

A Lightweight and Low-Power Activity Recognition System for Mini-Wearable Devices

Lisha Hu

Beijing Key Laboratory of Mobile Computing and Pervasive Device, Beijing, China
Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China
University of Chinese Academy of Sciences, Beijing, China
Email: hulisha@ict.ac.cn

Abstract—Recent years, miscellaneous mini-wearable devices (e.g. wristbands, wristwatches, armbands) have emerged in our lives to recognize daily activities for the users. Owing to the limitations of hardware, Activity Recognition (AR) models running inside the device are bound to certain challenges, such as processing power, storage capability and battery life. This paper proposes an activity recognition system by considering three limitations above, and a model generation framework to construct AR models which are lightweight in different phases in model generation.

Keywords—time complexity; space complexity; battery consumption; energy efficient learning; lightweight

I. INTRODUCTION

Extensive researches show that the knowledge of ADL (Activities of Daily Living, e.g. walking, running, going upstairs) can be mined based on data collected by on-body sensors. Especially with the development of mobile technology, the ADL of smartphone users can be precisely mined relying on the readings of sensors deployed in mobile phones. Today, miscellaneous mini-wearable devices (e.g. wristbands, wristwatches, armbands) emerge in our daily life. Mini-wearable devices also attempt to recognize users' daily activities and measure physical conditions (e.g. heart rate, weight changes) for the users. Those mini-wearable devices can be employed for non-intrusive health care for the elderly.

Most of these mini-wearable devices are customarily designed to be miniature and portable on purpose to be nonintrusive in users' daily lives. Unlike the smartphones today which have extremely high processing power (Quad Core CPU) and huge storage capacity (1 G RAM, 16G FLASH), mini-wearable devices still fall far from the smartphones in configurations, and are way below users' expectations. As a consequence, the hardware inside the mini-wearable devices inevitably owns several limitations because of the low processing power and limited storage capacity. Most seriously, the battery life of both smartphones and mini-wearable devices elapses too fast. Users always complain that these intelligent devices have to be charged very often [1, 2]. In a word, lightweight activity recognition (AR) models fitting limited resource scenarios should to be proposed for mini-wearable devices. Besides the power processing and storage capability limitations of mini-wearable devices, the lightweight

property of the AR model is essential because: the sensor data of user are acquired constantly in real-time. The AR Model should fulfill the activity recognition work in no time. So the user can see his/her on-going states in real time. For instance, a jogger should be able to see how many steps he/she has made when he/she is running, then to decide whether to continue or not.

Fig. 1 illustrates the model generation framework, which can split into two sections: offline section and online section. In the offline learning section, data are recorded first from massive users. After the noise filtering and feature extraction procedures, universal model is constructed and considered to be the initial model for mini-wearable devices in the online learning section. Once new data are acquired from a specific user, the model inside mini-wearable devices will predict some activities according to user-specific data, and then updates itself to adapt the user better. Three phases are contained in the model generation framework, they are (a) training phase, (b) predicting phase and (c) updating phase. Computational and storage requirements of a model should be measured for each phase.

We plan to work out three problems: How to construct AR models to decrease (1) computational requirement, (2) storage requirement and (3) battery life for mini-wearable devices? It should be emphasized here that when we are talking about decreasing computational and storage requirements, the predication performance of the model should be guaranteed. In other words, models generated at last can still recognize activities for user with comparable accuracy.

II. METHODOLOGY

Figure 2 illustrates the architecture of our AR system. The system is built on the data of sensors imbedded in mini-wearable devices. The AR model is constructed to approach the three objectives (Low Computational Requirement, Less Storage Requirement and Little Battery Consumption), which corresponds to the three problems above. Eventually, we hope to find much more effective and efficient solutions in some application scenarios such as Position Forecast, Activity Recognition and Health Perception. For instance, the data of accelerometer can be utilized to recognize daily activities for the user, whose health status can be perceived by detecting

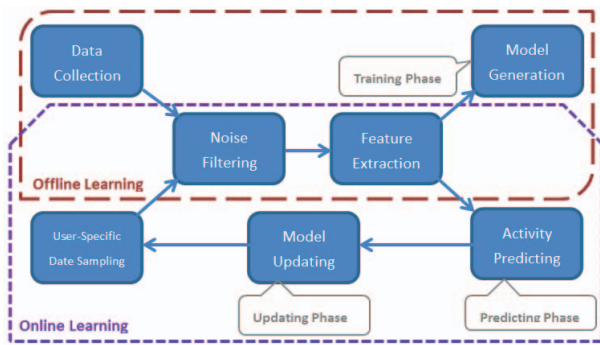


Figure 1. Model generation framework

anomalous behaviors. The data of GSM can be collected to learn daily routines of the user and forecast the user's next position (which place the user will go next).

A. Storage Requirement

The storage requirement can be measured by the Space Complexity. Owing to the fact that in-memory computation ought to be performed in mini-wearable devices, the AR model generated in the training phase should be represented with less storage occupancy. Recently, the optimization function of SVM (Support Vector Machine) is modified to construct a new model by importing the superiorities of ELM (Extreme Learning Machine) in the training phase.

B. Computational Requirement

Similar to storage requirement, computational requirement is measured by the Time Complexity of optimization problem of the model. We plan to generalize the above AR model into online sequential scenarios, in which the AR model is modified based on user-specific data in the updating phase.

Besides, we are constructing new kernels by certain specific mappings whose functional form is known. Those kernels can help to represent the learnt model by only a few constants. In other words, both the Space Complexity and the Computational Complexity will become negligible since neither support vectors nor Lagrange multipliers need to be stored for prediction.

C. Power Consumption

The battery consumption can be minimized by adaptive sensing techniques, trading off the energy for accuracy to reduce dispensable sensor samplings of the sensor [3,4]. For instances: If the user is recognized to be sleeping in the evening with high confidence, the sample rate of accelerometer sensor can be adaptively decreased or simply shut down for a while without any influence to the recognition accuracy.

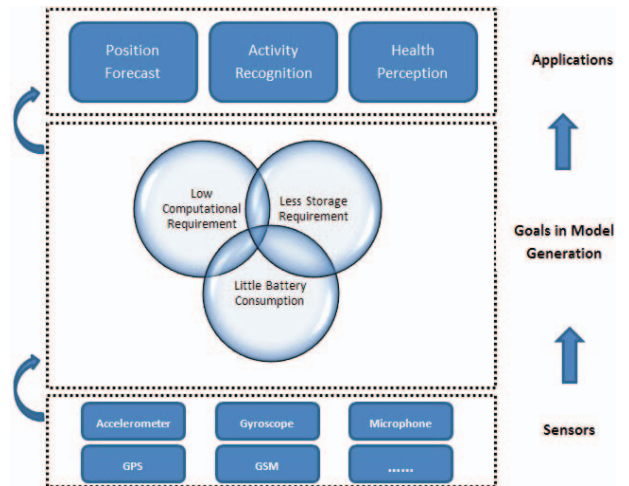


Figure 2. Activity recognition system architecture

III. PRELIMINARY RESULT

A new AR model has been proposed to recognize daily activities for the user of mini-wearable devices. Extensive experimental results have shown that the proposed model retains the generalization ability of SVM and decrease the computational requirement to a higher level.

IV. CONCLUSION AND FUTURE WORK

An activity recognition system considering the limitations of processing power, storage capability and battery life is proposed in this paper. Our research focus is to construct lightweight activity recognition models with little battery consumption for mini-wearable devices. Our future work is to deal with each of the three problems in other phases.

ACKNOWLEDGMENT

The author would like to thank Prof. Yiqiang Chen and co-advisor Prof. Shuangquan Wang for their invaluable guidance and support.

REFERENCES

- [1] K.K. Rachuri, C. Efstratiou, I. Leontiadis, C. Mascolo, P.J. Rentfrow, "METIS: Exploring mobile phone sensing offloading for efficiently supporting social sensing applications", Proc. PerCom, pp. 85-93, 2013.
- [2] D.T. Nguyen et al, "Storage-aware smartphone energy savings", Proc. UbiComp, pp. 677-686, 2013.
- [3] H. Lu, J. Yang, Z. Liu, N. Lane, T. Choudhury, A. Campbell, "The Jigsaw continuous sensing engine for mobile phone applications", In SenSys, ACM, 2010.
- [4] K.K. Rachuri, M. Musolesi, C. Mascolo, P.J. Rentfrow, C. Longworth, A. Aucinas, "EmotionSense: A mobile phones based adaptive platform for experimental social psychology research", UbiComp, pp. , 2010.