Real-Time, Model Based Algorithm Implementation for Human Posture Classification

Mohammed Aloqlah
Telecommunication Engineering Department
Yarmouk University
Irbid, Jordan
+962799504057
mohamads@yu.edu.jo

Rosa Lahiji
Department of Electrical Eng. and Computer Science, Case Western Reserve University
Cleveland, OH, USA
rosa.lahiji@case.edu

Mehran Mehregany
Department of Electrical Eng. and Computer Science, Case Western Reserve University
Cleveland, OH, USA
+12163680755
mehran@case.edu

ABSTRACT

A generic platform for continuously and unobtrusively monitoring human motion activity is deployed. Wirelessly transmitted data from a single three-axis accelerometer integrated into the headband is collected in real time on a laptop, and then analyzed to extract two sets of features necessary for posture/movement classification. The received acceleration signals is decomposed with discrete wavelet transform (DWT) to extract the first set of features; any change of the smoothness of the signal that reflects a transition between postures is detected at the finer DWT resolution levels. Fuzzy logic inference system (FIS) then uses the previous posture transition and the second set of features to choose one of eight different posture categories, namely sit, stand, lie on back, lie on left, lie on right, bend, walk, and run. Using the classifier in typical everyday activity among multiple users indicated more than 96.9%, 94.2%, 97.5% accuracy in detecting the static postures, walking, and running, respectively. Identifying the dynamic transitions among these steady postures achieved 92.6% accuracy.

Keywords

Real-time classification, kinematic model, discrete wavelet transform, fuzzy logic inference system

1. INTRODUCTION

Most ambulatory systems use accelerometers to sense linear accelerations and gyroscopes to sense angular velocity. Human movement is generally assessed in the laboratory or clinic environment. Although laboratory techniques can provide accurate and valuable clinical insight on human activities, the obtained results can be significantly different from those recorded in the unrestricted environment outside the laboratory [1-2]. Technological advancements in the past few decades have led to development of miniature, light weight and low cost accelerometers; hence increasing the interest in using accelerometry as a tool for assessing human ambulatory movement. Studies in which accelerometers have been applied for this purpose mostly indicated their competency for monitoring free-living subjects [3-5]. Accelerometers can provide objective as well as quantitative information about human movement, which along with their small size and relatively low cost makes them convenient tools for motion monitoring applications.

An extensive amount of research has been performed using body worn sensors for human posture classification and gait analysis [1, 6]. Today, we see even more research on human motion analysis, mainly focusing on developing wireless health systems with fully integrated, wearable, multifunctional designs [7-8]. In addition to the aforementioned developments, which are mainly developed in academia, some of the commercially-available ambulatory systems for human posture detection and gait analysis are based on accelerometers and gyroscopes embedded in a Wireless Body Area Network (WBAN), which is a particular implementation of a Personal Area Network (PAN) structure. Performance may be further improved by attaching magnetometers and other sensors, depending on the specific types of motion, as well as the data to be collected [9-10].

The process of human posture classification from accelerometer data cannot be obtained by a simple look-up-table, as the accelerometer signature for different human postures is not mutually exclusive and unique. Current state-of-the-art involves use of several of the accelerometer data features and some empirical knowledge to arrive at a decision on the posture type. If done properly, this manual procedure is reliable, however it is labor intensive and due to large amount of data it can be very inefficient. Therefore, it is important to develop an autonomous posture classification system. Some potential techniques that can be used for automatic posture classification are: (i) fixed threshold methods [11-12]; (b) pattern recognition strategies [3]; (c) neural network techniques [2,13]; and (d) fuzzy logic [14-16]. Among these methods, fuzzy logic is perhaps the best suited for the problem at hand as rationalized in [16].

In this study, the sensing unit for the headband consists of a miniature tri-axial accelerometer. This system is used to detect and distinguish between various human activities, namely, static postures (sit, stand, lie, bend) or dynamic postures (transition between static postures as well as walking, running, etc.). Internally referenced inertial sensing technology is well suited for this application, where head movements during both static and dynamic postures are to be sensed. This setting is compelling from a technical standpoint as it meets all mandatory technical specifications, including both the frequency content of

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.
BODYNETS 2011, November 07-08, Beijing, People's Republic of China
Copyright © 2012 ICST 978-1-936968-29-9
DOI 10.4108/icst.bodynets.2011.247123

active human motion and the peak resolution of the MEMS accelerometer devices.

The development of a fuzzy logic system for posture classification is described in this paper. The fuzzy logic classification algorithm is implemented using MATLAB. This implementation is suitable for modification and expansion of the designed system without increasing the effort and cost, which provides a convenient way to improve performance of the system with accumulation of more empirical and theoretical knowledge about the classification thresholds.

2. KINEMATIC MODEL

2.1 System Configuration

The three-dimensional (3D) headband system illustrated in Fig. 1 consists of a single tri-axial accelerometer worn at the forehead. Building a system based on the accelerometers alone will require developing a kinematic model to capture additional degrees of freedom beyond the three linear accelerations measured by the sensor. The acceleration data from the headband system is used to determine the orientation of the system with reference to the global system. To simplify the calculation and conversions from the individual accelerometer's coordinate system frame to the fixed navigation frame, the orientation of the accelerometers are chosen as depicted in Fig. 1, showing the layout of sensors and coordinates of the navigation frame (∑n) and the body frame (∑b).

The navigation frame, ∑n, is fixed and X_n, Y_n and Z_n axes are perpendicular to each other, where the direction of X_n is along the gravitational force. The body frame ∑b on the headband is movable and X_b, Y_b and Z_b axes are perpendicular to each other. The body frame origin is located at the midway between the left and right ears. This way, the X_b axis is aligned in opposing direction to the normal of the plane formed by the accelerometer position and the two ears location. The orientation of the headband system is represented by the three Euler angles, yaw (ψ), pitch (θ), and roll (φ), where the order of rotation is about the X_b, Z_b and Y_b axes, respectively.

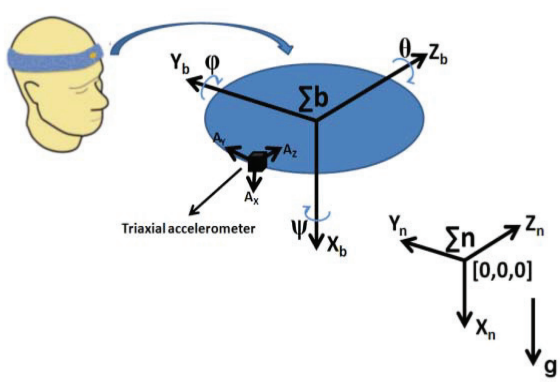

Figure 1. Coordinate systems of navigation frame (∑n) and body frame (∑b), along with sensor orientation.

2.2 System Modeling

Assume that a single-axis accelerometer is modeled by (1).

$$S_a = \vec{a}_{eq}(t).\hat{n} = (\vec{a} - \vec{g}).\hat{n} \tag{1}$$

Where S_a is the measured electrical signal, $\vec{\boldsymbol{a}}$ is the inertial acceleration of the body on which the accelerometer device is mounted, g is the gravitational acceleration constant, and $\hat{\boldsymbol{n}}$ is the unit vector in the direction of the sensitive axis.

Extending this to a tri-axial accelerometer system with sensitive axes along $\hat{\boldsymbol{a}}_x$, $\hat{\boldsymbol{a}}_y$ and $\hat{\boldsymbol{a}}_z$ given that the body frame (∑b) is aligned with the axes of the sensors:

$$S_a = \left.\begin{matrix} (\vec{a} - \vec{g}).\hat{a}_x \\ (\vec{a} - \vec{g}).\hat{a}_y \\ (\vec{a} - \vec{g}).\hat{a}_z \end{matrix}\right\} \tag{2}$$

The posture of the head can now be represented by the three Euler angles yaw (ψ), pitch (θ), and roll (φ) and their corresponding rotation matrices T_φ, T_θ, and T_ψ. Hence, the rotation matrix from the body frame to the navigation frame is defined as follows:

$$\begin{bmatrix} a_x^n \\ a_y^n \\ a_z^n \end{bmatrix} = T_j \begin{bmatrix} a_x^b \\ a_y^b \\ a_z^b \end{bmatrix} \tag{3}$$

where $\boldsymbol{a}_i^n$ and $\boldsymbol{a}_i^b$ are the acceleration with respect to the navigation frame and the body frame, respectively, as shown in Fig. 1. i= X, Y, and Z, while j in T_j's corresponds to φ, θ, ψ, respectively.

According to [17], seeking a matrix $\boldsymbol{T}_b^n$ that transforms the body frame of the head into that of the navigation frame will facilitate the calculations.

$$T_b^n = T_\phi T_\theta T_\psi$$
$$= \begin{bmatrix} \cos\phi\cos\theta & \begin{pmatrix} \cos\phi\sin\theta\cos\psi \\ +\sin\phi\sin\psi \end{pmatrix} & \begin{pmatrix} \cos\phi\sin\theta\sin\psi \\ -\sin\phi\cos\psi \end{pmatrix} \\ -\sin\theta & \cos\theta\cos\psi & \cos\theta\sin\psi \\ \sin\phi\cos\theta & \begin{pmatrix} \sin\phi\sin\theta\cos\psi \\ -\cos\phi\sin\psi \end{pmatrix} & \begin{pmatrix} \sin\phi\sin\theta\sin\psi \\ +\cos\phi\cos\psi \end{pmatrix} \end{bmatrix} \tag{4}$$

T_b^n is also known as Direction Cosine Matrix (DCM) which is used for vector transformation of the accelerations from the body frame to the navigation frame.

In the stationary position of head, one can easily determine the posture, because there is no external force applied to the system except the gravity. However, since the rotation plane of the angle ψ is perpendicular to gravity, we cannot calculate ψ from the accelerometer measurement alone. Thus, we assume ψ to be zero to solve for the static case.

Therefore the acceleration in the navigation frame ($\vec{\boldsymbol{A}}^n$) is gravity $\vec{\boldsymbol{G}}$, while the acceleration in the body frame ($\vec{\boldsymbol{A}}^b$) is the accelerometer measurement. The following equation models the stationary situation.

$$\vec{G} = T_b^n \vec{A}^b \qquad (5)$$

where $\vec{G} = [9.81 \quad 0 \quad 0]^T$ is the gravitational constant vector in the navigation frame and $\vec{A}^b = [a_x^b \quad a_y^b \quad a_z^b]^T$ is the acceleration in the body frame introduced in Fig. 1. This is the measured acceleration from the calibrated accelerometer without any transformation.

By the orthogonal property of the DCM and assuming ψ=0:

$$\begin{bmatrix} a_x^b \\ a_y^b \\ a_z^b \end{bmatrix} = \begin{bmatrix} g\cos\phi\cos\theta \\ g\cos\phi\sin\theta \\ -g\sin\phi \end{bmatrix} \qquad (6)$$

Based on equation (6), one can derive the following relations:

$$\frac{a_y^b}{a_x^b} = \frac{g\cos\phi\sin\theta}{g\cos\phi\cos\theta} = \tan\theta \qquad (7.a)$$

$$a_z^b = -g\sin\phi \qquad (7.b)$$

$$g = \sqrt{\left(a_x^b\right)^2 + \left(a_y^b\right)^2 + \left(a_z^b\right)^2} \qquad (7.c)$$

and hence the mathematical parameters for head posture modeling can be derived from acceleration data:

$$\theta = \tan^{-1}\left(\frac{a_y^b}{a_x^b}\right) \qquad (8.a)$$

$$\phi = \sin^{-1}\left(\frac{-a_z^b}{g}\right) = \tan^{-1}\left(\frac{-a_z^b}{\sqrt{\left(a_x^b\right)^2 + \left(a_y^b\right)^2}}\right) \qquad (8.b)$$

3. ALGORITHM

3.1 General System Descriptions

Herein, a fuzzy logic system is intended to infer the possible posture types based on the available orthogonal acceleration measurements by using fuzzy logic reasoning. Hence within any time frame of analysis, the acceleration measurements reflect the relative characteristics of the posture in the time window under consideration. Furthermore, the proposed algorithm requires computational capabilities which are not feasible for mobile and handheld devices.

3.2 Output of the System

By careful analysis of the acceleration data, different variety of postures can be assessed, and mainly categorized as: static postures or dynamic activities. Static posture can be classified as sitting, standing, lying on different sides, and bending. The dynamic activity can be more specifically discriminated as walking, running, and posture transition among different static postures based on acceleration amplitude and intensity.

In reality the possibilities of posture states are endless, however, in this fuzzy logic classification system the attention is only on the dominant posture types in ones daily physical activities. Therefore 14 categories have been chosen as the outputs of the classifier and are summarized in Table 1. . There can be many variations on human postures among subjects, such as difference in preferred orientation of the head, the velocity of the center of the body, and the kinematic properties of the head during different postures which may result in different acceleration signatures. Hence classification based on acceleration measurements is a challenging task. Input of the System

Utilizing the combined features of time-domain, frequency-domain and time-frequency-domain (i.e., wavelet) is a useful framework for posture classification. Therefore, to distinguish between the static/dynamic postures presented in Table 1 the parameters extracted from the time domain (i.e. mean and tilting angle) and the frequency-domain (i.e. energy) are utilized. To detect the dynamic transitions, the wavelet domain features (including the mean difference between consecutive windows, standard deviation derived from the approximated version of the signal, and signal approximation/detail at different scales using different mother wavelet functions) are used.

Table 1. output of the fuzzy classifier system

Posture Type	Classifier Output
Sit	1
Stand	2
Lie on back	3
Lie on left	4
Lie on right	5
Bend forward	6
Walking	7
Running	8
Sit-to-stand	9
Stand-to-sit	10
Lie-to-sit	11
Sit-to-lie	12
Lie-to-stand	13
Stand-to-lie	14

3.3 Data Acquisition and Feature Extraction

The linear accelerations of the head due to different static postures and dynamic activities measured in three orthogonal sensitive axes X, Y, and Z are recorded and transferred wirelessly to a laptop using the prototype system; further details are available in our previous work described in [16]. The digital signals are calibrated upon reception and are converted to ‘g’ values using equation (9).

$$\alpha = \frac{AR - v_{go}}{S} \qquad (9)$$

where A is the output of the analog to digital converter (ADC), R is the resolution of the ADC, v_{go} is the zero-g voltage, and S is the accelerometer’s sensitivity.

Data acquisition for test and evaluation of six different static postures (sitting, standing, lying on back, lying on left, lying on right, and bending forward), dynamic activities (walking and running), as well as dynamic transitions among them, are performed by a 30 years old (male) and 23 years old (female) healthy subjects. After calibrating the digital signals, different features are extracted from the raw accelerometer data using a window size of 64 samples, with 25% of window size overlapping between consecutive windows. This method allows features to be extracted from 1 second-long acceleration measurements. As mentioned earlier, for static posture identification, two sets of features are utilized: the first set (including mean, energy, and tilt angle) is used to identify the static or dynamic postures using fuzzy logic based algorithm, while the second set (including the standard deviation, mean difference between consecutive windows, and the difference between the signal approximations at Level 9 and Level 1) are used to distinguish between dynamic transitions (i.e., postures 9-14 in Table 1) using the threshold method. The second set is extracted from the approximated acceleration signals (i.e., results from the Discrete Wavelet Transform (DWT)) of the three axes of the accelerometer and are calculated in real-time using the wavelet toolbox in MATLAB.

Signal mean $\bar{a}_j$ and tilting angle (φj) are used herein to detect the head posture. The signal mean is calculated using (10a) and tilting angle is estimated by (10b). Standard deviation which is calculated based on (10c) is a clear choice for estimating the intensity of an activity. This is a measure of the effective energy or power content of the vibration signal along with the spectral features like energy.

$$\bar{a}_j = \frac{1}{n}\sum_{i=1}^{n} \left(a_j\right)_i \tag{10a}$$

$$\varphi_j = \cos^{-1}\left(\frac{a_j}{g}\right) \tag{10b}$$

$$\bar{\sigma}_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left(a_j\right)_i - \bar{a}_j\right)^2} \tag{10c}$$

In these equations, ‘n’ is the sampled window length and ‘j’ corresponds to either of X, Y, or Z axes, respectively.

Signal energy (Ej) is derived by obtaining the Fast Fourier Transform (FFT) of the accelerometer measurements as presented in (11). FFT is applied on the same 64 sample windows that are used to extract other features for each axis. Once the FFT is obtained, signal energy is calculated by summing the discrete FFT component magnitudes and dividing the sum by the sampled window length ‘n’ for normalization;

$$E_j = \frac{\sum_{i=1}^{n}\left|A_{j_i}\right|^2}{2} \tag{11}$$

where A_{j_i} is the ith FFT component of the acceleration sampled window, while j corresponds to X, Y, and Z axes, respectively.

For better clarity, the aforementioned time domain features are extracted and displayed in Fig. 2 from the raw acceleration measurement data.

3.4 Architecture of Human Posture Classifier

The 3-axis accelerometer is first calibrated in the sitting mode; all other postures are referenced to this state. Figure 3 shows the measurement flow from the acquired acceleration signals in the X, Y and Z directions. The data is captured in a time window of 64 samples and calibrated to remove the DC offset. The two sets of previously defined features are then calculated. A dynamic posture transition is detected using the second set of features. For example, if a posture transition has been detected, the sampling process continues until the acceleration signal settles and the posture transition is completed. The second set of features of the resultant sample window is extracted and used to identify the type of posture transition. If no posture transition is detected, then according to either the initial or previous condition, the relevant static/dynamic posture is identified using the fuzzy logic inference system.

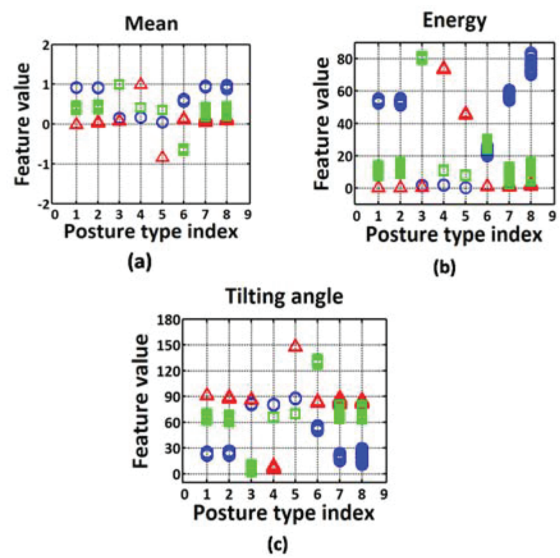

Figure 2. The extracted feature values using time sample window of length 64 from X (blue), Y(red), and Z(green) for the static/dynamic postures listed in Table 1: (a) mean; (b) energy; and (c) tilting angle.

The core of the classification procedure is the fuzzy logic inference system (FIS; classifier II depicted in Fig. 3). First, the 9 extracted features (mean, energy, and tilt angle for each acceleration axis, i.e., X, Y, Z) are fuzzified by using membership functions (µs). Several functional forms can provide adequate representation of membership functions, such as triangle, trapezoidal, Gaussian shapes, S and Z curves, and beta functions. In human posture classification problem, we expect that most membership functions have a wide flat region with maximum value equal to 1. One posture type such as lying can have a wide range of mean acceleration in the Y direction. In other words, there is no single value of mean acceleration for lying, but rather a preferred region, such as -1.2 to -0.8 m/s2. The best MBF to represent this is a function that is flat over the preferred region and tapers off outside this range. The beta function has these desired characteristics; therefore, this form of the membership functions is chosen. The robustness of the static posture classifier is guaranteed by the long tail of the beta function [16].

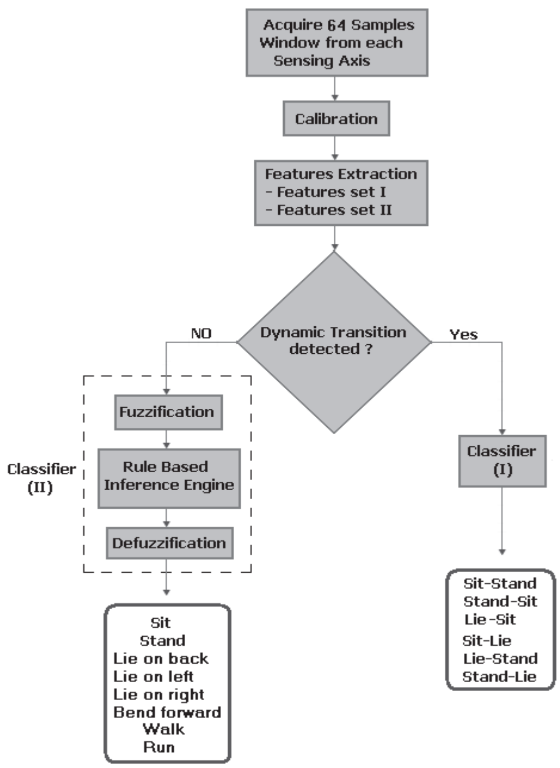

Figure 3. The architecture of static/dynamic human posture classification model.

Once the acceleration features are selected and extracted, two threshold levels (namely τ_1 and τ_2) are used to describe the membership function for each feature related to the first eighth posture types defined in Table 1. A good approach to extract τ1 and τ2 of the source feature is by variable thresholding using mean (μ_F) and standard deviation of the feature values (σ_F) as described in (12) [18].

$$\begin{aligned} \tau_1 &= \mu_F - 3 \times \sigma_F \\ \tau_2 &= \mu_F + 3 \times \sigma_F \end{aligned} \tag{12}$$

The extracted thresholds of these features related to basic static postures are tabulated in Table 2.

The three corresponding parameters of the beta function, namely m, a, and b (see Fig. 4) for $\bar{a}_x$ related to the static/dynamic postures are listed in Table 3. The center of the function 'm', the half-width at inflection point 'a', and the slope of the curve 'b' are extracted. The width of the beta function is determined from 50 percent amplitude points. The slope of the curve 'b' is derived by selecting the threshold levels τ1 and τ2 to be 95 percent of the maximum beta function amplitude, and finally, 'm' is simply calculated as $\frac{\tau_1 + \tau_2}{2}$.

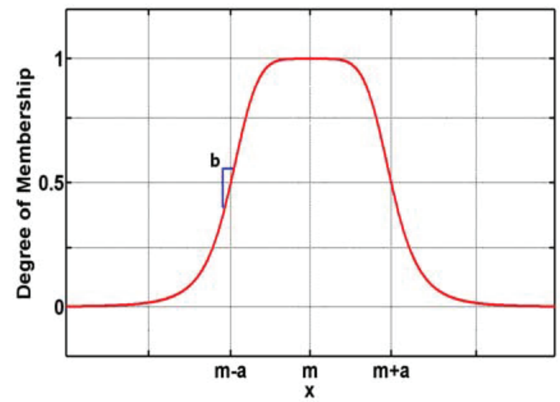

Figure 4. Beta membership function.

There are 8 membership functions (one for each static/dynamic posture type) related to each of the 9 input variables in the FIS. After fuzzification, the IF–THEN rule inference is carried out based on the rule base for the classification system. To consider the effect of all the rules, rule aggregation is applied. The last step is defuzzification, which converts the aggregated result to a single posture type.

Table 2. Calculated thresholds of acceleration-based feature values for different static human postures

Posture Type		$\bar{a}_x$	$\bar{a}_y$	$\bar{a}_z$
Sit	τ_1	0.91	-0.03	0.31
	τ_2	0.93	-0.01	0.44
Stand	τ_1	0.89	-0.00	0.33
	τ_2	0.94	0.05	0.52
Lie on back	τ_1	0.13	0.05	0.98
	τ_2	0.17	0.06	1.00

Table 3. Membership functions parameters ($\bar{a}_x$)

Static/dynamic posture type	m	a	b
Sit	0.92	0.03	2.07
Stand	0.92	0.04	3.77
Lie on back	0.15	0.04	2.95
Lie on left	0.17	0.03	2.35
Lie on right	0.05	0.03	2.32
Bend forward	0.59	0.09	8.74
Walk	0.98	0.05	4.65
Run	0.93	0.11	11.51

4. EXPERIMENTAL RESULTS

Head acceleration measurements due to different static and dynamic postures (Table 1) were recorded at a sampling frequency 64 Hz from 4 healthy subjects (one female and three males) with age ranges 22-30 years old. The volunteers were asked to naturally perform a series of activities without any specific constraints on the speed or the order of activities.

The raw data received in real- time from tri-axial accelerometer worn on the forehead are processed using the classification algorithm. The time stamp of each activity performed by the subject is manually reported by the observer. This method allows a comparison between the classifier output and the actual performed posture/activity (i.e., to evaluate classification performance) and was averaged to obtain overall classification accuracy as illustrated in Table 4.

The data recorded from one of the subjects is used to enhance the algorithm and self-train the classifier, after which the overall performance was re-evaluated by other subjects.

Table 4 presents the classification accuracies of detecting different types of static/dynamic human postures and activities; showing lower accuracy in detecting overall posture transition compared with the steady postures. Two main reasons affect this result: (i) people can perform posture transition faster or slower depending on their movement manners; and (ii) the classification algorithm is based on a threshold in the signal from the difference between wavelet approximation at level 9 and level 1. It can be noted that sit and stand was classified with the lowest accuracies, 91.4% for sit and 93.2% for stand. This could also be due to the similarity in the direction of acceleration during these two postures and/or also due to misclassification of possible dynamic posture transitions between sit and stand. However, different lying states and bend postures were classified with the highest accuracies due to significant differences in DC components of the acceleration signal related to these postures. Moreover, Table 4 shows about 6% error in classifying walk because subjects naturally have their own style of walking, leading again to large variance within the performance of this movement.

Table 4. Average classification accuracy of different static/dynamic human postures

Posture type	Classification accuracy (%)
Sit	91.4
Stand	93.2
Lie on back	99.6
Lie on left	99.2
Lie on right	98.6
Bend	99.4
Walk	94.2
Run	97.6
Dynamic posture transition	92.6

5. CONCLUSION

A novel fuzzy logic classification algorithm based only on raw accelerometer data and with high classification rate is developed for real-time assessment of human postures and ambulatory movements. In this work accelerometer data is analyzed and specific features are extracted from it to facilitate the classification process. The performance is validated by close comparison between the recorded activities by an observer and the classifier output. This unique algorithm is strong and yet easy to expand by integrating additional static/dynamic postures into the classifier to enhance the performance for certain applications.

6. REFERENCES

[1] Bao, L. and Intille, S.S., 2004. Activity recognition from user-annotated acceleration data. In proceedings of the 2nd International Conference on Pervasive Computing and Communications, 1-17.

[2] Kiani, K., Snijders, C.J. and Gelsema, E.S., 1997. Computerized analysis of daily life motor activity for ambulatory monitoring. Technology and Health Care, 5(4):307-318.

[3] Veltink, P.H., Bussmann, H.B. et al., 1996. Detection of static and dynamic activities using uniaxial accelerometers. IEEE Transactions on Rehabilitation Engineering, 4(4):375—385.

[4] Bouten, C.V., Koekkoek, K.T., Verduin, M., Kodde, R. and Janssen, J.D., 1997. A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity. IEEE Transactions on Biomedical Engineering, 44(3):136—147.

[5] Aminian, K., Robert, P., Buchser, E.E., Rutschmann, B., Hayoz, D. and Depairon, M., 1999. Physical activity monitoring based on accelerometry: validation and comparison with video observation. Medical and Biological Engineering and Computing, 37(3):304—308.

[6] Najafi, B., Aminian, K., Paraschiv-Ionescu, A., Loew, F., Bula, C. J. and Robert, P., 2003. Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly. IEEE Transactions on Biomedical Engineering, 50(6):711-723.

[7] Wu, W., Au, L., Jordan, B., Stathopoulos, T., Batalin, M., Kaiser, W., Vahdatpour, A., Sarrafzadeh, M., Fang, M., and Chodosh, J., 2008. The smart-cane system: an assistive device for geriatrics. Third International Conference on Body Area Networks (BodyNets 2008), 13-17.

[8] Jovanov, E., Milenkovic, A., Otto, C. et. al., 2005. A wireless body area network of intelligent motion sensors for computer assisted physical rehabilitation. Journal of NeuroEngineering and Rehabilitation, 2(6).

[9] Xsens MVN—Wireless inertial motion capture system: www.xsens.com, 2010.

[10] WirelessInertiaCube3: www.intersense.com, 2010.

[11] Fahrenberg, J., Foerster, F., Smeja, M. and Müller, W., 1997. Assessment of posture and motion by multichannel piezoresistive accelerometer recordings. Psychophysiology, 34(5):607—612.

[12] Foerster F., Smeja, M. and Fahrenberg, J., 1999. Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring. Computers in Human Behaviour, 15:571–583.

[13] Aminian, K., Robert, P., Jequier, E. and Schutz, Y., 1995. Incline, speed, and distance assessment during unconstrained walking. Medicine and Science in Sports and Exercise, 27:226–23.

[14] Winters, J.M., Wang, Y. and Winters, Y., 2003. Wearable sensors and telerehabilitation. IEEE Engineering in Medicine and Biology Magazine, 22(3):56-65.

[15] Jin, G.H., Lee, S.B. and Lee T.S., 2008. Context awareness of human motion states using accelerometer. Journal of Medical Systems, 32(2):93-100.

[16] Aloqlah, M., Lahiji, R., Loparo, K. and Mehregany, M., 2010. A headband for classifying human postures. IEEE Engineering in Medicine and Biology conference, 382-385.

[17] Craig, J.J., "Introduction to Robotics Mechanics and Control." 3rd ed. 2004: Prentice Hall.

[18] Ritter, G.X. and Wilson, J. N., "Handbook of Computer Vision Algorithms in Image Algebra." 2001: CRC Press.