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Human Activity Recognition Based On Wearable Flex Sensor and Pulse Sensor

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HUMAN ACTIVITY RECOGNITION BASED ON WEARABLE FLEX SENSOR AND PULSE SENSOR

BY

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THESIS ACCEPTANCE PAGE

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This thesis is approved as a creditable and independent investigation by a candidate for the master's degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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CONTENTS

ABBREVIATIONS....v

LIST OF FIGURES....vi

LIST OF TABLES....vii

ABSTRACT....viii

INTRODUCTION....1

BACKGROUND....3

A. HAR....3

B. Flex Sensor....3

C. Pulse Sensor....4

D. LSTM....4

RELATED WORKS....6

PRELIMINARIES....10

A. Sensor Setup....10

B. Data Collection....12

C. Data Preprocessing....15

IMPLEMENTATION AND EXPERIMENT....18

A. Training Phase....18

B. Testing Phase....20

C. Evaluation Experiment....20

EXPERIMENTAL RESULTS ANALYSIS....22

A. Angular Data-Based HAR System vs. Acceleration Data-Based HAR System...22

B. Among Neural Network Structures....25

CONCLUSION....26

REFERENCES....28

ABBREVIATIONS

HAR	Human Activity Recognition
WBAN	Wireless Body Area Network
BPM	Beats Per Minute
MEMS	Micro Electro Mechanical Systems
LSTM	Long Short Term Memory
RNN	Recurrent Neural Network
DBN	Deep Belief Network
HZ	Hertz
GHz	Gigahertz
CNN	Concurrent Neural Network
CSI	Channel State Information
CARM	CSI-based human Activity Recognition and Monitoring
UDP	User Datagram Protocol

LIST OF FIGURES

Figure 1. Accelerometer Reading Example……………………………………………6

Figure 2. Flex Sensor Reading Example……………………………………………….8

Figure 3. Sensor Attachment and Data Collection Overview………………………...10

Figure 4. Implemented Joint Angle Sensor and Pulse Sensor………………………...12

Figure 5. Angle Change of Left Knee During Activity Example……………………..13

Figure 6. Angle Change of Right Knee During Activity Example……………………14

Figure 7. BPM Change During Activity Example……………………………………14

Figure 8. Data Preprocessing Overview……………………………………………...15

Figure 9. Process of Generating Activity Dataset and Its' Subsets……………………16

Figure 10. Process of Linking All Types of Activity Datasets………………………..17

Figure 11. System Implementation Overview………………………………………..18

Figure 12. Angular-Acceleration Accuracy Comparison Result……………………..23

LIST OF TABLES

Table 1. Recorded Activity with Label..13

Table 2. Confusion Matrix for Proposed Angular Data-Based HAR System............23

Table 3. Confusion Matrix for Acceleration Data-Based HAR System..................24

Table 4. Recognition Accuracy List...25

ABSTRACT

HUMAN ACTIVITY RECOGNITION BASED ON WEARABLE FLEX SENSOR AND PULSE SENSOR

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In order to fulfill the needs of everyday monitoring for healthcare and emergency advice, many HAR systems have been designed [1]. Based on the healthcare purpose, these systems can be implanted into an astronaut's spacesuit to provide necessary life movement monitoring and healthcare suggestions. Most of these systems use acceleration data-based data record as human activity representation [2,3]. But this data attribute approach has a limitation that makes it impossible to be used as an activity monitoring system for astronavigation. Because an accelerometer senses acceleration by distinguishing acceleration data based on the earth's gravity offset [4], the accelerometer cannot read any type of acceleration when it is in the actual free fall environment. Since astronauts will experience microgravity and/or zero environments in outer space, all existing acceleration data-based HAR systems cannot fulfill this requirement. Therefore, it is necessary to design a new data attribute for HAR systems to specifically work under microgravity and zero gravity environments. The angular change of body joints during activity can be a good solution. By attaching sensors onto body joints, the system can recognize an activity by analyzing the change pattern of bend angles similarly to how people recognize others' activity by looking at their posture during movement. Considering the possibility of overlapping data from multiple different activities that may have similar angular changes, a life activity related

data called Beats Per Minute (BPM) is thus used to differentiate overlapping activities. With the new compilation and format of activity data, the HAR system should be able to work under both microgravity and non-gravity environments with similar or better accuracy than existing HAR system implementations.

This paper demonstrates the implementation of new data attributes based on existing HAR systems by using angular data and BPM data, then makes comparison between acceleration data-based HAR and angular data-based HAR systems to verify the performance similarities, and comparison among different neural network structures to analyze and provide the most suitable machine learning technique to train the system.

INTRODUCTION

HAR is a field of study to recognize and research human activities and behaviors using data collected by sensors to create useful medical, military or security applications [2]. As one of the applications that can cooperate with WBAN, HAR systems have been extensively studied due to their application in areas such as healthcare and smart environmental monitoring [5]. By attaching multiple sensors to become a WBAN, the system can continuously read activity data and send them to the monitoring servers via wireless signals such as Wi-Fi or Bluetooth. Based on these life data readings, a doctor could make fast, accurate diagnoses and provide feedback quickly to the remote user. Also, if the monitoring server finds any unusual activity, it can provide a timely warning to both the user and doctor to prevent any kind of emerging situation.

Astronaut healthcare monitoring is one of the biggest concerns in space program research. For modern space program, all astronauts are strictly selected and trained to work under an extremely dangerous outer space environment, and therefore, losing any single astronaut is an incalculable loss for humankind. Finding medical personnel for space trips is inefficient because they are even harder to recruit than normal astronauts, therefore, astronauts need a specially designed HAR system with WBAN to remotely provide professional healthcare monitoring services to maintain their life status and work efficiency.

Existing HAR systems mainly use body acceleration data as activity representation. These systems use sensors such as MEMS, which includes an accelerometer to collect the body acceleration data during movement [6].

Acceleration-based activity data is very understandable by a machine to recognize the pattern of different activities so that the HAR system as trained by acceleration data-based data, will always have very accurate activity recognition ability. In addition, the accelerometer can be miniaturized and therefore easily integrated into a single device that is very convenient to attach.

However, since accelerometers measure acceleration by using the earth's gravity as an offset, the existing HAR systems should be modified to use new types of data attributes for activity representation instead of being directly used. The objective of this paper is to introduce the implementation of a new HAR system data attribute for existing HAR system using Flex sensors and a Pulse sensor installed in wearable equipment, modify the system's machine learning structure to fit in with the new data attribute, and compare the overall performance with an accelerometer data-based HAR system.

BACKGROUND

This section will explain all terminologies related to the proposed implementation to help readers to have better understanding of how the proposed objective was achieved in later sections.

A. HAR:

HAR system is a field of study to recognize and research human activities and behaviors using data collected by sensors to create medical, military, or security applications [2]. As one of the applications to cooperate with WBAN, HAR systems have been extensively studied due to their wide application in various areas such as healthcare and smart environmental monitoring [5]. Most existing HAR systems use the subject’s moving acceleration as input data [6]. Since these acceleration data are collected by using accelerometer that cannot work properly in outer space, making a HAR system for an astronaut needs to use new types of input data. One of the key aspects of research in HAR systems is to use the joint angles of the human body during daily activities as input data [7]. Therefore, replacing acceleration with body joint’s angular change is a possible solution to make HAR system work in outer space. In order to overcome current limitations to assessing and monitoring joint movement, flexible sensors (such as Flex sensors) are being researched in combination with the study of HAR systems.

B. Flex Sensor:

The Flex sensor is a specially designed flexible resistor strip to measure the amount of deflection or bending. While bending the Flex sensor, the resistance of the resistor strip embedded in the sensor body is modified based on the bending angle and thus the bending angle can be calculated by using concurrent resistance change. When Flex sensors are attached to each joint of the human body, the angular change during movement can be recorded as data for activity recognition, and based on the joint angle change pattern, we can determine what activity the user is doing. Because body joints' angle change during activity and measurement of the bending angle with Flex sensor are not influenced by micro gravity and zero gravity environments, The Flex sensor can become an activity data collector for HAR systems in outer space.

C. Pulse Sensor:

A pulse sensor is a sensing device that can detect pulse (blood pushing through human arteries) and is especially used in medical equipment to detect and evaluate the body heart rate. The pulse sensor can be attached over the user's skin where it can sense the pulse. When the sensor starts working, it will shoot a specific amount of infrared light which is then reflected by the blood circulating inside the body. Every time a pulse occurs, the heart pumps a huge amount of blood into circulation. As the blood wave passes through the body spot where the Pulse sensor is shooting the infrared light, the blood pressure rise (caused by the heart pumping) will change the amount of infrared light reflected back to the sensor and thus the sensor detects that pulse. By calculating the elapsed time between two pulses, we can calculate the heartbeat rate per minute which is known as Beats Per Minute (BPM).

D. LSTM:

Most existing HAR systems are implemented by using deep learning technique. Deep learning is one of the most popular fields of study to implement smart and efficient systems. By inputting activity data and expected answers into the deep learning model, the model will automatically summarize the change patterns of activity data for each activity and use these experiences for the activity recognition based on activity data without pre labeling. LSTM is one example of deep learning techniques that have been used in implementing HAR systems [8, 9].

The LSTM is an implementation of RNN in the study area of deep learning and was designed to solve the gradient vanishing problem from traditional RNN [10]. The RNN is a neural network technique that recurrently runs the function to generate the output based on the current input and outputs from previous computations. While using RNN to train a machine with high repetition, as the iterations go on, the outputs learned from very early iterations will lose their effect on the current training. To ensure that every previous output is fully used, the LSTM added extra cell state and logic gates such as input gate and forgetting gate into the traditional RNN cell to store useful information and remove harmful information from all computed memory cells. The basic unit in a LSTM network's hidden layer is the memory block, which contains one or more memory cells and a pair of adaptive multiplicative gating units that gate input and output to all cells in the block [11]. The memory cells are often combined with standard RNN where LSTM is for memory units through gradient descent to decrease the error throughout propagation when the hidden layers are too deep [12].

RELATED WORKS

The implementation of the proposed system has two main parts: the hardware part (sensor) and software part (system). This section will introduce some existing HAR systems to show that most existing HAR systems will not work for astronauts because of the accelerometer and then verify that Flex sensors can be used in HAR systems along with LSTM as deep learning technique to train the system.

For the sensor setup part, the accelerometer measures the acceleration's direction and magnitude by measuring acceleration's projection at x, y, and z axes as shown in Figure 1. Since the accelerometer measures relative acceleration referenced with the earth gravity, when the sensor is attached to a stationary user, the internal accelerometer reads zero. Once the subject starts moving, the accelerometer can sense the force and measure the projected accelerations in 3 axes of direction. During movement, the sensor continuously records all the readings and integrates them as a time-based activity dataset.

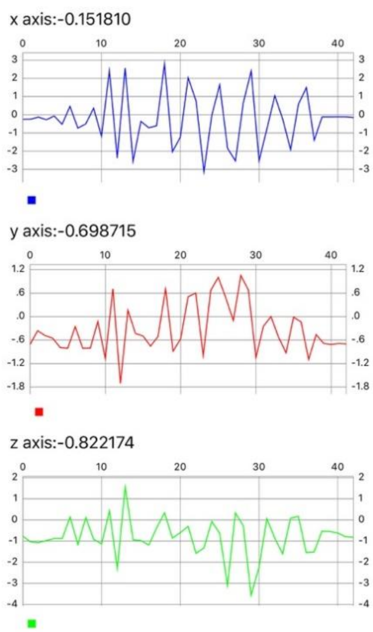

Figure 1. Accelerometer Reading Example

Most existing HAR system projects use an accelerometer as the sensor to collect activity data. For example, Zubair et al. [13] designed a HAR system using a public domain HAR dataset provided by Ugulino et al. [14] and had 99.87% overall accuracy. The project collected activity data from 4 healthy adults wearing 4 tri-axial accelerometer sensors at different body positions (waist, left thigh, right ankle, and right arm). Each subject performed 5 different activities including sitting, sitting down, standing, standing up, and walking. The activity classification was implemented by using two different algorithms including Random forest and ensemble method of C5.4 in connection with AdaBoost learnt from Baldominos et al. [15]. Also, Ignatov et al. [16] implemented an online HAR system by using single tri-axial accelerometer sensor (smartphone) in which they collected activity data by attaching the sensor to the user's thigh and made up a 3*N time series dataset and ran through it with a specially designed k-nearest neighbor method to build up classifications. Another HAR system project that used a smartphone's accelerometer as the activity sensor is from Hassan et al. [17], along with kernel principal component analysis and linear discriminant analysis to extract features. For system implementation, they used Deep Belief Network (DBN) to train the system, which resulted in a HAR system with 95% average accuracy by using smartphone sensors. However all the above implemented HAR systems cannot be directly used by astronauts because the accelerometer cannot sense and measure acceleration under zero gravity or the micro gravity environment of outer space.

Therefore, the proposed project uses Flex sensors to implement a HAR system designed for astronauts. The Flex sensor hasn't been widely used for implementing

HAR systems, but Chaudhary et al. [18] proved it to be a suitable activity data collection device. The bend angle of body joints as a new data attribute that ignores the influence of gravity is a good replacement of acceleration, and by attaching the Flex sensors to the user's body joints, the angular change of each joint part during activity can be measured. As joints will normally do a series of bending and straightening movements, the joint's angle change record can be displayed as a waveform as shown in Figure 2.

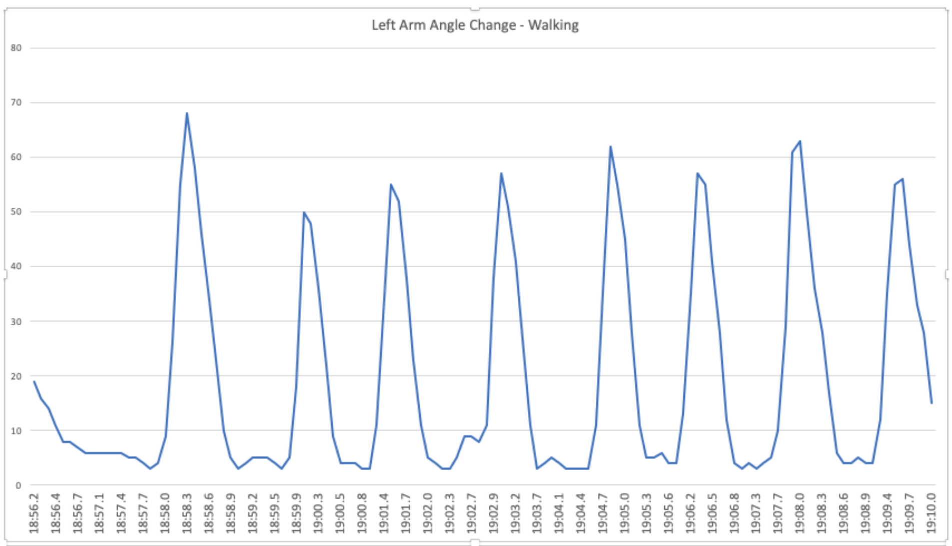

Figure 2. Flex Sensor Reading Example

Without using attached sensors for data collection, a device-free HAR system is another direction of HAR system research. Instead of directly attaching the sensor to a user's body, human activities can be monitored by using ambient devices around the user's activity location. Jiang et al. [19] made an experiment to verify the function of a device free HAR system, in which they tested 4 different data collection techniques including Wi-Fi, ultrasound, 60 GHz mm Wave, and visible light, in addition to using a deep learning method CNN to train the system for each scenario. In addition, Wang et al. [20] proposed a Channel State Information (CSI) based HAR system which used Wi-Fi signals to sense the activity and used a Wi-Fi device as the CARM framework to collect user activities. They inserted a pre-processed activity dataset into a Hidden Markov Model to train the machine into the HAR system. However these HAR systems can only work at specific indoor locations with multiple sensing devices installed inside, therefore, this method is highly limited by location.

For the system implementation part, deep learning technique LSTM was chosen to train the system. The LSTM and its variants are one of the most popular methods to train a system to recognize activity based on collected data and can be used in different neural network structures. For example, Piennar et al. [21] used RNN combined with LSTM cells to train with shared activity data containing 6 different activities (jogging, sitting, standing, walking, going upstairs and downstairs), and reached 90% of accuracy for training and testing. Mutegeki and Han [22] implemented the LSTM technique into CNN to train their acceleration data-based HAR system with both a self-collected activity dataset and a shared activity dataset provided by another organization. Hernández et al. [23] implemented a HAR system by training the activity data collected by smartphone with bidirectional LSTM network in which their system was trained to recognize 6 different activities (standing, sitting, laying down, walking, walking downstairs, and walking upstairs) with overall accuracy of more than 92%. Wang and Liu [24] implemented a HAR system using a shared acceleration data-based activity dataset with Hierarchical Deep LSTM structure, but instead of using only one layer of network as a traditional LSTM model, they built a LSTM network with two hidden layers and achieved recognition accuracy of more than 91%.

PRELIMINARIES

This section will explain the process of hardware implementation and data collection. To obtain angle-based activity data for implementing the proposed HAR system, a WBAN containing a Flex sensor and Pulse sensor was designed.

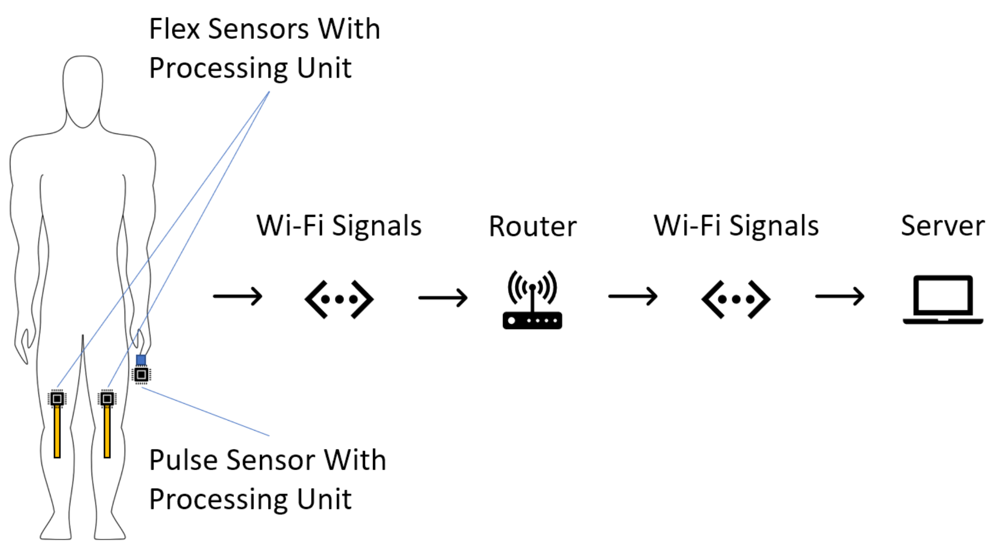

Figure 3. Sensor Attachment and Data Collection Overview

A. Sensor setup:

As illustrated in Figure 3, the proposed approach attached Flex sensors to users' knees to represent the movement of the knees' changing angles. Each sensor was connected to a processing unit that was made with an Arduino board as illustrated on left side of Figure 4. During activity recording, the Flex sensor bends at the same angle as the body joint, which causes a change in the sensor body's electrical resistance, and simultaneously, the Arduino board uses a C based program with 20 milliseconds frequency to calculate the sensor's bending angle by measuring the sensor's resistance and using the UDP protocol module to send angular data to the server via Wi-Fi signal. To make the sensor easier to attach, the Flex sensor was attached with a knee brace. Human knees have two positions for sensor attachment: front and rear. When people bend their legs, the muscles and skin in the rear side of the knee folds and compresses. If the Flex sensor is attached to the rear position, the sensor will experience a compressing force that exceeds the sensor flexibility and causes the sensor body to fold. Such deformation will permanently change the overall sensor resistance that influences the accuracy of angle measurements. Therefore, the proposed thesis's choice was to attach the Flex sensor on the front side of the knee. However, the muscles and skin on the knee's front position exhibit stretching, which is the opposite action as the compression at knee's rear position. Since the Flex sensor is flexible but not stretchable, if user directly attach the sensor on the knee's front position, the sensor will either break the attachment or tear the sensor. To add stretchability to the Flex sensor, a rubber band strip was attached to one side of the sensor body. When the knee starts bending, the Flex sensor can bend with the knee while the rubber band strip can stretch with the skin and muscle. The implemented wearable Flex sensor device is displayed on the left side of Figure 4, showing the connection with the processing chip and rubber band attachment. The sensor-rubber band combination was attached straight on the center of the knee brace's surface. To wear the device, the user simply needs to wear the knee brace and make sure the Flex sensor is aligned with the center of the kneecap.

For the pulse sensor, the device is displayed on the right side of Figure 4. To wear the sensor, the user attaches the sensor body to the top of the third finger with the sensor bubble facing the finger skin and was kept in place by a hooked tape.

During recording, the tester needs to keep the hand at a specific height and stay static in order to prevent blood pressure changes caused by height differences during hand movement to influence the pulse measurement. To read and record the data, the Pulse sensor was connected to the Arduino board working as a processing unit. The board receives heartbeat signals from the sensor and uses them to calculate the frequencies of heartbeat as BPM and sends the results to the server via Wi-Fi signal.

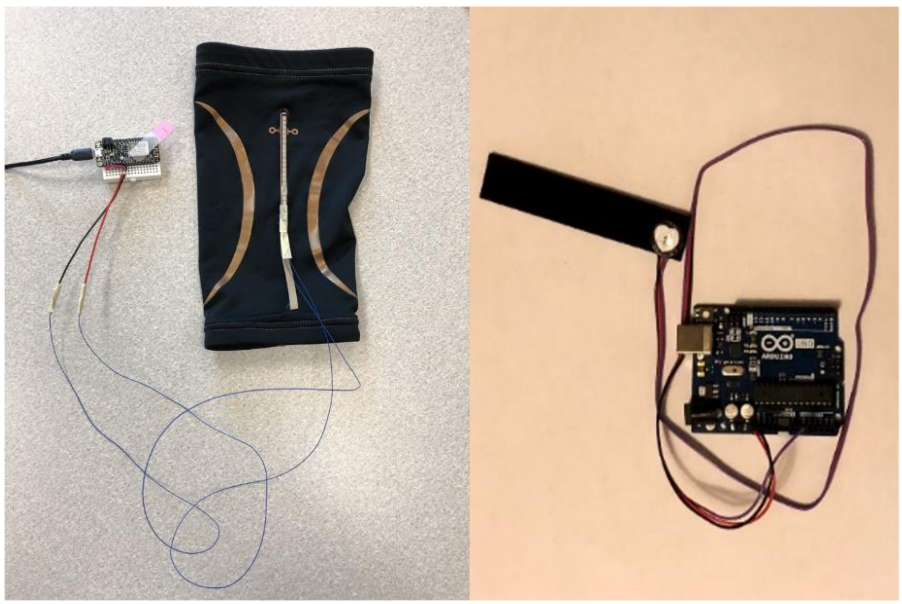

Figure 4. Implemented Joint Angle Sensor and Pulse Sensor

B. Data Collection:

The proposed project collected activity data from three volunteer subjects. The subjects performed four different activities: standing, sitting, marching in place, and running in place with each movement lasting approximately sixteen minutes. To make the system understand the difference among these four activities, standing was labeled as number “0”, sitting was labeled as number “1”, marching in place was labeled as number “2”, and running in place was labeled as number “3”. The activity data was labeled with these numbers as extracted features to make the machine learn the recognition by analyzing the change pattern of data based on paired labels.

Activity	Label
Standing	0
Sitting	1
Marching in Place	2
Running in Place	3

Table 1. Recorded Activity with Label

Once the activity recording was done, there were a total of 3 streams of time-series data collected by the server including left and right knee angle records and BPM record. The overall data group can be displayed as a line chart shown in Figure 5, 6, and 7.

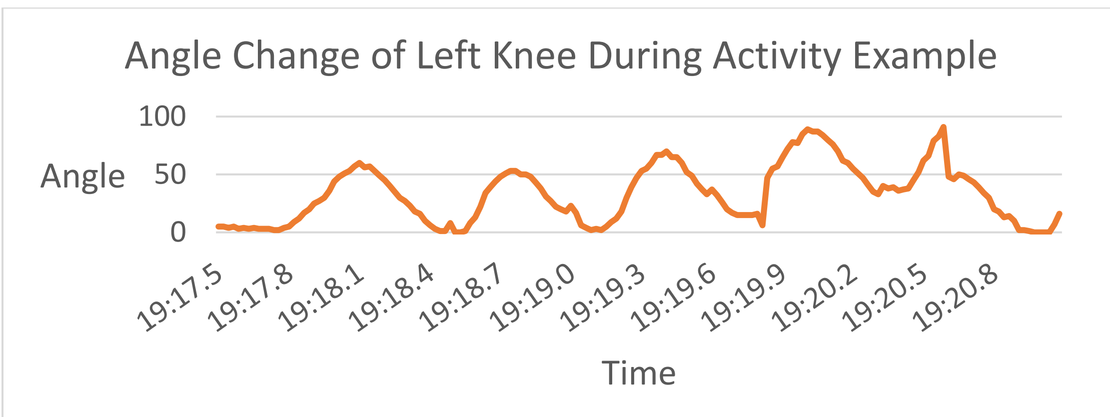

Figure 5. Angle Change of Left Knee During Activity Example

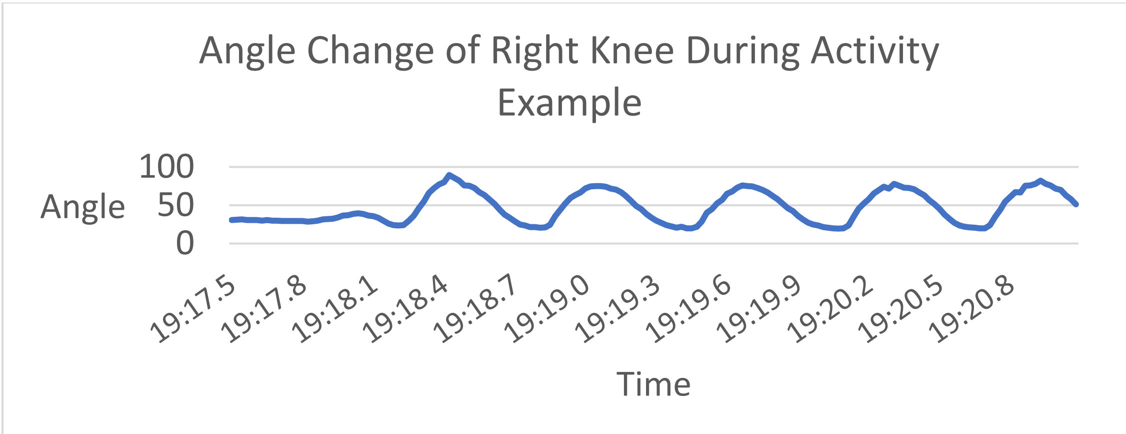

Figure 6. Angle Change of Right Knee During Activity Example

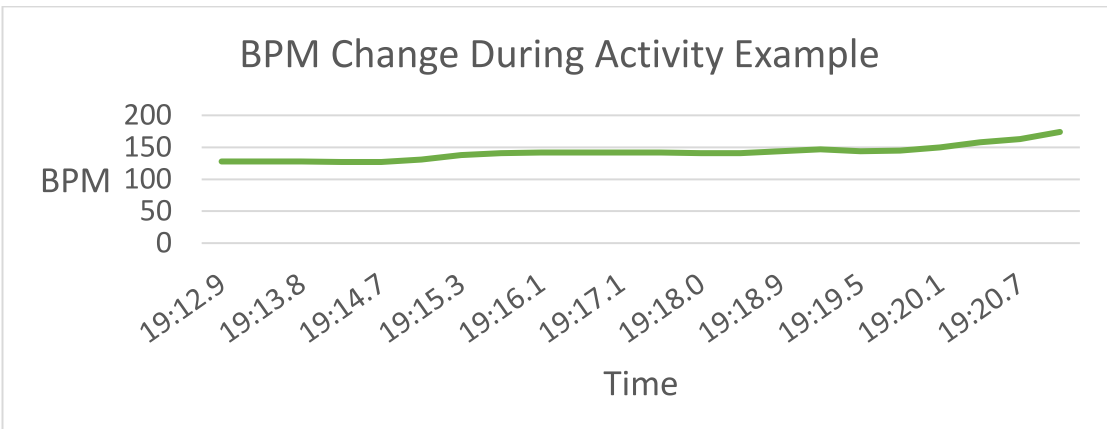

Figure 7. BPM Change During Activity Example

To make comparisons with the proposed HAR system, the acceleration-based activity data was collected at the same time as the proposed angular activity data collection. Each subject's acceleration activity was collected by using an accelerometer implanted in a smartphone and recorded using the smartphone's acceleration recording app.

C. Data Preprocessing:

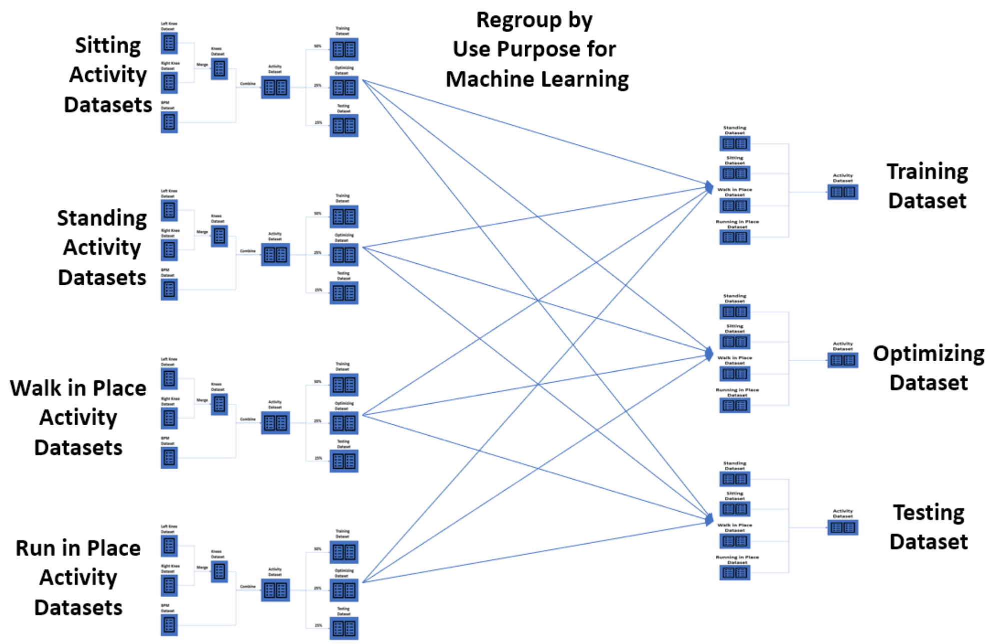

Figure 8. Data Preprocessing Overview

After combining all subjects' activity data for each type of activity, there were 3 datasets: the left knee dataset, the right knee dataset, and the BPM dataset. As illustrated in left half of Figure 9, the left knee dataset was merged with the right knee dataset by time sequence as knees angle dataset. Next, the knees angle dataset was combined with BPM dataset by time sequence as a 2 dimensioned dataset. For acceleration-based activity data, 3 datasets: x-axis dataset, y-axis dataset, and z-axis dataset were combined as a 3 dimensioned dataset. Based on the type of activity, the label dataset containing the paired label number was generated as the feature extraction and expected output for machine learning.

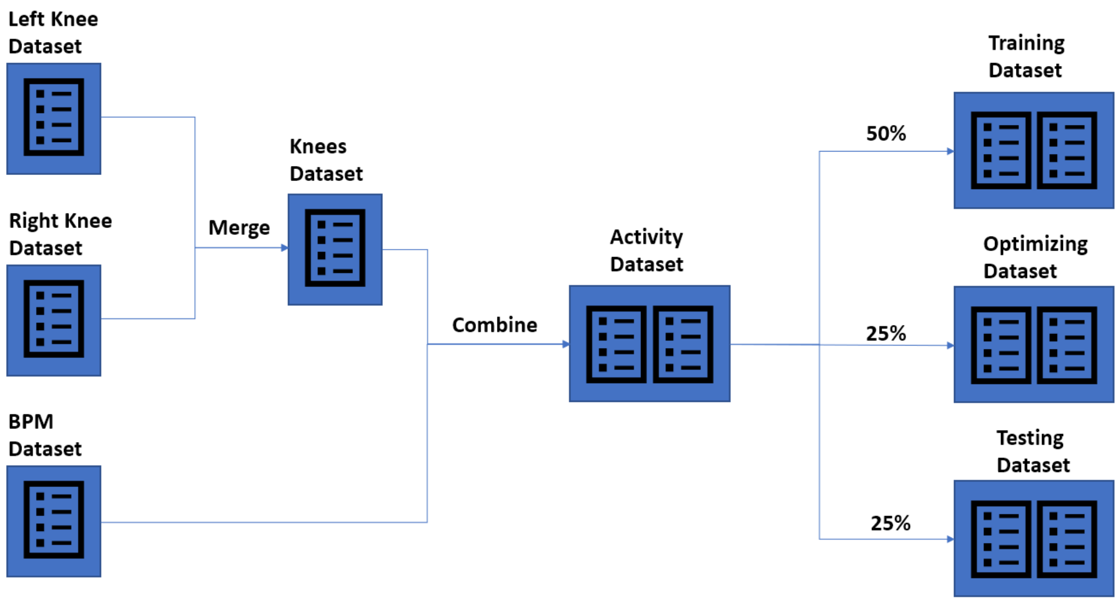

Figure 9. Process of Generating Activity Dataset and Its' Subsets

After getting datasets for all types of activity by repeating previous steps, but before linking all 4 activity datasets and their paired label datasets, as illustrated in right half of Figure 9, each dataset was separated into 3 subsets for different machine learning phases: 50% of the original dataset as a training dataset, 25% of the original dataset as an optimizing dataset, and 25% of the original dataset as a testing dataset. Then all subsets were grouped by their use phases, and for each group, all subsets were linked together as the input dataset containing all types of activity data for the specific machine learning phase. In the end, 48 datasets with 1,102,260 lines of angular data and BPM data were integrated and separated into 6 datasets: the training dataset with paired label dataset, the optimizing dataset with paired label dataset, and the testing dataset with paired label dataset as input data for implementation as explained in the next section.

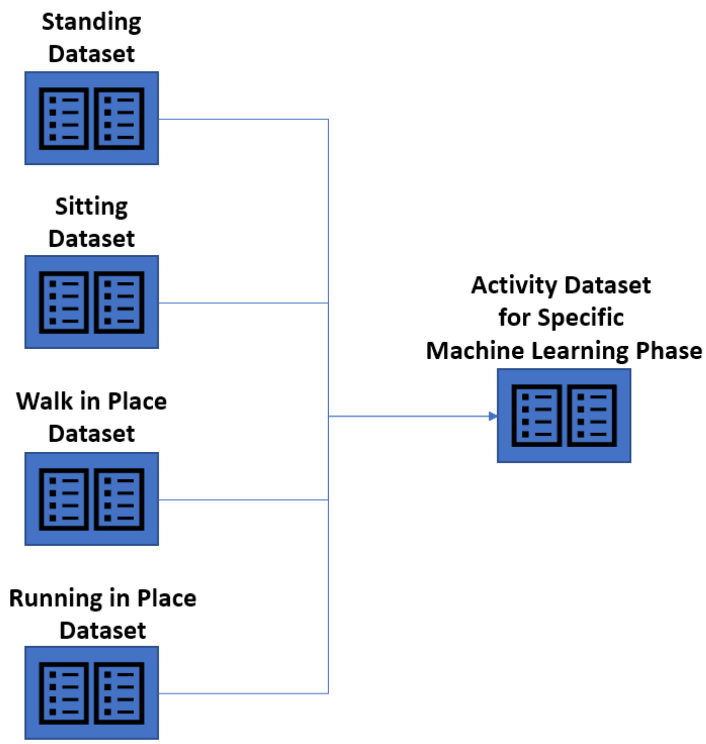

Figure 10. Process of Linking All Types of Activity Datasets

IMPLEMENTATION AND EXPERIMENT

This section explains the process of implementation of the proposed HAR system and the process of experimentally evaluating system performance. The proposed HAR system implementation contained two steps: training and testing. In the computer server, as illustrated in Figure 11, the training phase put the training dataset generated from the previous section into the neural network generated by the LSTM algorithm to train the system to understand the change pattern of activity data with paired labels so that the system could recognize and label all 4 recorded activities correctly at most of the times from the testing dataset.

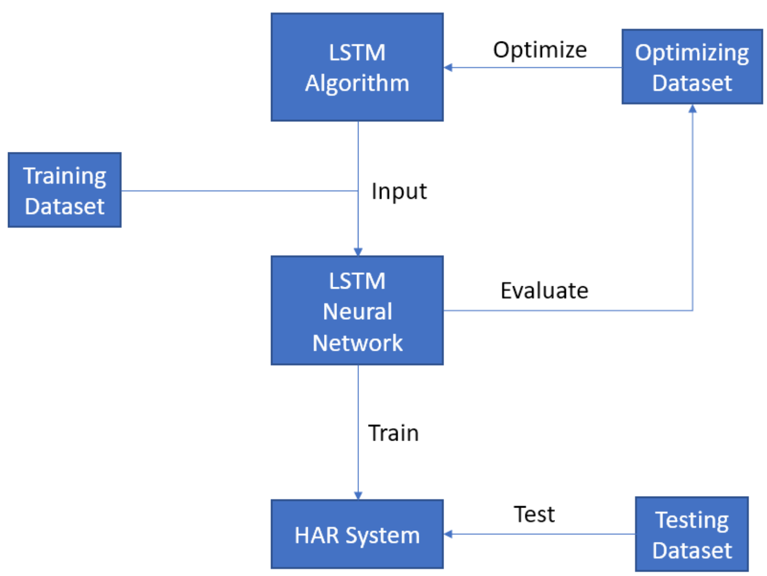

Figure 11. System Implementation Overview

A. Training Phase

The proposed default machine learning program was modified from the existing acceleration data-based HAR system [10] and was redesigned as a triple stacked RNN-LSTM neural network with 32 hidden layers and 0.00025 learning rate that can process 1,500 unit groups of data as one batch at a time. Within the machine learning program and after reading the activity data and paired label data x-y dataset, the LSTM algorithm continuously inserted the input dataset into the LSTM neural network for training by 1,500 unit groups of data as one batch with each unit group containing 20 lines of data for every iteration until the whole training dataset was trained 150 times. During the training loop iteration, each unit group of data was sequentially processed into a memory cell and ran through the formula [11]:

$$y^{c_j}(t) = y^{out_j}(t)h(s_{c_j}(t)) \quad (1)$$

Where the $s_{c_j}(t)$ is

$$s_{c_j}(0) = 0, s_{c_j}(t) = s_{c_j}(t-1) + y^{in_j}(t)g(net_{c_j}(t)) \; for \; t > 0 \quad (2)$$

From above equations:

j is the sequence number of unit input data,

t is the current running time for process j^{th} unit data,

$y^{c_j}(t)$ represents result learnt by system from j^{th} input at time t,

y^{out_j} represents output label set paired with input data,

y^{in_j} represents for input data including current input unit data and other useful output from previous computations,

h represents differentiable function that scales memory cell outputs from s_{c_j}.

s_{c_j} is the internal state inside net_{c_j},

g represents differentiable function that squashes net_{c_j} by summing up results from time earlier than t,

and net_{c_j} is the network state value for jth input unit data.

In each memory cell, at t^{th} time of process, the algorithm uses current unit input data x inserted at j^{th} iteration and paired label as the expected output, with calculation results from previous processes to calculate the current process result and keep it as one of the input data for the next process or discard it if it does not match with paired output. Every time after processing a specific number of iterations, the neural network will read 1500 unit groups of data as one batch from the optimization dataset and recognize the labels based on the neural network's trained knowledge and compare the output label dataset with the input expected label dataset. Based on the comparison result, the algorithm will adjust the calculation parameters in the memory cell to make the next training iteration be able to get more helpful experience for recognition.

B. Testing Phase

The proposed HAR system was implemented once the training process was completed. For further testing and performance evaluation. the proposed HAR system passed the testing dataset into the neural network to make a recognition and labeling for each batch of data from the input dataset based on experience gained from the training phase. The machine then evaluated the accuracy of the testing phase by comparing the recognition result, as predicted by the trained neural network, with the expected output read from the input label dataset to calculate the testing phase's overall recognition accuracy and detailed recognitional accuracy for each activity which was displayed as a confusion matrix.

C. Evaluation Experiment

The proposed project designed a series of comparison experiments to evaluate the proposed HAR system's recognition effectiveness. The proposed project trained an acceleration data-based HAR system with the same neural network structure as the proposed HAR system and then compared the recognition accuracy between these two HAR systems to evaluate the capability of the proposed HAR system based on the recognition accuracy similarity with traditional acceleration data-based HAR system.

To find the best LSTM neural network structure to replace the proposed neural network for training the proposed HAR system, the proposed HAR system implementation was reproduced multiple times with different neural network structures. The proposed HAR system project tested single stacked LSTM-RNN structure, single stacked RNN structure, triple stacked RNN structure, and Bi-directional LSTM-RNN structure. A comparison among all of the recognitional accuracy results was completed to determine whether the angular activity data was as good as the acceleration activity data, and which machine learning technique was the best choice to train the angular data-based HAR system.

EXPERIMENTAL RESULTS ANALYSIS

A. Angular Data-Based HAR System vs. Acceleration Data-Based HAR System:

After inserting 14,400 groups of angular activity data into the trained proposed HAR system, and 1,497 groups of acceleration activity data into the trained existing HAR system. As illustrated in Figure 12, the proposed HAR system achieved 85.72% overall recognition accuracy and the acceleration data-based HAR system achieved 91.26% overall recognition accuracy. In more detailed review, both systems had good and similar performance on recognizing Standing and Sitting activities, but could not clearly recognize the Marching in Place activity, and was especially evident in the proposed HAR system which had only 59.79% recognition accuracy. For the Running in place activity, the acceleration data-based HAR system had better recognition accuracy than the proposed HAR system. Analyzing Table 2 and Table 3, the proposed HAR system failed to clearly recognize the Marching in Place activity by mistaking 28.59% of its data as Running in Place activity and 11.54% of its data as Standing activity, and didn’t clearly recognize the Running in Place activity either by mistaking 13.83% of its data as Marching in Place activity. Similar to the proposed HAR system, the acceleration data-based HAR system could not clearly recognize Marching in Place activity by mistaking 31.30% of its data as Running in Place activity, but correctly recognized all Running in Place activity data.

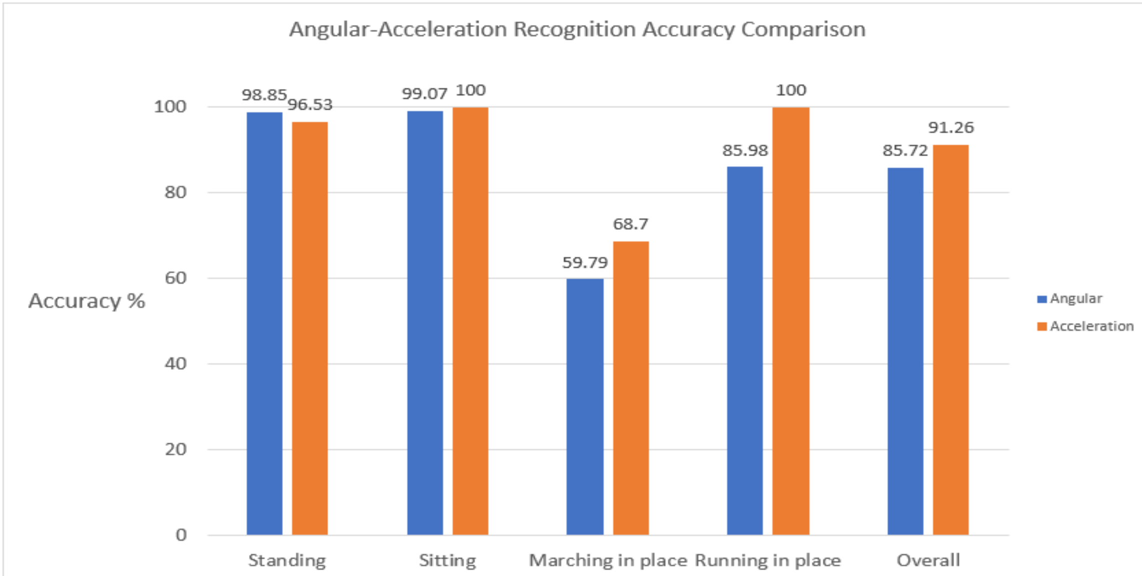

Figure 12. Angular-Acceleration Accuracy Comparison Result

Number of data group	Recognized as Standing	Recognized as Sitting	Recognized as Marching in place	Recognized as Running in place	Accuracy %
Standing	3519	0	41	0	98.85
Sitting	0	3497	2	31	99.07
Marching in place	422	3	2187	1046	59.79
Running in place	0	7	505	3140	85.98
Overall Accuracy % From Whole Dataset	24.44	24.28	15.19	21.81	85.72

Table 2. Confusion Matrix for Proposed Angular Data-Based HAR System

Number of data group	Recognized as Standing	Recognized as Sitting	Recognized as Marching in place	Recognized as Running in place	Accuracy %
Standing	362	1	12	0	96.53
Sitting	0	375	0	0	100.00
Marching in place	0	0	259	118	68.70
Running in place	0	0	0	370	100.00
Overall Accuracy % From Whole Dataset	24.19	25.05	17.30	24.72	91.26

Table 3. Confusion Matrix for Acceleration Data-Based HAR System

In summary, the acceleration data-based HAR system had better overall recognition accuracy by having relatively better performance in recognizing Marching in Place and Running in Place activity. For the proposed HAR system, the ambiguity of Marching in Place activity data and Running in Place activity data might have come from the similarity of these two activities and differences of physical status among participating subjects. Marching in Place and Running in place are activities that can only be figured out by analyzing the pace and range of joint angle change during activity. Therefore, as all subjects had different physiques, each subject's pace of movement during the Marching in Place activity could be similar with other subjects' pace of movement of other activities. In addition, the diversity of each individual tester's heart rate might possibly enlarge the ambiguity, as two different people can have a similar heartrate change when one is walking and another is running.

B. Among Neural Network Structures:

To improve recognition accuracy of the proposed HAR system, the angular activity dataset was put into multiple neural network models which were modified from the original triple stacked LSTM neural network. According to the recognition accuracy comparison results as shown in Table 4, the best deep learning technique to train the angular data-based HAR system was the bidirectional LSTM, which had 90.42% accuracy and which is similar to the recognition accuracy of the acceleration data-based HAR system. In comparing single stacked RNN and multiple stacked RNN, the multiple stacked RNN had insignificantly better performance than single stacked RNN. However, in comparing single stacked LSTM and multiple stacked LSTM, the two different LSTM structures did not show a significant change to overall performance. Comparing LSTM with RNN, the HAR system trained with the LSTM technique had better overall performance than the HAR system trained with RNN.

Scenario	Accuracy
Acceleration Activity Data	91.25%
Single Stacked RNN	81.57%
Multiple Stacked RNN	82.53%
Single Stacked LSTM	85.97%
Multiple Stacked LSTM	85.26%
Bi-directional LSTM	90.42%

Table 4. Recognition Accuracy List

CONCLUSION

In conclusion, an angular data-based HAR system for astronauts based on a new WBAN was constructed using multiple Flex sensors and one Pulse sensor for data collection. By using joints angle change records during activity, the proposed activity data type can allow the HAR system to negate the influence of microgravity and magnetic field changes. According to the experimental results, the angular data-based HAR system trained by bi-directional LSTM neural network achieved 90.42% overall recognition accuracy which was similar to the existing acceleration data-based HAR system trained with triple stacked LSTM neural network [10]. Considering the lower cost of Flex sensors versus traditional HAR system sensors which contain accelerometers, gyroscopes and/or magnetometers, the Flex sensor can become a new popular option in this field of study because of its’ huge potential. The recognition accuracy of the proposed HAR system was restricted by the number of joints being analyzed, number of subjects participating, length of recording for each type of activity, and ambiguities of BPM among different subjects. For the number of joints, the proposed HAR system data was generated based only on knees’ angle change during activity. As for the number of participating subjects and length of recording, the proposed project only collected 3 subjects activity data, and each activity was only recorded for 16 minutes. Regarding BPM ambiguities, different people have different average heartbeat based on their health status and other factors, it is possible that different people’s BPM during performance of different activities are similar. In the future, the proposed implementation can be improved by adding more body joints into the data collection, recording each activity for longer time, adding more subjects, and normalizing BPM differences among people. The Flex sensor will be attached not only on the knees, but also on the neck, elbows, shoulders, wrists, and ankles to generate more detailed and complex angular activity datasets. With more test subjects and longer recording time, the machine can uncover more change patterns of joint angle change during activities with huge amounts of input data. By developing a normalization algorithm, BPM data can be preprocessed to make different subjects' BPM value for the same activity be significantly identical, and BPM values for different activities to show significant variation. By using larger and more complex activity data, the proposed HAR system can have similar or even better recognition accuracy than existing HAR systems.

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