34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Estimation of Accelerometer Orientation for Activity Recognition*

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Abstract— **Tri-axial accelerometers have been widely used for human activity recognition and classification. A main challenge in accelerometer-based activity recognition is the system dependence on the orientation of the accelerometer. This paper presents an approach for overcoming this challenge by calibrating the accelerometer orientation using pre-defined activities alongside automated correction algorithms. This method includes manipulation of data via rotation matrices estimated from the pre-defined activities. The system is subsequently tested with real data where sensors were placed in the wrong orientation. A control set of correctly oriented sensors were also placed for validation purposes. We show that our approach improves the accuracy from 38% to 92% for the wrongly oriented sensors, when the control sensors achieve 95%. A GUI was also created in order to make the tool easily available to other researchers.**

I. INTRODUCTION

Activity monitoring is a new and important field in healthcare and sports. Its uses include stroke rehabilitation, athletic training, out-patient health monitoring, early fall detection, and gaming [1], [2]. It is revolutionizing the health profession by providing detection and care that is not possible through conventional means. The most popular methods for activity monitoring use cameras and portable sensors. Portable sensors are more scalable, effective for personalization for the system, and cost efficient. In this paper, we focus on systems using portable accelerometers. In real world applications, many activity classification algorithms are not robust due to issues related to sensor orientation. In this work we use personalized and supervised learning methods where a training is used to build an activity classifier for each user. For these methods, a classifier would be build using accelerometer places in a specific orientations. The robustness issue comes to play, when there is a mismatch in the accelerometer orientation between the training, and the testing or subsequent use of the system. This is a very practical problem since the users will wear their accelerometers at different times and use their trained classifier built in a previous time. Activity recognition algorithms areexecutedon training under known sensor orientations, subsequently the classifications are sensitive to those orientations as well.In order to make the systems more robust, calibration algorithms must be in place to manipulate and correct data produced by incorrectly oriented sensors placed unintentionally wrong by the patient or subject. There are two traditional means for dealing withproblems revolving around theorientation of sensors. The first is to findorientation-invariant features, using mathematical manipulations such as power spectral density or a Fourier Transform [1]. The other is calibration through a series of movements.In this paper we propose and evaluate a method to calibrate a system of sensors through a series of simple pre-defined movements.Additionally we propose an algorithm to automate the system of sensors calibration using orientation invariant motion recognition methods. This method is then tested on real data for human motion recognition.

Very few researchers considered this problem. In [3], the authors use a similar approach but do not report the improvement you could get from such a method. We think that this is a very important step in realizing accelerometer-based activity recognition systems. The contribution of this paper is that it shows the effectiveness of accelerometer orientation calibration using pre-defined movements on real data. Our results are based on real experiments using three sensors, for seven daily-life activities.

II. METHODOLOGY

A. System Description

In this project we use the GCDC Miniature 3-axis Accelerometer Data Logger X6-2mini [7]. Our accelerometers sample at 160Hz, with a range of ±6g, recording at 16 bits of resolution. For classification purposes, the algorithms include a naïve Bayes classifier, combined with a decision tree. At each node of the decision tree, one or two mathematical features are extracted from each sensor. Features include mean values, standard deviations, and energy, among others. The specific features and activities used for experimentation purposes are discussed in the experiments and evaluation section.

B. Rotation Matrix Estimation Method

We use rotation matrices to calibrate the disoriented data measured by a disoriented sensor. Each sensor measure the acceleration in a 3-D space relative to the sensor orientation, we refer to that space by sensor space. We use a reference 3-D space that corresponds to gravity, and we call it hand space. In this space gravity is aligned with the y-axis.

For each sensor, a 3x3 rotation matrix is constructed to calibrate the disorientated data. Orientations in three-dimensions can be used to represent one system's orientation relative to another [4]. In this method we use a fixed system where gravity is aligned with the y-axis. In this paper, it

*This work was supported by the National Science Foundation under Center for Embedded Networked Sensors, CCR-0120778

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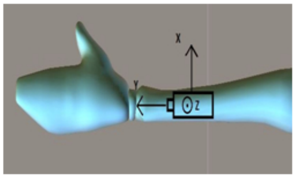

Fig. 1. Three Dimensional Acceleration Signals

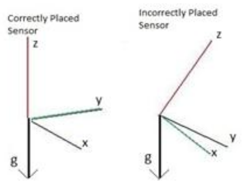

Fig. 2. The figure on the left shows the system for a correctly placed sensor. The figure on the right shows the system for an incorrectly placed sensor

will be referred to as hand space, as we use gravity as a reference to align with the hand. The sensor has its own orientation however, which can be represented relative to the hand. Thus if we have a rotation matrix that represents the sensor in hand space, it will make the sensor data appear to come from a sensor that is aligned with the hand as shown in Figure 1. This is doable because all sensor data is related by an absolute, the gravity vector, as shown in Figure 2.

Using a feature of rotation matrices, if an inverse is performed on the 3x3 matrix of the hand in sensor space, it becomes the sensor in hand space. This rotation matrix can then be multiplied by the data being recorded by the sensor, and the sensor data be manipulated to look as though it is being produced from a correctly oriented sensor.

C. Estimating the Orientation

An algorithm was developed to automate sensor calibration for systems of sensors simultaneously. Having the user perform movements shown in Fig. 3 and 4, an algorithm (described in detail below) recognizes those movements, records the acceleration signatures, and applies rotation matrices to correct the data. The correction motion is easy for the naïve users to perform, so that the rotation matrix can be automatically built and applied on the subjects' data for researchers to utilize without difficulty.

The first step is aligning the signals. To do this, the sensors are all held together in the same orientation and violently shaken. Once the time signature on all the sensors is clear, the signals are time shifted to make all movements recorded from the individual in sync. The data are also put through a low pass filter prior to processing. This ensures that shaking dynamics are kept at a minimum and tilt is emphasized. This also makes the method more robust to deal with individuals that have trouble holding still, such as Parkinsons disease. The sensors would otherwise produce sudden spikes in the data, creating a high standard deviation, giving the illusion of movement indication.

The second stage consists of finding the time period

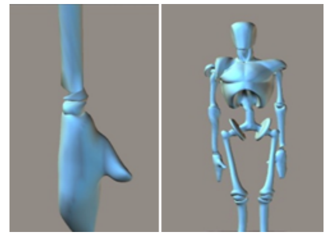

Fig. 3. Calibration Action 1.

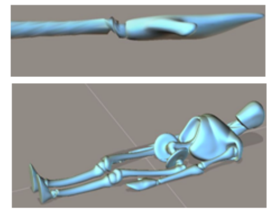

Fig. 4. Calibration Action 2.

when the individual was standing upright. Regardless of orientation, the sensors must be worn flat against the skin. This ensures that if the individual is standing upright, the sensors z-axis will always be perpendicular to gravity and read zero. The other indication that the individual is standing upright and still, is the data produced by the accelerometers will have minimal movement, indicated by a low standard deviation. Within the signal, a time frame of 10 seconds is searched for, where the accelerometers z axis is parallel with the ground, and the individual is holding still. This is marked by an average z-reading of less than $0.2g$, and a low standard deviation in x and y indicating stillness in the subject. These values are then recorded and placed into the second column of the rotation matrix.

The transitional period from standing to lying down is marked by a very high average standard deviation on the three sensors attached to the individual. The individual lying down, is found by a period following the transitional period with a low standard deviation on all three axes. This ensures that as long as the individual stands upright, and then subsequently lies down, all of the needed signals will be found for rotation matrices processing.

Once these time periods are found, average values over 10 seconds are now available for each of the sensors in each of the needed axes. The values are put into a rotation matrix, inverted and then multiplied by the sensor data as described in the previous sub-section. The method is robust and user friendly, as it can automatically calibrate data, rather than having individuals finding time signals visually or recording them from an external device.

III. Results and Evaluation

A. Single Sensor Experiments

An initial experiment was conducted to test the effectiveness of this calibration method on the subjects wrist. One sensor was correctly oriented, while two sensors were placed

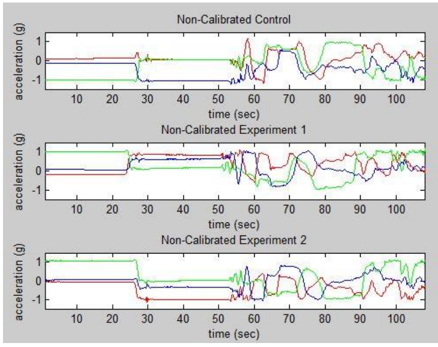

Fig. 5. Data from non-calibrated sensors.

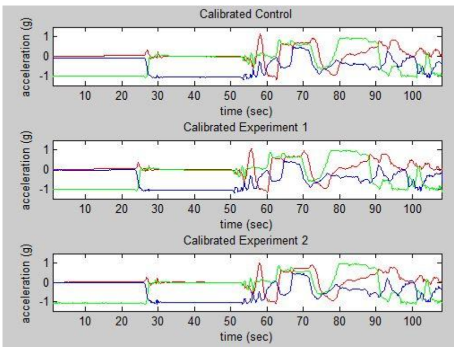

Fig. 6. Data from calibrated sensors.

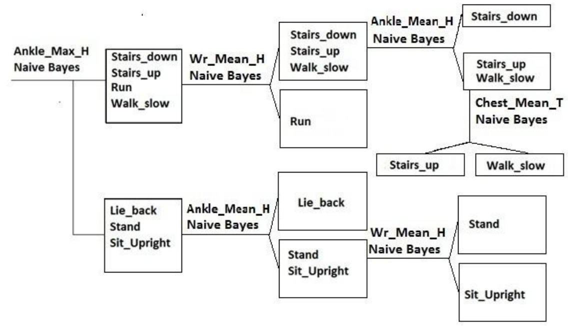

Fig. 7. The Decision Tree Used. The features used are shown on every node.

Classification

True Class	Unknown	Lie Back	Sit_Uprigh	Stand	Run	Stairs_Down	Stairs_Up	Walk_slow
Unkown	0.1566	41.3307	28.9237	5.9883	3.9922	8.0235	5.5577	6.0274
Lie_back	0	100	0	0	0	0	0	0
Sit_Uprigh	0	0	100	0	0	0	0	0
Stand	0	0	0	100	0	0	0	0
Run	0	0	0	0	100	0	0	0
Stairs_Do	0	0	0	0	0	91.3043	0	8.6957
Stairs_Up	0	0	0	0	0	20.4082	79.5918	0
Walk_Slo	0	0	0	0	0	15.3846	0	84.6154

Fig. 8. Confusion Matrix for Correctly oriented Sensors

in incorrect orientations on various parts of the wrist, as well as tilted to different angles. Control indicates the sensor that was correctly oriented. Experiments 1 and 2, denote the sensors that were incorrectly oriented. The x, y, and z axes are denoted as, red, green, and blue lines in that order.

A series of movements were performed, and the rotation matrices were applied via the calibration algorithm. In Figure 5, it is seen that the signals from the sensors are related, but yield vastly different results. In Figure 6 however, the signals all look almost indistinguishable from one another aside from a time delay, and the control is unchanged. These early experiments were an indication that the algorithm was successful.

B. Multiple Sensor Activity Classification

In this experiment, the calibration algorithm was tested on two systems of 3 sensors attached to different locations on the subjects body. Three sensors represented the control, as well as the base of the training data, and the other three are the experiment, placed at identical locations with different orientations. These locations were the right ankle, the right wrist, and the chest of the test subject. The activities being trained and classified were slow walking, running, walking up stairs, walking down stairs, sitting, lying down, and standing upright.

Our naïve Bayes decision tree classifier is shown in Figure 7. The first distinction between motion activities and still poses was made in the first branch. This distinction is of importance to us, because still motion activities can be determined only through tilt, and are subsequently much more dependent on the orientation of sensors. Motion activities can be determined often times through motion invariant features, such as average standard deviation of the x, y, and z axes.

In this experiment the calibration algorithm was applied to two systems of 3 sensors attached to different locations on the subject's body. Three sensors represent the control, and the other three represent the experiment, as incorrectly oreiented sensors. The individual wearing the sensors underwent 7 activities to be classified: slow walking, running, walking up stairs, walking down stairs, sitting, lying down, and standing. The three experimental sensors were tested for accuracy both before and after the calibration algorithms, and compared to the control experiment. The sensors were located on the right ankle, the right wrist, and the chest of the test subject.

Our naïve Bayes decision tree classifier is shown in Figure 7. For example, the first distinction made was between motion activities and still poses. It was found that the maximum value of the y-axis was the most accurate feature for separating these sets using cross validation. Subsequently nodes are added to the tree until all 7 activities have their distinguished sets of features.

Figure 8 represents the control of the experiment using correctly oriented sensors. The activities were classified correctly with an accuracy of 96%. The incorrectly oriented sensors in Figure 9 had only 38% accuracy. Once the algorithm was run on the data, the data was again tested for activity classification and an accuracy of 93% was achieved . Also, it is clear that some activities are accurately classified regardless of orientation. The reason is that still activities are entirely orientation dependent, while mobile

Classification

True Class

	Unknown	Lie Back	Sit_Uprigh	Stand	Run	Stairs_Down	Stairs_Up	Walk_slow
Unkown	0.1537	46.1183	46.1568	5.9883	7.5711	0	0	0
Lie_back	0	100	0	0	0	0	0	0
Sit_Uprigh	0	0	2.381	0	97.619	0	0	0
Stand	0	0	6.8627	100	93.1373	0	0	0
Run	0	0	0	0	100	0	0	0
Stairs_Do\	0	0	100	0	0	0	0	0
Stairs_Up	0	0	100	0	0	0	0	0
Walk_Slo\	0	0	100	0	0	0	0	0

Fig. 9. Confusion Matrix for Non-Calibrated Incorrectly Oriented Sensors

Classification

True Class

	Unknown	Lie Back	Sit_Uprigh	Stand	Run	Stairs_Down	Stairs_Up	Walk_slow
Unkown	0.1566	50	19.2544	6.6487	4.5734	6.0338	3.4973	9.8386
Lie_back	0	100	0	0	0	0	0	0
Sit_Uprigh	0	0	100	0	0	0	0	0
Stand	0	0	0	100	0	0	0	0
Run	0	0	0	0	100	0	0	0
Stairs_Do\	0	0	0	0	0	34.7826	0	65
Stairs_Up	0	0	0	0	0	18.3673	69.3878	12
Walk_Slo\	0	0	0	0	0	8.7912	0	91

Fig. 10. Confusion Matrix for Calibrated Incorrectly Oriented Sensors

activities can be classified on a range of features, some being more orientation dependent than others. For example high average standard deviation, can mark running, which is also rotation invariant. The data indicated that with very poor placement, the algorithm could make sensor data on average, accurate within 3% of the correctly oriented sensor data. This indicates a successful method to be used and developed further in the future.

C. Graphical User Interface

A GUI was created so that researchers could choose to calibrate individual body parts, or a system of three sensors simultaneously. After choosing the body part(s) that need calibrating, the individual selects the data file that needs to be preprocessed, and a message will appear indicating its success. Figure 11 is the first screen, and after selecting Full Body, Figure 12 is the second screen showing the positions needed for calibration and a sample to show a successful calibration.

IV. Conclusion

In this paper, we presented an approach for correcting the data recorded by misoriented accelerometers used for activity recognition purposes. This approach uses rotation matrices estimated from pre-defined activities done by the user at the initialization of the system. We show that it improves the accuracy from 38% to 92% for a real data set of 7 activities. Based on these promising results we are pursuing an extension to this work. This involves automatic recognition of activities that may be used for calibration of sensor orientation, rather than requiring the subject to engage in a set of prescribed activities, which may themselves be subject to error. This requires collection of a large training sets over multiple subjects that include many orientation errors so that the classifier may be self-calibrating through recognition of error states. While the work involved in

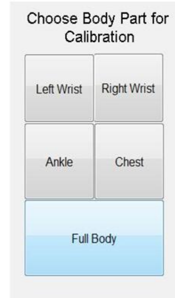

Fig. 11. GUI Home Screen

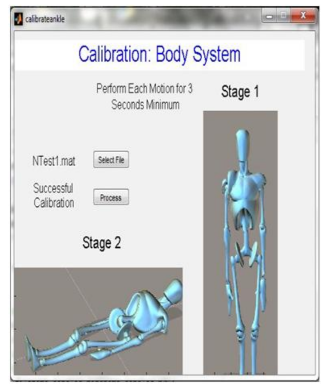

Fig. 12. Gui Final Screen

model creation is larger, methods that further reduce what is demanded of users may ease scaling to very large numbers.

Acknowledgment

The authors would like to thank many people who helped with this project: Prof. Bill Kaiser, James Xu, Celia Xu, Maxim Batalin, Ben Fish, Ammar Khan, Travis Rodriguez, Pinar Ozisik, James Gomes, Wes Uehara, and Jonah Friedman.

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