NANYANG TECHNOLOGICAL UNIVERSITY

Human Activity Recognition through Wearable Devices

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by

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Abstract

Acknowledgment

I would like to thank my research supervisor, Professor Tan Ah Hwee.

1. Introduction

1.1 Background and Motivation

With increasing life expectancy and lower birth rates trends in Singapore, the number of citizens aged 65 and above has increased significantly in the last few years. In addition, this trend is expected to continue in the next few years and by 2030, the number of citizens aged 65 and above will be doubled [1]. Furthermore, according to a survey [2], it is shown that almost 90% of those aged 65 or above indicate that they want to stay at home as long as possible. Thus, there is an increasing demand of technologies which are capable of continuously monitoring elderlies without being intrusive to the users.

Human activity recognition technology is the key technology for monitoring elderlies in an effective manner. This research area has been studied by many for the last decade. Researchers have presented a number of different ways for recognizing human activities using different kind of technologies. Initially, researchers used specially made sensors which are expensive and need to be placed in certain positions [3, 4]. This setting is not suitable for conducting daily activities. Thus, in recent years, researchers are focusing more on using non-intrusive technologies to perform human activity recognition.

Video surveillance is one of the most commonly used technologies. Cameras are installed inside a house and the system is also capable of providing live video streaming to the caregivers. In recent years, with the advancement in artificial intelligence and machine learning, video surveillance systems are now able to detect the activities performed by the elderlies [5, 6]. With this capability, caregivers need not constantly check the live video. The system would be able to notify caregivers only when important events occur. However, video surveillance systems may cause privacy issue in case the video is accessed by an unauthorized party.

Smartphone is another commonly used technology for recognizing human activities. Smartphones are equipped with many sensors such as accelerometer, gyro meter, and barometer which can be used for recognizing human activities. The smartphone only needs to be put inside the user’s pants. One major drawback of only using smartphone for recognizing human activities is that it will not be able to accurately distinguish hand-based activities.

Beside smartphone, wearable devices are also increasingly prevalent. Smartwatch, for example, is an emerging wearable device and there are many kind of smartwatches commercially available [7]. A commercial smartwatch has multiple embedded sensors which are suitable for recognizing human activities. By using sensory data retrieved from both smartphone and smartwatch, one can now also recognize hand-based activities much more accurately. This will allow people to track what the elderlies are doing at home more accurately and can cover a wider range of different activities.

1.2 Project Objectives

There are 3 main objectives this project would like to achieve:

a. **Build a new human activity recognition system using features extracted from sensory data gathered from both smartphone and smartwatch.** The system developed by the previous students in [8] and [9] was only using sensory data collected from a commercial smartphone. In this project, sensory data collected from a commercial smartwatch will also be incorporated to improve the prediction accuracy. Furthermore, more activities will be considered in this project, especially activities which involve hand movements.

b. Collect dataset from multiple test subjects. The dataset will be mainly used for thorough experimentation and testing of the developed human activity recognition system. This dataset will be used for not only K-Fold Cross Validation, but also for Leave-One-Out (LOO) Cross Validation to ensure the system's ability of accurately predicting activities conducted by a new user not in the dataset.

c. **Build a system which is capable of recognizing the motions of an individual with minimum delay.** This objective includes the development of an Android smartphone application and a Tizen smartwatch application for collecting the sensory data, a web application for showing the predicted activity, and a backend system for processing the collected sensory data and predicting the activity using the human recognition system developed.

1.3 Scope and Limitations

The main scope of this project is the development of a human activity recognition system for detecting different physical activities of an individual. This involves the creation of an end-to-end data pipeline for model training and testing, including data sampling, data windowing, and features extraction. In addition, training and testing data will be taken from 15 test subjects within the age range of 18-24 years old and motion transitions are not covered in this project. Finally, an ensemble machine learning classification algorithm called Random Forest [10] will be used in this project.

Comment [#C1]: Do we need to include SVM?
If yes, then do we need to include both algorithm results for each different experiments conducted later?

The project also involves the development of a web application which is able to recognize an activity with minimum delay. As such, a system needs to be developed with a separate pipeline to process incoming sensory data sent from the smartphone and smartwatch periodically. Furthermore, delays are inevitable since only after one data window with a configurable number of seconds is obtained, then it can be sent for processing. Network latency is also another source of delay since data is sent to the backend server through the internet.

1.4 Report Overview

This report is organized as follows:

a. **Section 1** introduces the background and objectives of this project.

b. **Section 2** provides the literature review of related work done in the field of human activity recognition technology as well as the work done by the two previous students.

c. **Section 3** provides an analysis over the work done by the two previous students.

d. **Section 4** introduces the frameworks, technologies, and tools used in this project.

e. **Section 5**

f. **Section 6**

g. **Section 7**

h. **Section 8**

2. Literature Review

Human activity recognition is a technology for recognizing actions performed by a human by processing a series of observations. These observations are usually obtained using sensors found on smart devices such as smartphones and smartwatches. In the recent years, there have been a lot of studies conducted in this area. Researchers have studied various data collection, data pre-processing, and model building methods.

Many data collection methods have been investigated by researchers. Researchers in [8], [11], [12], [13], and [14], for example, used devices strictly placed at fixed positions and orientation on the test subject's body. In [13] and [14], the data collection is done by using a specially made hardware with one or more sensors while in [8] and [12], a smartphone with multiple embedded sensors is used. The hardware or smartphone is placed in a fixed place around the test subject's pelvic region or waist. As the same setup condition is imposed on all test subjects, the data variance is minimized and the model can perform much better.

In order to handle varying positions and orientations of the mobile phone, researchers in [15] introduced the usage of the accelerometer magnitude as a feature. They proved that the model can handle various smartphone positions and orientations. As a result, the authors of [15] achieved better results for human activity recognition with more natural data collection settings. The same technique was also used in [9] and [16]. The authors in [9] and [16] reported that the trained model can produce very accurate predictions using the Support Vector Machine (SVM) machine learning algorithm.

Research in human activity recognition technology has been a hot topic in the past few years. Much work has been conducted on a number of basic physical activities recognition such as standing, sitting, lying, walking, and running. There are many ways available for performing human activity recognition. In [5], the researchers used five biaxial accelerometers placed on the right ankle, the left thigh, the waist, the left upper arm, and the right wrist. Researchers in [3] made use of accelerometer sensors commonly found in smartphones. Although they only used 22 features, their model can achieve 99.67% in a 10-fold cross validation. Moreover, one of the most commonly used classifier algorithms for human activity recognition is the Support Vector Machine (SVM). This algorithm has been used in [3], [6], and [7] which has been shown to achieve quite accurate results.

In recent years, there have been initiatives from some researchers to use other wearable devices to perform human activity recognition. Researchers in [4] made use of a smart-watch to perform basic activities and hand-based activities recognition using random forest, J48 decision tree, IB3 instance-based learning algorithm, Naïve Bayes, and multi-layer perceptron algorithm. By using smart-watch, they can recognize more advanced activities that involve a lot of hand movements such as drinking, eating, dribbling, etc. In [8], researchers used sensory data extracted from a smart-watch and building a Restricted Boltzmann Machines (RBM) deep learning model to perform human activity recognition.

3. Issues and Challenges

a. Human Activity Recognition

As the human activity recognition technology relies mostly on machine learning algorithm, firstly, there will be a number of challenges related to data pre-processing steps. For example, a lot of experiments must be conducted to find the best data sampling rate and window size. Moreover, there will be a lot of time spent on understanding the machine learning classifier algorithms, especially the Support Vector Machine (SVM). Experiments will also be needed to find out the best hyper parameters for the SVM model training.

Another possible issue is related to the variability of how people use a smart-watch and their hand positions when performing certain activities. This may affect the sensor data readings and hence a more complex data pre-processing steps may be needed. Lastly, as there seems to be no previous research work on human activity recognition using both a smartphone and a smart-watch as complimentary smart devices, this may require efforts on synchronization. A new classification paradigm must be devised such that data from both devices can be used to improve the accuracy and to include more hand-based activities.

b. Real-time Recognition System

The current human activity recognition model needs a stream of data segmented into data windows of equal length. Each data window must be long enough so that there is enough context to predict an activity, but short enough so that the activity can be recognized as soon as possible. Finding the balance between the prediction accuracy and the time needed to get a prediction is hard and needs to be determined by experiments. If the accuracy is high but the user needs to wait for too long, it is bad for the application's user experience. On the other hand, if the user receives the prediction quickly but the prediction is not correct, the prediction result will be useless.

4. Approaches and Technologies

a. Tools

1) Python

Python is one of the most popular programming languages in the world nowadays. It is popular due to the fact that it is easy to learn, powerful, and supported by a huge community. Python will be used for training and predicting activities using the LibSVM library. As one of the project objectives is providing real time activity recognition, Python will also be used as a server and provide endpoints for the Android application.

2) **Android and Java**

An Android application will be needed since the accelerometer sensor data will be taken from an Android based smartphone. The Android framework includes APIs needed for collecting accelerometer sensor readings.

3) **Tizen-based Smart-watch**

As mentioned in the objectives, this project is going to incorporate sensor data taken from a smart-watch. This project will be using a Tizen-based smart-watch, a Samsung Gear S. A simple application for collecting sensor data will also be developed.

b. Data Pre-processing and Prediction Pipeline

Data pre-processing plays a very important role in any machine learning projects, including this project. Currently, there is no data pipeline for data pre-processing and activity prediction. According to the previous student's guidelines, each step is performed manually. As a result, it is very error prone and may slow down the development.

This project aims to build a data pipeline such that all data pre-processing steps including the activity recognition step is automated. Given a stream of raw sensor data, the pipeline will produce the activity recognized as the final results. Please note that this pipeline is only applicable for real-time human activity recognition system. That being said, however, the data sampling and feature extraction code can be used for pre-processing the training data as well. Figure 1 illustrates the data pipeline.

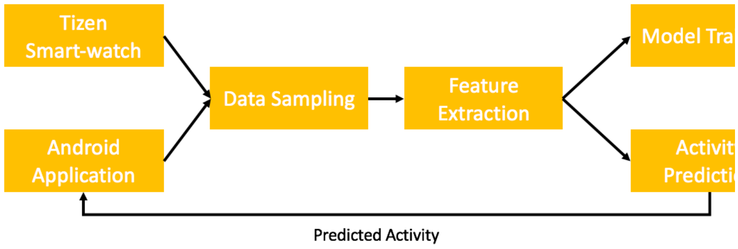

Figure 1: Data pipeline diagram.

5. Project Tasks

a. Code Rewriting

The code written by the previous student is currently very messy as it seems the previous student wrote the code for the purpose of research and model building. Since this project aims to create a simple application which is able to recognize human activities in real-time, rewriting the code from scratch is needed as it will increase the readability and help the next student who is going to extend the project in the future. The code rewriting will include the Android application as well as porting the Matlab codes into Python. Moreover, rewriting the existing code also helps me understand the existing algorithm and processes better along the way.

b. Building Data Pipeline

The next important task is to build a data pipeline to streamline the data pre-processing which includes data sampling and feature extraction. As mentioned previously, this data pipeline is important as it can reduce the human error rate. I believe the previous student conducted all data pre-processing steps manually whenever new data are obtained, which is very tedious. By using a data pipeline, it will improve the development time as well.

c. Enhance the Android Application to Perform Real-time Recognition

The Android application should be able to perform real-time activity recognition. This involves building a simple backend server which will read the serialized classifier model and use the model to predict an activity given a stream of sensor data. It is worth to mention the Android application will be rewritten as well since there are many unused lines of code. Thus, it is very hard to make changes to the existing code and will require a lot of time.

d. Data Collection and Model Building using Sensor Data from Smart-watch

Once the basic foundation of the smartphone activity recognition is settled, the project will continue working on the smart-watch activity recognition process. This involves creating a simple Tizen application to read and send sensor data to the backend server. Next, there will be data pre-processing steps and model building as well as devising an algorithm to use sensor data from both smartphone and smart-watch to improve the prediction accuracy results.

e. Model Testing and Improvement

This task focuses mainly on thorough testing using multiple data sets from various sources. Other improvements needed will also be conducted in this period. Since there is a lot of variables involved in this project, there are uncertainties involved and hence I could not mention other specific improvement tasks at the time this project plan is written.

6. Schedules

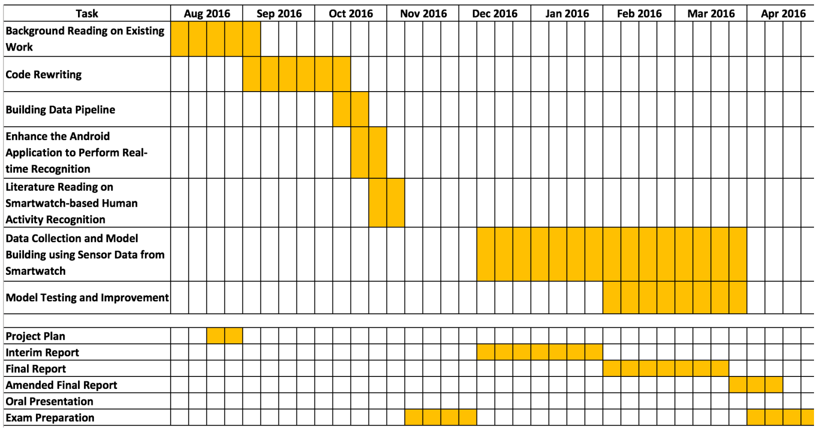

Figure 2: Project schedule

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