1,\ldots,M_i$.

$$S(A_i)=\{(A_{i,1},\alpha_{i,1}),(A_{i,2},\alpha_{i,2}),\ldots,(A_{i,M_i},\alpha_{i,M_i})\} \tag{3}$$

Based on the information regarding antecedents in forms of belief distributions as presented in (3), and knowledge regarding the relations among antecedents and consequence denoted by belief rules as shown in (2), the next step is to conduct inference such that meaningful results can be generated. In this paper, the