Proactive Recommendation System Based on Hybrid Neural Network and Fuzzy Knowledge Base

Fedorov A.V.; Shkodyrev V.P.

Abstract

Recommendation systems usually divided into two types: collaborative filtering and content recommendation systems. Recently, a new kind of hybrid methodical systems based on knowledge bases has been singled out; an example of such a hybrid system is given in [1]. In the case of application of advisory systems in conditions of uncertainty, such term as intelligent proactive recommendation system (IPRS), in the form of artificial intelligence, is acceptable. In the presence of uncertainties, soft calculations, Markov models, fuzzy systems, genetic algorithms or neural networks are usually used among the input parameters of the system. This article describes new view to recommendation systems with application in prediction of danger situations on the road and manufacture with help of knowledge base and hybrid neural networks. IPRS is understood as an intelligent system consisting of a complex of components that allows the user of the computer to obtain operational solutions for complex situations. The IPRS system, in analogy with other intelligent systems, can consist of several subsystems: a learning adaptive part; interactive for interaction with users and the environment; processing for reading data about the world; subsystems of the withdrawal of recommendations and a block representing the external environment, as given in [2]. The benefits of proposed approach with two applications are described in this paper.

1 INTRODUCTION

In next chapters we describe the difference between proactive and classic recommendation systems. Introduced view to architecture of proactive recommendation system.

1.1 INTELLIGENT PROACTIVE RECOMMENDATION SYSTEM

The conceptual scheme of IPRS is shown in Fig. 1. As the set $U = \{U_1, U_2, ..., U_n\}$ there will be many users of the system. The Dialog Processor (DP) is the user interface. To improve user interaction, the interactive processor must be able to develop linguistic solutions.

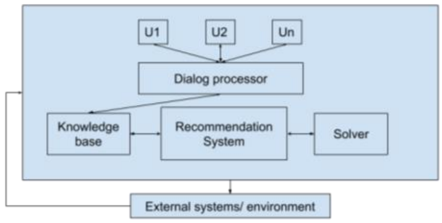

Fig. 1 IPRS Conceptual Framework

The main purpose of the recommendation system is information processing. Depending on the values of environmental parameters, several options are chosen to solve the problem in the event of its approach or occurrence. Based on the knowledge base (KB), the recommendation system searches for the most appropriate solution for the given situation. Solver translates the inference from rules and decisions from recommendation systems.

1.2 KNOWLEDGE BASED RECOMMENDATION SYSTEMS

A significant role in IPRS is played by two elements - the recommendation system and the knowledge base. Knowledge - these are the rules, laws and patterns obtained as a result of professional activities within the subject domain.

The knowledge base is a database containing the rules of inference and information about human experience and knowledge in a certain subject area. In other words, it is a set of such patterns that establish the links between input and output information. To solve expert-level problems, recommendation systems need effective access to a knowledge base with substantial knowledge, as well as a mechanism for justifying the application of knowledge to the problems that are assigned to them.

The process of data extraction for knowledge bases is shown on Fig. 2.

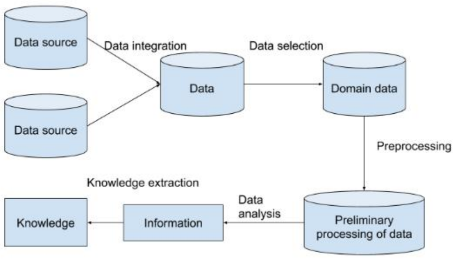

Fig. 2 General process of data analysis and data selection

1.3 FUZZY KNOWLEDGE BASE

In the case of production systems, the analysis process consists in finding all possible sensors and actuators in the system, as well as all possible elements in the environment of the production line, which can introduce uncertainty. Based on the data of sensors and actuators, the process of operating the line is studied - what elements are connected with which element, which element can affect the other. After all the elements of the system are examined by the expert, all possible rules are created for the various emergencies that may occur. The rule can look like a sequence of if-then conditions, for example:

If the pressure in the tank B1 > 1.2 atm. and reactor temperature < 20, then urgently increase the pressure or increase the temperature.

If the inference system allows you to uniquely select one action, then the recommendation system can be included in the control loop to exclude the delays caused by the human factor.

At the computational level, the fuzzy system can be considered as a multilevel structure (network), similar to artificial neural networks such as RBF. To optimize parameters in a fuzzy system, learning algorithms such as gradient descent, known from the field of neural networks, can be used.

Consider first a simple example of a fuzzy TS model of zero order with the following two rules:

If x_1 is A_{11} and x_2 is A_{21} then y = b_1

If x_1 is A_{12} and x_2 is A_{22} then y = b_2

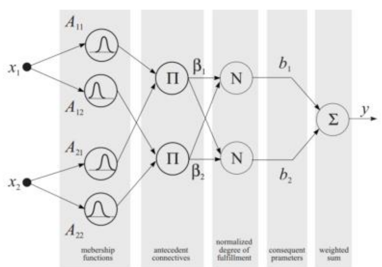

Fig. 3 Example of a fuzzy model with zero order with two rules represented as a neural-fuzzy network.

Fig. 3 shows a network view of these two rules. The nodes in the first layer compute the degree of belonging of the inputs in antecedent fuzzy sets.

2 NEURAL NETWORK FUZZY LOGIC CONTROLLER

NNFLC - fuzzy controller based on neural network and fuzzy logic. Structurally, NNFLC is a multilayer network of direct signal propagation that implements the principles of the neural network of knowledge, with different layers performing different functions. The NNFLC system allows the presentation of fuzzy production classification systems such as Max-Min or Takagi-Sugeno type in the form of ANN. When designing, a four-layer fuzzy FF-network arises, in which each layer is formed by neurons of a certain type. The weights of the bonds are either constant or vary in the learning process. By using different learning algorithms, both free parameters and the structure of the neural network can vary, and in real time.

2.1 HYBRID NEURAL NETWORK LEARNING PROCESS

The training of the NNFLC of complex architecture takes place in several stages: at each stage different learning algorithms are used: preschooling, online, without a teacher, with a teacher. The general training scheme for NNFLC includes the following steps:

- formation of training data;
- self-organizing clustering (setting of membership functions);
- Competitive training (algorithm of the winner);
- removal of rules;
- combination of rules;

Final tuning of the parameters (tuning) of the membership functions using the algorithm for back propagation of the error.

3 RECOMMENDATION SYSTEM FOR MANUFACTURING

Based on proposed mechanism were created two prototypes of recommendation systems – first one for manufacturing and second one for driving assistance.

3.1 RECOMMENDATION SYSTEM FOR CHEMICAL STATION

The chemical station consists of four modules - a filter, a reactor-station, mixing stations and bottling. The station can be represented as a small plant consisting of 20 controllers and 44 sensors. For simplicity, only the subset of sensors is considered in this paper:

- Temperature of the mixture of liquids in the reactor
- Status of the three valves of the filtration station
- Mixer status in the mixing station
- Liquid level in the mixing station
- Mixing time

Depending on the combination of these sensors, the adaptive neuro-fuzzy logic inference system can generate an objective function from which we can obtain information, for example, exceeding the permissible temperature or liquid level, the system can, as a result, display a message or warning to the user if the expert enters the parameter limits for that parameter.

3.2 MATHEMATICAL MODEL

The mathematical model of the entire production line system can be represented in the following form:

1. $X = \{x_1, \dots, x_n\}$ - input parameters;
2. $Y = \{y_1, \dots, y_z\}$ - are the estimated parameters;
3. $S = \{s_1, \dots, s_h\}$ - states;
4. $P = \{p_{11}, \dots, p_{mm}\}$ - transactions;
5. $A = \{a_1, \dots, a_k\}$ - action;
6. $D = \{d_1, \dots, d_l\}$ - decisions;
7. $R = \{r_1, \dots, r_h\}$ - rules;
8. $MF = (mf_1, \dots, mf_g)$ - membership functions.

Then a set of actions can be represented as:

$$A = D((s_{i+1}(P(x_{i+1}, y_i)), R(MF_1..MF_g(y_{i+1}))) \quad (1)$$

3.3 STRUCTURE OF THE NEURAL NETWORK KNOWLEDGE BASE

At the stage of identification of the neural network it is necessary:

- Identify all significant sensors in the system.
- Identify all the relationships between components.
- Define the membership functions for all components.
- Set a list of actions to take the system out of an emergency

Data obtained from a laboratory stand are transferred to the inputs of three classifiers based on neural networks, each of which is a multi-layer perceptron [3].

Each of the perceptrons consists of 3 layers and includes 3 neurons in the input layer, 8 neurons in the hidden layer and 1 neuron in the output layer.

The developed neural network recognizes 9 classes of pre-emergency situations, which from the outputs of the neural network are input to the inputs of the fuzzy logic inference system.

4 DRIVER ASSISTANT RECOMMENDATION SYSTEM

The distribution of emergencies on video recordings is as follows - 42.6% the motorcycle collides with the car, 19.7% the machine collides with the car, 15.6% the motorcycle collides with the machine and 20% other types of accidents.

The ability to prevent accidents is an extremely difficult task, since accidents are very diverse, and they tend to occur suddenly. Drivers learn from experience to pay attention to implicit signals, including the semantics of the scene, the appearance of the object and the movement. In this paper, situational control based on a recurrent neural network (RNN) is proposed for predicting accidents before they occur. The system consists of such components as:

- NNFLC - Neuro-fuzzy controller for the output of human-understandable commands or descriptions of the current situation

- RNN for Long-Term Term Term Term Termination (LSTM) is used to predict the emergency situation for the long-term dependencies of all signals and for the prediction of accidents [4].

- Exponential-loss: by analogy predicting driver maneuvers, the exponential decay function is used as a function of losses for positive examples.

For effective forecasting, the method of in-depth training is used. All these components together provide prediction of accidents, based on a cheap sensor based on machine vision [5].

The program module developed as a result of the work includes a full-fledged application and adaptation for the Raspberry Pi 3B microcomputer, and the standard Tensorflow model for the "inception graph" image recognition was supplemented by a trained recurrent neural network based on 1730 VSLab video recordings from DVRs in Taiwan. An example of how the program works is shown on Fig. 4.

Fig. 4 Results of working software module for predicting danger situations

5 RESULTS

Without the use of distributed methods, the total delays for prediction of emergency situations on production line are 0.85 s - i.e. recommendation system works out less than a second after the occurrence of a pre-emergency situation. A hybrid neural network in combination with NNFLC as a part of proactive recommendation system can detect an emergency situation in 1.8 seconds with 80% recall and 68.9% accuracy. The average accuracy is 76.6%. The average learning time of the model is approximately 8 hours. These results shows that recommendation system can predict emergency situation before the accident and user oft he system could have time to react. Developed system with Raspberry Pi are shown on Fig. 5:

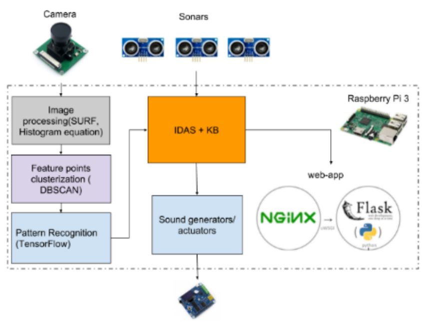

Fig. 5 Developed prototype

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Author:	Fedorov Aleksandr
University:	Peter the Great St.Petersburg Polytechnic University
Department:	Control Systems and Technologies
E-Mail:	aleksandr.v.fedorov@gmail.com