A Framework for Daily Activity Monitoring and Fall Detection Based on Surface Electromyography and Accelerometer Signals

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***Abstract*—As an essential branch of context awareness, activity awareness, especially daily activity monitoring and fall detection, is important to healthcare for the elderly and patients with chronic diseases. In this paper, a framework for activity awareness using surface electromyography and accelerometer (ACC) signals is proposed. First, histogram negative entropy was employed to determine the start- and end-points of static and dynamic active segments. Then, the angle of each ACC axis was calculated to indicate body postures, which assisted with sorting dynamic activities into two categories: dynamic gait activities and dynamic transition ones, by judging whether the pre- and post-postures are both standing. Next, the dynamic gait activities were identified by the double-stream hidden Markov models. Besides, the dynamic transition activities were distinguished into normal transition activities and falls by resultant ACC amplitude. Finally, a continuous daily activity monitoring and fall detection scheme was performed with the recognition accuracy over 98%, demonstrating the excellent fall detection performance and the great feasibility of the proposed method in daily activities awareness.**

***Index Terms*—Activity awareness, entropy, fall detection, surface electromyography (SEMG).**

I. Introduction

With the development of wireless network and wearable sensing technology, context awareness becomes an important characteristic of pervasive computing and ambient intelligence. Context provides plenty of information about the present status of people, places, things, and devices in environment [1], [2]. As a fundamental aspect of contexts, ongoing activity recognition is one of the essential bases for context-aware applications, which can foster many innovative and attentive services, such as patient monitoring, rehabilitation, and emergency response, etc. [1]–[3].

In the past decade, there has been a steady growth of aging population. More and more elders are living alone as the sole occupant than any other population group. Helping them to live a better life has great social benefits. Activity recognition, which makes contributions to daily activity monitoring and emergency detection, has caught the attention of researchers in many fields [4]–[6]. One important application is fall detection system [7], [8]. Another potential application is to offer intelligent assist for patients suffering from cognitive disorders, such as Parkinson's or Alzheimer's disease [9].

Currently, the approaches employed to sense the activities could be majorly classified into three categories [10], [11], detailed as 1) *computer vision-based method:* real-time movements of subjects are detected by videos; 2) *acoustic and ambient sensor-based method:* the frequency component of vibration produced by the fall is processed to detect a fall; 3) *wearable sensor-based method:* kinematic or electrophysiological signal sensors, such as surface electromyography (SEMG) sensors, are utilized to detect daily activities [6], [12]–[14].

The existing methods show their drawbacks as well as merits when used for activity awareness. Computer vision-based techniques provide an unobtrusive way, and one setup could work for multiple users. However, due to the fixed nature of the camera, it is preferred to be used indoors for reliable detection, and it is costly to install multiple cameras to cover the entire area of interest [15], [16]. Compared with the computer vision-based techniques, the acoustic and ambient ones exhibit their advantages including relatively cheap hardware and simple realization. However, such acoustic approaches are not suitable in general living conditions, since their performance could be degraded due to external noises and over tens-of-meters distance transmission from the acoustic sensors array [17], [18]. The kinematic sensor-based techniques need to wear additional devices. However, with the kinematic sensors becoming smaller, lighter, and wireless, they can be worn in the band- and ring-like even embedded in clothes, which causes little obstructive when employed for activity awareness applications. This kind of techniques overcomes the range limitation due to the distributed wearable characteristic [12]–[14], [19].

The accelerometer (ACC) is a wearable sensor that calculates velocity and trajectory information by integrating acceleration data with respect to time, as well as provides inclination information with respect to the reference planes [20], [21]. Thus, it is preferred to be used in activity recognition and assessment, including posture and movement classification, energy expenditure estimation, balance control evaluation, and fall

Manuscript received February 21, 2012; revised June 4, 2012 and September 29, 2012; accepted October 22, 2012. Date of current version February 4, 2013. This work was supported in part by the Fundamental Research Funds for the Central Universities of China under Grant WK2100230005 and Grant WK2100230002, the National Nature Science Foundation of China under Grant 61271138, and the Graduate Innovation Foundation of the University of Science and Technology of China.

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Digital Object Identifier 10.1109/TITB.2012.2226905

detection [20], [22]–[25]. In this paper, our work focuses on daily activity monitoring and fall detection for promoting the life quality of the elders. In previous studies, divergent methods and findings about fall detection based on acceleration signals were described. The simplest one is the threshold selection algorithm. The disadvantage of threshold-based methods due to some normal daily activities, which produced large ACC vector amplitude, would be misclassified for falls, resulting in false positives (FPs) [26]. To reduce FPs, other researchers made many efforts [25], [27], [28]–[30], summarized mainly as three categories: 1) *computational intensive algorithm:* Zhang *et al.* [29] employed one-class support vector machine to detect falls. Shi *et al.* [30] adopted hidden Markov models (HMMs) to categorize five kinds of human motions. 2) *Body posture-based algorithm:* Li *et al.* [20] proposed body postures to help detect fall activities. They demonstrated that posture information interpreted from ACC and gyroscope sensors placed on chest and thigh could decrease the FPs. 3) *Multisensors strategy:* Yang and Hsu [31] and Tapia and Intille [32] used multiple sensors for activities recognition. In [32], five wireless triaxial ACCs and a wireless heart rate monitor were developed to classify 30 physical gym activities.

SEMG measures the electrical potentials generated by muscle activity using noninvasive electrodes placed on the skin surface. SEMG recording can not only reflect the levels and patterns of muscle activation during human activities, but also distinguish active and passive movements or degree of loading [13]. Previous pieces of research have exhibited that SEMG signals were successfully applied to gesture recognition, gait analysis, limb prosthetic control, etc. [33]–[35]. Besides, Zhang *et al.* [36] demonstrated that the combination of SEMG and ACC signals had the superiority of representing both fine subtle actions and large-scale movements. Roy *et al.* [6] studied functional activity monitoring and muscular activity interpretation using SEMG and ACC sensors, achieving satisfactory results for 11 identification tasks.

Based on the aforementioned pieces of research, this paper proposed a novel framework for daily activity monitoring and fall detection based on SEMG and ACC signals. The proposed framework can be concluded as follows: 1) histogram entropy was employed for the static and dynamic active segmentation. 2) Static active segments were identified as body postures using angles calculated from ACC signals, and the pre- and post-posture classification results of the dynamic active segments were further utilized as inference information for dynamic transition activity and dynamic gait activity recognition. 3) Dynamic transition activities were distinguished into normal dynamic activities and falls by the use of ACC amplitude threshold and dynamic gait activities were classified based on SEMG and ACC signals by double-stream HMMs. The experimental results demonstrated the excellent fall detection performance and the great feasibility of the proposed method in daily activities awareness.

The rest of this paper is structured as follows. Section II provides activity definition and data acquisition instructions, and Section III presents background information about the employed methods. Experiments were performed and results were analyzed in Section IV. Finally, conclusions and discussions were made in Section V.

II. Activity Definition and Data Acquisition

A. Activity Definition

For the purpose of daily activity monitoring, normal activity recognition and abnormal fall detection are the two most important issues. In this paper, the two categories of activities were not strictly separate. Both of them were separated into static body postures and dynamic transition periods. Dynamic transition periods could be recognized combined with the pre- and post-posture information. For instance, the transition period with the preposture sitting and the postposture standing represents *Standing Up*. *Walking* represents the transition from one position standing to another position standing. And *Going to Bed* or *Falling Down* indicates the transition from standing to lying, etc. Thus, the specific identification tasks studied in our study were defined as three sets: *POSTURE*, *DYNAMIC-Trans*, and *DYNAMIC-Gait*, where *POSTURE* = {Standing, Sitting, Squat, Face-up Lying, Face-down Lying, Left-side Lying, Right-side Lying}, which consists of some typical postures during daily life. *DYNAMIC-Trans* = {x | x = Dynamic activities with pre- and post-postures are A and B, where A $\neq$ B, and A $\in$ *POSTURE*, B $\in$ *POSTURE*}. Then, *DYNAMIC-Gait* was enumerated as four kinds of gait styles, namely *DYNAMIC-Gait* = {Walking (WALK), Upstairs (UPST), Running (RUNN), Downstairs (DNST)}. The set *DYNAMIC-Trans* include two activity categories, called normal dynamic transition activities and falls. According to the *DYNAMIC-Trans* definition, 42 (A_7^2) normal dynamic transition activities are included. Statistically, the face-up lying, face-down lying, left-side lying, and right-side lying could cover most ending postures of fall situations. Thus, four kinds of falls (mentioned as "Fall with four ways" in Fig. 2) are included, with transitions from standing to the four defined lying postures and accompanied with much larger resultant ACC amplitudes. Summarily, the number of dynamic activities was 50. Additionally, for the activity definition completeness, other dynamic transition activities between the same postures, such as sitting to sitting and squat to squat, should be included. Nevertheless, they had little influence on falls; therefore, in this paper, they are omitted.

B. Data Acquisition

The SEMG and ACC database was collected by a portable measurement system, Delsys Myomonitor IV (Delsys Inc., Boston, MA). It measures only 375g and supports up to 16 channel signal inputs (both SEMG and ACC). The dimensions of the device are 140 mm × 71mm × 40 mm and the signal resolution is 16-bit accuracy. Each SEMG sensor consists of two silver bars to perform single differential detection, and is amplified by 1000. Both the SEMG and ACC signal sampling rates are 1000 Hz. The ACC measuring range is ± 2 g.

Referring to the concept of walking pattern strides [37], four SEMG electrodes were placed upon muscles of the right lower limb, illustrated by small circles in Fig. 1, marked as Ch1 to Ch4.

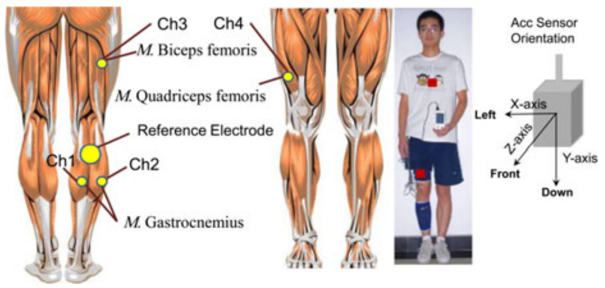

Fig. 1. Description of muscle location and SEMG electrodes placement, as well as two triaxial ACC sensors placement and orientations. The anatomical pictures of lower limb muscles are adapted from [46].

M. *Gastrocnemius* is mainly supportive to standing and walking activities. M. *Quadriceps Femoris* is involved during upstairs, and M. *biceps femoris* makes contributions during downstairs. The SEMG electrodes were attached to the surface skin by an elastic band. Meanwhile, a reference electrode was placed near the SEMG electrodes to supply a voltage baseline, seen as the big circle in Fig. 1. The two triaxial ACCs were placed on the chest and the right thigh, seen as the rectangles. Both the ACC orientations are the same, shown as the right part in Fig. 1. Y-axis is the direction from the subject's head to the toe, X-axis is from the left arm to the right arm, and Z-axis is from the back to the chest.

III. Proposed Methods

An overview of the proposed framework is illustrated in Fig. 2. When a subject executed daily activities, the SEMG and ACC signals were continuously acquired. First, a moving average algorithm [38] was employed to calculate histogram negative entropy values of the resultant ACC amplitude acquired from the thigh. Then, onset and offset thresholds were determined to decide the start- and end-points of the static and dynamic active segments. Afterward, the body postures were classified by the axial angles processed from the static active segments. Second, dynamic active segments were classified into *DYNAMIC-Gait* and *DYNAMIC-Trans* activities by judging whether both the pre- and post-postures were standing or not. Third, different approaches were employed for both dynamic segments. For *DYNAMIC-Gait* activity segments, the overlapping window technology [39] was carried out to produce signal frames. Then, two streams of SEMG and ACC feature sequences were extracted and HMMs were used for specific *DYNAMIC-Gait* activity recognition. For *DYNAMIC-Trans* activity segments, the postures extracted from the previous and the next static active segments helped to determine the certain dynamic transition activity category. Additionally, the resultant ACC amplitude threshold was employed to determine whether the dynamic transition activity, with the pre- and post-postures from standing to lying, were falls or not.

A. Histogram Entropy-Based Static and Dynamic Active Segmentation

Before feature extraction and classification tasks, the first mission addressed here was static and dynamic active segmentation. Shannon's entropy [40] offers methods for information uncertainty measurement, based on that the information obtained from the event is related to the probability of occurrence. When static activities were acted or the muscle was relaxed, it was supposed to have the lowest negative entropy, whereas the dynamic activities have significantly higher negative entropy [37], [41]. Thereby, the histogram negative entropy [42] was employed for data segmentation. In order to avoid the occasional short-duration movement or sharp noise influence, averaged entropy values were calculated referred to (1), where N is the total length of entropy values

$$En_{\mathrm{Averaged}}(n) = \sum_{i=-2}^{2} \frac{En(n+i)}{N}, \quad 3 \le n \le N-2. \quad (1)$$

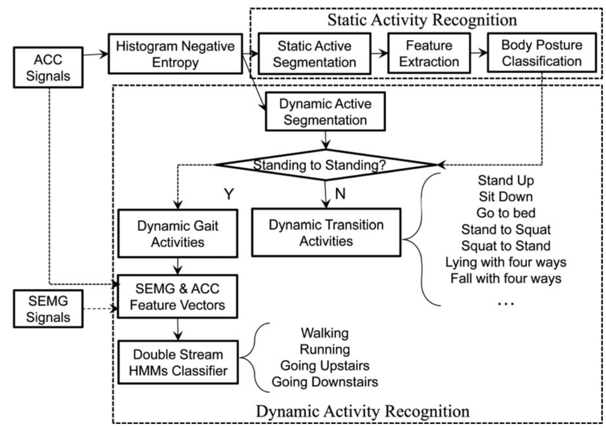

Fig. 2. Overview of the data analysis flow.

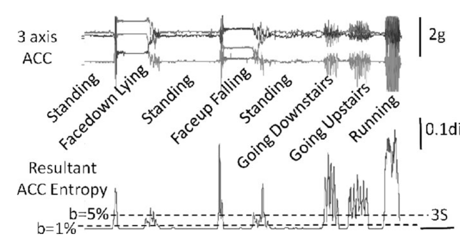

Fig. 3. Demonstration of the smoothed histogram negative entropy values of some daily activities and the two levels of thresholds.

Fig. 3 demonstrated the smoothed entropy values and two levels of onset and offset thresholds of some activities. The start point of the segment was where the entropy value was higher than the onset threshold and the following dozens of entropy values stayed higher, whereas the endpoint was where the entropy value was lower than the offset threshold and the following dozens of entropy values kept lower. In this paper, the onset threshold was equal to the offset one. Previous research [35], [36], [43] pointed out that a lower threshold dramatically increased the possibility of false active segment, whereas a higher one was likely to increase the delay of detected onset or fail to response to the active segment with relatively lower values. Considering the level of dynamic activity entropy with respect to the static activity entropy, one level of the threshold was determined as 1% increment of the maximum entropy and the minimum entropy subtraction, and the other was selected as 5% increment of the subtraction. Based on the experimental

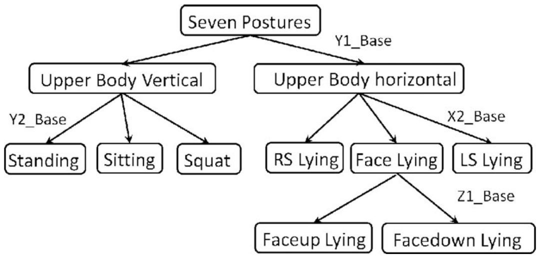

Fig. 4. Static body posture recognition based on decision-tree structure.

results, it was found from Fig. 3 that the threshold set as 1% obtained optimal segmentation performance. The data from the ith start point to the ith endpoint represented the ith dynamic active segment, whereas the $(i-1)$th endpoint to the ith start point represented the ith static active segment.

B. Body Posture Recognition

The ACCs placed both on the chest and the thigh could display different angles of various body postures, and each axial angle could be calculated from the static active segmentation according to (2), where S_{Mean} was the mean acceleration value of each axis of static active segmentation

$$s_{\mathrm{angle}} = \arccos({}^{S_{\mathrm{Mean}}}/_{g}) \times \frac{180}{\pi}, \quad S = X, Y, Z. \tag{2}$$

A decision-tree structure as Fig. 4 shows was adopted for body posture recognition. The first layer employed the y-axis angle of the ACC placed on the chest, denoted as Y1, to represent the differences between vertical and horizontal postures. The second layer included two subsets. One subset employed the y-axis angle of the ACC placed on the right thigh, marked as Y2, to distinguish standing, sitting, and squat postures, whereas the other utilized the x-axis angle of the ACC placed on the right thigh, marked as X2, to discriminate right-side lying (RS Lying), left-side lying (LS Lying), and face lying postures (both face-up and face-down lying). The last layer used the z-axis angle of either ACC, e.g., placed on the chest, marked as Z1, to classify face-up lying and face-down lying.

C. Dynamic-Trans Activity Recognition

When the pre- and the post-postures were both standing, it indicated a certain *DYNAMIC-Gait* class. Otherwise, it meant a specific *DYNAMIC-Trans* type. The *DYNAMIC-Trans* activity was recognized as a normal one or fall by the resultant ACC amplitude threshold. Traditional threshold-based fall detection led to FPs when some normal displacement daily activity happened. However, not only the resultant ACC amplitude, but also the pre- and post-postures were regarded in this study. If a large displacement *DYNAMIC-Trans* activity was detected, and the transition postures were identical to the aforementioned fall patterns [28], then a fall was detected.

D. HMMs for DYNAMIC-Gait Recognition

When the *DYNAMIC-Gait* activities were detected, both the SEMG and the ACC signals were framed by the overlapping window. Based on the optimal parameters chosen from the previous findings in [36], [39], and [43], and our pretest data, the window length was selected as 256 and the overlapping rate was 50%. As for each channel of an SEMG frame, mean absolute value and four-order LPCs (Linear Predictor Coefficients) were extracted. As for each axial ACC frame, 32 down sampling points were extracted. Afterward, the double-stream HMMs were employed for recognition.

HMMs [44], [45] are a double stochastic process composed of Markov chains and general stochastic process. The formal definition of a HMM is as follows: $\lambda = (A, B, \pi, N, M)$, where N is the number of hidden states, M is the number of possible observations of each state, A is the state transition probability matrix, B is the observation probability distribution given the state, and π is the initial state probability distribution, usually uniform at the beginning. The two-stream feature sequences were modeled as $O = \{O^E, O^A\}$, where O^E were SEMG observations and O^A were ACC observations, which were utilized to train each stream HMMs model denoted as $\lambda_c = \{\lambda_c^E, \lambda_c^A\}$, where c was the index of the gait patterns to be recognized. Baum–Welch algorithm [33] was utilized to train HMMs models. N was empirically set as 5, and each observation probability was modeled by three-component Gaussian mixture distribution [36].

For an unknown gait activity, first two stream model likelihoods for all possible gait patterns were calculated and denoted as $P(O|\lambda_c^E), P(O|\lambda_c^A) 1 \le c \le C$, where C was the total number of patterns. Then, it was recognized as the category c^* following the criterion that the sum of the likelihood of double stream models was the highest

$$c^* = \arg \max_{1 \le c \le C} (P(O^E|\lambda_c) + P(O^A|\lambda_c)). \tag{3}$$

IV. Experiments and Results

Ten healthy subjects (four females), numbered 1 to 10, with ages varying from 22 to 26 years, were voluntarily involved in experiments. Each subject had no neuromuscular or joint disease history. Totally, seven kinds of postures as well as 50 categories of dynamic activities were performed on a hard thick gymnasium mat, with dimensions 200 cm $\times$ 100 cm $\times$ 10 cm. Each subject repeated the procedure six times during different days according to their own customs, making sure that the samples of each *DYNAMIC-Trans* activity was at least 20, and the total strides of each *DYNAMIC-Gait* activity was over 60.

A. Acquired SEMG and ACC Data Analysis

A qualitative analysis of the raw data demonstrated that the SEMG and ACC data were different from each identification tasks. Fig. 5 showed raw SEMG and ACC signals of some typical activities. All the signals were different among activity patterns. SEMG signals only burst at the transition period when *DYNAMIC-Trans* activities conducted. Periodic SEMG signals appeared when *DYNAMIC-Gait* activities executed. Besides, the SEMG signals of the four gait activities were visibly different.

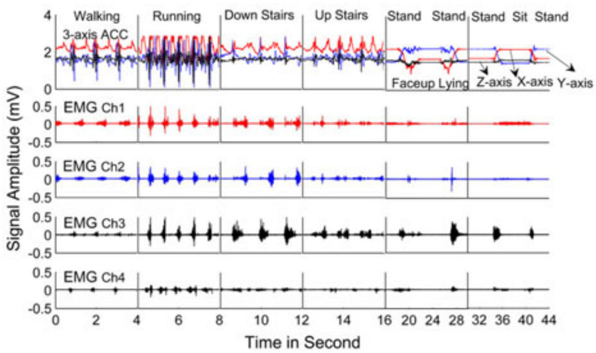

Fig. 5. Examples of raw SEMG and ACC signals. The ACC data were captured from the ACC placed on the thigh.

TABLE I
ANGLE DISTRIBUTIONS OF BODY POSTURE

	X1	Y1	Z1	X2	Y2	Z2	Uint(Degree)
ST	88(6)	14(8)	87(10)	98(3)	22(8)	106(14)	standing
SI	85(3)	8(8)	93(12)	78(8)	77(6)	16(4)	sitting
SQ	87(8)	23(5)	113(11)	75(7)	109(13)	22(5)	squat
UL	88(4)	96(6)	8(3)	71(3)	81(17)	25(4)	faceup lying
DL	87(2)	70(12)	158(10)	88(11)	89(13)	166(9)	facedown lying
LL	165(6)	78(5)	84(5)	159(2)	90(3)	68(6)	leftside lying
RL	12(2)	79(4)	89(5)	22(6)	80(2)	110(7)	rightside lying

TABLE II
RESULTS OF BODY POSTURE RECOGNITION

	ST	SI	SQ	UL	DL	LL	RL	Mean(%)	
ST	500	0	0	0	0	0	0	100.0	standing
SI	0	477	23	0	0	0	0	95.4	sitting
SQ	0	13	487	0	0	0	0	97.4	squat
UL	0	0	0	500	0	0	0	100.0	faceup lying
DL	0	0	0	0	500	0	0	100.0	facedown lying
LL	0	0	0	0	0	500	0	100.0	leftside lying
RL	0	0	0	0	0	0	500	100.0	rightside lying

B. Body Posture and DYNAMIC-Trans Recognition Results

As for the recognition of body postures and *Dynamic-Trans* activities including falls, only the ACC data were interpreted for analysis. The angles of all the body postures were calculated and the angle distributions were given in Table I in the form of Mean (Std.). By the mentioned decision-tree structured classification scheme, the threshold Y1_Base $= 50^\circ$ of the first layer was defined to separate standing, sitting, and squat from different lying postures. In the second layer, the thresholds Y2_Base1 $= 60^\circ$ and Y2_Base2 $= 95^\circ$ were determined to recognize standing, sitting, and squat. Meanwhile, X2_Base1 $=$ 50° and X2_Base2 $= 130^\circ$ were chosen for face lying and side lying postures classification. When it comes to the third layer, the threshold Z1_Base $= 100^\circ$ was selected for distinguishing face-up and face-down lying postures. The body posture recognition results based on these thresholds were displayed in Table II. The averaged recognition accuracy was about 99%, demonstrating the potential of *DYNAMIC-Trans* activities recognition based on pre- and post-postures. Only the sitting and squat postures were occasionally misclassified.

After body posture recognition, the resultant ACC amplitude threshold was employed for normal dynamic activities and falls recognition. Perry *et al*. [27] pointed out that the resultant ACC amplitudes of most daily activities are lower than 2.5 g. The similar conclusion was drawn from our experimental data, but the appropriate threshold *Th* was experimentally set as 2.0 g by using Delsys ACC sensors. Table III gave the recognition results of *DYNANIC-Trans* activities. The sensitivity 95.33% of 107 samples demonstrated excellent fall detection performance. The false negatives were mainly caused by the implement of slowly falling down by holding the wall, producing the resultant ACC amplitude lower than the threshold, which failed to trigger the alarm criterion. Meanwhile, the specificity was 97.66% of 512 samples. It was found that sometimes quickly lying to bed triggered the FPs.

TABLE III
RESULTS OF *DYNAMIC-TRAN* ACTIVITY RECOGNITION

	Normal	Falls	Sensitivity	Specificity
Normal	500 (TN)	12 (FP)	$\frac{TP}{TP+FN}$ =95.33%	$\frac{TN}{TN+FP}$ =97.66%
Falls	5 (FN)	102 (TP)		

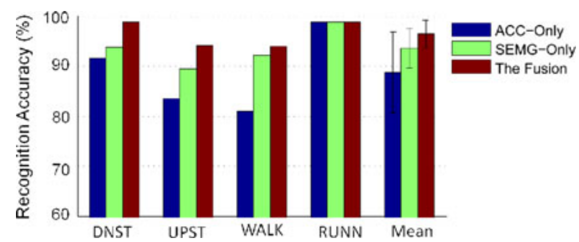

Fig. 6. Accuracies of HMMs-based activity recognition in three conditions.

C. Dynamic-Gait Pattern Recognition Results

As for the *Dynamic-Gait* activities recognition, both SEMG and ACC signals were employed. Many researchers demonstrated that the fusion of SEMG and ACC could achieve better classification performance [34], [43], [46]. For a further investigation on the superiority of the fusion strategy, the SEMG-only HMMs and ACC-only HMMs were also conducted for comparison.

In the ACC-only and SEMG-only condition, just one stream feature vectors of ACC or SEMG were extracted. Fig. 6 gave the recognition accuracies in three conditions. It was found that the recognition performance in SEMG-only condition was better than that in ACC-only condition, especially for upstairs or downstairs. Running was well distinguished in all the three conditions. Additionally, the proposed fusion strategy achieved the best classification performance, with the averaged recognition accuracy over 95%, demonstrating the feasibility of gait activity recognition based on the fusion strategy.

D. Continuous Activity Monitoring and Fall Detection

In order to evaluate the whole framework performance, the same device was employed to capture SEMG and ACC signals of one subject's daily activity execution from 8:00 A.M. to 10:00 P.M., in which all the body postures, some dynamic transition, and all the gait activities as well as some simulated falls were included. The number of related activities and the recognition rates were presented in Table IV.

TABLE IV
NUMBERS AND RECOGNITION RATES OF DAILY ACTIVITIES

	Num	Rates		Num	Rates
ST	28	100.0%	RL	9	100.0%
SI	30	98.7%	WALK	149	96.0%
SQ	4	100.0%	UPST	48	93.8%
UL	13	100.0%	DNST	48	97.9%
DL	2	100.0%	RUNN	35	100.0%
LL	6	100.0%	Falls	15	93.3%

It was found from Table IV that using the proposed method, the averaged recognition accuracy of total 387 activities was 98.3%. None of the normal dynamic activities triggered the FPs, and only one fall was missed, due to that the subject fell down with a seated-like ending posture.

V. Conclusion and Discussions

So far, the feasibility of the framework of daily activity monitoring and fall detection based on SEMG and ACC signals had been demonstrated. Compared to the related work listed in Table V, our proposed framework revealed at least three comparative merits.

1) The computational cost using pre- and post-transition postures information was lower than that of without posture information. Referring to [20], human daily activities were separated into two categories: static postures and dynamic transitions between these postures. The similar idea was used in [12]; excluding hand gestures, daily activities were sorted into three types called zero-displacement, transitional, and strong displacement activities. On the basis of the aforementioned activity category concept, our study made some combinations and extensions. The computation cost was reduced due to that only *DYNAMIC-Gait* activities were further distinguished by HMMs with posture information, whereas about 50 dynamic activities would be recognized by HMMs without posture information. The cost comparison tests of posture-based and HMM-based were executed on a PC (AMD Athlon 7750 at a 2.7-GHz CPU with a 4G RAM), using MATLAB R2009a (The Mathworks, Inc., Natick, MA). It was found that the time consumption for 50 kinds of dynamic activities recognized by HMMs was 556.80 s, and the averaged recognition percentage was only 65.03%. Inversely, with the proposed body posture scheme, the averaged time consumption decreased to 11.77 s and the averaged recognition performance improved to 90.41%.
2) The proposed combination mechanism of body postures and the resultant ACC amplitude threshold had the ability of accurately distinguishing normal dynamic transition activities and falls. Usually, one triaxial ACC sensor was employed for fall and nonfall classification tasks and received satisfactory performance [47]–[49]. However, as for accurate and concrete daily activity and fall detection, many efforts were made on applying multiple sensors and more advanced classifiers. For instance, Bao [19] demonstrated that using five biaxial ACC sensors on different parts of body, the overall recognition accuracy of 20 everyday activities reached 84%, whereas Zhu [12] employed HMMs for gait activities with 89% averaged accuracy. Besides, the appropriate sensor configuration scheme employed for daily activity and fall detection proved to be the two triaxial ACCs placed on the chest and the thigh, respectively. Bourke *et al*. [27] conducted normal activities and falls detection based on dual-thresholds algorithm using two triaxial ACCs on the chest and the thigh, resulting in 100% fall-detection accuracy and 67–100% normal daily activities classification performance, and Li *et al*. [20] achieved 91% sensitivity and 92% specificity for 18 kinds of daily activities, fall-alike motions, and falls detection based on body postures extracted from the two triaxial ACC sensors and two gyroscopes of the same placement configuration. In this paper, the same ACCs placement scheme was adopted for the recognition of body postures, *Dynamic-Trans* activities, and consequently achieved good results, with 95.33% sensitivity and 97.66% specificity, which were comparable to other single-sensor approaches, or the use of two or more ACCs, as well as the use of two ACCs accompanied with other sensors.
3) The SEMG signals are introduced to the lower limb activity awareness and fall detection. Roy *et al*. [6] adopted multiple SEMG electrodes and triaxial ACC sensors for identification and nonidentification tasks recognition, but most of the tasks were forearm related. The proposed fusion strategy in this paper achieved the averaged recognition accuracy over 95%, which demonstrated the feasibility of lower limb dynamic gait activities awareness applications based on SEMG and ACC signals. Additionally, the potential of distinguishing more kinds of postures and dynamic activities could be further investigated.

Although the proposed approach could distinguish the activities well, it might be helpless to some specific fall types, e.g., faint with a seated posture, fall from the bed while sleeping, etc. Besides, compared to the simple threshold approach, the proposed method took advantages in improving the recognition performance. However, it was at the expense of using somewhat complicated classifier. It had no influence when several activities were recognized on PC platform, but may cause burden when the proposed framework is probably conducted on an embedded system. Nevertheless, with the development of computer science technology and the integrated circuits, the operation speed and the storage capacity of the embedded system are dramatically increased, which helps the realization of the proposed approach for pervasive monitoring on embedded systems or smart cell phones. Additionally, because that the dynamic transition activities were classified depending on pre- and post-postures, there existed one situation that when someone fell without conscious, the framework will wait a long time for static active segment extraction, which would lead to a great time latency for immediate alarm. Consequently, when applied in real-time platforms, time thresholds can be added.

Furthermore, for a better aware of abnormal activities, more contexts related to physiological, behavioral, and psychological information could be considered. For instance, continuous behavior monitoring mechanism could be introduced. If the slowly

TABLE V
LIST OF SOME TYPICAL RELATED WORK

Author	Sensor Types	Activity Num	Classifiers	Body Posture	Accuracies
S. H. Roy [6]	8 SEMGs 8 tri-axis ACCs	11 identification and 10 non identifications	Neural Network	N	Above 90%
L. Bao [19]	5 bio-axis ACCs	20	Decision Tree	N	Overall 84%
Q. Li [20]	2 gyroscopes 2 tri-axis ACCs	14 daily activities and 4 falls	Rules &Threshold	Y	Sensitivity 91% Specificity 92%
C. Zhu [12]	3 inertial sensors	13 daily activities & 5 Hand gestures	Heuristic Discrimination & HMM	N	Hand gestures 92% Daily activities 89% & 98.3%
A.K. Bourke [27]	2 tri-axis ACC	8 daily activities and 8 falls	Threshold	N	Activities 67~100% Falls 100%
Jantaraprim P. [47]	1 tri-axis ACC	6 daily activities and 4 falls	Threshold	N	Falls sensitivity 96.11% Specificity 98.33%
M. R. Narayanan [49]	1 tri-axis ACC	6 categories of activities including falls	Kernel Fisher Discriminant	N	Averaged 84.6%
Our Work	2 tri-axis ACCs 4 SEMGs	46 daily activities & 4 falls	Entropy & HMM	Y	Postures >95% Gait activities >95% Sensitivity 95.33% Specificity 97.66%

"lying" posture occurred during the unnatural acts transition process, it might indicate a fall. Meanwhile, environmental context information could be taken into account. For example, when the outdoors context was detected and there happened to be a slowly "lying" posture, it probably indicated a fall. It was reported that falls are prone to happen during dynamic gait activities, thus currently we conducted research on gait activities recognition based on SEMG signals. In the future, the potential of distinguishing more kinds of postures and other dynamic activities, reflecting the muscle fatigue degree and physiological state based on EMG signals, could be investigated.

To realize the ultimate aim of pervasive monitoring of the elders and the patients, the proposed approach currently evaluated by the healthy subjects would take consideration of two influential factors. On the one hand, due to the aging of the body function and the decrease of the coordinate abilities, the movements acted by the elders were much slowly compared to the healthy young people. Besides, due to the degenerative disorder of the central nervous system, the behavior manners of patients might be slowly. Thus, the resultant ACC amplitude threshold of the system would be adjusted according to the user's customs. On the other hand, humpback usually occurred to the elders. The criterion employed for body postures recognition, especially standing and sitting postures, should be further adjusted accordingly. Additionally, tremors sometimes related to neural disorders, resulting in the acquired static active signals accompanied with trembling waveforms. Consequently, the preprocessing method for the static active segmentation would require special attentions. Furthermore, although the wired sensors was employed for current use, many commercial wireless products, which could be worn in the form of wrist- and band-like, are available, and will make the monitoring device more natural and portable.

ACKNOWLEDGMENT

The authors would like to thank Q. Wang, B. Chen, and C. Li for their assistance in the experiments and other volunteers in data acquisition.

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