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Dynamic Activity Classification Based on Automatic Adaptation of Postural Orientation

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***Abstract*— we propose a dynamic activity classification system with tri-axial accelerometer sensor using adaptation of user's postural orientation. In general, the sensor module is worn at a fixed position such as waist, head, wrist, thigh, and so on. However, in reality, the tilt of the attached sensor could be changed from time to time in actions such as sitting down, standing up, lying, walking or running. Moreover, most of the users want to wear the sensor at their own favorite positions instead of a recommended position. In these cases, the activity detection methods based on fixed tilt value may produce serious problem in their performance. Therefore, we propose a user adapted activity classification method which enables users to freely wear the sensor everywhere on their torso. In order to decide tilt values corresponding user's postural orientation, we focused on tilt-free activities such as walking and running. While walking, the algorithm tries to modify the predefined reference tilt values for the three axes, X, Y and Z. From an experiment, we have achieved 88% of the activity classification accuracy even though the tilt angle is changed while wearing sensors.**

I. INTRODUCTION

MONITORING the activities of the elderly or children is becoming very essential for various healthcare applications, such as ambulatory care for the elderly, behavior-driven assistance, ambient assisted living and health monitoring. One of the most popular methods for those applications is acceleration sensor based activity monitoring. Many researches on activity classification using triaxial accelerometer have been introduced [1, 2, 4, 5, 6, 7]. Most of them have been focused on how well detect activities or postures of subjects wearing one or more acceleration sensors. From a practical point of view, forcing users to wear a device at a fixed position such as on one's waist or ankle would make them uncomfortable or even hesitating to buy it. But that does not seem to be avoidable until now. That's why most of the algorithms are essentially based on the tilt information as well as acceleration of the sensor attached to user's body. So, if a reference axis (tilt in general) is changed from one angle to another while acting, the detected activities (especially static activity) such as Lie, Stand, Sit, etc are almost unreliable because the role of the reference axis (usually Z axis) is critical in most of the activity detection algorithms [1, 2, 4, 5, 6, 7].

In fact, the reference axis varies person to person in reality even though subjects have been noticed about where and exactly how to wear the sensor, because of the personal difference of body shapes and acting habits. Moreover, the reference axis can be changed during lively actions such as running, walking, sitting, lying, etc., which may cause deciding errors such as classifying Sit instead of Stand and Lie instead of Sit, based on the tilt values from the sensor. In order to deal with those errors, we propose a user adapted and dynamic reference based activity classification method, which makes it possible to move the wearing position or to adapt itself to the slope change of the attached sensor while user acts.

II. METHOD

A. Devices

Figure 1 shows a subject wearing the sensor which includes a Freescale MMA7260Q chip as tri-axial accelerometer and a TI's CC2410 chip for real-time RF transmission of the acceleration data. It also shows a RF receiving module pluggable to a host via USB. The sensor and the RF receiving module communicate with each other through 2.4GHz RF. For saving the amount of battery consumption, the sampling frequency for the acceleration values in the sensor was limited at 10 Hz, which is relatively small compared to [2] which sampled acceleration values at a rate of 45Hz. The number of sampling frequency tends to be proportional to the performance of the activity detection algorithm. However, we need to think of as battery loss problem for commercial product. Actually, the high battery consumption is one of the most important problems as for the company which has a plan to launch its own product in Korea. So we also designed our

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system to minimize the communication between the sensor and its receiving module which could be a USB dongle in this experimental setup and also be a cellular phone with the Bluetooth facility. In fact, we made another type of Bluetooth based sensor which is easily coupled with commercialized cellular phones. The algorithm embedded in the sensor is tightly designed to reduce the battery loss as much as possible even though the accuracy might be sacrificed a little.

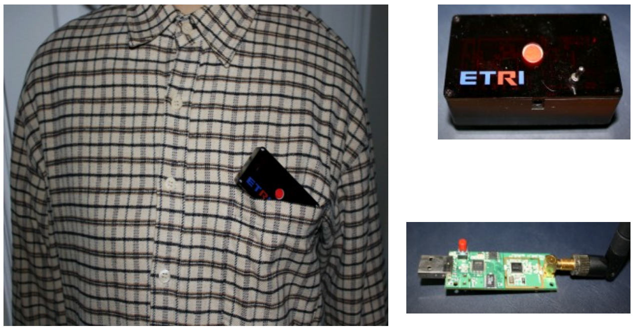

Fig 1.A sensor attached at a subject's chest pocket and a USB dongle to receive data from the sensor

B. Algorithm

Basically, the proposed activity classification method used in this work is similar to [2] because we utilized SMA (Signal Magnitude Area), SVM(Signal Magnitude Vector), and tilt signals. The definition of the SMA is as follows.

$$SMA = \frac{1}{t}\left(\int_0^t |x(t)|\,dt + \int_0^t |y(t)|\,dt + \int_0^t |z(t)|\,dt\right)$$

where *x(t)*, *y(t)*, and *z(t)* refer to the body components of the *x*, *y*, and *z* axis samples, respectively.

The SVM was used to detect an abnormal peak of shock. It is the total value of the acceleration vector from all directions of tri-axial and defined as follows.

$$SVM = \sqrt{x_i^2 + y_i^2 + z_i^2}$$

where $\boldsymbol{x}_i$ is the ith sample of the x-axis signal (similarly for $\boldsymbol{y}_i$ and $\boldsymbol{z}_i$).

At last, the Tilt angle (Φ) was used to find static activity due to angle change in vertical direction of sensor (y axis) and related activity changes.

$$\Phi = \arccos(z)$$

Figure 2 illustrates an overview of how the tilt angle relates to the various postural orientations, which comes from [2].

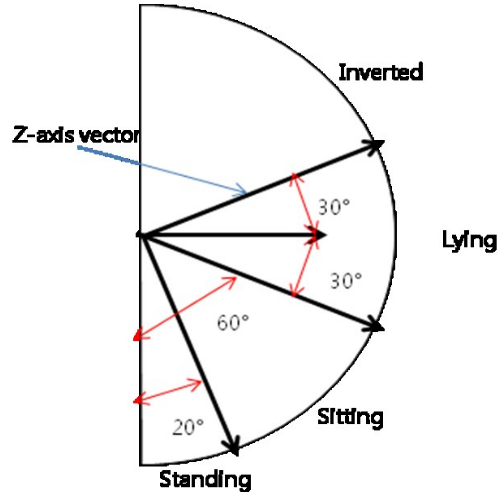

Fig.2. Method for determining the postural orientation of the user.

However, figure 3 intuitively reveals the problem of user variations in sitting habit when we use the method illustrated in figure 2. If we consider the two angle variations at the same time, we can easily imagine that the above method using static thresholds will be confronted with a serious problem

Based on the algorithm explained until now, we built an activity detection algorithm as a baseline. This is just for comparison with our proposed method.

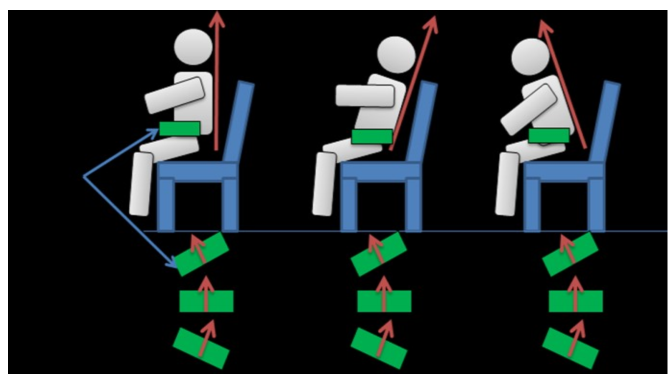

Fig 3. The variation of postural orientation according to user's sitting habit and the tilt changes according to the wearing sensor's slope

In order to make an algorithm tolerant of changing tilt, we need to dynamically figure out the postural orientation of the subject. In other words, we have to assume that the sensor could be located at unexpected position such as breast pocket or waist, so the sensor's tilt could be changed while acting. In order for capturing the dynamic postural orientation, we focused on Walking activity because the walking does not rely on the tilt angle and the postural orientation on walking could be a best candidate for referencing postural orientation. On walking, the sensor's tilt values could be obtained by averaging them if it continues enough times. In general, the activities including Lie, Stand, Sit and Fall are dependant on the tilt values whereas the Walking (or Run) can be obtained by finding pit or peak in the SVM and/or SMA signals.

Actually, the Fall event also could be done just with SVM, but we utilized the posture status just after the Fall event in order to reduce false alarms.

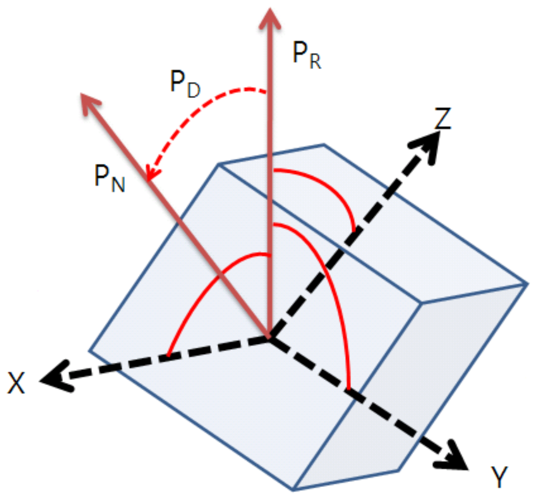

Fig. 4. Depiction of calculating tilt difference in dynamic orientation system: P_R=Reference Postural Orientation, P_N =New Postural Orientation, P_D =Difference between P_R and P_N.

Figure 4 depicts the basic idea of calculating the postural orientation vector at any situation. The box stands for the sensor attached to one's torso, and P_R means the reference postural orientation vector obtained while walking. Here, we assume that the average of the tilt values during enough times of Walking can represent the user's posture orientation. P_R and P_N consists of three tilt values from the X, Y and Z axes. The reference orientation (or posture), P_R, could be computed from the WMAs (weighted moving average) [3] of all three axes, after the user walks around for predefined times. The WMA is any average that has multiplying factors to give different weights to different acceleration values [3]. The following WMA formula is used in this research.

$$WMA = \frac{w_n x_n + w_{n-1} x_{n-1} + \ldots + w_2 x_2 + w_1 x_1}{\sum_{i=1}^{n} w_i}$$

where w_i is the weight of i^{th} value(x_i), x_i is replaced by y_i and z_i for computing the three acceleration values.

Once we find the referencing virtual axis, P_R, we can compute the P_D whenever the P_N occurs. The formula for calculating P_D is as follows.

$$P_D = \sqrt{(x_N - x_R)^2 + (y_N - y_R)^2 + (z_N - z_R)^2}$$

where P_R =(x_R,y_R,z_R) and P_N =(x_N,y_N,z_N).

The user's activities can be classified similar to the way based on tilt angles introduced in [2]. But we use P_D instead of tilt angles with three predefined thresholds for the three activities. Simply speaking, the angle vector in figure 2 is replaced by the vector P_D .

III. EXPERIMENTAL SETUP

For the experiment, six simulated activities were performed with four healthy volunteers: two females (32 years on average) and two males (36 years on average). The subjects were guided to perform scheduled activities six times repeatedly according to the orders described below. They performed the activities three times out of six attaching a sensor embedding a legacy algorithm which utilizes the tilt angle. And during the rest three times, they acted with the other sensor embedding the proposed algorithm in this work. They were also noticed to change the wearing position at every time among left waist, right waist and chest.

The scenario is as follows:
- Wear a sensor and remain standing,
- Tilt up or down more than 10 degree,
- Walk around (30s) for posture adaptation,
- Remain standing (20s),
- Sit down and remain seated (20s),
- Stand up and walk around (30s) for posture adaptation,
- Lie down and remain lying (20s),
- Stand up and walk around (30s) for posture adaptation,
- Intentional falling down (5 times),
- Stand up and walk around (30s) for posture adaptation,
- Walk around (20s),
- Run (20s).
- Change the wearing position and start again in the beginning

The most important parts in the scenario are "Intentional Tilting up or down more than 10 degree" and "Walking around for posture adaptation". The former makes the algorithms suffer from the tilt change so as to test their tolerances from unexpected situations. The latter is for the proposed method to train itself and modify its reference postural orientation during the activity.

IV. RESULTS

Table 1 shows the result of 88.6 % of accuracy in the proposed method while 81.07 in the baseline. The accuracy in table 1 stands for the number of correctly classified activities over all of action periods, because the activity classification has been performed in every one second. It shows that the classifications for Walk and Run are generally quite accurate whereas Sit and Stand are not in both algorithms. However, the legacy algorithm is suffering from differentiating between Sit and Stand while the proposed one works relatively well as we mentioned earlier.

TABLE 1. COMARISON OF BASELINE WITH THE PROPOSE ALGORITHM

Position	Activities	Legacy	Dynamic	% Increase

Chest	Lie	89.5	88.8	-0.78%
	Sit	61.7	76.3	23.66%
	Stand	65.8	78.1	18.69%
	Walk	97.1	94	-3.19%
	Run	95.3	93.6	-1.78%
	Fall	88.8	89.2	0.45%
	Total	**83.03**	**86.67**	**4.38%**
Left Waist	Lie	81.4	94.5	16.09%
	Sit	62.4	78.5	25.80%
	Stand	59.5	86.1	44.71%
	Walk	95.4	97	1.68%
	Run	93.3	94.2	0.96%
	Fall	78.3	87.7	12.01%
	Total	**78.38**	**89.67**	**14.40%**
Right Waist	Lie	78.9	95.2	20.66%
	Sit	73.3	82.7	12.82%
	Stand	69.5	79.9	14.96%
	Walk	95.2	97.5	2.42%
	Run	93.7	93.6	-0.11%
	Fall	80.1	88.3	10.24%
	Total	**81.78**	**89.53**	**9.48%**
	Total	**81.07**	**88.62**	**9.32%**

One thing we have to recognize is that the result on chest was inferior to the other two. We found that the sensor on chest vibrated more frequently and strongly. Sometimes it swings. If the sensor is not tightly fastened, its tilt would be trembled in actions.

V. CONCLUSIONS AND FUTURE WORKS

In conclusion, we presented that the dynamic posture adaptation method for the activity detection makes people free from the strict rule for wearing activity sensors. After comparing it with a legacy algorithm, we found that our method could be useful in reality even though the absolute accuracy is still not so high enough. However, we showed the availability of making adaptable activity monitoring sensor.

As for future works, we will perform more experiments with additional subjects and focus on improving the accuracy of detecting human activities.

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