SUITABLE FEATURES FOR ACCELEROMETER-BASED NURSING ACTIVITY RECOGNITION SYSTEM

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INTRODUCTION

Approximately 1 of 10 patients admitted to North American hospitals pick up infections from the hospital environment while being treated for something else. Hospital Acquired Infections (HAI) are believed to be responsible for up to 88,000 deaths in the U.S. [1] and 8000 death in Canada [2]. HAIs cost 4.5 billion to the North American health care system annually [1, 3]. Several studies have shown that HAIs can be prevented if hospital staff practice optimal hand hygiene [4-6].

At Toronto Rehabilitation Institute in Canada we are developing technologies to promote optimal handwashing. We have developed a handwash reminder system that reminds caregivers to wash their hands before and after visiting a patient [7]. We are working on enhancing this system to help remind caregivers to wash their hands between nursing procedures, as required by the guidelines.

To achieve this, we are investigating the possibility of using wearable accelerometers to identify relevant nursing activities. Accelerometers have been used to identify simple human activities such as walking, running, and sitting [8-12].

In the literature human activities are usually classified using pattern recognition approaches, such as Decision Tables, Decision Trees (DT), Naïve Bayes (NB), and 1-Nearest Neighbour (1-NN) [8, 9, 11, 13-16]. In this approach the original signal is approximated by suitable features over a sliding window. The extracted features form a multi-dimensional feature space. Some of the data points are used to train supervised classifiers. The rest of the data are used to validate and test the classifiers' performances.

Previous researchers mostly used the signal statistics of accelerometers as their preferred feature sets, including mean, standard deviation, energy, and correlation between accelerometer axes [8, 9, 11, 12, 17]. Recognition accuracy of up to 80% was reported in classifying simple human activities including sitting, standing, walking, and running.

Later, Khan et. al. [18, 19] used a novel feature set that included autoregressive (AR) model coefficients [20], Signal Magnitude Area (SMA) [10, 21], and tilt angles (TA) of accelerometer signals. They obtained impressive 99% accuracy in recognizing lying, standing, walking and running activities.

Although the above methods have shown success in their respective research areas it is not clear how these successful feature extraction methods perform in identifying nursing activities, where the activities are more complex than sitting, standing, walking and running in nature.

The objective of this work is to evaluate and compare the performance of the above two feature extraction methods in identifying simple nursing activities using accelerometers.

METHOD

<u>Data collection</u>

We used 5 Sony PlayStation® 3 (PS3) DUALSHOCK®3 SIXAXIS™ game controllers to record acceleration data from 8 subject nurses wirelessly. The subjects wore the controllers on their left and right wrists, left and right upper arms, and their backs.

Each PS3 controller included a KXPC4 3-axis accelerometer (Kionix Inc., Ithaca, New York, the U.S.A.) and a XV3500 1-axis gyroscope (Epson-Toyocom Corporation, Tokyo, Japan). As these controllers were designed to capture hand accelerations while the user was playing

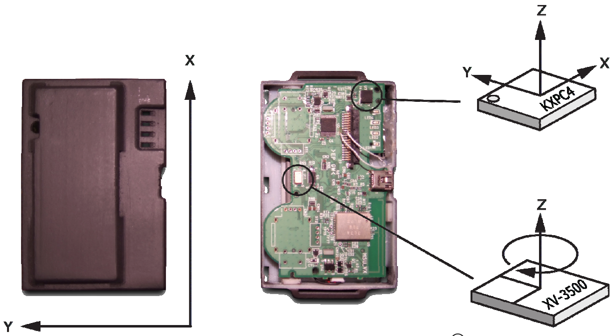

Figure 1: The Sony PlayStation® 3 (PS3) DUALSHOCK®3 SIXAXIS™ hardware and the custom box

an intensive game, we expected these controllers would be suitable in recording accelerations from nursing activities.

Figure1 illustrates the PS3 hardware, housed in a custom box that was designed and manufactured in our in-house rapid-prototyping facility. Figure2 illustrates a nurse wearing 5 PS3 controllers while replacing an IV bag.

We established a wireless link between the PS3 controllers and a laptop computer (Intel Celeron 1.6GHz, 1.5 GB RAM) running Ubuntu Linux 8.04 (Hardy) operating system (Kernel 2.6.24-24), based on the protocol provided by the publicly available instructions [22]. We developed a software program (C programming language) to receive raw acceleration packets from each PS3 controller, and save them to a simple text file. The program time-stamped the arrival of each data packet with 1 microsecond accuracy. The PS3 sampling frequency was estimated to be 44.41 Hz.

We used an additional unmodified PS3 controller (the 6th controller) to label and time-stamp the nursing activities; we assigned start, stop, and nursing task events to separate buttons on the controller. This controller was connected to the same computer as the other PS3 controllers wirelessly.

The subjects performed 10 trials of each of the following nursing activities in sequence: 1) talking to a patient, 2) checking on vital signs, 3) replacing an intravenous (IV) bag, 4) checking on blood sugar, 5) placing a bedpan under the patient, and 6) giving oral medication to a surrogate patient.

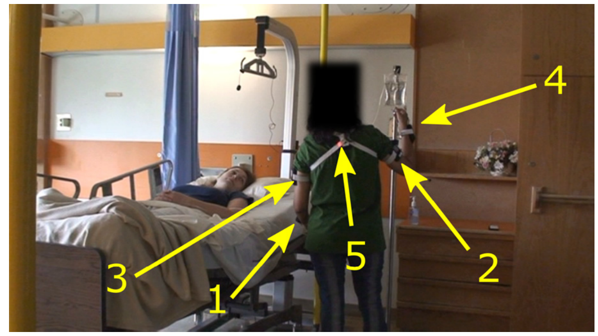

Figure 2: A nurse wearing 5 PS3 sensors while replacing an IV bag

We wrote a program in MATLAB® (The MathWorks Inc. Natick, the U.S.A.) to automatically segment the complete data to the corresponding nursing activity intervals based on the start and stop time of each nursing activity recorded by the 6th controller. In total, 300 data segments (10 trials * 6 activities * 5 sensors) were saved in MATLAB® standard data file for each subject.

<u>Data analysis</u>

We extracted the features on 256-sample windows of acceleration data (N=256) on each axis with 50% overlapping between consecutive windows and created two separate feature spaces.

One of the feature spaces included the mean, standard deviation, energy, and correlation between accelerometer axes calculated for each accelerometer axis. From now on we refer to this feature space as *time-domain feature space*.

The mean of the acceleration signal calculated over the feature extractor window is the DC component of the signal. The standard deviation of the acceleration signal is useful in capturing the range of possible acceleration values to separate activities that may look similar in nature but different in their speed and acceleration (e.g. walking vs. running). The energy of the signal is a measurement of the signal strength and it is useful to capture the intensity of an activity and can be obtained either in the time or frequency domain. The correlation among accelerometer axes is useful in distinguishing activities that may appear similar but are performed in different dimensions.

We referred to the second feature space as *the augmented AR coefficients feature space* including third-order AR coefficients, SMA, and TA as disclosed by Khan et. al. [18, 19]. The AR model of the current sample of the signal *x(n)* is described as a linear combination of previous samples plus an error term *e(n)* which is independent of past samples and is calculated by [20] :

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n) \quad (1)$$

, where *x(n)* is the current sample of the modeled signal, a_k are the AR coefficients, *p* is the model order, and *e(n)* is the prediction error. SMA is the signal magnitude calculated over all axes and it has been shown to be useful in identifying static vs. dynamic activities [10, 18, 19]. SMA is calculated by:

$$SMA = \sum_{n=1}^{N} \left(|x(n)| + |y(n)| + |z(n)| \right) \quad (2)$$

, where *x(n)*, *y(n)*, *z(n)* are the acceleration samples for each axis at time *n*, and *N* is the number of samples in the feature extraction window. TA is the tilt angel from the gravity vector and is calculated by:

$$TA = ar\cos(\bar{z}) \quad (3)$$

, where $\bar{z}$ is the mean of the *z* axis signal calculated over the feature extraction window and it is parallel to the gravity vector.

We wrote a program in MATLAB to extract the features and converted them into Attribute-Relation File Format (ARFF) recognizable by the Weka machine learning tool [23]. Weka is a very powerful open source data mining tool developed by the University of Waikato - New Zealand, and has been used in human activity data mining research [8, 9]. We used the Weka Experimenter tool to analyze and compared the performance of 1-NN classifier on the two different feature spaces. The 1-NN algorithm is a method in pattern recognition for classifying data points based on the distance between a data point and the training sets in the feature space [23].

Table 1: Comparison of overall sensors' accuracies, evaluated by 1-NN classifier, averaged over all activities for all subjects.

Sensor location	**Average 1-NN Classifier Accuracy (%)**	
	Time-domain features	***Augmented AR coefficients features***
Left Wrist	84.88±3.81	57.63±4.91
Right Wrist	85.42±5.44	60.84±4.42
Left Upper Arm	81.42±5.78	64.47±5.05
Right Upper Arm	82.51±5.43	63.42±3.90
Back	84.76±3.75	71.69±3.95
Average	**83.80±4.92**	**63.61±6.55**

RESULTS

Table 1 illustrates the sensors' average accuracies computed by 1-NN classifier based on 10-fold cross-validation test on both feature spaces. In the k-fold cross-validation method the data is randomly divided into k segments. Each segment is used as a test set and the remaining k-1 segments serve as the training set. Later, this procedure is repeated k times and then the average result is reported. In this research we chose k=10 which is a common practise in machine learning applications [23]. It can be seen that the time-domain features outperformed the augmented AR model coefficients features on average by 20%.

CONCLUSIONS

We compared the performance of two separate feature sets that had previously shown success in recognizing simple human activities such as lying, sitting, standing, walking, and running.

Although the augmented AR model coefficient features had shown superior performance in recognising simple human activities [18, 19], on average they showed 20% less accuracy performance than the time-domain features in recognising nursing activities. On average the 1-NN classifier was able to identify 6 different nursing activities with 83.80%±4.92% accuracy using the time-domain feature set.

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