An Evolutionary Emergency Model of Home Network Environment

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Abstract

In this paper, we propose an evolutionary emergency model of home network environment (EEMHNE). This model not only can do self-tuning to fit the home network environment but also detect the emergency event automatically. There are three modules in this model, namely, emergency process module (EPM), emergency knowledge base (EKB), and knowledge base evolution module (KBEM). EKB includes three components and can provide rules to EPM for fuzzy inferences. EPM determines the emergency situations by fuzzy inferences and send warning messages to the users. KBEM can adjust all components in EKB by using genetic algorithm. Via this model, we can have the more reliable and safer home network environment

1. Introduction

Nowadays information appliances (IAs) have became available to all, there are more and more varied IA products appeared. IA plays an important role in home network environment. In home network environment, an IA control mechanism can provide the better control capability of IA devices [8].

Lee and Huang [7] proposed an IA controlling model (IACM), which can control IA devices through home management broker. Lee et al. [6] came up with the idea of IAs intelligent agent model (IAIA), which can make home environments more comfortable and convenient. Lee et al. [12] proposed fuzzy neural network model of information appliances with the functions of self-learning and fuzzy inference, it can enables IAIA to enhance the IA's efficiency. Lee and Mao [10] proposed a clustering model of information appliance, it processes user's recognitions of IAs to cluster IA devices, and it facilitates the management of control. Lee et al. [11] proposed a fuzzy aggregative clustering model of information appliances (FACIA) which is capable to cluster the IAs, filter and extract the IAs' messages automatically. Lee et al. [8] proposed a remote authentication model of information appliances which can improve security of the home network system, and promote authorization control mechanism. Wu and Jan [16] proposed home network management system which can monitor the situation of home network environment. However, when the abnormal events occurred, if there is an active response mechanism, then we can avoid the serious accident in home network environment and enhance the capability of IA control mechanism.

In this study, we proposed an evolutionary emergency model of home network environment (EEMHNE). There are three modules in this model, saying emergency process module (EPM), emergency knowledge base (EKB), and knowledge base evolution module (KBEM). EKB includes three components and can provide rules to EPM for fuzzy inference. EPM determines the emergency situations by fuzzy inferences. KBEM can adjust all components in EKB by using genetic algorithm. Via this model, we can have the more reliable and safer home network environment.

2. EEMHNE

In this Section, we present an evolutionary emergency model of information appliances (EEMHNE) under the supervision of IAIA [6], as shown in Fig. 1. There are three modules in EEMHNE, saying emergency process module (EPM), emergency knowledge base (EKB), and knowledge base evolution module (KBEM), as shown in Fig. 2.

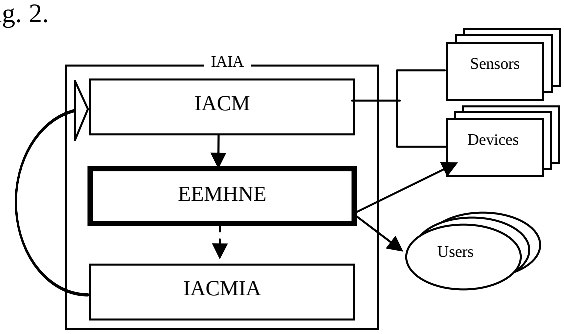

Fig. 1 Evolutionary Emergency Model of HNE
(Dotted line is normal event)

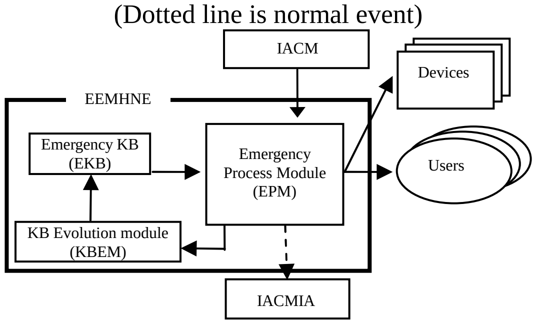

Fig. 2 Architecture of EEMHNE
(Dotted line is normal event)

The functions of these modules are as the following:

- EKB: It includes the rule base and data base which can provide EPM to inference.

- EPM: After receiving the messages from EKB, it can determine the emergency events by using fuzzy inferences. Depending on the inference results, it will send the warning message to remote users.
- KBEM: It not only can tune the data base but also can adjust the rule base in EKB by using genetic algorithm.

2.1 EPM

After receiving the messages from IACM, EPM can determine the emergency events by fuzzy inferences and send warning message to users. There are two components in this module, saying fuzzy inference engine (FIE) and emergency report component (ERC). FIE can reason the emergency events by fuzzy inference. If the emergency event occurred, ERC will start the devices up and send the warning message to remote users. If the events are not emergent, FIE will let the message pass by, as shown in Fig.3.

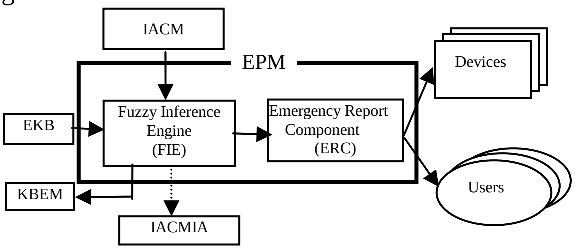

Fig.3 Architecture of EPM
(Dotted line is normal event)

2.2 EKB

There are three components in EKB, saying emergency data base (EDB), emergency rule base (ERB) and inference data integrator (IDI). EDB and ERB can provide EPM to reason the emergency events. IDI can integrate data from EDB and ERB, as shown in Fig.4.

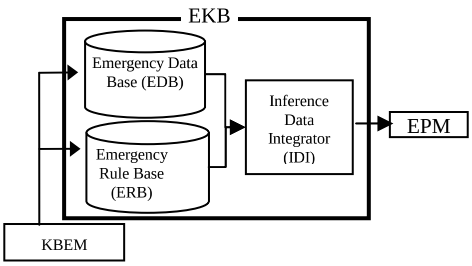

Fig. 4 Architecture of EKB

2.3 KBEM

KBEM can not only tune the membership functions in the EDB but also adjust the rules in the ERB. It comprises of three components, saying genetic processor (GP), training rule base (TRB) and training data base (TDB). While KBEM receives the environment reaction and environment information from EPM, it can tune the membership functions in the EDB and adjust the rule in the ERB by using genetic algorithm, as shown in Fig.5.

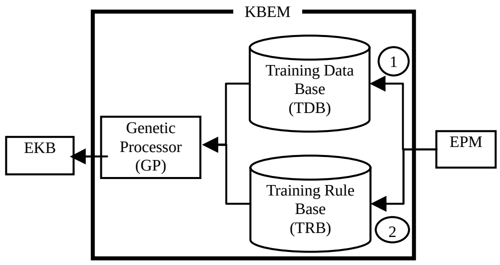

Fig. 5 KBEM
(1: environment information, 2: environment reaction)

2.3.1 Tuning Membership Process

In order to fit the real situation in home network environment, the proposed model will tune the membership functions of parameters by using genetic algorithm [1, 3-4, 15]. Since the shape of membership function is trapezoidal shape, the left, right and the two central points parameterize the membership function [3], we encode the four points as genotype in binary code, as shown in Fig.6.

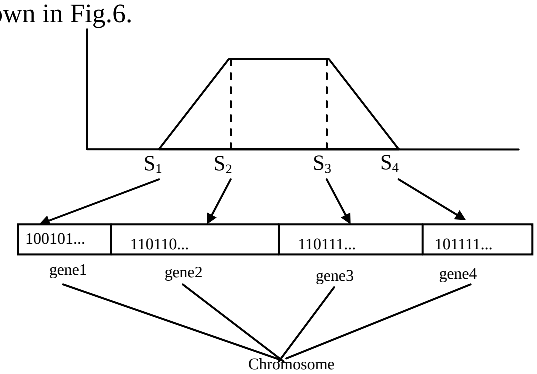

Fig. 6 Initial population encode approach

The trapezoid fuzzy number is defined by four parameters (S_1, S_2, S_3, S_4), and intervals of performance that we define are the following [3]:

$$S_1 \in \left[S_1^l, S_1^r\right] = \left[S_1 - \frac{S_2 - S_1}{2}, S_1 + \frac{S_2 - S_1}{2}\right] \quad (1)$$

$$S_2 \in \left[S_2^l, S_2^r\right] = \left[S_2 - \frac{S_2 - S_1}{2}, S_2 + \frac{S_3 - S_2}{2}\right] \quad (2)$$

$$S_3 \in \left[S_3^l, S_3^r\right] = \left[S_3 - \frac{S_3 - S_2}{2}, S_3 + \frac{S_4 - S_3}{2}\right] \quad (3)$$

$$S_4 \in \left[S_4^l, S_4^r\right] = \left[S_4 - \frac{S_4 - S_3}{2}, S_4 + \frac{S_4 - S_3}{2}\right] \quad (4)$$

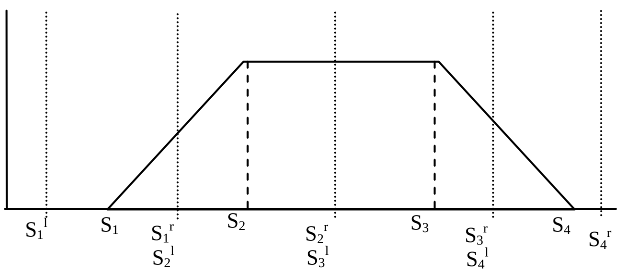

Fig. 7 Intervals of parameter

As shown in Fig.7, every gene will be produced randomly from the respective interval of its parameter. Then we can start genetic operator to optimize the membership functions.

2.3.2 Rule Training Process

For the sake of getting comprehensive rule base, we can train the rule base by using genetic algorithm [1-4]. The encode approach is shown in Fig.8.

$\{C_{21}, C_{22}, C_{23}\ C_{24}, C_{25}\}$

$\{C_{11}, C_{12}, C_{13}\}$ 0 0 0 1 0

0 1 0

If X_1 is C_{12} and X_2 is C_{24} then X_3 is D_{14}

0 0 0 1 0

$\{D_{11}, D_{12}, D_{13}\ D_{14}, D_{15}\}$

Fig. 8 Rule encode approach [3]

After encoding the rule base, we can train the rule base by using genetic algorithm according to environment reactions.

3. Model Implementation

In order to present the efficacy of this model, we implement it in this section.

3.1 Practical Environment

For the purpose of ease manipulation, crossing platform, and remote controlling capability, we have adopted Java Server Page (JSP) and Java Servlet written Web Server structure, Java 2 Platform, Standard Edition, v1.4.2 API Specification and MATLAB 7.0 are utilized for constructing EEMHNE prototype. Above-mentioned are done with Pentium 4 1.6G desktop that is powered by O/S Windows Professional and Microsoft Access 2002.

3.2 Implementation

We take the membership function of temperature as an example. We set the parameters as followings:

- Population size: 30
- Probability of crossover: $P_c = 0.6$
- Probability of mutation: $P_m = 0.3$
- Selection: roulette wheel
- Elite: enable

The membership function before tuning is shown in Fig.9 and the tuning one is shown in Fig.10.

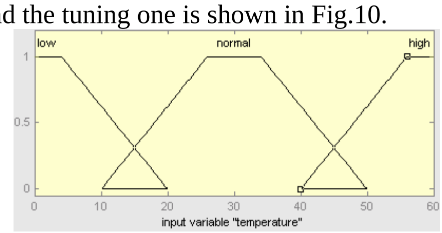

Fig. 9 Membership function before tuning

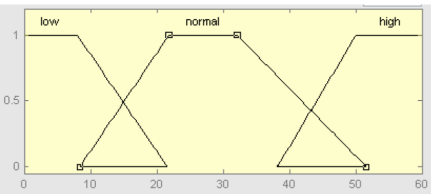

Fig. 10 Membership function after tuning

On the other side, we take two parameters as condition and one parameter as consequence. Our set on rule base training is as following:

Table 1 Rule Setting

Parameter	Linguistic labels	Type
Temperature	3	Condition
Visibility	5	Condition
Emergency degree	5	consequence

- Population size: 20
- Probability of crossover: $P_c = 0.7$
- Probability of mutation: $P_m = 0.2$
- Selection: roulette wheel
- Elite: enable

The training results are shown as following:

Table 2 Rule Training Result

	Rules
Before Training	3
After Training	13

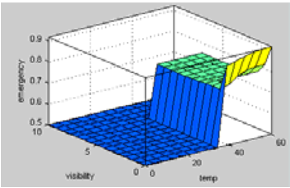

Fig. 11 Rule base before training

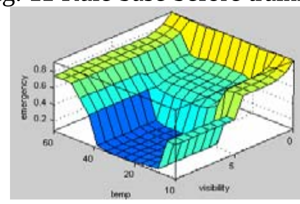

Fig. 12 Rule base after training

After training, we have that the rule base has become more robust and reasoning has become more approximate.

4. Conclusion

At present, there are more and more varied IA products appeared in home network environment. Therefore, emergency process mechanism is the most significant in home network environment. In this study we propose an evolutionary emergency model of home network environment (EEMHNE). This model can not only doing self-tuning to fit the home network environment but also detect the emergency event automatically. Via this model, we can have the more reliable and safer home network environment.

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