Wearable Recognition System for Sports Activities

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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 sports activities recognition system that is practical, reliable, and can be used for health-care related applications. We propose to use the axivity device which is a readymade, light weight, small and easy to use device for identifying basic physical training activities (i.e., using elliptical trainer, butterfly, bench-press and pull down) and different swimming styles (i.e., dolphin, back-stroke, breast-stroke and free-style) using decision tree classifier, Averaged one-dependence estimators (AODE) and Neural networks. 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 20 different subjects. Our results indicate that the system has a good rate of accuracy.**

Keywords- Physical activities; accelerometer sensor; classifier.

I. INTRODUCTION

Human activity recognition by using body worn sensors has received attention in recent years. An activity recognition system in health care support, especially in elder care, long-term health/fitness monitoring, and assisting those with cognitive disorders is demanded. Therefore, recognizing human physical activities with body worn sensors is not a new research field; most 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][8].

With some diseases like diabetes, heart problems, mentally disabled persons, elderly patients are required to perform some physical activities or training exercises in order to make them physically fit. Similarly, in some cases, patients need to be monitored by nurses/trainers 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 annually dying as a result of physical inactivity [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 urged and reminded about physical training exercises. Probably automatic and personal reminders can be very helpful if they can monitor one's physical training exercises and persuade people to perform them regularly.

Activity recognition technology can tackle this problem as it is able to monitor an individual's physical training exercises and their duration in order to estimate how much calories are being consumed on a daily basis. Those systems can also provide recommendation when they fail to complete enough exercise and it also encourages people to conduct more activities [12][13][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 an activity recognition system using a minimum amount of sensors which should be able in identifying different physical exercises(using elliptical trainer, butterfly, bench-press and pull down) and different swimming styles (i.e., dolphin, back-stroke, breast-stroke and free-style).

In our research, we want to prove that it is possible to identify the aforementioned activities by using a 3D accelerometer. In next section, the related work will be discussed. Hypothesis and research question will be discussed in the section III. Experimental methodology will be discussed in the section IV. Evaluation will be discussed in the section V, and conclusion and future work will be in the last.

II. RELATED WORK

There are several ways to recognize a person's physical 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 already 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 [8]. 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,

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vacuuming, folding laundry, lying down & relaxing, brushing teeth, climbing stairs, riding elevator and riding escalator, by using Decision Table, Instance-based learning (IBL), C4.5 and Naive Bayes algorithms [26]. Similarly, researchers identified 12 activities using 3 sensor boards [3]. Researchers identified 3 activities i.e., walking, climbing stairs and descending stairs using 9 tilt switches, by using K-means clustering and brute force algorithms; these sensors were worn just above the right knee [4]. Researchers also identified a few physical activities and strength-training techniques using a 3D accelerometer sensor [9][20][21].

Researchers also have identified different swimming styles by using wearable devices [22][23][24][25].

In our work, we want to develop a single system for recognizing few physical training exercises (i.e., using elliptical trainer, butterfly, bench-press and pull down) and different swimming styles (i.e., dolphin, back-stroke, breast-stroke and free-style).

Physical training exercises are already identified by using a 3D accelerometer [21], but we found following drawbacks:

- Data were not preprocessed before applying machine learning algorithms.
- Only two machine learning algorithms were used.
- It is stated that "For every user, the system needs to be trained with the sensor data so that it would be able to predict physical training exercises using the axivity device" [21].

In this work, we want to pre-process our data before applying any machine learning algorithms. Additionally, we want to use Neural networks [26] because it is known for pattern recognition. We also want to develop a generic system for both physical training activities and swimming styles.

III. Hypothesis and Research Question

The acceleration measured by a 3 axis accelerometer (X,Y,Z) at a specific point (upper-arm), indicates which activity a person is performing (using elliptical trainer, butterfly, bench-press, pull down, dolphin, back-stroke, breast-stroke and free-style), by using J48 [26], AODE [26] and Neural Networks [26].

In this paper, we investigate the practical aspects of creating an automatic, personal activity recognition system. Through our experiments, we want to find the answer of the following question: Is it possible to identify which activity the person is performing (using elliptical trainer, butterfly, bench-press, pull down, dolphin, back-stroke, breast-stroke and free-style) by using a 3D wearable accelerometer sensor on participants' arm?

IV. Experimental Methodology

We used AX3 data logger [1] in order to identify physical activities which is also a water proof device (as shown in Figure: 1).

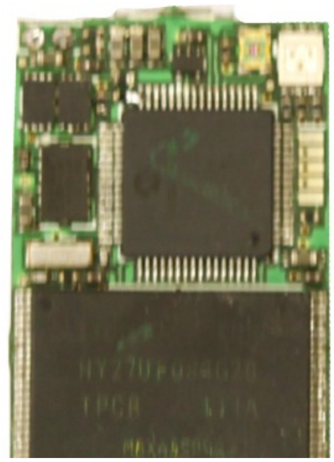

Figure 1: Axivity device

It was worn on the participants' arm and they wore it on the right hands' upper arm (as shown in Figure: 2).

Figure 2: Location for axivity device

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 comma-separated values (CSV) format.

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 training data. It also stores the participants' personal information i.e., age, gender, height, and weight. We implemented another application in Java for analysis. This application requires two input files: time stamp for physical activities 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 data files in ARFF format. Later, it pre processes the data (which is described below) and then we applied machine learning algorithms (J48, AODE and Neural Networks) on training data in order to get results from all mentioned algorithms (as shown in Figure 3).

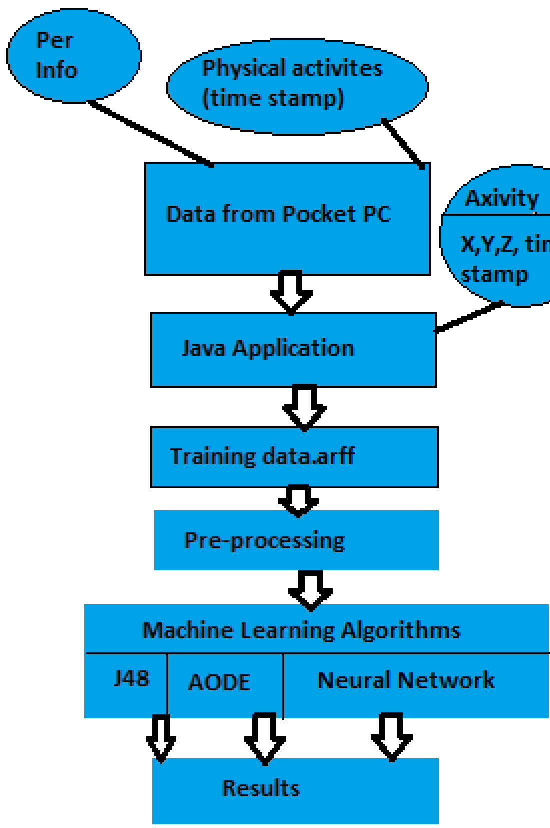

Figure 3: Architecture

A. *Data collection from Axivity device*

We conducted two user studies in order to prove our hypothesis. One was for identifying physical training exercises and other one was for identifying different swimming styles.

For identifying physical training exercises, we recruited 14 participants (9 males, 5 females) for our experiment setup as shown in Figure 3. The range of participants' age was from 20 to 41 (mean 29.14, SD 10.11) and ranged in BMI (body mass index) [10] from 19.6 to 27.8 (mean 23.03, SD 2.39). They performed each physical training exercises (using elliptical trainer, butterfly, bench-press and pull down) for a minute.

For identifying different swimming styles, we recruited 6 participants (5 males, 1 female) for our experiment setup as shown in Figure 3. The range of participants' age was from 19 to 42 (mean 29.17, SD 19.58) and ranged in BMI (body mass index) [10] from 19 to 24.8 (mean 21.48, SD 2.16). They were required to swim 30 meters in each swimming style (dolphin, back-stroke, breast-stroke and free-style). Our participants had different swimming levels, some of them were beginners and some of them were expert in swimming. Some participants were not able to swim in dolphin style.

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. At the end, we collected data from 20 participants out of both studies (physical exercise activities and swimming styles).

B. *Ground truth*

Participants' were continuously observed during experiments. An observer was stating starting/ending time of each activity.

C. *Pre-processing*

Each window represents a data of 5 seconds and it contains correlation of (X, Y), correlation of (Y, X), correlation of (Z, X), average of X, average of Y and average of Z.

D. *Classifications*

The 10-fold cross-validation is used to evaluate the J48, AODE and Neural networks (Multilayer perceptron) models. We used WEKA toolkit [17] for evaluating our results.

V. EVALUATION

Our results (Table 1) show that “Using elliptical trainer” activity was predicted with an accuracy of 90.64% by the J48. J48 was also able to predict other activities with better accuracy than other classifiers except “Back-stroke” and “Breast-stroke” activities. “Back-stroke” activity was better recognized by AODE classifier and “Breast-stroke” activity was better recognized by Neural Networks. “Free-style” was recognized by all classifiers with same accuracy.

TABLE I. COMPARISON WITH OTHER CLASSIFIERS

	J48	**AODE**	**Neural networks**
Using elliptical trainer	90.64%	68.98%	89.84%

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Butterfly	74.42%	47.09%	66.86%
Pull down	83.15%	79.35%	76.63%
Bench-press	77.66%	45.74%	68.09%
Dolphin	80.00%	80.00	26.67%
Back-stroke	64.52%	70.37%	68.97%
Breast-stroke	77.78%	59.26%	81.48%
Free-style	52.38%	52.38%	52.38%

VI. Conclusion and Future Work

Our system is able to recognize a high percentage of the aforementioned activities with the help of the J48 (decision tree) classifier. These preliminary results have shown that one 3D accelerometer sensor may be enough for identifying a few physical activities (using elliptical trainer, butterfly, bench-press, pull down, dolphin, back-stroke, breast-stroke and free-style). We may get different results when we use another 40 or more samples, 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 participants' backbone in order to predict the participants' activities successfully. 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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References

[1] Axivity - http://axivity.com/v2/index.php?page=product.php&product=index.php?page=product.php&product=ax3 (01/04/2014)

[2] Xsens MVN - http://www.xsens.com/en/general/mvn (01/04/2014)

[3] J. Lester, T. Choudhury, and G. Borriello, “A practical approach to recognizing physical activities,” Lecture Notes in Computer Science 3968 (2006): 1–16.

[4] K. Laerhoven and A. K. Aronsen, “Memorizing what you did last week: Towards detailed actigraphy with a wearable sensor,” in Distributed Computing Systems Workshops, 2007. ICDCSW'07, 27th International Conference

[5] T. Choudhury et al., “The mobile sensing platform: An embedded activity recognition system,” IEEE Pervasive Computing (2008): 32–41.

[6] N. Kern, B. Schiele and A. Schmidt, “Multi-sensor activity context detection for wearable computing,” Lecture Notes in Computer Science (2003): 220–234.

[7] U. Maurer, A. Rowe, A. Smailagic and D. Siewiorek, “Location and Activity Recognition Using eWatch: A Wearable Sensor Platform,” Lecture Notes in Computer Science3864 (2006): 86.

[8] L. Bao and S. S. Intille, “Activity recognition from userannotated acceleration data,” Lecture Notes in Computer Science (2004): 1–17

[9] A. M. Khan 2011, "Recognizing Physical Activities using Wii remote", ICIKM 2011; Haikou, China.

[10] World Health Organization: Move for Health, http://www.who.int/moveforhealth/en (01/04/2014)

[11] J. E. Manson, P. J. Skerrett, Philip and B. Theodore, “The Escalating Pandemics of Obesity and Sedentary Lifestyle: A Call to Action for Clinicians”, Arch. Intern. Med. 164(3), 249–258 (2004)

[12] S. Consolvo et al, “Activity Sensing in the Wild: A Field Trial of UbiFit Garden”, CHI 2008 (2008)

[13] J. J. Lin, L. Mamykina, S. Lindtner, G. Delajoux and H. B. Strub, “Fish’n’Steps: Encouraging Activitiy with an Interactive Computer Game”, Dourish, P., Friday, A. (eds.) UbiComp 2006. LNCS, vol. 4206, pp. 261–278. Springer, Heidelberg (2006)

[14] I. Anderson, J. Maitland, S. Sherwood, L. Barkhuus, M. Chalmers, M. Hall, B. Brown and H. Muller, “Shakra: Tracking and Sharing Daily Activity Levels with Unaugmented Mobile Phones”, Mobile Networks and Applications, 185–199 (2007).

[15] P. Turaga, R. Chellappa, V. S. Subrahmanian and O. Udrea, “Machine Recognition of Human Activities: A survey”, IEEE Transactions on Circuits and Systems for Video Technology 18(11) (2008)

[16] W. Hu, T. Tan, L. Wang and S. Maybank, “A survey on Visual Surveillance of Object Motion and Behaviors”, IEEE Transactions on Systems, Man, and Cybernetics. Part C: Applications and Reviews 34(3) (2004).

[17] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann and I. H. Witten, “The WEKA Data Mining Software: An Update”, SIGKDD Explorations, Volume 11, Issue 1.

[18] Body Mass Index - http://www.nhlbisupport.com/bmi/ (01/04/2014)

[19] A. M. Khan, “Personal state and emotion monitoring by wearable computing and machine learning”, BCS-HCI 2012, Newcastle, UK

[20] A. M. Khan, "Recognizing Physical Activities Using the Axivity Device", eTELEMED 2013; Nice, France. IARIA, ISBN: 978-1-61208-252-3 : 147-152.

[21] A.M. Khan, G. Kalkbrenner, M. Lawo, "Recognizing Physical Training Exercises Using the Axivity Device", ICT meets Medicine and Health 2013; Bremen, Germany.

[22] P. Siirtola, P. Laurinen, J. Röning and H. Kinnunen, "Efficient Accelerometer-Based Swimming Exercise", Paris, CIDM 2011.

[23] M. Bächlin, K. Förster and G. Tröster, "SwimMaster: a wearable assistant for swimmer", Florida, UbiComp 2009.

[24] M. Bächlin and G. Tröster, "Swimming performance and technique evaluation with wearable acceleration sensors", Pervasive and Mobile Computing 8 (2012), 68–81.

[25] J. Pansiot, B. Lo and G. Yang, "Swimming Stroke Kinematic Analysis with BSN", BSN '10 Proceedings of the 2010 International Conference on Body Sensor Networks.

[26] R. S. Michalski, J. G. Carbonell and T. M. Mitchell, Machine learning, 1986, Los Altos, CA: Morgan Kaufmann Publishers.

[27] www.usefil.eu (01/04/2014)

 ISBN: 978-1-61208-327-8