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Human–computer interaction-based Decision Support System with Applications in Data Mining

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ABSTRACT

Human–computer interaction (HCI) plays a vital role in modern intelligent systems, such as brain–machine integration, human action recognition, telemedicine, and somatosensory game. A decision support system is a combination of the information system and decision-making technology. Visual human–computer interaction decision-making is a key technique in the decision support system. This paper proposes a new visual decision-making system applicable for industrial applications, i.e. data mining topics. To assist the performance of the proposed visual decision-making system, it is designed for data mining technique applications. Furthermore, the architecture of the decision support system is analyzed based on practical data mining case study. The comprehensive experiment shows that the proposed method is effective and robust in comparison to other methods.

1. Introduction

With its development, the database technology built based on business operating environment and platform cannot meet the needs of people in analysis and decision-making layers. The decision support system (DSS) has been developed based on the information management system [1–3]. To effectively provide important information for corporate and government management, data mining technology is applied in the field [4]. Data mining can be defined as a method to obtain useful knowledge and information by analyzing data in the database and data warehouse [5–7]. Data mining has shown an effective performance in the decision-making system [8–11]. The basic architecture of DSS is depicted in Fig. 1. The decision support system usually focuses on semi-structured or unstructured decisions. There is no certain pattern or procedure to be followed in solving these two kinds of decisions, which need to be decided based on previous experiences and insights. The decision support system applies computer technology to make the analysis and solution methods logical, digitize, and program the logic judgment program into the computer.

The intelligent decision-making system helps decision-makers to make semi-structured and unstructured decisions. It combines database, model base, method base, and knowledge base techniques [12]. In general, an intelligent decision support system consists of a decision support system and intelligent modules. Besides, systematic human–computer interaction is also a key component of the decision support system. To this end, system developers not only need to study the overall structure of the software but also need to understand the user's concept of interaction and the degree of mastering the computer, to design the interface of layout and platform management and the auxiliary control function that can automatically adjust and guide users to better conduct decision-making. The intelligent human–computer interaction system utilizes artificial intelligence and expert systems in the user interface; thus, the interface contains the most knowledge while users are required to learn the least knowledge. In general, the decision support system is used by users to input decision requirements to the computer through interactive devices, and then select the output form, such as image, and table, on the screen. Then, the computer processes these requests and outputs an optimal solution [13].

Data mining aims to discover the informative relationship, model, and trends of big data [14,15]. Data mining extracts implicit, unknown knowledge, and rules from a large number of noisy, fuzzy, or random data, which have potential value for

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decision-making, and can make result prediction for the non-occurrence behavior according to the existing information, providing the basis for business decision-making and market planning. Data mining technology is a new business information processing technology in essence, which improves the user's application of data from low-level online query operation to higher-level application of decision support, analysis, and prediction. Data mining can deal with massive data, and even if these data are incomplete, redundant, and random, the user data can be chosen for building a knowledge model through data cleaning methods. Data mining technology has brought about the structural change of the traditional decision support system. The existing database system can achieve the effective input, modification, statistics and query functions, but it fails to find the relationships and rules in the data, and it cannot predict the future development trend according to the existing data.

In this paper, we propose a visual decision-making system based on data mining. Likewise, we analyze the basic structure of the decision support system. Further, a human–computer interaction system is designed to provide feedback to modify the decision. The main contributions of this paper include:

- The proposal of a novel visual decision-making system.
- The approval of the proposed decision support system performance on data mining topics.
- Designing a new HCI system for providing feedback and notifications.

The rest of this paper is organized as follows. The related works including HCI and data mining are given in Section 2. The proposed method is introduced in Section 3. Section 4 presents the experiment analysis and results, while Section 5 concludes.

2. Related work

The research work presented in this paper is related to three research topics, i.e. human–computer interaction (HCI) [16,17], decision-making system [18], and data mining. These topics are introduced and discussed briefly in the following subsections.

2.1. Human–computer interaction

HCI studies the interaction between people and computers. It is worth mentioning that the user interface is the medium and dialog interface between people and computers to transfer and exchange information. Ideally, human–computer interaction does not depend on machine language. In the absence of keyboard and mouse equipment, human–computer communication can be realized anytime and anywhere. Hayes [19] discussed the relationship between human action and human–computer interaction. The author described the historical context of action research (AR). Bulling et al. [20] proposed an eye tracking-based human–computer interaction. Since the human real-time gaze is a powerful communication way for humans with computer devices. Zander et al. [21] proposed a brain–computer interaction system. Hollender et al. [22] conducted a review of the theory and concepts of human–computer interaction, where two conceptual models were presented.

Human–computer interaction is widely applied in modern intelligent systems, such as human action recognition, hand gesture recognition. In general, a camera-equipped on the computer can capture human actions. In addition, the computer will make corresponding actions according to different instructions of people. As described in [20], human gaze, hand gesture, and body movement can be used as the means of communication between humans and computers. Zabulis et al. [23] proposed vision-based

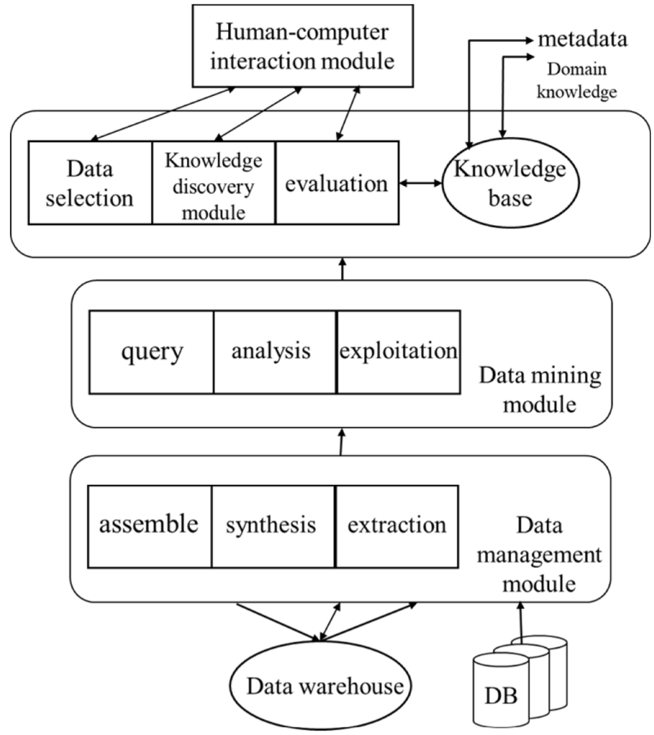

Fig. 1. The basic architecture of the decision support system.

hand gesture recognition. Hidden Markov Model (HMM) is generally used for hand gesture recognition since HMM processes a strong ability in analyzing time-related tasks. In addition, recurrent neural network algorithms are applied in hand gesture recognition [24,25]. Recognizing human gesture is significant for HCI applications.

The decision-making system aims to obtain the best solution. The decision support system (DSS) was proposed by Scott in 1970 [26]. DSS consists of a decision module, support module, and system module. Sprague [10] proposed that DSS should support not only structural decision-making but also semi-structural and non-structural decision-making. The author gives the general structure of DSS and points out that DSS can only provide useful information for decision-makers, but cannot specify decision. Traditional DSS uses various quantitative models, which play a great role in quantitative analysis and processing. It supports semi-structured and unstructured decision-making problems. However, DSS has some limitations [11,27]. The function of the system in decision support is passive, it cannot provide active support according to the change of decision environment and it cannot provide support for the common unstructured problems in decision-making. Based on the quantitative mathematical model, it lacks corresponding to the common qualitative, fuzzy and uncertainty problems in decision-making means of support [28].

2.2. Data mining

Data Mining (DM) can be divided into five methods, i.e. predictive modeling, clustering, summarization, dependency modeling, and change and deviation detection [29]. Predictive modeling is based on some fields to predict one or several fields in the database. When the predicted field value is a continuous value, the task is a regression problem. While when the predicted field value is an enumeration value, the task is a classification problem. The genetic algorithm and decision tree algorithm are widely

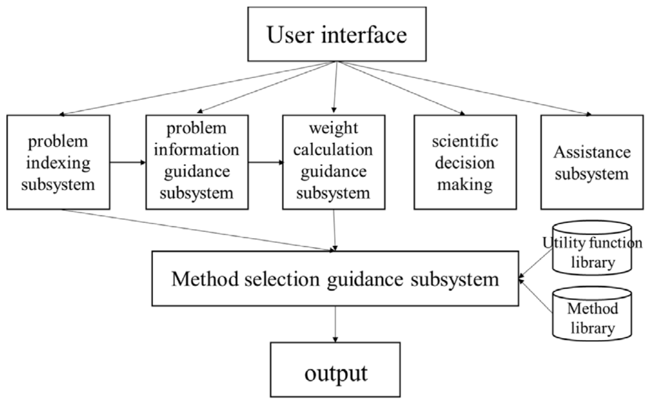

Fig. 2. The framework of our proposed decision support system.

used in classification methods [30]. Clustering is an unsupervised classification task, which is classified as several subsets based on feature representations. Clustering algorithms can be grouped into three categories: metric-distance based methods, model-based methods, and partition-based methods. Summarization methods can generate the Feature Generalization of each data subset and find the relationship between data fields. Dependency modeling is to find the causal relationship from the data. By exporting the irregular structure in the data, it can usually deepen the understanding of the data. The causal model can be random or deterministic. Change and deviation detection is used to interpret the information of time series or other types of series, such as the change of quantity value with time, and detect abnormal situations. The order in which information is observed is an important factor in such methods. W. H. Inmon [31] proposed the concept of the data warehouse. The data warehouse is a subject-oriented, integrated, time-varying and non-volatile data collection in enterprise management and decision-making. Different from other database applications, the data warehouse is more like a process of integration, processing and analysis of business data distributed throughout the enterprise. The fuzzy method, rough sets, and cloud methods are usually used in data mining techniques. In recent years, with the development of neural networks, an artificial neural network (ANN) is also used for DM. In data mining, the neural network is mainly used to obtain classification patterns. However, since the patterns obtained by the neural network classification method are hidden in the network structure rather than expressed as rules, it is not easy to be understood and interpreted by people [32]. In addition, the training time of the network is longer when training data is scanned many times. Therefore, different from other data mining methods, the neural network used for data mining should solve two key problems: training time reduction and comprehensibility of mining results.

3. Proposed method

Decision support system (DSS) is a semi-structured or unstructured decision-making computer application system through data, model, and knowledge. In our work, we design a human–computer interaction decision-making system. The framework of our method is shown in Fig. 2.

3.1. Visual HCI decision system

3.1.1. Utility function

When making decisions, the utility is a key metric to measure different functions of the conditional result. In the decision support system, utility refers to the subjective and objective comprehensive effect or value of each alternative condition result on the decision-maker in the same decision-making problem. The utility is the mapping from preference set X to the real number set R. Utility function aims to express utility as a real number. The utility value is a relative index. Generally speaking, the utility value of the most favorite event and the least favorite event is 1 and 0 respectively. By using the equivalence principle to test the utility value, we can get the utility function curve of each decision-maker. It can be used to analyze the effect of utility on decision-making. As a quantitative description of subject preference, the utility function model can be established in the range of elementary function as long as preference satisfies rational behavior and has structural characteristics of the system. As a quantitative constraint, the utility point measurement in the preference element is used to determine the value of unknown parameters in the model and obtain a specific algorithm.

The utility curve plots the performance of the utility function. Suppose the decision-maker faces two alternative schemes A_1 and A_2, where A_1 denotes that one can get a fund amount r without risk, and A2 means that a fund s can be obtained by probability p, or the loss amount t can be obtained by probability $(1-p)$. Here we define $t > r > s$. Let $U(s)$, $U(r)$, and $U(t)$ represent the utility value of s, r, and t. If A_1 and A_2 are equivalent, then it can be formulated as:

$$PU(s)(1-P)U(t) = U(r) \tag{1}$$

Formula (1) denotes that the utility value of r is equivalent to the utility expectation value of s and t. In our implementation, we fix the values of P, s, and t, and we can obtain the utility curve of the decision-maker by using the iterative algorithm [33].

3.1.2. Utility curve construction

In multiple attributes decision-making, there are three issues that should be solved: (1) the utility values of some representation discrete points in the scheme set should be measured. (2) designing a mathematical model suitable for describing the behavior of subjects is still a challenging task. (3) how to put forward some questions to the decision-maker to investigate the risk attitude of the decision-maker, so as to select a certain kind of function model as the qualitative constraint of the utility function of the decision-maker. We introduce a method to construct the utility function by interacting with decision-makers.

We calculate the utility value of several representative points:

$$u(y) = (1-\alpha)u(x) + \alpha u(z) \tag{2}$$

where $\alpha \in (0, 1)$. We leverage two points x and z with known utility value. In general, we choose the minimum and maximum elements of X, and we define $u(x) \equiv 1$, $u(z) \equiv 0$. If there is no maximum or minimum element in X, you can also use the upper or lower bound of X and select the appropriate benchmark.

3.1.3. Preference visualization

To make decision-makers express their preferences simply and clearly, we propose the concept of preference visualization. Preference visualization refers to the process that the decision-maker transforms the preference information in the decision-making problem into an intuitive, easy to understand, interactive analysis and control dynamic picture by using the visualization method through the computer.

Unified modeling language [34] can be used to design a control system. UML captures the static structure and dynamic behavior information of the system. The system is modeled as a collection of independent objects, which interact with each other to achieve functions. Static structure defines all kinds of objects and

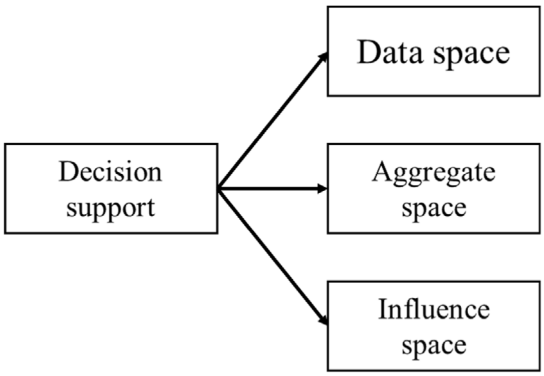

Fig. 3. Hierarchical space of data mining.

implementations that are important to the system, as well as the relationship between them. Dynamic behavior defines the history of the object time and the communication between the objects to achieve the goal. In our work, the visual human–computer interaction decision system is modeled by the UML method.

3.2. Data mining in DSS

Data mining is a decision support process of finding patterns in the observation data set. The hierarchical space of data mining is shown in Fig. 3. We divide data mining into three hierarchical space: data space, aggregate space, and influence space.

The data space leverages the query and reports function of the existing database management system to carry out the decision-making query based on keywords and realize the online transaction processing (OLTP). The aggregate space leverages aggregation operation, multi-dimensional analysis, and statistical analysis to realize on-line analysis and processing to provide statistical analysis data for decision-making reference. According to the clustering of similarity and the classification method of difference, the influence space discovers the relevance and structural pattern, the sequential pattern, establishes the prediction model, and finds the hidden useful information from the database. Each level of data mining reflects different levels of query requests. This division is conducive to the gradual extraction of knowledge, which is the decision support process. In the traditional decision support system, the knowledge and rules in the knowledge base are established by experts or programmers and input from the outside, while data mining is a process of automatically obtaining knowledge from the inside of the system. Compared with the query and retrieval information of the database management system, the knowledge of data mining is implicit, concise, and high-level.

4. Experiment and analysis

In this section, a comprehensive experiment is conducted to verify the effectiveness of data mining applying in the decision support system (DSS). The data mining evaluation is given in Section 4.1 and the parameter analysis is presented in Section 4.2.

4.1. Data mining evaluation

In this paper, the performance of the proposed method is firstly evaluated under different data mining algorithms including decision tree (DT), Bayes network, association rules (AR), concept lattice (CL), and clustering. Decision support system evaluation refers to the user's positive or negative evaluation of DSS. Generally speaking, if users like DSS, they can make a short positive

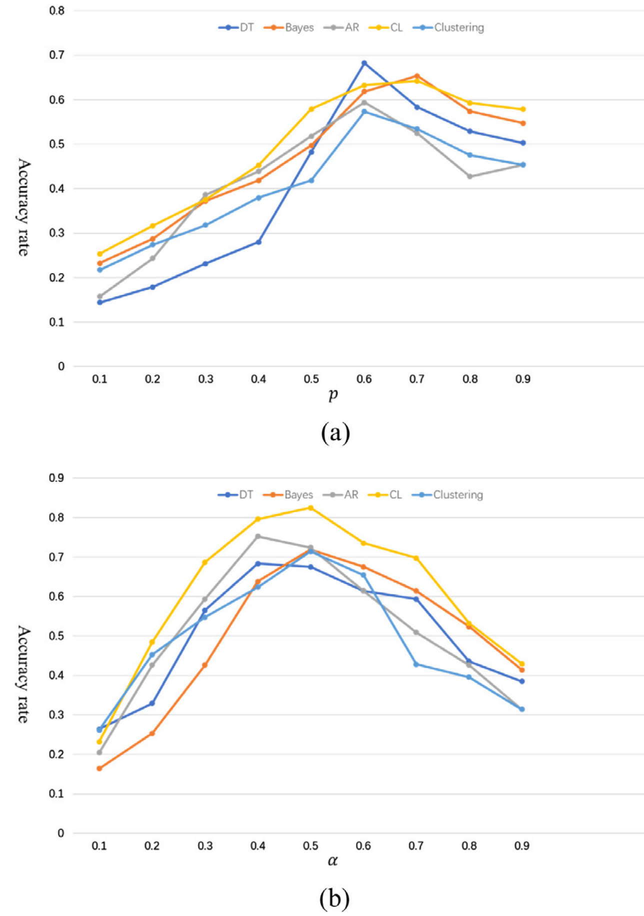

Fig. 4. The comparative result under the different parameters. (a) the accuracy rate under the different values of p; (b) the accuracy rate under the different values of α.

evaluation of it. While if users do not like DSS, they can also make a negative evaluation of why they do not like DSS. To quantify the accuracy rate of the decision support system, we gather the users' comments on the DSS. We define the accuracy rate as follows:

$$accuracy = \frac{the\ number\ of\ positive\ evaluation}{total\ number\ of\ evaluation} \tag{3}$$

Table 1 reports the performance of the DSS under different data mining algorithms. The experiment is repeated 10 times and we calculate the average value as the final result. As we can see from Table 1. Concept Lattice-based method achieves the best performance. Concept lattice can be used not only as a new method of decision support system, but also as a good representation of concept level. Concept lattice applying in DSS can solve the problem of concept validity after knowledge updating in a case-based reasoning system.

4.2. Parameter analysis

There are two key parameters in our work α balancing two terms of formula (2) and p denoting the probability of the fund s. We conduct experiments under different parameters of α and p. The comparative result is shown in Fig. 4. As we can see from Fig. 4. When the probability value p is set to 0.6, the clustering method can achieve the best performance. When $\alpha = 0.5$, the concept lattice method achieves the best performance.

Table 1
The accuracy rate of the DSS under different DM algorithms.

	DT	Bayes	AR	CL	Clustering
1	0.6284	0.7250	0.7893	0.8676	0.7327
2	0.6410	0.7392	0.7908	0.8762	0.7426
3	0.6513	0.7017	0.8093	0.8902	0.7897
4	0.6034	0.6993	0.8137	0.8365	0.6937
5	0.6197	0.7183	0.7900	0.8638	0.7213
6	0.5920	0.7427	0.7857	0.8365	0.7430
7	0.6211	0.7083	0.7902	0.8783	0.7104
8	0.6392	0.7200	0.8013	0.8607	0.7642
9	0.5907	0.7221	0.8109	0.8730	0.7553
10	0.6253	0.7173	0.7902	0.8635	0.7432
Ave.	0.6212	0.7194	0.7971	**0.8646**	0.7396

5. Conclusion

Data mining provides an effective and feasible solution for the decision support system design. Data mining based DSS can effectively predict and analyze enterprise decisions. In this paper, we designed a visual decision-making system, where the data mining technique is used to assist the system. We analyzed the architecture of the decision support system based on data mining. Furthermore, a comprehensive experiment has shown the effectiveness of our proposed method.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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