Recognition and Incremental Learning of Scenario-Oriented Human Behavior Patterns by Two Threshold Models

Gi Hyun Lim
Department of Electronics and Computer Engineering
Hanyang University
Seoul, Korea
hmetal@hanyang.ac.kr

Byoungjun Chung
Department of Electronics and Computer Engineering
Hanyang University
Seoul, Korea
luinhon@incorl.hanyang.ac.kr

Il Hong Suh *
Department of Computer Science and Engineering
Hanyang University
Seoul, Korea
ihsuh@hanyang.ac.kr

ABSTRACT

Two HMM-based threshold models are suggested for recognition and incremental learning of scenario-oriented human behavior patterns. One is the expected behavior threshold model to discriminate if a monitored behavior pattern is normal or not. The other model is the registered behavior threshold model to detect whether such behavior pattern is already learned. If a behavior patten is detected as a new one, an HMM is generated to represent the pattern, and then the HMM is used to update behavior clusters by hierarchical clustering process.

Categories and Subject Descriptors

I.2.10 [**Artificial Intelligence**]: Vision and Scene Understanding—*Motion,Perceptual reasoning*

General Terms

Algorithms.

Keywords

Behavior pattern recognition, incremental learning, hidden Markov model, threshold model

1. INTRODUCTION

To provide services which may have sequences of scenarios, an intelligent service robot needs to know human behaviors are in accord with service scenarios. Those human behaviors have diversity even if they have same meaning, and sensory data that observe human behaviors are noisy. Thus, a human behavior can be observed by a various patterns. Moreover, a human does not always act on scenario but does as his pleasure. That must be abnormal situation to obstruct a robot to complete its service tasks [3]. In this paper, recognition method of scenario-oriented human behavior pattern is proposed to determine behavior patterns follow service scenario. The recognition method uses hidden Markov model(HMM) to handle dynamic human behaviors. Additionally, an incremental learning method [1] is applied to register new behavior patterns which are almost abnormal human behavior patterns. because of diversity in human behavior patterns, it is impossible to initially register all possible abnormal behavior patterns. For the each method, two kinds of threshold models are used.

*All correspondence should be addressed to the author.

HRI'11, March 6–9, 2011, Lausanne, Switzerland.
ACM 978-1-4503-0561-7/11/03.

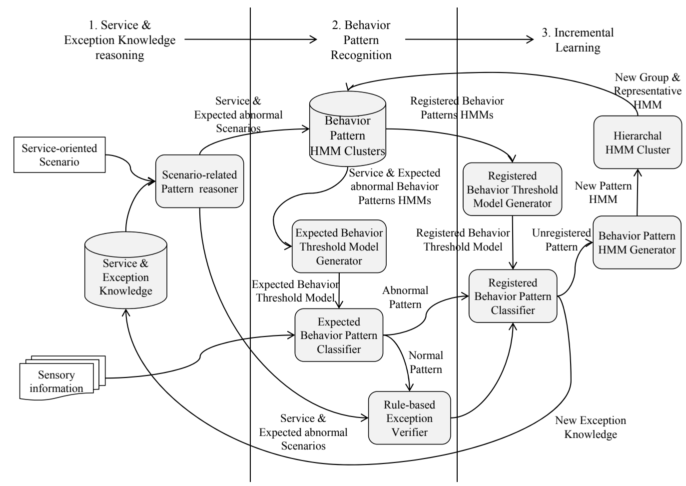

Figure 1: Overall architecture of proposed approach.

2. OVERALL ARCHITECTURE

As illustrated in Fig. 1, proposed architecture consists of three phases: 1) service and exception knowledge reasoning, 2) behavior pattern recognition, and 3) incremental learning. In the service exception knowledge reasoning phase, scenario-related pattern reasoner infers expected service scenarios and their relevant abnormal behavior patterns which might occur on expected scenario [4]. The next phase is probabilistic reasoning of behavior pattern recognition using HMMs. HMM reasoning discriminates normal behavior pattern from abnormal behavior pattern using sequence of sensory data. Here, the HMM candidates which participate in expected behavior pattern evaluation are expected service models and expected behavior threshold model which is adaptively constructed using expected service models and their relevant abnormal models which are determined in the first phase. If the evaluation result is abnormal, it enters the incremental learning phase. Firstly, registered behavior pattern classifier estimates likelihoods of registered representative model of HMM clusters in the system and registered behavior threshold model which is constructed by collecting the states of all representative models to determine behavior pattern is registered or not. If there is unregistered pattern, Behavior pattern

HMM generator build a new HMM using a sequence of sensory inputs of the unregistered pattern, and then hierarchal HMM clustering procedure is invoked to modify HMM cluster or form new HMM cluster.

2.1 Two Threshold models

In behavior pattern recognition phase and incremental learning phase, two expected behavior threshold model and registered behavior threshold model are utilized to discriminate behavior pattern is normal and to detect whether pattern is already learned, respectively. It is not easy to select a fixed threshold to compare the likelihood of original models. Lee et al. [2] proposed an HMM-based adaptive threshold model which is built by fully connecting states which are sub-patterns of their full behavior patterns. The threshold model are the combination of all possible states of the participated patterns in arbitrary order. The threshold model is ergodic model to enable each state to be reached by all other states in a single transition. Observation probabilities and self transition probabilities of threshold model are kept as in the participated models, but all outgoing transition probabilities are equally assigned as

$$a'_{ij} = a_{ij}, \text{ for all } i = i \text{ and j} = \text{j}, \tag{1}$$

$$a'_{ij} = \frac{1 - a_{ij}}{N - 1}, \text{ for all } i \neq i \text{ or j} \neq \text{j}. \tag{2}$$

where, N is the number of states of HMMs.

Thus, the threshold models determine whether a pattern is one of patterns which participate to build threshold model. In this paper, two threshold models are suggested. One is expected behavior threshold model which is adaptively built using expected service models and their relevant abnormal models. The expected behavior threshold model is utilized to discriminate whether behavior pattern is normal using not all model evaluation but only two models-expected service model and threshold model. The expected behavior threshold model has the advantage of calculation cost. If there is no expected model at a given time, all models should be evaluated and compared their likelihoods. On the other hand, the other is registered behavior threshold model to detect a pattern is already learned or not. The registered behavior threshold model is built by fully connecting states in the learning phase using all representative models in behavior pattern HMM clusters.

2.2 Recognition and Incremental Learning

The recognition phase is composed of three steps: start point detection, evaluation between expected service model and expected behavior threshold model, and end point detection. The start point and end point detection is the segmentation of the observation sequence which determines when a service scenario starts and ends has a great effect in recognition phase. A start point of sequence in continuous observations is notified by service and exception knowledge reasoning [4]. Because scenario-oriented behavior pattern knowledge is modeled from sequence of service scenarios, the start of a sequence of recognition phase for HMM reasoning is the end point of previous service scenario. If it is time to seat a student to prepare English conversation practice, it is the starting-point of the sequence of the seating scenario. The accumulated observation sequence from the start point of the scenario to the latest observation is utilized as the observation sequence of HMMs. After detecting start point, the expected behavior pattern classifier is performed by evaluating likelihood of the expected service and expected behavior threshold model.

If the likelihood of the expected behavior threshold model is higher than that of the expected service model, it enters the incremental learning phase as a new pattern of sensory observation sequences. When a new human behavior pattern is observed, it has to be determined that the observed pattern is one of the previously registered pattern cluster, or a new pattern to be learned. In a case of building HMM using just one or few sequences of pattern, the model might be overfitted. In the proposed approach, a hierarchical structure is incrementally formed representing the patterns. The pattern is encoded into HMM and is compared to existing behavior clusters using the symmetric model distance measure [5], and placed into the closest cluster. When a new pattern is added into cluster, a hierarchical agglomerative clustering algorithm is performed within the cluster.

3. CASE STUDY

To evaluate the proposed approach for human behavior pattern recognition and incremental learning on English teaching scenario in smart space, four kinds of ubiquitous sensors are used in the classroom: twelve passive infrared (PIR) sensors, three seat sensors on student chairs, two radio-frequency identification (RFID) readers and two sound sensors. The training set consists of three normal service scenarios and six abnormal behavior pattern which have been modeled and instantiated as scenario-oriented services.

As the result of case study, six abnormal behavior patterns are all registered, and the total proportion of scenario-oriented service model is 71.7% and that of abnormal behavior pattern is 80.8%. Indeed, almost recognition failures occur near the start point of sequence. Because the threshold model has many kind of states and their observation models, the threshold model might be in advantage position than expected model before transition is made.

4. CONCLUSION

This paper proposed recognition and incremental learning of scenario-oriented human behavior pattern using two threshold models. It enables a service robot to provide service even human do not follow the service scenario.

5. ACKNOWLEDGMENTS

This work was one of the 21st Century Frontier R&D Programs funded by Korea Ministry of Commerce, Industry and Energy

6. REFERENCES

[1] D. Kulić and Y. Nakamura. Incremental learning of full body motion primitives. *From Motor Learning to Interaction Learning in Robots*, pages 383–406, 2010.

[2] H. Lee and J. Kim. An HMM-based threshold model approach for gesture recognition. *IEEE Transactions on pattern analysis and machine intelligence*, 21(10):961–973, 1999.

[3] G. H. Lim, K. Kim, B. Chung, I. H. Suh, and H. Suh. Service-oriented Context Reasoning Incorporating Patterns and Knowledge for Understanding Human-augmented Situations. In *Proceedings of the IEEE Ro-Man 2010*, 2010.

[4] G. H. Lim, I. H. Suh, and H. Suh. Ontology-based Unified Robot Knowledge for Service Robots in Indoor Environments. *IEEE Transactions on Systems, Man, and Cybernetics, Part A*, accepted for publication.

[5] S. Schaal, A. Ijspeert, and A. Billard. Computational approaches to motor learning by imitation. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 358(1431):537, 2003.