FINAL YEAR PROJECT PLAN

Human Activity Recognition through Wearable Devices
SCE16-0405

Edwin Candinegara
U1320135K

NTU Supervisor: Prof. Tan Ah Hwee
Project Manager: Dr. Wang Di

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School of Computer Science and Engineering

Table of Contents

List of Figures

1. Introduction

a. Background and Motivation

With increasing life expectancy and lower birth rates trends in Singapore, the number of citizen population will start declining from 2025 [1]. As a result, the number of citizens aged 65 and above will increase in the next few years. Moreover, 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 monitoring elders without being intrusive to the users.

Activity recognition technology is the key technology for monitoring elders in an effective manner. There are many studies in this area and researchers have presented many ways to recognize human's activities. One of the most popular methods is using sensors embedded in smartphones. Researchers have shown that using only 22 features extracted from a smartphone's accelerometer, their model can achieve 99.67% accuracy in a 10-fold cross validation for 5 different activities: lying, sitting, standing, walking, and running [3].

Although researchers have been using smartphones in many of their works, research into smart-watch based activity recognition is still not popular. One study [4] indicates that by using smart-watches, there are activities that can be identified with much higher accuracy compared to using smartphones. Thus, this Final Year Project (FYP) aims to find out how sensory data extracted from smart-watches can be used to improve the accuracy of basic human activities recognition as well as exploring additional activities recognition.

b. Project Objectives

The previous student has already developed a robust activity recognition model with the capability of detecting motion transitions. The recognition model is able to recognize 5 basic low level motions: lying, sitting, standing, walking, and running. This model is built only using sensory data taken from an Android smartphone. The motion transition recognition is done by reading consecutive sensory readings and performing a rule based algorithm on the data.

Furthermore, the model built has been thoroughly tested using various data set collected by the previous student. The data set collected also captured human behaviour in their most natural environment settings. Using this data set, the recognition model can achieve 90% accuracy on average for both low level motion and motion transition recognitions.

There are two main objectives of this project:

1) Extending the human activity recognition framework done by the previous student such that the Android application is able to perform a real-time human activity recognition.
2) Incorporating sensor readings from a smart-watch to the activity recognition model.

In addition to these two main objectives, this project will also try to increase the existing model's accuracy along the way. This may include modifications to the existing algorithms like the data pre-processing steps. Moreover, this project would also add more activities such as brushing, eating, typing on a computer, etc. to the recognition model. This would be possible with the usage of the additional sensor data from the smart-watch.

c. Scopes and Limitations

1) **Scopes:**
   - Familiarization with the existing Human Activity Recognition model developed previously
   - Extending the Android application such that it allows real-time activity recognition (may involve code rewriting)

- Collecting sensory data from the smart-watch while conducting certain activities
- Build a model making use of the sensory data from both smartphones and smart-watch

2) Limitations:

- Delays in real-time activity recognition are inevitable since performing real-time activity recognition requires window slicing and due to network transmission delays.
- The smart-watch is placed on the wrist of the user's dominant hand

2. Related Work

Human activity recognition is a technology which is able to recognize actions performed by a human by processing a series of observations. These observations usually come from sensors found on smart devices such as smartphones and smart-watches. This technology offers many possible benefits, especially to children and elders who need more assistance and monitoring in their daily living. For example, a person could monitor an elder's activities just by using a smartphone or other wearable devices.

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.

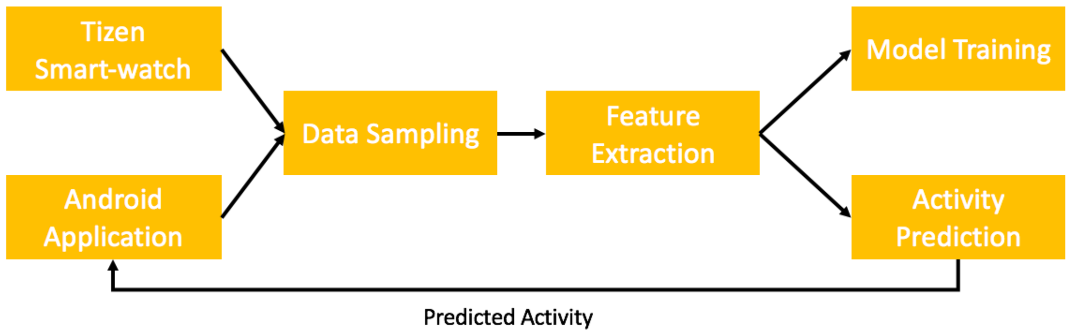

Figure 1: Data pipeline diagram.

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

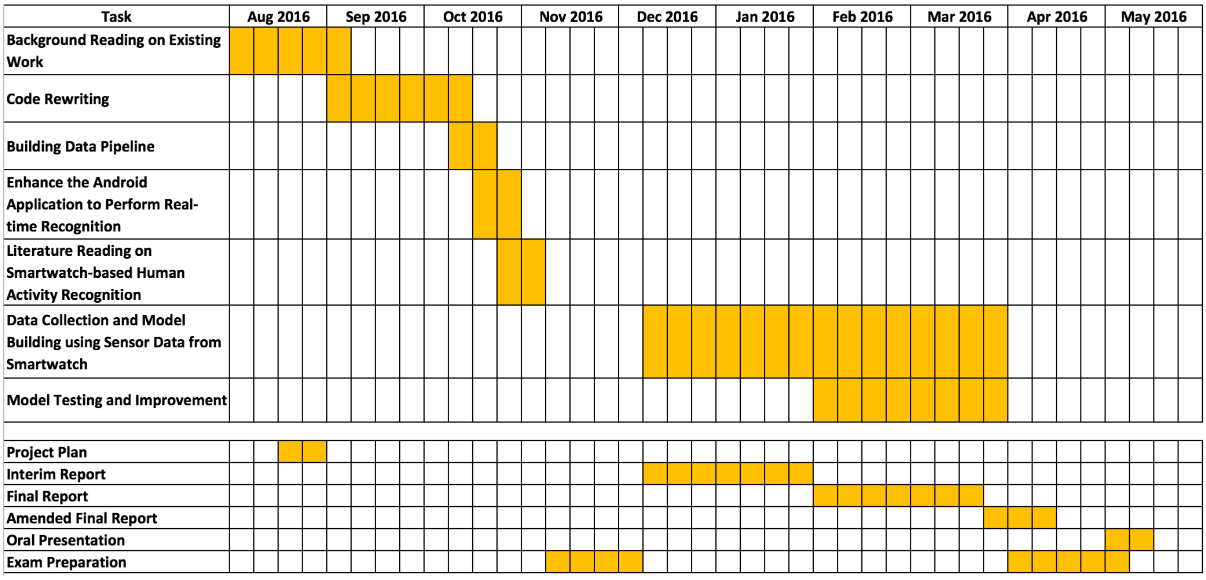

Figure 2: Project schedule

7. References

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