Multi-sensor Fusion for Human Daily Activity Recognition in Robot-assisted Living

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ABSTRACT

In this paper, we propose a human activity recognition method by fusing the data from two wearable inertial sensors attached to one foot and the waist of a human subject, respectively. Our multi-sensor fusion based method combines neural networks and hidden Markov models (HMMs), and can reduce the computation load. We conducted experiments using a prototype wearable sensor system and the obtained results prove the effectiveness and the accuracy of our algorithm.

Categories and Subject Descriptors

H.4.m [**Information Systems Applications**]: Miscellaneous; I.5.4 [**Pattern Recognition**]: Applications

General Terms

Algorithms, Design, Documentation, Experimentation, Verification

Keywords

Activity Recognition, Assisted Living, Sensor Fusion, Wearable Sensor

1. INTRODUCTION

During the past decade, there has been a steady growth of elderly population. Helping them to live a better life is very important and has great societal benefits.

We are developing a smart assisted living (SAIL) system [1, 2] to provide support to elderly people in their daily live. As shown in Figure 1(a), the SAIL system consists of a body sensor network (BSN) [3], a companion robot, a Smartphone, and a remote health provider. In order to enable natural human-robot interaction, the robot needs to infer the human intentions and situations from the motion data and vital signs of the human subject. Therefore, it is necessary for the robot to have the capability to recognize the human's activities.

HRI'09, March 11–13, 2009, La Jolla, California, USA.
ACM 978-1-60558-404-1/09/03.

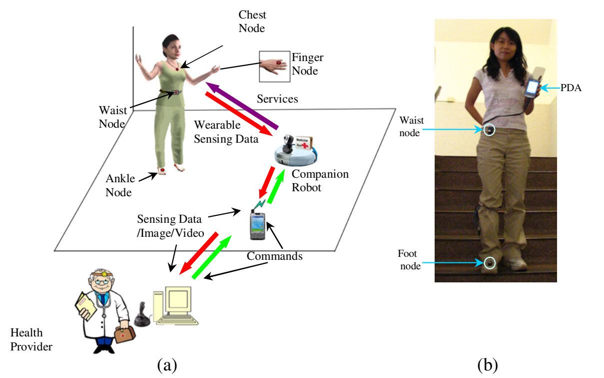

Figure 1: (a) The overview of the Smart Assisted Living (SAIL) system; (b) the prototype of the wearable sensor system for human activity recognition.

Traditional human activity recognition is through visual information [4, 5]. Recently, due to the advancement in MEMS and VLSI technologies, wearable sensors-based activity recognition has been gaining attention. Wearable inertial sensors and fiber sensors can be attached to different human body parts to capture kinetic data. Many solutions have been developed for human activity recognition, including the heuristic analysis methods [6], the discriminative methods [7, 8], the generative methods [9], and some combinations of them. Although each method has disadvantages, the combination of different methods can usually achieve better performance than any single method.

Our wearable sensor system for human activity recognition is shown in Figure 1(b). Two inertial sensors (nIMU) from MEMSense, LLC are attached to one foot and the waist of the human subject. The PDA collects and sends data to a desktop computer for activity recognition. We use two steps for human daily activity recognition as shown in Figure 2. First, the fusion of the data from the two wearable sensors generates a coarse-grained classification of human activities, which consist of three types: zero displacement activities, transitional activities, and strong displacement activities. Second, a heuristic discrimination module for zero displacement activities and transitional activities, or an HMM-based recognition algorithm for strong displacement activities is used for fine-grained classification. In this way, the coarse-grained classification controls the direction of the data flow to trigger either the heuristic discrimination module or the HMM-based recognition module so as to save the computation time and enhance the efficiency.

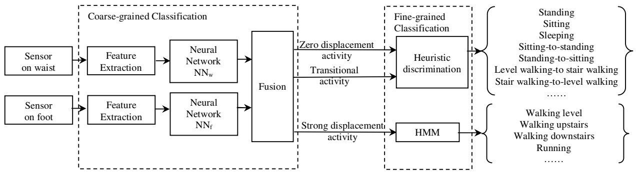

Figure 2: The overview of the human daily activity recognition algorithm.

Table 1: Sensor fusion rules

		Foot sensor A_f Stationary	Transitional	Cyclic
Waist	Stationary	A_Z	A_Z	A_Z
sensor	Transitional	A_T	A_T	–
A_w	Cyclic	–	–	A_S

2. COARSE-GRAINED CLASSIFICATION

The coarse-grained classification module classifies the activities into the following categories: (1) A_Z = *zero displacement activities*: standing, sitting, and sleeping; (2) A_T = *transitional activities*: sitting-to-standing, standing-to-sitting, level walking-to-stair walking, stair walking-to-level walking, lying-to-sitting, and sitting-to-lying; (3) A_S = *strong displacement activities*: walking level, walking upstairs, walking downstairs, and running. Two neural networks NN_f and NN_w are designed for the data from the foot and the waist sensor, respectively. The outputs of the NN categorize the data into three types: (1) *stationary*, (2) *transitional*, and (3) *cyclic*. The outputs of the neural networks are fed into the fusion module, which integrates the individual types of foot and waist activities and categorizes the human activities according to the rules in Table 1. All other combinations of foot and waist activities are rare activities and we do not consider them.

3. FINE-GRAINED CLASSIFICATION

To further distinguish the stationary activities (such as "sitting" and "standing") and the transitional activities (such as "sitting-to-standing" and "standing-to-sitting"), a heuristic discrimination module is applied to consider the previous stationary activity state and decide the type of the current transitional activity. An HMM-based recognition algorithm is applied to further determine the types of the strong displacement activities, which recognizes the patterns of the continuous time series of data.

4. EXPERIMENTAL RESULTS

In our experiments, the human subject performed regular daily activities: "standing", "sitting", "walking level", "walking upstairs", "walking downstairs", "running", and "sleeping", etc. The final result after the fine-grained classification is a sequence of decisions. Figure 3 shows the acceleration of the foot sensor (the top figure), and the decision results compared with the ground truth (the bottom figure). The two circles on the bottom figure show that the errors are caused by the HMM-based recognition algorithm for the strong displacement activities. The accuracy of the HMM-based recognition module is shown in Table 2, where the

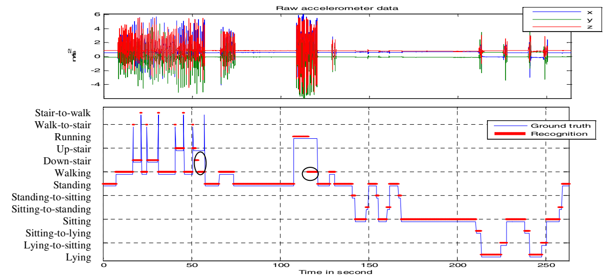

Figure 3: The final results of the daily activity classification.

Table 2: Decision accuracy of the HMM-based recognition.

Activity Type	HMM decision Type Walking	Walking downstairs	Walking upstairs	Running
Walking	**0.9030**	0.0581	0.0360	0.0029
Walking downstairs	0.0478	**0.9250**	0.0270	0.0020
Walking upstairs	0.0759	0.0289	**0.8915**	0.0037
Running	0.0901	0.0120	0.0278	**0.8701**
Accuracy	**0.9030**	**0.9250**	**0.8915**	**0.8701**

values on the diagonal indicate the classification accuracy for each activity.

5. CONCLUSIONS

We introduced a robot-assisted living system for elderly people, patients, and the disabled. To facilitate natural HRI, a multi-sensor fusion based activity recognition algorithm is purposed to combine the neural networks and the hidden Markov models. The HMM-based recognition algorithm is applied only to strong displacement activities. Therefore, the calculation complexity has been reduced and the efficiency of the algorithm is enhanced by the fusion of the data from these two sensors.

6. REFERENCES

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