# A Computing-Efficient Algorithm for Accelerometer-Based Real-Time Activity Recognition Systems

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## ABSTRACT
Considered as fundamental part of many pervasive applications, human Activity Recognition (AR) systems have recently attracted interest of the research community. One of the many challenges in developing reliable AR systems is accurate recognition of human daily physical activities while maintaining simplicity of the recognition algorithm, essential to meeting real-time functionality of AR systems as well as dealing with their processing ability constraint. In this paper, we propose a real-time computing-efficient AR algorithm for accelerometer-based AR systems. Evaluation of the proposed algorithm is conducted in a laboratory setting using a simple learning based AR system with single wearable triaxial accelerometer attached to human thigh or wrist. Simple sequential human gestures are shown to be recognized with an average recognition accuracy of 98.8% and 96% for ambulatory movements and hand gestures, respectively.

## Categories and Subject Descriptors
I.5.2 [**Pattern Recognition**]: Design Methodology – *Classifier design and evaluation.*

## General Terms
Algorithms, Performance, Design.

## Keywords
Activity Recognition Systems, Real-time and embedded systems, Pervasive Computing,

## 1. INTRODUCTION
Recent advancements in pervasive computing have introduced new potential applications of which healthcare monitoring, ambient assisted-living and rehabilitation supervision are only a few to be named. As number of the elderly prone to health complications continues to grow provision of cost-effective future-friendly healthcare solutions seems indispensable. Due to substantial benefits of indoor human Activity Recognition (AR) systems in helping the elderly complete Activities of Daily Living (ADLs) as well as easing human-robot interactions for ambient assisted living applications, extensive research has been conducted in recent years to achieve accurate real-time AR systems.

The wide range of AR systems proposed by research community can be classified as either computer vision-based or wearable sensor-based systems. Although the former is prevalent in surveillance applications, the latter is favored in health-care monitoring applications for its cost-efficiency and the ability to provide heterogeneous information such as motion, location or physiological states. In sensor-based AR systems, multiple wearable sensor nodes are used to form a self-managing wireless body area network. Sensed data is continuously transmitted to a sink node for further processing. There are however arising challenges essential to be dealt with in developing accurate reliable sensor-based AR systems.

It is often required that stream of sensor data be processed in real-time. Considering the fact that wearable sensor nodes have limited processing capabilities, it is inevitable that sensed data of multiple sensor nodes be collected and processed in the sink node through a one-path algorithm [1]. Furthermore, recognition of complex activities using conventional data-driven or knowledge-driven activity modeling either requires implementing more sensor nodes or using complex algorithms; both leading to more computations in the sink node. In addition, most of healthcare monitoring systems are based on a PDA platform with limited processing capabilities. As relatively high sampling rate is required for human AR applications, the real-time requirement causes constraints in terms of data processing time. Consequently, developing computing-efficient algorithms, while maintaining the recognition accuracy, is considered a major issue of concern.

In this paper, we propose a simple computing-efficient algorithm for accelerometer-based AR systems that not only grants proper real-time functionality of the system by significantly reducing required data processing but also proves useful in recognition of more complex activities by generating probabilistic activity models. We believe that the algorithm could well be adopted in more complex AR systems where multi-modal sensors are used.

## 2. RELATED WORKS
Wearable human activity recognition systems are well researched in recent years. Earlier non-visual AR systems concentrate on recognition of simple human postures via


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accelerometer [2], gyroscope [3] or wrist-worn RFID reader [4]. Studies have shown that combining multi-modal sensors in AR systems leads to additional improvement in recognition accuracy. [5] has improved recognition accuracy of a motion-based AR system using multiple cameras for location detection. In addition to accuracy improvement, multi-modal AR systems offer recognition of more complicated activities. [6] made possible recognition of highly complicated multi-user activities by integrating accelerometers, wrist-worn RFID readers and body-worn microphones. A major challenge in developing multi-modal AR systems, however, is the large data processing requirement. Taking into account the limited processing ability of sensor platforms as well as PDA devices usually used in pervasive AR applications, computing-efficient classification algorithms are necessary to avoid real-time delays.

Most of existing works in accelerometer-based AR systems suffice to processing raw accelerometer sensor readings. Challenges in raw data analysis rise from the inaccurate nature of activity patterns. Pattern recognition techniques are obviously not acceptable for their high computational cost. Several different approaches are thus suggested to dealing with activity patterns. [6] treats accelerometer readings as signals and extracts DC mean, variance, energy, correlation and frequency domain entropy for a fixed time interval of 1 sec. [7] used noise reduction and signal features such as mean, standard deviation, spectral entropy and correlation. For AR systems based only on accelerometers, adapting such methods may ensure recognition of simple postures. However, more complex activities are hard to distinguish for their similar signal features. Although mentioned approaches result in acceptable recognition accuracy, they mainly suffer high computational costs and real-world deployment of such algorithms is questionable.

In this study, we propose a novel data-driven discriminative activity classification algorithm for accelerometer-based AR systems. This approach enables accurate recognition of human activities from simple gestures to more complex activities, based on tri-dimensional data representation and spatial data segmentation. Since complex classifiers are avoided, our proposed method meets real-time functionality while maintaining recognition accuracy. 3D data representation has previously been suggested in [1] and [8] yet for visualization purposes only.

## 3. METHODOLOGY

We propose continuous spatial segmentation of sensor readings that will lead to personalized activity models generated based on data acquired during activity observation phase. Generated activity models will later be used to be compared with models obtained during AR phase for each fixed-size time window.

To describe the procedure, we assume a tri-axial accelerometer of fixed sampling rate attached to human wrist. A subject is requested to perform simple sequential hand gestures, each for 1 minute. Raw accelerometer sensor readings are shown in Figure 1 for (a) *walking* and (b) *waving* activities. Obviously, distinction of the two activities seems impossible without using previously discussed techniques. For AR systems based only on accelerometers, adapting such methods may ensure recognition of simple postures. However, more complex activities are hard to distinguish for their similar signal features.

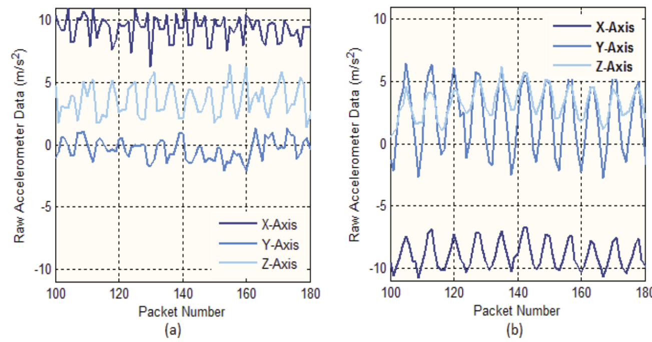


Figure 1. Raw data of a triaxial accelerometer attached to wrist during (a) walking (b) waving activity

As three data is available for each packet, we propose using tridimensional representation of raw accelerometer data for distinction of different activities. Spatial representation of the two activities shown in Figure 1 is illustrated in Figure 2.

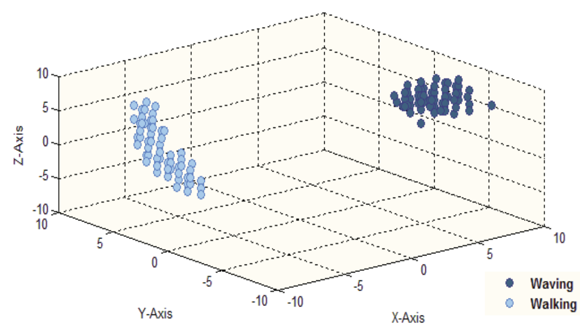


Figure 2. 3D representation of raw accelerometer data

The two activities are shown to differ completely when represented in space. Although slight signal errors may significantly change raw accelerometer signal features in Figure 1, these errors hardly change the spatial pattern of the activity. Furthermore, detection of major errors seems easier when represented in space. For modeling simplification and with no loss of recognition accuracy, we neglect the slight variance in radial distance component and assume that all data points are located on a sphere. Figure 3 represents packet data of Figure 1 plotted in terms of azimuth and elevation components.

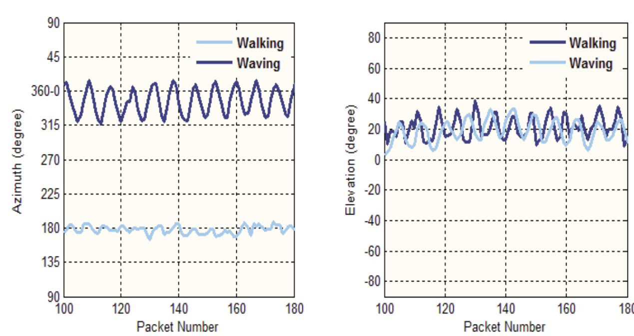


Figure 3. Number of regions in terms of number of elevation divisions

Although developing features from signals in Figure 3 is far easier, it still requires conventional signal analysis techniques. To avoid further computational complications, we propose that the imaginative *recognition sphere* be segmented into regions of approximately equal surfaces, in terms of elevation and azimuth components. Although there are many ways to divide a sphere into regions of equal surface, to avoid further computations, we propose the sphere be first divided to regions of exactly equal elevation angles and then to regions of equal azimuth angles. Different regions of approximately equal surfaces will then be easy to recognize.

The total number of regions shall be enough to make possible distinction of different activities but not so many that results in activity misrecognitions. As will be discussed in next section, based on experimental results, we believe that eight elevation divisions and thus 26 regions will lead to best recognition accuracy. Figure 4 illustrates segmentation of our proposed recognition sphere into 26 regions. The numbering procedure of the regions is downward and clockwise. Since numbering is only performed for naming the regions, the mathematical value of region numbers is of no significance and the best numbering method is the simplest.

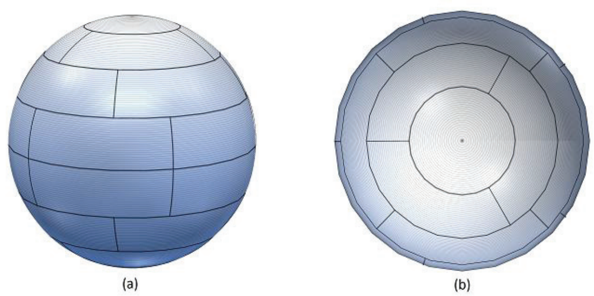


Figure 4. Proposed recognition sphere with eight elevation divisions and 26 regions (a) 3D view (b) top view

The procedure of determining the region the accelerometer data points to is so simple that could be conducted in the sensor platform. This way, due to distribution of the algorithm, computing-efficiency of the AR system is further improved. Hence, instead of transmitting the raw axial accelerometer readings, region of the recognition sphere sensor data points to, is sent in each packet.

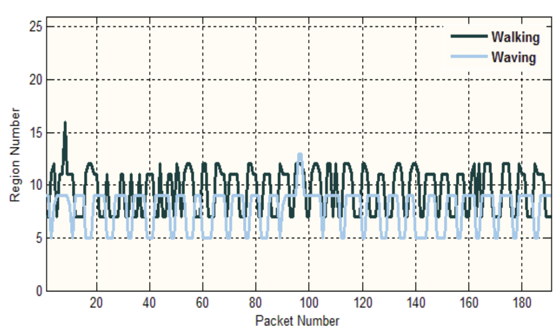


Figure 5. Regional segmentation of sensor data

Figure 5 illustrates plot of region numbers for *walking* and *waving* activities presented in Figure 1. As is seen, the regions involved during a walking activity are 7, 11 and 12. While the regions involved during a waving activity are only 5 and 9. Also, based on region numbers detecting errors is comparatively simpler than from raw accelerometer data. As both *walking* and *waving* activities are sequential, the periodic nature of the activities can also be inferred from Figure 5. Therefore, regional segmentation of accelerometer data can be said to preserve the history of conducted activities.

For recognition of ADLs, we are more interested in accurate recognition of the activity type than details of the recognized activity. In this case, a more statistical approach is required to generate accurate activity models and discriminate different observed activities. Figure 6 shows the percentage of occurrence of different regions in a fixed time window of 1 minute. Interestingly, changing the size of time window to 5 seconds changes the activity model by an average of only 8 percent.

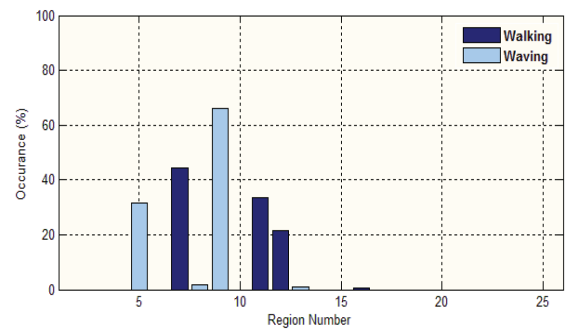


Figure 6. Distribution of accelerometer data between different regions

Since Figure 6 is almost window-size independent, it could best serve to model activities either for learning or recognition. Upon completion of each time window, the observed activity model is to be compared with already learned activity models. To compare generated *code* with activity *codes*, we used the feature of average standard deviation.

As recognition of activities is sufficed to calculating percentage of occurrence of each region and classification methods of technical complications are avoided, the proposed algorithm is claimed to be computing-efficient. Thanks to the simplicity of the algorithm as well as its distributed nature, the conventional tradeoff between real-time functionality and recognition accuracy is avoided. In addition, recognition of complex ADLs is possible by developing specific activity models.

Although the activity modeling phase of our proposed system is introduced as person-specific, experimental results show only slight decrease in recognition accuracy for scenarios in which once learned models are used for recognition of activities of other people. However, due to the limited number of observed activities in our experiment, we believe we have insufficient data to claim subject-independency of our proposed system.

## 4. EVALUATION RESULTS

To evaluate our proposed algorithm, a simple AR system consisting of a laptop computer and a single accelerometer, attached to human wrist or thigh is used. A subject is first asked to perform 10 different sequential hand gestures and 5 different ambulatory movements to be observed by the system, each for 1 minute. Ambulatory movements included *walking*, *sitting*, *standing*, *ascending* and *descending*. Observed hand gestures consist of simple hand gestures such as (1) *moving hand upward,* (2) *moving hand downward,* (3) *moving hand up and down,* (4) *waving with tight hand* and (5) *waving with loose hand* as well as a number of activities of daily living such as (6) *biking,* (7) *driving,* (8) *talking on the phone,* (9) *walking* and (10) *eating.* Activity models are then generated for each observed activity as shown in Figure 6.

To evaluate recognition accuracy, each activity is performed for a total duration of 6 minutes in a laboratory-setting and with controlled conditions. Using fixed-size time windows of 15 seconds, recognition accuracy of the AR system is evaluated. Recognition accuracy of 98.8% and 96% was achieved for ambulatory movements and hand gestures performed by one person, respectively. We have performed the recognition algorithm for different number of elevation divisions, as described in section III. Figure 7 illustrates smoothed plot of achieved recognition accuracy of the system in terms of different elevation divisions. Based on our evaluation, best recognition accuracy is achieved with eight elevation divisions.

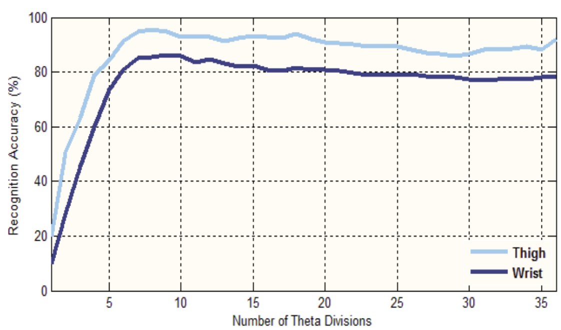


Figure 7. Smoothed plot of model efficiency in terms of different number of elevation divisions

Evaluation of the recognition accuracy based on experimental results is performed for different time window sizes. Results show that for time windows of more than 5 seconds, recognition accuracy of more than 90% is achieved. Figure 8 illustrates recognition accuracy of the system in terms of time window sizes.

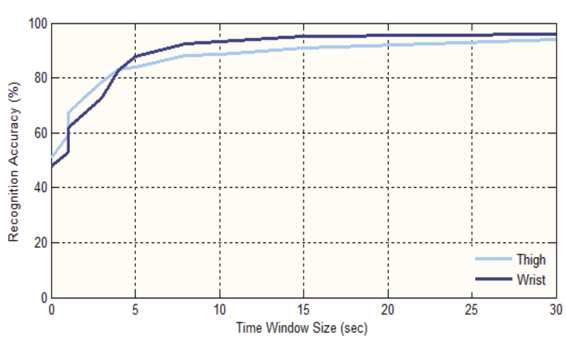


Figure 8. Recognition accuracy for different time window sizes

## 5. CONCLUSION

A novel computing-efficient discriminative algorithm is introduced for accelerometer-based activity recognition systems. Accurate recognition of Activities of Daily Living is achieved through tridimensional representation of raw accelerometer data and segmentation of elevation and azimuth components of their spherical coordinates. Computing-efficiency of the proposed algorithm is granted by avoiding use of complicated discriminative classifiers as well as distributing processes between sensor platform and the sink node. A simple AR system is introduced for experimental evaluation purposes. Evaluation of the recognition algorithm is performed in a laboratory-setting and for 10 different hand gestures and 5 types of ambulatory movements; resulting in recognition accuracy of 96% and 98.8%, respectively.

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