Design of a Fuzzy based Recommendation System for Travel Destination Selection

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여행지 선정을 위한 퍼지기반의 추천시스템 설계

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Abstract

오늘날 인터넷의 출현과 확산으로 인하여 정보의 홍수를 이루게 되었고, 고객들은 자신이 원하는 제품이나 서비스를 선택하기 위해서 정보를 탐색하는 작업이 더욱 어려워지게 되었다. 이러한 고객들에게 좀 더 편리하게 자신이 원하는 제품이나 서비스를 선택하도록 도와주는 것이 추천 시스템으로써, 고객 관계 관리의 중요한 부분으로 자리잡게 되었다. 본 연구에서는, 인터넷상의 여행사 사이트 등에서 고객이 여행지를 선택할 때 고객이 관심을 가질만한 여행지를 추천하여 줌으로써 고객이 최적의 여행지를 선택할 수 있는 새로운 추천 시스템을 개발하였다. 기존의 여러 추천 시스템에서 적용되던 협업 필터링 기법의 문제점으로 나타나고 있는 희소성과 확장성을 해결하기 위하여 본 연구에서는 퍼지로직과 인공신경망을 결합한 하이브리드 접근 방법인 뉴로 퍼지 기반의 여행지 추천시스템을 개발하였다. 제안한 추천시스템을 적용하여 실험한 결과 제안 시스템이 기본의 방법들보다 우수함을 입증하였다.
Keywords : Fuzzy Logic, Neuro-fuzzy, Recommendation System, Travel Destination Selection

1. Introduction

Among the fastest growing service industries are international tourism and the hospitality industry which have grown dramatically. In fact, it is projected that international tourism will be one of the service-led economies of the 21st Century. It is always important for tourists to select travel destinations which meet their preference. For some tourists identifying a satisfactory travel destination is a time-consuming and difficult task, as some factors affecting travel destination selection require rather personal judgements. In this paper, a fuzzy based recommendation system has been designed and developed to facilitate travel destination selection. By using the proposed system, which incorporates linguistic terms normally used by tourists, travel destination selection is made simply. Especially, the proposed system adapts the neuro-fuzzy approach. Neural networks recognize patterns and adapt themselves to cope with changing environments, while fuzzy inference systems incorporate human knowledge and expertise for inferencing and decision making.

Integration of the two complementary approaches, together with certain derivative-free optimization techniques, results in neuro-fuzzy models [4,7]. The proposed system also improves operations, reduces the cost of inquiries, and provides information very quickly. We believe that it cannot only help the tourism industry, but also the approach may be applied to the other areas.

There are many published studies focused on applications of artificial intelligence technology which support the tourism and hospitality domain. McCool [2] discussed some considerations necessary for developing expert systems for the hospitality industry.

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The design and development of an expert system for a tourist information center was outlined by Tsang et al. [9]. The expert system was built to recommend a suitable travel schedule that satisfies user input constraints such as time period, budget and individual preferences. Yeung et al. [10] discussed the implementation on the Internet of a multi-agent based tourism industry. The system allowed the users to retrieve the most up-to-date information through a web browser.

Fuzzy logic has proved useful for developing many practical applications, especially in the field of engineering, as it can handle inexact and vague information. Even though an abundance of research in fuzzy logic has been conducted in the past, relatively little attention has been paid to applications of fuzzy logic technology in tourism-related industries.

Petrovic-Lazarevic and Wong [6] underlined the significance of an application of fuzzy control in the hospitality industry in order to achieve or sustain competitive advantage. They applied general fuzzy control model in the hospitality industry to monitor and control the level of service quality provided.

Ghalia and Wang [3] proposed an intelligent system using fuzzy logic to estimate the future tourism demand. However, the applications of fuzzy logic in travel destination selection research are almost non-existent based on the results of a literature review conducted by the authors.

This paper describes the design and development of a neuro-fuzzy based recommendation system that can be used effectively to assist in travel destination selection.

Prior to the emergence of neuro-fuzzy techniques, most design methods used only linguistic information to build fuzzy logic controllers. Pure fuzzy logic based systems are not easily formalized and it is more of a trial and error effort than an engineering practice to define and fine-tune parameters of membership functions. When using learning algorithms in the proposed approach, membership functions may be refined in a systematic way based on numerical information input - output data pairs provide. Linguistic information can be used to identify the structure of a fuzzy controller, and then numerical information can be used to identify parameters such that the fuzzy controller can reproduce desired actions more accurately[4, 5, 7].

The paper is organized as follows. In Section 2, we present the proposed system based on neuro-fuzzy approach. Section 3 shows the experimental results of the proposed system. Section 4 provides concluding remarks of the paper.

2. The Proposed System Based on Neuro-fuzzy Approach

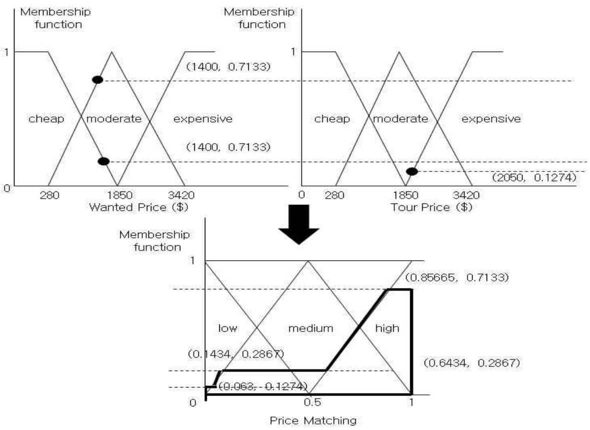
Basically, the construction of a neuro-fuzzy model consists of two main parts: the construction of a fuzzy logic system, and the parameters adjusting it. The procedures for each part are described below [7].

2.1 The Construction of a Fuzzy Logic Model

Fuzzy logic deals with the extent to which a subject belongs to a fuzzy set. Subject x belonging to fuzzy set A is usually expressed as $\mu_A(x)$. Although the mapping function among variables described by "IF - THEN" rules is still the underpinning of a "fuzzy" expert system, the fuzzy logic system distinguishes itself from "traditional" expert systems by using linguistic terms instead of mathematical expressions in describing linguistic variables. To clarify, we assume that a fuzzy logic system contains only one rule which can be described below.

IF A is low and B is high;
THEN C is high (1)

where A, B and C are called linguistic variables; low and high are called the linguistic terms. The whole statement, Eq. (1), is called a fuzzy rule. Several rules constitute a fuzzy logic model. The procedure to construct a fuzzy expert system consists of three steps: fuzzification, construction of the knowledge base, and defuzzification.



<Fig. 1> Graphical representation of max-min inference of "price matching"

2.2.1 Fuzzification

Each variable in the fuzzy rule can be defined by several linguistic terms. Each linguistic term has a corresponding membership function. For example, an input value of “Tour Price” $2,050 results in a degree of membership in the set labelled “moderate” of 0.8726 and a degree of membership in the set labelled “expensive” of 0.1274 as shown in <Fig 1>.

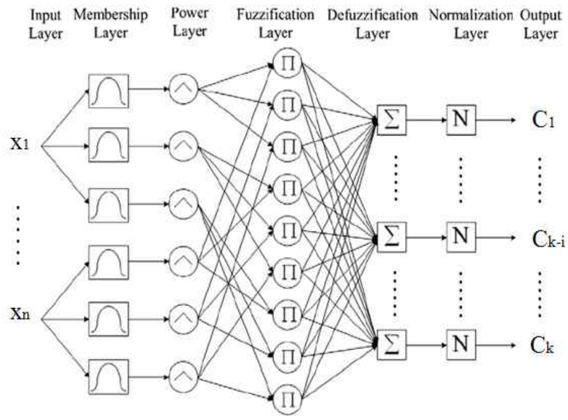
2.1.2 Construction of the Knowledge Base

The knowledge base is a function of a series of “IF - THEN” statements. Assume that a neuro model is constructed with three independent variables and three dependent variables. Each independent variable is described in three linguistic terms, each dependent variable in five. That means the complete knowledge base consists of 3×3×3×5 = 135 rules. Each rule contains an “IF” and a “THEN” constituent. The former evaluates the extent to which the objects satisfy the requirements, and the later represents the response of the system. According to the definition of the composite fuzzy set [8], the validity of “THEN” depends on the minimum value of the membership function values stated in the “IF” part.

Taking the above example for instance, the validity extent of the “THEN” part is 0.1274, i.e., min{0.7133, 0.1274} = 0.1274; the validity extent of the system response, that "Price Matching" is medium, is 0.1274.

2.1.3 Defuzzification

When the inference process is complete, the resulting data for each output of the fuzzy classification system are a collection of fuzzy sets or a single, aggregate fuzzy set. The process of computing a single number that best represents the outcome of the fuzzy set evaluation is called defuzzification. There are several existing methods that can be used for defuzzification. These include the methods of maximum or the average heights methods, and others. These methods tend to jump erratically on widely non-contiguous and non-monotonic input values [1]. We chose the centroid method, also referred to as the “center-of-gravity (COG)” method, as it is frequently used and appears to provide a consistent and well-balanced approach. For each output using this defuzzification method, the resultant fuzzy sets are merged into a final aggregate shape and the centroid of the aggregate shape computed. (See < Fig. 1>).



<Fig. 2> A overall framework of neuro-fuzzy model

What we have introduced above is called the fuzzy expert system. However, having each rule treated as equally important by the system is hardly pragmatic in the real life. One method to rectify such a shortcoming is to assign each rule a weight, namely the degree of support (DOS), which represents the relative importance of each rule. The validity of the “THEN” fraction is hence a function of the validity of the “IF” fraction multiplied by the DOS.

Unfavorably, how to decide the DOS value for each rule is an imperfection that needs improvement.

The learning ability of neural networks among all the possible solutions can be an advanced alternative.

Neural networks can be used to fine-tune the parameters of the fuzzy expert system, which is what we call neuro-fuzzy.

2.2 The Learning of the Fuzzy Expert System

Essentially, neuro-fuzzy model utilizes the functionality of the fuzzy expert system to construct a relationship amongst variables, with the characteristics of fuzzy logic to tolerate uncertainty and inaccuracy of variables, and utilize the learning ability of neural networks to fine tune the parameters of the fuzzy expert system. Overall, the framework of neuro-fuzzy based recommendation system is shown in <Fig. 2>.

The procedure to construct a neuro-fuzzy system can be described as follows:

Step 1: Divide the data set into training and testing data sets.

Step 2: Construct a complete knowledge base and set all the DOS values equal to 0 as an initial solution.

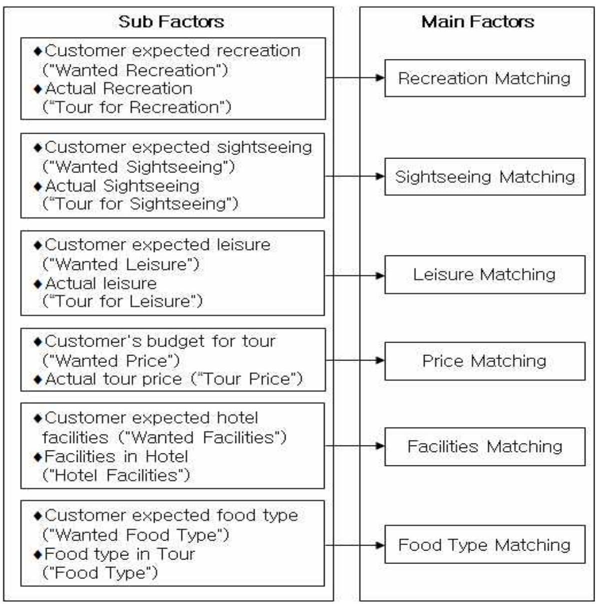
Step 3: Use the learning ability of a neural network to fine-tune the DOS value of each rule. If a specific relationship among variables described by a rule does exist in the data set, the DOS value of this rule will be strengthened; otherwise, the DOS value still remains at 0. Sometimes the summation of weights may be bigger than 1. Therefore, the outputs of the network should be normalized.

Step 4: The training process will be terminated when the mean squared error between the predicted value and the real value is less than a predetermined threshold value. Afterwards, all the rules with DOS values less than certain threshold values will be deleted (this is what we call α cut), and the left rules present the relationship among variables in the data set.

Step 5: If the predictive accuracy is high for the test data set based on the knowledge base, then the model is already established; otherwise, repeat steps 3 and 4.

3. Experiments using the Proposed Approaches

In this study, we gather the dataset by tourists to demonstrate the performance of the proposed neuro-fuzzy model. We construct the neuro-fuzzy system on the subject of tour packages which are selected in the Web site of tourism companies.



<Fig. 3> Critical Factors for Travel Destination Selection

3.1 Data Gathering

The dataset has 240 samples, six features and five classes. In each feature, while two of five classes can be easily separated, the other class is overlapped with the other classes. The six inputs and five classes are derived from the tour packages as shown in <Fig. 3>. The six inputs consist of critical factors for travel destination selection such as recreation, sightseeing, leisure, price, facility and food type. The five classes are compromised of five tour types such as rest, rest+sightseeing, sightseeing, leisure and resort+club types. The dataset obtained from the survey questionnaires of tourists. In order to validate the data, we perform the reliability analysis for consistency and the factor analysis for validity.

Reliability analysis adapts the Chronbach's α value and factor analysis applies to the principal component method and varimax rotation. After analyses, all factors are acceptable, so we use the all factors in our experiments.

To discover the capability of the proposed systems to make accurate classification, in general, an attempt was drawn from some of the data, but not the total dataset. To do so, the sample set of 200 cases was subdivided into a training sample and a test sample based on random numbers generated by the computer. The training sample has 140 dataset, whereas the test sample has 60 dataset.

3.2 Experimental Results

In oder to validate the performance of the proposed neuro-fuzzy system, we compare with the traditional classification algorithms such as K-Nearest Neighbors (KNNs), Neural Networks (NNs), Gaussian Mixture Density (GMD), and Support Vector Machines (SVMs) in terms of the classification accuracy (%).

<Table 1> Classification results of experimental dataset with different methods

Methods	Training data(%)	Test data(%)
KNNs	94.29	93.33
NNs	93.57	91.67
GMD	86.43	81.67
SVMs	96.43	95.00
neuro-fuzzy	99.29	98.33

The classification results of experimental dataset with different methods are shown in <Table 1>.

According to <Table 1>, the neuro-fuzzy system gives the best classification performance. These experimental results demonstrate that, using of learning algorithm and fuzzy logic improves the success of the classifier.

4. Conclusion

This paper has described the design and development of the fuzzy based recommendation system which is used to assist tourists by facilitating travel destination selection. By developing the proposed system, we have shown that it is a feasible procedure to use fuzzy logic and learning algorithm to assist with travel destination selection. It provides the best match between the customer's requirements and available travel destination selection. The performance of the proposed system based on neuro-fuzzy classifier was demonstrated by employing it for travel destination classification problems and comparing them with several other classification methods and the proposed method was superior to previous recommendation systems. The usage of linguistic membership in neuro-fuzzy classifier improves the classification accuracy according to the combined neural networks and fuzzy logic approach.

Eventually, the proposed system clearly demonstrates the potential of neuro-fuzzy based modeling for a personalized recommendation system of various areas including travel destination selection.

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