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ORIGINAL ARTICLE

A Wrist Worn Acceleration Based Human Motion Analysis and Classification for Ambient Smart Home System

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Abstract

In recent years, health-care industry has received a major boost due to sensors i.e., accelerometers, magnetometers etc., which allow its user to get instant updates about their current health status in indoor/outdoor environments. The real driving force behind the usage of accelerometer has been the fitness industry but it also holds a prominent place in ambient smart home to monitor resident's life-style. In this paper, we proposed a novel triaxial accelerometer-based human motion detection and recognition system using multiple features and random forest. Triaxial signals have been statistically processed to produce worthy features like variance, positive and negative peaks, and signal magnitude features. The proposed model was evaluated over HMP recognition data sets and achieved satisfactory recognition accuracy of 85.17%. The proposed system is directly applicable to any elderly/children health monitoring system, 3D animated games/movies and examining the indoor behaviors of people at home, malls and offices.

Keywords Body sensors · Human motion detection · Regression trees · Smart home

1 Introduction

Tracking Indoor environments equipped with smart sensors and gadgets have allowed us to capture human motion for the better development of health-care systems [1]. In a smart home environment [2], detection of human motion has become easy, especially due to the abundance and ubiquity of sensors in gadgets and smart phones that allow real time data from such sensors [3]. While, the usage of such data for the recognition of an activity is still a research area requiring work to be done. Monitoring for indoor environment holds a key importance for kids, elderly and patients [4] with disorders related to movement i.e. epilepsy and unsaved movements.

In order to address the monitoring issues, a variety of sensor classes have been used that involve vision sensors, motion sensors etc. [5, 6]. Vision sensors provide good results when the subject motion is limited and background is separable from foreground [7]. On the other hand, motion sensors allow capturing motion irrespective of the environment being used in. Internet of Things (IoT) has made major advancements and secured homes to ensure the quality of life [8]. With smart technologies and sensors [9], the traditional way of medication is now getting changed by employing sensors and gadgets; that are bringing ease in elderly monitoring system at homes or the outdoors [10].

In this field, researchers have put forward different models to enhance the resident's care in indoor/outdoor environments [11]. Nam et al. [12] captured human motion data with wrist worn sensors including a tri-axial accelerometer, to make a recommender system for balanced exertion and intake. Thanh et al. [13] proposed a system to detect unintentional fall for elderly by analyzing the subject velocity before and after the abrupt change along with comparison of thresholds for the sudden acceleration produced by accelerometer. Moussa [14] used depth sensor for study the body skeletal structure while performing an activity. But here the subject movement was restricted due to cameras involved in setup. Yoon et al. [15], used acceleration signals from

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accelerometers and gyro-meters to identify the axial movement of human chest. Their research focused on identification of human respiration rate in real time for both indoor and outdoor exercises. Based on overall conclusion, body-attached sensors are preferred to be more accurate because they are specifically designed to produce body data. Another important aspect of body-attached sensors is that they remain intact with respect to calibrated position unlike smartphone where position/orientation gets changed with the subject's motions. Therefore, our research is mainly focused on body-attached sensors.

In this paper, we proposed statistical feature extraction techniques to better detect human activities with respect to complex motions. The three pillars of the proposed model involve preprocessing of accelerometer's signal, statistical feature extraction and random forest-based feature classification. In pre-processing stage; signals are prone to noise by considering 5th order Butter-worth filter with a cutoff frequency of 0.3. Extracted features are then fed to the random forest classifier to pick optimal features; so that the classification can be carried out with maximum recognition accuracy of different activities.

The remaining parts of this paper are organized as follows: Sect. 2 provides the overall architecture of proposed system which includes noise reduction, feature extraction and classification method. In Sect. 3, we present the experimental results, dataset descriptions and the classifier's output. Finally, Sect. 4 presents the conclusion.

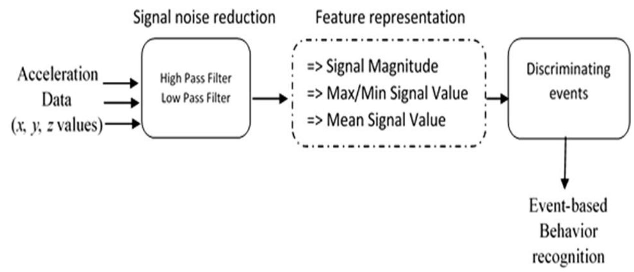

Fig. 1 Block diagram for the proposed AR model

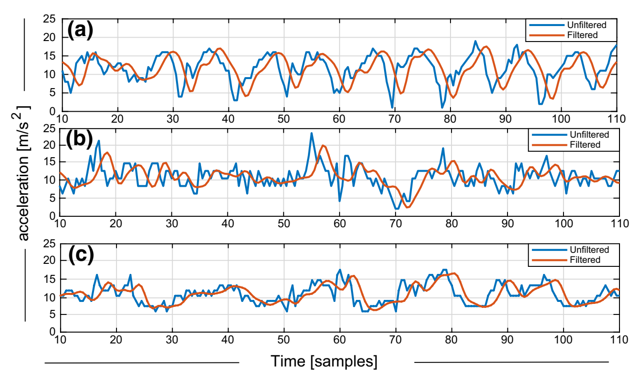

Fig. 2 Triaxial (x, y, z) accelerometer signal of walking activity having **a** x signal component **b** y signal component, and **c** z signal component, respectively

2 System Design

2.1 Proposed System Architecture

The proposition presented in this paper starts with preprocessing that involves 5th order low pass Butter worth filter with a cut off frequency of 0.3. In order to maximize the accuracy of the model, the signal needs to be brought to a shape where features and noise don't get intermixed. After pre-processing; the next step involves the feature extraction techniques such as magnitude, variance, mean, min, and max. Then, the classifier is fed into these feature vectors to find the clear discrimination boundaries [16] among the activity classes (see Fig. 1).

2.2 Calibration of Triaxial Accelerometer Sensor

As an accelerometer produces raw signals, so before the accelerometer could be used for experimentation, it is needed to be calibrated. A reference position needs to be made in order to calculate the changes in acceleration [17]. Due to observer's movement, the accelerometer signals are compared against the reference points to get respective signals coordinates as:

$$(x_{cal}, y_{cal}, z_{cal}) = g, \tag{1}$$

where x_{cal}, y_{cal}, z_{cal} represent the calibrated values of three coordinates and g is for gravitational acceleration. Then, for any change in the orientation of observer or sensor, we can calculate it by taking difference from calibrated position as:

$$(x, y, z) = (x_{new}, y_{new}, z_{new}) - (x_{cal}, y_{cal}, z_{cal}) \tag{2}$$

where x, y, z represent values with respect to new position. Here, x_{cal}, y_{cal}, z_{cal} represent the calibrated signal values and the x_{new}, y_{new}, z_{new} are new coordinate points due to various motions.

2.3 Data Processing and Noise Reduction

Accelerometer is very sensitive to small amount of changes in orientation, which causes small peaks in the signals. In order to cope with such peaks, a 5th order low pass Butter-worth filter with normalized cut off frequency of 0.3 has been applied to all 3 coordinate signals as shown in Fig. 2.

2.4 Feature Extraction

This section is focused on transformation of raw accelerometer data into meaningful features. For this, statistical features like signal magnitude, mean, peaks and variance have been extracted.

2.4.1 Magnitude Signal Feature

Magnitude of a signal which is a combination of 3 axis components extracted from accelerometer is defined as:

$$Mag(Sig) = \sqrt{(x_k^2 + y_k^2 + z_k^2)}, \tag{3}$$

where k is the measure of data points in a signal and x, y, z are the signal components. These 3 axis signal components can be seen in Fig. 3.

Magnitude feature calculates [18] the acceleration as a sum of the signal coordinates [19] involved in the system i.e. x, y, z. The magnitude feature is depicted in Fig. 4.

2.4.2 Min Signal Feature

In min signal feature, the troughs of the signal represent the minimum feature value. To be sure that the minimum value is not a sudden peak due to noise, the signals have been processed using filtering algorithm [20] to get actual feature contents. Such values are usually the outcomes of abrupt movements i.e., falling, jumping etc. which is formulated as:

$$\min(Sig) = \min(a_0 \cdots a_n). \tag{4}$$

Equation (4) shows the extraction of min feature from the acceleration signal, and a is used to represent the acceleration in range of *0–n* and *Sig* shows the signal under processing.

The negative peaks in brush teeth activity can be seen in Fig. 5 taken after every 100th sample. This feature has

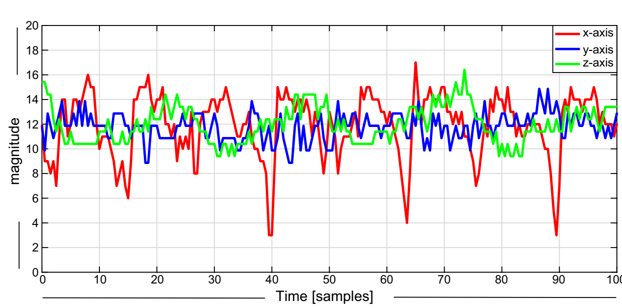

Fig. 3 Tri-axial components for climbing stairs activity

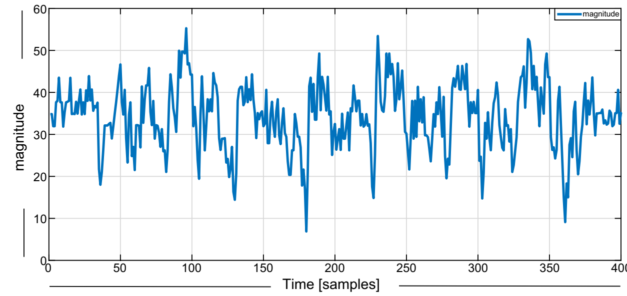

Fig. 4 Magnitude vector for climbing stairs activity

been extracted for x, y, z and magnitude components for each activity. The peak features i.e., min, max etc., contribute enormously in drawing classes away in classification plane, creating a boundary between activities [21, 22].

2.4.3 Variance Feature

Variance features are prominent to describe dispersion around the mean. The signals generated by accelerometer are never uniform in amplitude; this is because accelerometers are very sensitive to even very small amount of change and defined as:

$$\mathrm{var}(sig) = \sum_{\mathrm{i=1}}^{\mathrm{n}} (X_i - \overline{X})^2. \tag{5}$$

Equation (5) shows how the variance is calculated for each signal component. Variance is calculated for x, y, z and magnitude acceleration components.

The variance of the magnitude signal can be seen in Fig. 6. The mean is represented with red line and variance can be seen as vertical bars directed away from mean.

2.5 Classification Among Different Motions

After pre-processing and feature extraction steps, the classification is the most important step which mainly relevant to

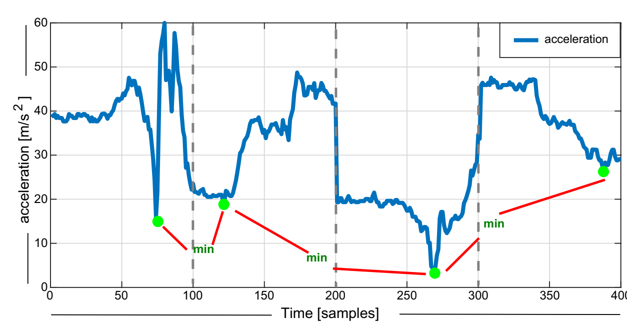

Fig. 5 Min signal feature applied over brush teeth activity sequence

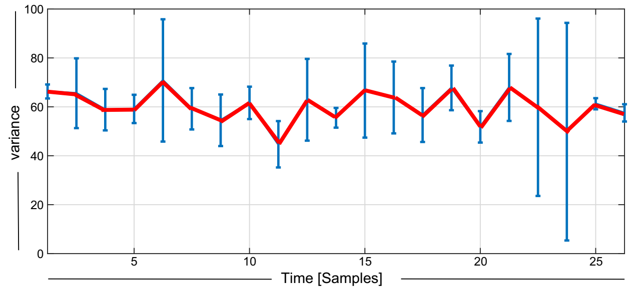

Fig. 6 Variance (blue) along with mean (in red)

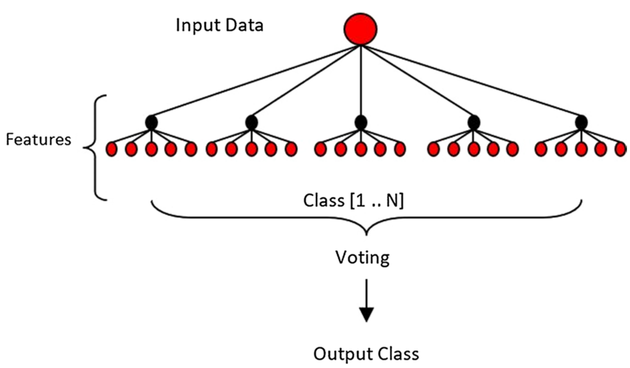

Fig. 7 Proposed feature vectors are applied over random forest

its previous steps to enhance performance accuracy [23]. As the processed classes are known, therefore, we employed one of the supervised learning techniques called the random forest [24]. For forest generation, we used the Bootstrap aggregation [25] to somehow compensate for the high variance due to the nature of data under process or due to classifier [26] itself as shown in Fig. 7.

In order to predict the desired output class, bootstrap aggregation is operated in random forest for the prediction of closest regression tree [27]. These regression trees are made to fit the training data by randomly sampling [28, 29] their replacement.

3 Experimental Results

Following subsections will explain the dataset description, experimentation, results and comparison with state-of-the-art models.

3.1 Dataset Description

HMP dataset [30] contains data taken from triaxial accelerometer sensor. The captured data involves 14 different motion primitives i.e. brush teeth (BT), comb hairs (CH), drink glass (DG), pour water (PW), eat soup (ES), eat meat (EM), climb stairs (CS), descend stairs (DS), walk (WK), get up bed (GB), lie down bed (LB), standup chair (SU), sit down chair (SD) and use telephone (UT). For the experimentation, the 16 volunteers are contributed having ages range between 19 and 81. The sensitivity of accelerometer lied between + 1.5 to − 1.5 g.

3.2 Experimental Evaluation of HMP Recognition Dataset

For the experiment, activities have been split into two sets; static and dynamic based on their movements. Static activities comprise of brush teeth, comb hair, drink glass, pour water, eat soup and eat meat. These activities do not require whole body movements such as brushing teeth or combing hair does not require any feet movement during stationary status. Table 1 shows the random forest results applied solely on static activities only. The accuracy achieved by static activities is 92.16% due to less inter activity familiarity.

Likewise, dynamic activities deal with complex and critical movements. Table 2 presents the confused and correctly classified feature sets in the form of confusion matrix. The *lie down bed* can be seen as highly confused with *sit down chair,* because of correlation of these activities in terms of axial information from accelerometer.

Finally, we applied classifier both on the static and on the dynamic activities together to get an aggregate recognition result as shown in Table 3. It is observed that few static

Table 1 Confusion matrix of six different static activities on the HMP dataset

Static activities	BT	CH	DG	EM	ES	PW
BT	**85**			1		14
CH	5	**90**	5			
DG	2		**96**			2
EM				**86**		14
ES				1	**99**	
PW		1	2			**97**
Mean recognition = **92.16%**						

Table 2 Confusion matrix of eight different dynamic activities on the HMP dataset

Dynamic activities	CS	DS	GB	LB	SD	SU	UT	WK
CS	**74**	7	4	1		7	1	6
DS	14	**79**						7
GB	1		**82**	2	3	12		
LB	1	2	5	**65**	25			2
SD				4	**94**	1		1
SU	1	1	12		3	**82**		1
UT			11				**89**	
WK	14	3	2	1	3	2		**75**
Mean recognition = **80.0%**								

Table 3 Overall classification results by applying random forests on static and dynamic activities together

Activity	Accuracy (%)	Activity	Accuracy (%)	Activity	Accuracy (%)
BT	97.5	CH	88	DG	91.23
PW	70	ES	98.66	EM	97
CS	84.41	DS	69	WK	95.81
GB	89.15	LB	70	SU	93.52
SD	91.16	UT	57		
Mean recognition = **85.17%**					

activities such as *Pour water* (PW) and *comb hair* (CH) reduced recognition accuracy.

To observe training/testing routines, computational time comparison between activities are examined by extracting the statistical features from the signal coordinates. Figure 8 demonstrates the time taken (in s) to process each set of activity during experimentation.

Table 4 shows the comparison between our proposed method and other state-of-the-art methods using HMP recognition dataset.

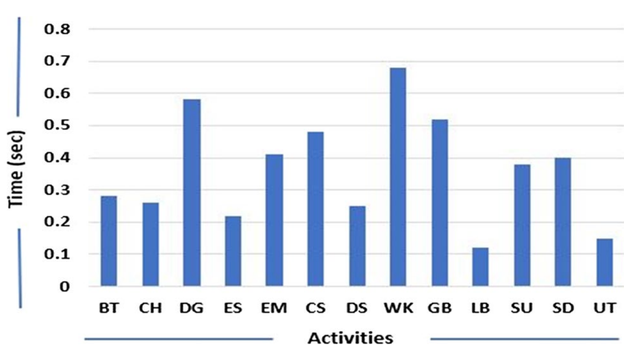

Fig. 8 Histograms of measurements for computational time during HMP dataset

4 Conclusion

In this paper, we proposed a recognition model for a smart home environment to detect indoor home activities. The proposed model includes analytical and statistical methodologies for the processing and feature extraction phases. In terms of accuracy, proposed model produces better results for some activities as compared to state-of-the-art systems. In the future, we will bring more improvement to our features extraction methodologies. For the analysis of signal patterns, we will employ Gaussian mixture model (GMM). We are also planning to develop our own dataset using accelerometers.

Table 4 Comparison between the proposed method and other state-of-the-art methods using HMP dataset

	DG	CS	GB	PW	SD	WK
KNN [32]	82.15	75	64.29	73.17	66.67	78.57
CRC-RLS [32]	97	71.6	30	10	76.67	78.33
Bruno's model [31]	100	20	60	100	0	40
Proposed	91.23	84.41	89.15	70	91.16	95.81

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References

1. Saghafi B, Rajan D, Li W (2016) Efficient 2D viewpoint combination for human action recognition. Proc Pattern Anal Appl 19(2):563–577
2. Keceli A, Can A (2014) A multimodal approach for recognizing human actions using depth information. Proceedings of IEEE Conf. Pattern recognition workshops, pp 421–426
3. Kazama T (2018) Thermohydrodynamic lubrication model of a slipper in swashplate type axial piston machines-validation through experimental data. Int J Hydromechatron 1(3):259–271
4. Kamal S, Jalal A, Kim D (2016) Depth images-based human detection, tracking and activity recognition using spatiotemporal features and modified HMM. JEET 11:1921–1926
5. Lin X (2017) Magnetic orientation system based on magnetometer, accelerometer and gyroscope. CAAI Trans Intell Technol. https://doi.org/10.1049/trit.2017.0024
6. Mahmood M, Jalal A, Evans HA (2018) Facial expression recognition in image sequences using 1D transform and gabor wavelet transform. IEEE conf. on Applied and Engi. Mathematics, pp 21–26
7. Jalal A, Kamal S, Kim D (2014) A depth video sensor-based life-logging human activity recognition system for elderly care in smart indoor environments. Sensors 14(7):11735–11759
8. Jalal A, Kim JT, Kim TS (2012) Development of a life logging system via depth imaging-based human activity recognition for smart homes. Proc Inter Symp SHB, pp 91–95
9. Jalal A, Kamal S, Kim D (2015) Depth silhouettes context: a new robust feature for human tracking and activity recognition based on embedded HMMs. Proceedings of URAI, Korea, pp 294–299
10. Stetsyuk V, Kiong JCC (2018) Reynolds stress statistics in the near nozzle region of coaxial swirling jets. Int J Hydromechatron 1(3):332–349
11. Kim Y-N, Park J-H, Kim M-H (2018) Spatio-temporal analysis of trajectory for pedestrian activity recognition. JEET 13(2):961–968
12. Nam Y, Kim Y (2015) Individualized exercise and diet recommendations: an expert system for monitoring physical activity and lifestyle interventions in obesity. JEET 10(6):2434–2441
13. Thanh VP, Tran DT, Nguyen DC, Anh ND, Dinh DN, El-Rabaie S, Sandrasegaran K (2018) Development of a real-time, simple and high-accuracy fall detection system for elderly using 3-DOF accelerometers. Arab J Sci Eng 44:1–14
14. Moussa MM, Hemayed EE, El Nemr HA, Fayek MB (2018) Human action recognition utilizing variations in skeleton dimensions. Arab J Sci Eng 43(2):597–610
15. Yoon J-W, Noh Y-S, Kwon Y-S, Park S-B, Kim W-K, Yoon H-R (2014) Improvement of dynamic respiration monitoring through sensor fusion of accelerometer and gyro-sensor. JEET 9(1):334–343
16. Jalal A, Shahzad A (2007) Multiple facial feature detection using vertex-modeling structure. Proc ICL, pp 1–7
17. Zhao X (2017) Second order differential evolution algorithm. CAAI Trans Intell Technol 1:1. https://doi.org/10.1049/trit.2017.0006
18. Jalal A, Kim Y, Kamal S, Farooq A, Kim D (2015) Human daily activity recognition with joints plus body features representation using kinect sensor. Proceedings of ICIEV, Japan, pp 1–6
19. Jalal A, Kamal S, Kim D, Kim D (2015) Shape and motion features approach for activity tracking and recognition from Kinect video camera. Proceedings of WAINA Conference, Korea, pp 445–450
20. Johnson JL (2018) Design of experiments and progressively sequenced regression are combined to achieve minimum data sample size. Int J Hydromechatron 1(3):308–331
21. Jalal A, Kim S (2005) A complexity removal in the floating point and rate control phenomenon. Proc. of KMS, pp 48–51
22. Jalal A, Kamal S, Kim D (2016) Human depth sensors-based activity recognition using spatiotemporal features and hidden markov model for smart environments. JCNC 2016:1–11
23. Jalal A, Kamal S, Kim D (2015) Individual detection-tracking-recognition using depth activity images. Proc. of URAI, pp 450–455
24. Wei Z, Lee D, Nelson B, Archibald J (2008) Real-time accurate optical flow-based motion sensor. Proceedings of the IEEE Conference on PR
25. Jalal A, Kim S, Yun B (2005) Assembled algorithm in the real-time H.263 codec for advanced performance. Proc. of Healthcom, pp 295–298
26. Jalal A, Lee S, Kim J, Kim T (2012) Human activity recognition via the features of labeled depth body parts. Proceedings of ICOST, Italy, pp 246–249
27. Scornet E (2016) Random forests and Kernal methods. IEEE Trans Inf Theory 62(3):1485–1500
28. Jalal A, Mahmood M (2019) Students' behavior mining in e-learning environment using cognitive processes with information technologies, education and information technologies. Springer, New York
29. Jalal A, Kim Y-H, Kim Y-J, Kamal S, Kim D (2017) Robust human activity recognition from depth video using spatiotemporal multi-fused features. Pattern Recogn 61:295–308
30. Ivannikova E, Hamalainen T, Luostarinen K (2014) Variable group selection based on regression trees: paper machine case study. Proceedings of EAIS, Austria
31. Bruno B, Mastrogiovanni F, Sgorbissa A, Vernazza T, Zaccaria R (2013) Analysis of human behavior recognition algorithms based on acceleration data. Proceedings of IEEE International Conference on Robotics and automation, pp 1602–1607
32. De P, Chatterjee A, Rakshit A (2018) Recognition of human behavior for assisted living using dictionary learning approach. IEEE Sens J 18(6):2434–2441

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