Recognizing Physical Activities Using the Axivity Device

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***Abstract*— Physical activity is a major part of a user's context for wearable computing applications. The system should be able to acquire the user's physical activities by using body worn sensors. We want to develop a personal activity recognition system that is practical, reliable, and can be used for health-care related applications. We propose to use the axivity device [1] which is a ready-made, light weight, small and easy to use device for identifying basic physical activities like lying, sitting, walking, standing, cycling, running, ascending and descending stairs using decision tree classifier. In this paper, we present an approach to build a system that exhibits this property and provides evidence based on data for 8 different activities collected from 12 different subjects. Our results indicate that the system has an accuracy rate of approximately 92%.**

Keywords-component; Physical activities; accelerometer sensor; classifier.

I. INTRODUCTION

Human activity recognition by using body worn sensors has received attention in recent years. Activity recognition systems in health care support especially in elder care, long-term health/fitness monitoring, and assisting those with cognitive disorders [1, 2, 3] has been demanded. Therefore, recognizing human physical activities with body worn sensors is not a new research field; much research has already been done in this area. We can identify users' physical movements using a body movement suit [2]. We also have other research projects where researchers identify the users' physical activities using some sensors like [3, 4, 5, 6, 7 and 8].

In some diseases like diabetes, heart problems, mentally disabled persons, elder patients are required to perform some physical activities in order to make them physically fit. Similarly, in some cases patients need to be monitored by nurses which is very time consuming and expensive.

Modern day lifestyle has lead to various physical and mental diseases such as diabetes, depression and heart diseases as well. According to the World Health Organization, there are at least 1.9 million people dying as a result of physical inactivity annually [10].

Although, people are aware of the importance of exercise there is a lack of motivation due to their busy schedules. People need to be forced and reminded about physical activities. Probably automatic and personal reminders can be very helpful if it can monitor one's physical activities and persuade people to perform them regularly.

Activity recognition technology can tackle this problem as it is able to monitor an individual's physical activities and their duration in order to estimate how much calories are being consumed on a daily basis. Those systems can also provide recommendations when they fail to complete enough exercise and it also encourages people to conduct more activities [12, 13 and 14].

In some cases, especially in heart diseases, physical activities are also required along with the physiological information for doctors in order to examine their patient's conditions when he is away from the doctor's clinic [19].

We want to develop a physical activity recognition system using a minimum amount of sensors which should be able to identify the basic activities like lying, walking, running, sitting, standing, cycling, ascending and descending stairs.

In our research we want to prove that it is possible to identify the aforementioned activities for a specific user by using a 3D accelerometer. In next chapter, "related work" will be discussed, "hypothesis and research question" will be discussed in the 3rd chapter, "experimental methodology" will be discussed in the 4th chapter, "evaluation" will be discussed in the 5th chapter and "conclusion and future work" will be in the last.

II. RELATED WORK

There are several ways to recognize a person's daily activities. One way is using cameras to visually detect people's motion [15, 16].

The drawback of this solution is that a large number of cameras would be required in order to monitor a moving person. This system would also need to be designed to compute information from each camera and deal with other factors such as light, distance and angle, which make the system impractical.

Researchers have identified various physical activities using wearable sensors like sitting[3,6,7,8], standing [3,6,7,8], lying [6], walking [3,4,5,6,7,8], climbing stairs [3,4,6,7,8], running [5,7,8], cycling [5,8], strength training [8] etc. However for their recognition system they have used more than one sensor. For example, some researchers identified around 20 activities using 5 sensor boards. They identified walking, walking carrying items, sitting & relaxing, working on computer, standing still, eating or drinking, watching TV, reading, running, bicycling, stretching, strength-training, scrubbing, vacuuming, folding laundry, lying down & relaxing, brushing teeth, climbing stairs, Riding elevator and Riding escalator using Decision Table, IBL, C4.5 and Naive Bayes algorithms. They placed sensors on the limb positions and on the right hip [8]. Similarly researchers identified 12 activities using 3 sensor boards, they identified sitting, standing, walking, walking up stairs, walking down stairs, riding elevator down, riding elevator up, brushing Teeth[3], researchers identified 3 activities; walking, climbing stairs and descending stairs using 9 tilt switches using K-means clustering and brute force algorithms, these sensors were worn just above the right knee [4].

In our work, we want to use only one 3D accelerometer sensor in order to identify a few activities. A few of these physical activities (lying, sitting, walking, running) have already been identified by using a single device [9] but in our research we want to identify more physical activities by using a single wearable 3D accelerometer sensor and we also want to use different locations on a person's back, as opposed to the approach presented in paper [9] where the focus was only on the lower part of a person's backbone.

III. HYPOTHESIS AND RESEARCH QUESTION

The acceleration measured by a 3 axis accelerometer (X,Y,Z) at a specific point (backbone), indicates which activity the person is performing (lying, sitting, walking, standing, cycling, running, ascending and descending stairs), using classifier algorithms (J48, AODE).

In this paper, we investigate some practical aspects of creating an automatic, personal activity recognition system. Through our experiments, we want to find the answers of the following questions:

- Is it possible to identify which activity the person is performing (lying, sitting, walking, running, standing, cycling, ascending and descending stairs) by using a 3D wearable accelerometer sensor on participants' backbone?
- Which particular location on a person's backbone is better for identifying these activities?

IV. EXPERIMENTAL METHODOLOGY

We used AX3 data logger [1] in order to identify physical activities (as shown in Figure: 1).

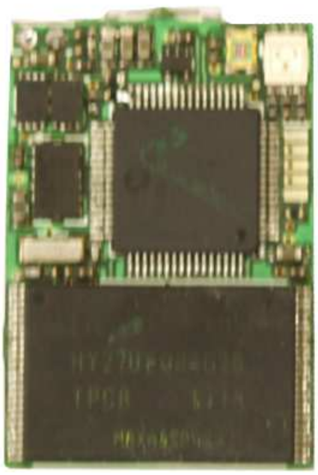

Figure 1: Axivity device

It was worn on the participants' backbone and they wore it on three different locations of their backbone; lower, middle and upper part respectively (as shown in Figure: 2). Participants were required to perform each activity for two minutes; one minute was meant for training data and other minute was for test data.

The AX3 data logger contains 3-axis of accelerometer with flash memory and clock. This device is small and easy to use, its dimensions are 6x21.5x31.5 mm and its weight is 9 grams.

The device comes with pre-installed software with the possibility to configure its settings. For example, we can configure sample rate, gravity etc. It continuously logs contextual information (time; hh:mm:ss and axis; X, Y, Z) to its internal memory. We can also set the duration for logging this information. There is also a possibility to export the logged data from the device to a computer in CSV format.

In order to attach this device on the participants' back, we used sticky tape which was directly placed on the skin. We logged continuous data with 8G and the sample rate was 100 Hz.

We implemented an application for 'Pocket PC' where we can state the starting and ending time for each physical activity during experiments. This application generates text files with this information for each physical activity for both training data and test data. It also stores the participants' personal information i.e. age, gender, height and weight. We implemented another application in Java for analysis; we used WEKA APIs [17] in order to use machine learning algorithms. This application requires three input files: both training and test data from 'Pocket PC' as well as the CSV file from the axivity device. Firstly, it filters needed data from the CSV file based on the time stamp from the files from the 'Pocket PC for each physical activity and generates training and test data files in ARFF format. Later, it applies J48 and AODE algorithms on training data for generating models from both machine learning algorithms. After-wards these models take data as an input in order to predict their values and compared with ground truth.

We recruited 12 testers (7 males, 5 females) for our experiment setup. The range of participants' age was from 20 to 30 and ranged in BMI (body mass index) [10] from 18.7 to 28.7 (mean 23.1, SD 2.98). They performed each physical activity (Lying, Sitting, Standing, Walking, Running, Cycling, Ascending and Descending stairs) twice. Two of our testers could not participate in 'Cycling' activity. Participants' were continuously observed during experiments.

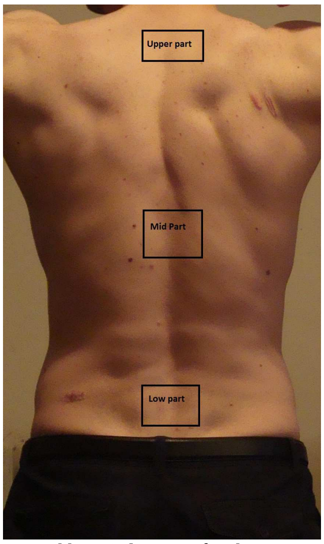

Figure 2: Backbone's location for the axivity device

V. EVALUATION

At the end we collected data from 12 participants and each participant performed eight different physical activities (except two participants who performed only seven), each physical activity contains a data of two minutes with a sample rate of 100Hz which implies we gathered (100X60X2X8) 96,000 instances for each data-set except two where we managed only 84,000 instances. We divided each data-set into two parts; one part was for training data and other was for test data. We generated a model from training data and then applied it to test data in order to predict the values. We got 100 values(X, Y, Z) from the axivity device for each second because the sample rate was set to 100 Hz and we also got 100 predictions for each second. We wanted to have a single prediction for each second, therefore the activity with the maximum number of instances per second was chosen. This resulted in a single value for each second, instead of the 100 values that are received from the axivity device every second, leading to a much easier analysis of the experiment. After-wards these single values were compared with the ground truth of the physical activity to realize the accuracy of our test.

TABLE I. PREDICTED RESULTS FROM BACKBONE'S LOWER PART

	Min *J48* *AODE*	**Max** *(J48)* *(AODE)*	**Avg** *(J48)* *(AODE)*	**SD** *(J48)* *(AODE)*
Lying	56.67	100	95.14	12.58
	93.33	100	99.31	1.94
Walking	100	100	100	0
	88.33	100	98.75	3.34
Running	81.67	100	97.3	5.6
	90.91	100	98.97	2.71
Sitting	65	100	96.14	9.93
	73.33	100	96.97	7.58
Standing	88.33	100	98.06	3.95
	86.67	100	97.51	4.52
Cycling	83.33	100	97	5.26
	80	100	96.5	6.16
Ascending stairs	0	98.33	84.4	27.62
	0	100	84.63	27.66
Descending stairs	18.33	100	82.15	21.65
	11.67	100	80.89	23.78

Our results (Table 1) show that placement of the axivity device on the lower part of the backbone was able to predict all physical activities with the accuracy of more than 80%. Lying, Walking, Sitting, Standing and Cycling activities were predicted with the accuracy of more than 95%. Walking activity was predicted 100% by J48 classifier.

TABLE II. PREDICTED RESULTS FROM BACKBONE'S MIDDLE PART

	Min ***(J48)*** ***(AODE)***	**Max** ***(J48)*** ***(AODE)***	**Avg** ***(J48)*** ***(AODE)***	**SD** ***(J48)*** ***(AODE)***
Lying	40	100	92.08	17.82
	93.33	100	99.16	1.94
Walking	96.67	100	99.58	1.04
	95.33	100	99.06	1.59
Running	91.38	100	98.84	2.81
	93.1	100	98.56	2.44
Sitting	46.67	100	90	18.33
	46.67	100	90	18.35
Standing	30	100	85.83	21.76
	35	100	86.66	20.65

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Cycling	81.67	100	97.83	5.8
	76.67	100	96.83	7.3
Ascending stairs	6.67	98.33	80.7	24.32
	23.33	100	83.05	21.12
Descending stairs	73.33	100	84.75	13.5
	63.33	100	88.35	10.42

Our results (Table 2) show that placement of the axivity device on the middle part of the backbone was able to predict all physical activities with the accuracy of more than 80%. Walking activity was predicted 99% by J48 and AODE classifiers.

TABLE III. PREDICTED RESULTS FROM BACKBONE'S UPPER PART

	Min	**Max**	**Avg**	**SD**
	J48	**J48**	**J48**	**J48**
	AODE	**AODE**	**AODE**	**AODE**
Lying	60.67	100	95.75	11.23
	96.67	100	99.72	0.96
Walking	48.33	100	92.78	15.1
	61.67	100	94.58	11.42
Running	93.1	100	97.9	3.45
	90	100	98.04	3.26
Sitting	1.67	100	80.7	37.59
	0	100	78.2	37.57
Standing	58.33	100	92.08	12.6
	61.67	100	90.97	12.15
Cycling	96.67	100	99.33	1.17
	95	100	99.17	1.62
Ascending stairs	15	100	80.03	24.37
	21.67	100	81.23	22.54
Descending stairs	43.1	93.33	75.95	20.34
	40	100	83.68	17.34

Our results (Table 3) show that placement of the axivity device on the upper part of the backbone was able to predict all physical activities with the accuracy of more than 75%. Cycling activity was predicted 99% by J48 and AODE classifiers.

TABLE IV. COMPARISON WITH ALL BACKBONE'S LOCATIONS

	Low	**Mid**	**Up**
	J48	**(J48)**	**(J48)**
	AODE	**(AODE)**	**(AODE)**
Lying	95.14	92.08	95.75
	99.31	99.16	99.72
Walking	100	99.58	92.78
	98.75	99.06	94.58
Running	97.3	98.84	97.9
	98.97	98.56	98.04
Sitting	96.14	90	80.7
	96.97	90	78.2
Standing	98.06	85.83	92.08
	97.51	86.66	90.97
Cycling	97	97.83	99.33
	96.5	96.83	99.17
Ascending stairs	84.4	80.7	80.03
	84.63	83.05	81.23
Descending stairs	82.15	84.75	75.95
	80.89	88.35	83.68

Our results (Table 4) show that "laying" activity was predicted with an accuracy of 99% by the AODE classifier from all locations, "Walking" was predicted with more than an accuracy of 98% from lower and middle parts of backbone, "running" was predicted with more than an accuracy of 97% from all locations, "sitting" was predicted with an accuracy of 96% from lower backbone, "cycling" activity was predicted with more than an accuracy of 96% from all locations, "ascending stairs" activity was predicted in the range of 80% to 85% by J48 and AODE classifiers from all locations and "descending stairs" activity was predicted in the range of 84% to 89% by J48 and AODE classifiers from middle part of backbone.

TABLE V. BACKBONE'S LOCATION-WISE PERFORMANCE

	Min	Max	Avg	SD
	J48	***J48***	***J48***	***J48***
	AODE	***AODE***	***AODE***	***AODE***
Low_backbone	82.15	100	93.77	6.66
	0	99.31	94.19	7.19
Mid_backbone	80.7	99.58	91.2	7.13
	83.05	99.16	92.71	6.43
Up_backbone	75.95	95.75	89.32	9.06
	81.23	99.72	90.7	8.6

Our results (Table 5) show that our system was able to predict physical activities with better accuracy rate (in terms of average) if acceleration data is coming from lower part of the backbone.

VI. CONCLUSISION AND FUTURE WORK

Our system is able to recognize a high percentage of the physical activities with the help of the decision tree and AODE classifiers. Results have shown that one 3D accelerometer sensor is enough for identifying a few physical activities (sitting, standing lying, walking, running, cycling, ascending and descending stairs). For every user, the system needs to be trained with the sensor data so that it would be able to predict the physical activities using the axivity device. This prototype is only a "proof of concept" and our results show that a single 3D accelerometer sensor can identify the above mentioned physical activities independent of BMI (body mass index) and age group. The accelerometer sensor has to be fixed properly on the backbone of the tester in order to predict the tester's movements successfully. To conclude our discussion we can safely lay claim to being able to identify the aforementioned physical activities by using a 3D wearable accelerometer sensor and our results show that lower part of the backbone can be a good location for the wearable 3D accelerometer sensor.

We will put the accelerometer sensor on other parts of the body in order to identify some other physical activities and we will use it for online machine learning.

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