Human Activity Recognition Using Heterogeneous Sensors

Muhammad Shoaib
Pervasive Systems Group, University of Twente,
The Netherlands.
m.shoaib@utwente.nl

Abstract

Physical activities play a very important role in our physical and mental well-being. The lack of physical activities can negatively affect our well-being. Though people know the importance of physical activities, still they need regular motivational feedback to remain active in their daily life. In order to give them proper motivational feedback, we need to recognize their physical activates first (in our case, the main target group is knowledge workers). Therefore, this research is about recognizing human context (condition, activity and situation etc.) using heterogeneous sensors. If recognized reliably, this context can enable novel well-being applications in different fields, for example, healthcare. As a first step to achieve this goal, we recognize some physical activities using smartphone sensors like accelerometer, gyroscope, and magnetometer. Moreover, we are simulating a smartphone on a wrist position as a smart watch and want to see the possibilities of activity recognition with upcoming smart watches. We want to reliably recognize physical activities using heterogeneous sensor information, that may be incomplete or unreliable. We are currently working on improving the existing work by investigating and solving the open challenges in activity recognition using smartphone sensors.

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ACM Classification Keywords

H.1.2 User/Machine Systems, H.2.8 Data Mining, I.5 Pattern Recognition, H.3.4 Performance Evaluation

General Terms

Algorithms, Design, Human Factors, Performance

Introduction

The current research in activity monitoring and reasoning has mainly targeted elderly people, or sportsmen and patients with chronic conditions. The concept of knowledge workers as a target group is relatively new. According to a yearly report on Dutch workforce, which analyzes their different aspects, many Dutch employees have unhealthy lifestyle [1].

According to this report, 50% of Dutch employees do too little exercise, 44% cope with overweight issues, 17 do not take their breakfast, and 28% smoke (out of which 82% smoke more than 10 cigarets per day). This unhealthy life style negatively affects their well-being as well as cost their employers, insurance companies and government a lot of money. Therefore, there is a need for a system which can play the role of a virtual coach by motivating them to remain physically active and adapt a healthy lifestyle.

State of the art approaches in activity recognition mainly use three type of sensors for a user context recognition: ambient sensors, body sensors, smartphones sensors (e.g. accelerometer, gyroscope, GPS etc.). We treat smartphone sensors different from body sensors because of its ease of use and adaption. Smart watches like pebble [2] will also come into this category due to its ease of use and adaption. We simulate a smartphone on wrist position as a smart watch in some of our experiments.

Based on our target group, we decided to use smartphones in our first study for activity recognition because nowadays it is being used by many people. Moreover, its potential for a user context recognition has already been shown by many researchers [3,4]. Although smartphones can help in recognizing a user context (activity), they need to be placed in a specific position and orientation on the human body because their motion sensors are sensitive to position and orientation. Though few studies in recent times have tried to solve the orientation and position problem, there is still room for improvements and it still need to be further explored [4]. Moreover, users in a home setting may not carry the smartphone all the time with them, which makes it a partially available source of information. We plan to use environment or ambient sensors (Passive Infrared sensors) in our future studies to cope with this kind of situations. Additionally, women tend to not wear smartphones on their body which is usually ignored in the state of art solutions. For example, [5] claims that 63% of the women carry smartphones in their hang bags. However, this study only used 35 female participants for this survey. We are currently collecting data for those women who carry smartphones in their hang bags and want to evaluate classification algorithms performance in such situations.

Problem Statement

We are currently looking at the following abstract research questions. These questions will be further refined during the coming months.

1. How to infer user context (activity, situation, and state) from heterogeneous and incomplete sensor data? The level of details about the user's activity, situation and state depends on the application demands and available sensing information.
2. How to detect user context on resource limited devices (smartphones) in an energy efficient way ?
3. How and when to use different sensors at any moment of time in a complementary and cooperative way to make the inference algorithms efficient, both in terms of performance as well as energy consumption?

Our Approach

We are currently using smartphone sensors to detect physical activities. The sensors which are currently being used are accelerometer, gyroscope, magnetometer. For reasoning part, we are using existing machine learning techniques and these will be optimized or modified accordingly if needed. Most of the existing work has analyzed classification algorithms in a fixed position and orientation. We are now evaluating the effect of position and orientation on classification performances using different experiments.

Work done so far

We developed an Android App for data collection which can collect data at different sampling frequencies. Currently, we are collecting data at 50 samples per second and are using only accelerometer, gyroscope, and magnetometer. However, more sensors can easily be added to this app. We observed that in many existing work in activity recognition, experiments cannot be reproduced because neither the datasets nor the data collectors are publically available. However, we will make both our data collector and dataset available publically so that our experiments can be reproduced as well as compared with for performance analysis. Based on this data collector, we conducted our first experiment.

Experiment Setup

We collected data using four participants (all male, age between 24-30) at University of Twente. Each of these participants was provided with four smartphones which were placed in right pocket, on their belt, wrist and arm. Then six activities were performed by them carrying all these four phones at the same time. This was done to compare classification accuracies for different positions for exactly the same activities. The six activities include walking, walking upstairs, walking downstairs, running, sitting and standing. Moreover, walking activity was performed by 4 participants while carrying a smartphone in their pocket but in 4 different orientations. This was done to see the orientation effect on different classification methods. Moreover, two female participants performed walking, walking upstairs and walking downstairs while carrying the smartphone in their handbags with two different positions.

Performance Analysis

We preprocessed the data by removing the noisy parts from the start and the end of the data. This is caused by the movements when we place and remove smartphones on participants bodies. Then three time domain features were extracted, namely mean, stand deviation, and magnitude. We started with time domain features because it is easy to compute and later on we plan to look at frequency domain features as well. This was done on sliding windows of 2 sec, 5 sec, and 10 sec with 50% overlap. The features were normalized. So at the end we prepared two datasets, one normalized and one without normalization in order to see the effect of normalization on different classification methods. We are currently analyzing different classification methods in WEKA [6, 7], a java based machine learning tool. For evaluation of classification methods, we are using 10 fold cross validation method. We are currently analyzing different classification method like k-nearest neighbor, decision trees(J48), rule based classifiers (PART, Ridor [6, 7]), Support vector machines (LIBSVM) etc. in different scenarios [6,7]. The sensitivity of features and classifiers, used in the state of the art, to the position and orientation of a smart phone is being analyzed. Moreover, different ways are being investigated for resource consumption analysis alongside accuracy. It is very important to include resource consumption analysis with accuracy based comparison as these algorithms will be used on smartphones, which may be resource limited.

Planned work

Next, we are planning to add more activities to our experiments like biking, riding a car or bus, smoking, eating, using elevator etc. The number of participants are to be increased as well to collect an extensive set of data. The data collection app needs to be improved to make this process easy. Moreover, we are planning to integrate environment sensors (PIR Sensors) to compensate for a situation when people are not carrying smartphones on their bodies when they are in home. In a later stage, it can be integrated with a body sensor as well, however, a use case needs to be defined for it. We are also planning to use Smartphone microphone for activity recognition as its potential usage is shown by [3]. Moreover, it is less sensitive to orientation and position unlike motion sensors in the smartphone. We will see how we can use different smartphone sensors in an adaptive, and cooperative way to detect different physical activities as well as situation of a user.

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