Recognizing Extended Surrounding Contexts via Class Incremental Learning

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Abstract
Benefit from widely used Bluetooth sensor, user surrounding contexts can be availably recognized leveraging Bluetooth data. Most existing studies seldom deal with newly extended surrounding contexts which results in degrading the recognition performance, in that the built classifier just basically recognizes limited classes learned in training phase. This paper proposes a fuzzy class-incremental learning method based on OSELM, named *FCI-ELM*, for continuously recognizing extended classes of contexts. The encouraging results of our experiments show that FCI-ELM can automatically and continuously recognize newly discovered classes of contexts in the real-world. Specifically, the method can not only achieve comparable accuracy for recognizing original known classes, but also significantly improve the accuracy for recognizing newly appeared unknown classes.

Author Keywords
Context-aware; Bluetooth; Surrounding Context; Class Incremental Learning

ACM Classification Keywords
H.5.m [Information Interfaces and Presentation]: Miscellaneous; I.5.2 [Pattern Recognition]: Design Methodology

Introduction

Recently, since a variety of mobile applications and services widely utilize context information, context-aware computing has emerged in the field of mobile and ubiquitous computing.

Most previous researches on context-awareness have focused on recognizing specific places or mobility modes. Some machine learning algorithms for detecting specific places have been proposed which attempt to find a meaningful locale to the user [4]. These techniques mainly extract significant places based on static radio signals, which are GPS coordinates, radio beacon fingerprints from WiFi access points, GSM cell towers, etc. Other researches have made use of visual or sound fingerprints by camera or microphone embedded in mobile phones [7]. Such research work has achieved certain results in clustering semantically similar places or recognizing meaningful events, but they also have some limitations, such as requiring careful and particular ways of placements of mobile phones. Moreover, these embedded sensors can only detect the individual user's behavior, while they can not detect the whole surrounding context which contains dynamic group behavior from multiple persons. Therefore, detecting the individual user's mobility status is not useful enough to sense the surrounding context. Besides, there are new classes of contexts continuously appeared in the people's daily life. These new classes of contexts probably cannot be recognized because the built classifier can often recognize the trained classes of contexts, but have not the recognition ability for incremental contexts which are totally new classes and have not been trained before.

In this paper, we focus on the case where the new classes of contexts have appeared and the people have kept joining the newly incremental contexts continuously. In real-world cases, the recognition techniques would be useful if the model can not only classify the underlying context of an individual but also accurately recognize the new classes where some kinds of incremental contexts has gradually appeared. Accordingly, we investigate the problem of context classification and incremental context recognition by only observing the surrounding Bluetooth devices. Bluetooth is a very popular method of exchanging data wirelessly which is supported by diverse types of mobile devices, such as mobile phones, laptops, and tablets. As Bluetooth technology could discover other Bluetooth devices nearby to initiate communication, some researchers often use Bluetooth as sensors.

Methodology

Given collected raw Bluetooth data log, our goal is to identify the dynamic behavior of the surrounding context via machine learning techniques. In this work, we use fuzzy clustering method combining with OSELM [6] based class-incremental learning algorithm to continuously recognize the newly incremental classes of contexts by utilizing the real-life Bluetooth traces [3] and extracted effective features [2].

Fuzzy ISODATA Clustering

F-ISODATA (Fuzzy Iterative Self-Organizing Data Analysis Techniques Algorithm) [1] is an extension of K-Means algorithm, which can update cluster number during the learning process. We employ F-ISODATA to cluster the outliers by learning an appropriate cluster number with splitting and merging clusters.

OSELM-based Class-Incremental Classifier

We propose an OSELM-based Class-Incremental Classifier, named Fuzzy Class Incremental Extreme Learning Machine (FCI-ELM), which aims to automatically recognize incremental multiple classes. First of all, derive from collected and labeled samples, an ELM model is learned on these label samples. Furthermore, for incremental samples without relevant labels, the ELM model has a unknown output node for fuzzy clustering. Next, this model can be updated to be a new model through fuzzy clustering by iteratively merging and splitting to form one/several new classes, then our proposed class-incremental learning algorithm can recognize known classes and new classes accordingly. Finally, the model is updated with additional output neutrons.

Evaluation

Data Collection

We collect Bluetooth data on Android platform with the sampling rate of 15 seconds. To evaluate our FCI-ELM, we gathered Bluetooth signals from people's common life trajectory in chosen situations, such as *working*, *taking subway*, *dining*, *go shopping*, and *watching movies*. We invite 13 volunteers to collect Bluetooth radio traces for 3-4 weeks in the daily life. They usually start the data collection program every morning and quit it before sleep in the evening.

Analysis of Incremental contexts

On one hand, Figure 1 shows the evaluation of accuracy in different phases by batch-mode ELM and FCI-ELM for known classes. We can see that our FCI-ELM achieves the comparable accuracy for recognizing original known classes. We set Class 1, 2, and 3 as known classes and Class 4 and 5 as unknown classes. In the phase of known three-class, we use labeled samples of known classes to learn an ELM model, which is considered as the initial model for class-incremental learning. So these two models are the same structure and the recognition ability keeps the same (i.e. 55.77%), where unknown Class 4 and 5 are wrongly regarded as the known classes, then the testing accuracy is a little bad. Besides, for two cases of learning new classes, our FCI-ELM almost keeps the same recognition ability with the batch-mode ELM, that is, the accuracy of Batch ELM is 77.64% and FCI-ELM is 76.99% for one new class, and the accuracy of Batch ELM is 81.30% and FCI-ELM is 80.89% for two new classes. However, Batch ELM cannot deal with the newly appeared classes but re-train the model to build a totally new classifier when new classes of samples are coming and added, which results in huge storage cost and time cost.

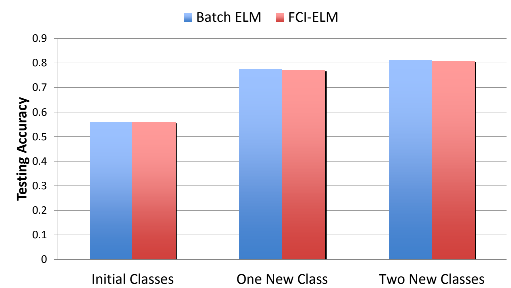

Figure 1: Evaluation of accuracy by batch-mode ELM and FCI-ELM (from unknown classes to known classes).

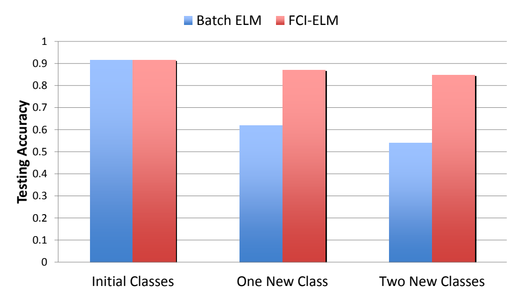

Figure 2: Evaluation of accuracy by batch-mode ELM and FCI-ELM (from known classes to unknown classes).

On the other hand, Figure 2 illustrates the evaluation of accuracy in different phases by batch-mode ELM and FCI-ELM for unknown classes. We can conclude that our FCI-ELM outperforms batch-mode ELM and significantly improve the accuracy for recognizing newly appeared classes. In particular, for two new unknown classes, our FCI-ELM almost achieves the comparable recognition ability with accuracy of 84.8%, while the recognition accuracy of batch-mode ELM declines to 61.9% for one new class and 53.9% for two new classes, respectively.

Discussion

Some previous algorithms using accelerometer, WiFi, and GPS have been implemented [8, 9, 5]. The main procedures are: 1) discover significant places; 2) estimate the mobility between different places. These approaches can discover important places like working context and perform well in terms of recognition accuracy. However, they have not provided the insight into the dynamic context transition, so that dynamic behavior information around the user-centric environment can not be intuitively identified. Therefore, one advantage of Bluetooth compared to Accelerometer/WiFi/GPS is that it is able to sense the number of people around the individuals, which can achieve better performance in contexts of dining, taking subway, go shopping and watching movies.

Conclusion

We propose an OSELM based fuzzy class-incremental learning method for continuously recognizing new extended classes of contexts using dynamic Bluetooth data, named *FCI-ELM*. We also discuss Bluetooth with accelerometer, WiFi, and GPS, to investigate their advantages and disadvantages. Then, we conclude the value of dynamic Bluetooth information in context awareness, especially for dynamic behavior information in surrounding contexts. The encouraging results validate the efficacy and efficiency of the proposed technique. Therefore, it's quite valuable to sense surrounding contexts from dynamic Bluetooth information.

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