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A SIMPLE HIERARCHICAL ACTIVITY RECOGNITION SYSTEM USING A GRAVITY SENSOR AND ACCELEROMETER ON A SMARTPHONE

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ABSTRACT

The routine daily activities that tend to be sedentary and repetitive may cause severe health problems. This issue has encouraged researchers to design a system to detect and record people activities in real time and thus encourage them to do more physical exercise. By utilizing sensors embedded in a smartphone, many research studies have been conducted to try to recognize user activity. The most common sensors used for this purpose are accelerometers and gyroscopes; however, we found out that a gravity sensor has significant potential to be utilized as well. In this paper, we propose a novel method to recognize activities using the combination of an accelerometer and gravity sensor. We design a simple hierarchical system with the purpose of developing a more energy efficient application to be implemented in smartphones. We achieved an average of 95% for the activity recognition accuracy, and we also succeed at proving that our work is more energy efficient compared to other works.

Keywords: Accelerometer; Activity recognition; Gravity sensor; Smartphone

1. INTRODUCTION

The routine daily activities that tend to be sedentary and repetitive may cause severe health problems. Several studies about health issues corresponding to sedentary daily life activities (Tremblay et al., 2010) have been conducted to show the seriousness of this problem. Proper health and lifestyle coaching is needed as a solution to this problem. This issue has inspired researchers to design a system to detect and record people activities in real time and thus encourage them to do more physical exercise. The core method and technology of this system is activity recognition, which has already become a hot topic for researchers in recent years. Many studies have been conducted in this field; however, some of them lack the requirements to implement this kind of system into a real-world application. One study (Gupta & Dallas, 2014) proposes an activity recognition system using a single tri-axial accelerometer attached to a user's belt. Their system requires additional electronic devices and processes the data separately, so it is not really usable for real-time data processing. Another work (Zhu et al., 2010) uses a camera as a sensor for data input, which means that the activity recognition is limited to a certain area and cannot be used for personalized activity data. To address this issue, gathering data from a smartphone's embedded sensor to recognize physical activity has been studied extensively (Anjum & Ilyas, 2013).

Nowadays, almost every individual already owns a smartphone. This means that using a smartphone as a sensor for recognizing daily activities could remove the obtrusive and

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disruptive factor of equipping other sensors for daily activities. In the state of the art research, the most common sensors used for activity recognition in the smartphone are accelerometers and gyroscopes. An accelerometer is used to capture the smartphone acceleration value, and a gyroscope is used to capture smartphone rotation. However, we observed the potential of an additional sensor to be used for the purpose of activity recognition: gravity sensor. A gravity sensor is used to capture a smartphone's position relative to the earth's surface. We propose a novel method to recognize activities using the combination of an accelerometer and a gravity sensor. We list below our main contributions:

1) To the best of our knowledge, our research is the first that includes the usage of a gravity sensor. One study (Anjum & Ilyas, 2013), uses the combination of an accelerometer, gyroscope, and magnetometer in activity recognition, but in our case, we use the combination of an accelerometer and gravity sensor. By doing so, we can show how the gravity sensor can form the motion pattern of each activity.
2) We propose a novel method for activity recognition by utilizing the combination of a gravity sensor and accelerometer on a smartphone. Our method can also detect whether a smartphone is equipped by the user or not.

We also include an energy consumption report of our prototype algorithm to be considered for real-case usage.

2. SYSTEM OVERVIEW

2.1. Proposed Method

In our proposed system, we use a hierarchy style system to differentiate a user's activities. We assume that a user will place his or her smartphone in a trouser pocket while performing activities. First, we try to classify the user into two types of activity: static and dynamic activity. Static activity represents activities that do not require the user to perform any significant motion or movement, such as sitting or standing. Additionally, we include the situation in which the smartphone is placed on a table which means that the smartphone is not being used for activity recognition by the user. The second group is for dynamic activities that require the user to perform dynamic motions or movement. Several activities that are included in this group are walking, running, ascending stairs, and descending stairs. A visualization of this activity hierarchical model can be observed in Figure 1.

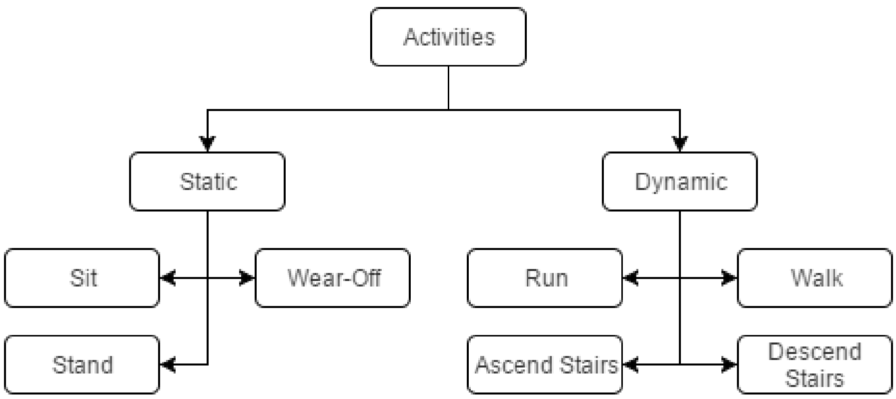


Figure 1 Activity hierarchical model

The overall system architecture is shown in Figure 2. We process the input from the smartphone sensor in batch-style processing. In this experiment**,** we consider that a 5-second window time is appropriate for recognizing the activity of the user. For each batch, we normalize the gravity sensor value input on a Z axis to adjust the sensor values from different scales to a notionally common scale. This is done to get the motion pattern needed for the first classification.

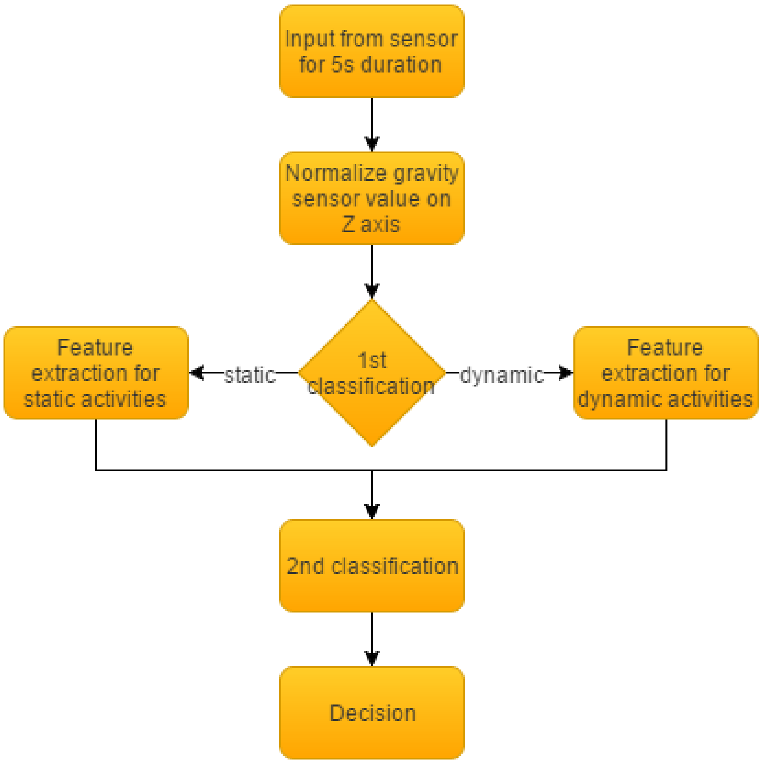


Figure 2 Overall system overview

To classify whether the user is involved in static or dynamic activity, we perform the first classification using a *dynamic time warping* technique on the input from a gravity sensor on the Z axis. After that, based on the result, we perform a different feature extraction method. Then, using the extracted features as input, we apply the *k-nearest neighbor* classification technique for the second classification to determine the final recognized user activity.

2.2. Sensor and Axis Selection

We use a gravity sensor as the main sensor to distinguish whether the phone is moving or not. The gravity sensor on a smartphone originates from a 3-axis accelerometer. It measures the vector components of gravity corresponding to the phone position. When the phone that is placed in the user's trouser pocket is in motion because of an activity, the leg movement will cause the gravity sensor to show a pattern, as shown in Figure 3. We only use the Z-axis and Y-axis on the gravity sensor because they capture the forward and backward leg motion, whereas the X-axis is not affected much by leg movement. When the leg gait cycle starts, as the leg moves forward, the gravity on the Z axis records a positive peak pattern, and when the leg moves backward, the value moves to the negative peak pattern because the phone orientation is also changing.

On further observation, we also found that gravity sensor values are more noise resistant compared to accelerometer values. This can be shown by a visualization of the raw data of both the gravity sensor and accelerometer values on running activities as shown in Figure 4. We can get a clear pattern of leg movement from the gravity sensor data without applying any complex pre-processing methods. Thus, we assume that by utilizing this sensor, we can save great amounts of computational resources on smartphones.

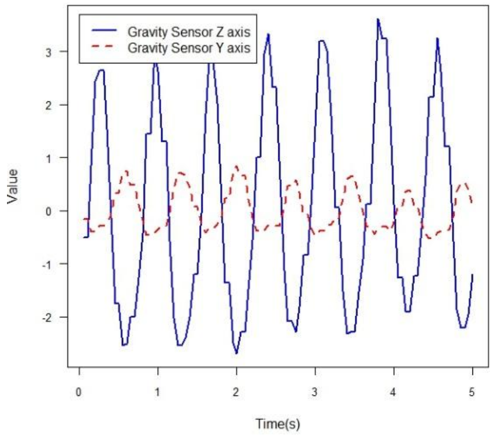
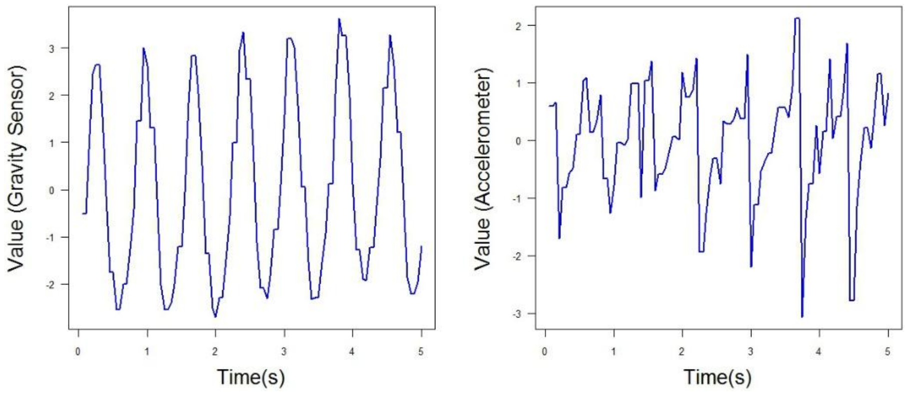


Figure 3 Pattern of a gravity sensor on running activity



(a) (b)

Figure 4 A pattern comparison of a (a) gravity sensor; and (b) accelerometer on running activity

2.3. Feature Extraction

Time domain features are extracted from the data depending on whether the activity is classified as dynamic or static in the first classification. The advantage with feature extraction is that it allows optimization and enhances the accuracy of the next classification. First, we try to extract all of these features from both groups of activity:

Table 1 Extracted features for each activity group

Group	Features
Static	- Root Mean Square on Gravity Y axis - Root Mean Square on Gravity Z axis - Standard Deviation on Magnitude Acceleration
Dynamic	- Mean on Magnitude Acceleration - Standard Deviation on Accelerometer Y axis - Standard Deviation on Gravity Z axis

- *Root Mean Square* – RMS is a statistical measure defined as the square root of the mean of the squares of a data. It is described in the following equation:

$$x_{RMS} = \sqrt{\frac{\sum_{i=1}^{n} a_i^2}{n}} \quad (1)$$

- *Magnitude Acceleration* – The values from the 3-axis accelerometer are calculated together to get the magnitude. This value shows the total acceleration from the 3-axis accelerometer. The formula is shown below:

$$|\vec{a}| = \sqrt{x^2 + y^2 + z^2} \tag{2}$$

- *Mean and Standard Deviation* – The mean is the average value of the data, and standard deviation is a measure of how spread out the data is.

From all the features extracted, we use the *Exhaustive Search Feature Selection* method to choose the best feature and to experiment with several combinations of features. From several tests, the minimum numbers of the combination of features that give the best accuracy are listed in Table 1 for each group of activity.

2.4. Classification Method

2.4.1. Dynamic time warping

Dynamic time warping (DTW) is used for the first classification. DTW is a method that calculates an optimal match between two given sequences. The sequences are "warped" non-linearly in the time dimension to determine a measure of their similarity. The DTW is used to distinguish a dynamic pattern from a static pattern using normalized data from a gravity sensor on the Z axis. In the beginning, we store template data that contain a basic data template for static activity and dynamic activity, which can be observed in Figure 5. The test data are then classified to the group of activity that gives the smaller distance result.

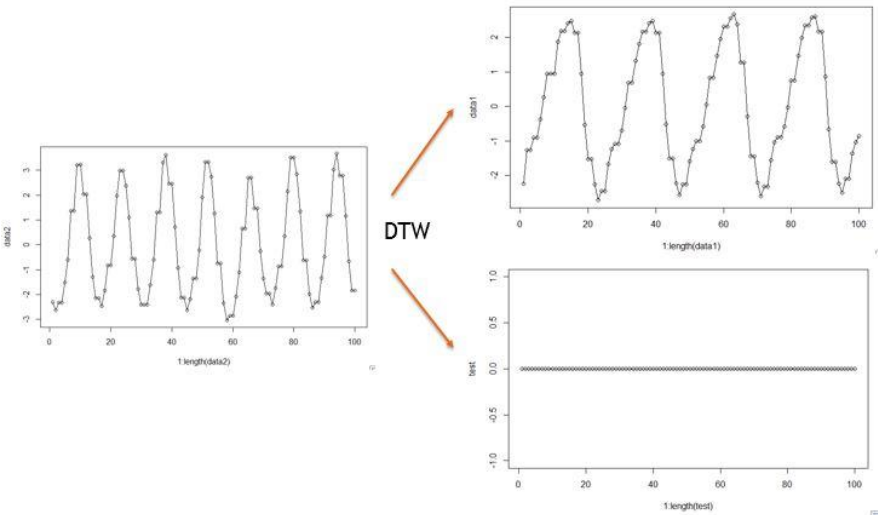


Figure 5 DTW classification of test data (left) with dynamic template (upper right) and static template (lower right)

2.4.2. k-nearest neighbor

After being classified into static or dynamic activities, we use the *k-nearest neighbor (k-nn)* classifier for a final decision. *K-nearest neighbors* is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions). A case is classified by a majority vote of its neighbors, with the case being assigned to the class most common amongst its K nearest neighbors measured by a distance function. If K = 1, then the case is simply assigned to the class of its nearest neighbor. We use this classifier for the second classification because of its simplicity and we did not use much training data. In this system, we set K=5 for an optimal result.

3. DATA COLLECTION AND EXPERIMENTAL IMPLEMENTATION

For the purpose of our research, we used the LG G2 smartphone as the medium to collect data. Choosing the best smartphone for this research was important because the phone dimension is critical in terms of whether it is fit to place in the front trouser pocket or not. The data was collected using an LGE accelerometer sensor embedded in the phone with a sampling rate of 20 Hz. In our research, the smartphone was placed naturally in the pocket, so the data were influenced by natural noise, but we could show that our method was robust in relation to those problems.

For each piece of activity data, the participant was asked to do each activity for 5 minutes to gather enough data. A total of 420 data points were used in this research, which were divided into 70 training sets for clustering and 350 data points for test data. To select the training data, we calculated the distance measurements in gravity sensor Z axis for each data point and compared them to each other. Top 10 data points with the smallest distance were chosen for each activity for cluster training data, and the rest became test data. We used our campus and laboratory environment to gather data. Some data, such as for sitting, standing, and wear off, were collected in our laboratory office. Walking data were collected in our faculty building hallway. Ascending and descending stairs data were also gathered using our faculty building stairs. The phone was placed vertically in the front trouser pocket.

The collected data were then processed using R language, which we also used for developing a prototype algorithm for measuring the energy used for computation, so we could measure the energy consumption. We used the R package's *dtw* and *class* to employ *dynamic time warping* and the *k-nn* classifier for the data. The prototype algorithm was then activated using the R Console for Android for several hours and compared to the normal condition. The battery log information recorded the energy depletion for two kinds of conditions: when activity recognition was running and not running.

4. PERFORMANCE ANALYSIS AND DISCUSSION

In this section, we present a performance analysis of the proposed method. We evaluate our system in two different parameters. The first is the accuracy, which shows the success rate of our system activity recognition, and the second one is the energy consumption rate of the prototype algorithm.

4.1. Accuracy

We present the performance parameters of our system in a confusion matrix that is shown in Table 2. We selected seven activities that could be considered primary activities, with the assumption that the other complex activities were activities that included primary activity in them. Because of the location-dependent nature of our proposed system, which depends on the smartphone's location in a user's pocket, the evaluation of our system by using these seven activities was the starting point to develop a more "complex" system to classify more activities. We could observe that several activities were misclassified during the process. From the dynamic activities, the misclassified activities were walk, ascend stairs and descend stairs. This misclassification occurred because of the similar leg motion and speed within those activities, resulting in a large within-class variance and a small between-class variance. This problem does not affect run activity because the difference in speed and leg motion is big compared to the other dynamic activities. A similar case occurred for static activities, where the condition for the sit activity is pretty similar with the wear off condition. However, stand activity could be accurately recognized.

Table 2 Confusion matrix of experimental results

Activity	Walk	Run	Ascend Stairs	Descend Stairs	Stand	Sit	Wear Off
Walk	**48**	0	2	0	0	0	0
Run	0	**50**	0	0	0	0	0
Ascend Stairs	0	0	**45**	5	0	0	0
Descend Stairs	7	0	1	**42**	0	0	0
Stand	0	0	0	0	**50**	0	0
Sit	0	0	0	0	0	**47**	3
Wear Off	0	0	0	0	0	0	**50**

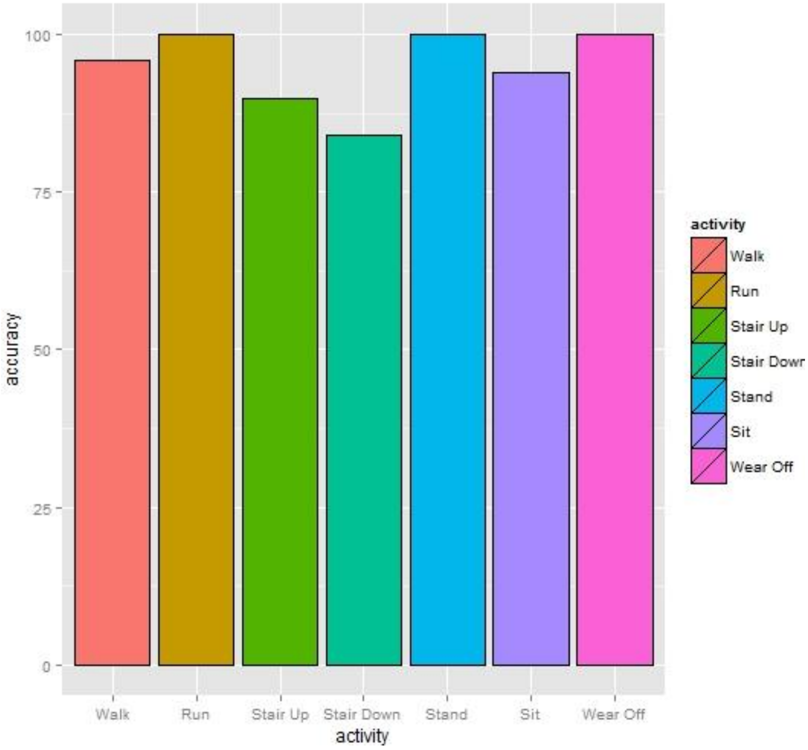


Figure 6 Overall system accuracy

Table 3 Comparison with other methods

Study	Sensors	Accuracy
(Ronao & Cho, 2014)	Accelerometer, Gyroscope	91.76%
(Bayat et al., 2014)	Accelerometer	91.15%
(Kwon et al., 2014)	Accelerometer, Gyroscope	>90%
Our Approach	Accelerometer, Gravity Sensor	95%

Even though there were some misclassifications on several activities, the accuracy for each activity, as shown in Figure 6, was very high (>80%). The average total accuracy from this method reached 95% correct activity recognition using a few simple features extracted from the gravity sensor and accelerometer values. We also compared our system performance with the state-of-the-art work that can be seen in Table 3. The table depicts that our work had a better performance compared to the others. Our system can achieve an average accuracy of 95%, which is better than the other works (<95%). This is because the gravity sensor data is more resistant to noise compared to the accelerometer and gyroscope (see Section 2.2). The noise-resistant feature of the gravity sensor reduced the error rate of the recognition process. This shows that the gravity sensor on a smartphone has the significant potential to be utilized in human activity recognition.

4.2. Energy Consumption

The battery is one of the important aspects to be considered when applying some kind of continuous application to a smartphone. Only a few studies have investigated energy consumption for the activity recognition application in the smartphone (Viet et al., 2012; Vo et al., 2013). For our work, we measured the energy consumption compared to the normal condition using the prototype algorithm on the LG G2.

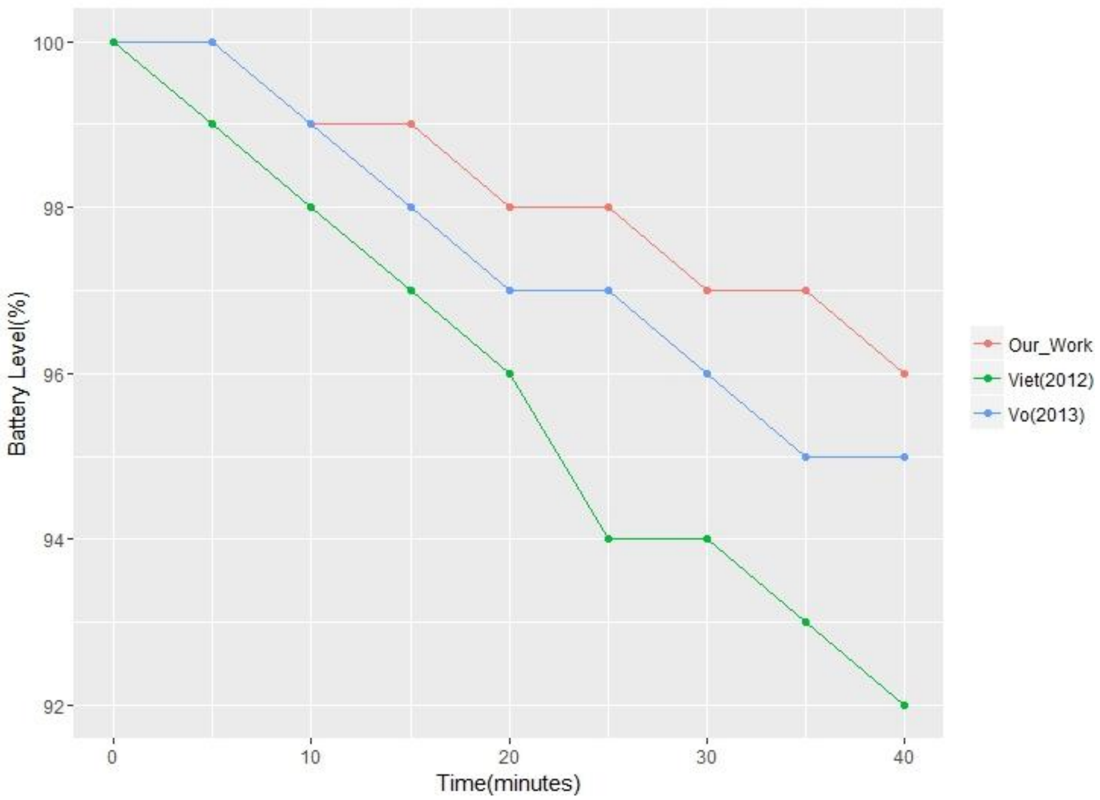


Figure 7 Average energy consumption

Figure 7 shows the power consumption comparison of our proposed system and the other works (Viet et al., 2012; Vo et al., 2013). We can observe that our system consumed less energy compared to the others. This is because we did not include any complex preprocessing method, such as noise elimination which may potentially consume more energy. In the other studies (Viet et al., 2012; Vo et al., 2013), the authors used peak detection, noise filtering, and a linear interpolation method in the preprocessing method. These processes consume more energy than necessary to enhance the accuracy. In our case, because of the noise-resistant feature of the gravity sensor, we can avoid this process; hence we can save more energy.

5. CONCLUSION AND FUTURE WORK

Our contribution with this paper is presenting a novel method in activity recognition using the combination of a gravity sensor and an accelerometer, and to the best of our knowledge, we are the first to introduce the usage of a gravity sensor in the field of activity recognition. We introduce and prove a more energy efficient activity recognition method compared with other methods. We successfully achieve high accuracy with an average of 95% and lower battery consumption compared to other works. In the future, the increasing number of more “smart” things can also be utilized to improve this system. Those new devices (e.g., the smartwatch) can be attached to other parts of the human body and can open new possibilities for improving our system by adding new inputs to our classification algorithm.

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