Wearable Sensor-Based Human Behavior Understanding and Recognition in Daily Life for Smart Environments

Ahmad Jalal
Dept. of Computer Science
Air University
Islamabad, Pakistan
ahmadjalal@mail.au.edu.pk

Majid Ali Khan Quaid
Dept. of Computer Science
Air University
Islamabad, Pakistan
171274@students.au.edu.pk

Abdul S. Hasan
Dept. of Biotechnology
Birla Institute of Technology and Science University
Dubai Campus, United Arab Emirates
s.hasan@dubai.bits-pilani.ac.in

Abstract*—Behavior recognition using motion sensors is getting prominence over other systems such as e-healthcare and life-log analysis systems especially in the healthcare domain for improving life expectancy and healthcare access. Accelerometers have been used in smart environments to recognize behavior since the last decade but heavy computation involved in recognizer model made them less acceptable. This paper proposed a computationally less expensive model with better recognition results for improved human behavior understanding system. Hierarchical features are used to ensure robustness as a performance attribute in the proposed system. These hierarchical features involve statistical features like signal magnitude, abrupt changes, and temporal variation among coordinates. Moreover, the extracted features are examined through the process of learning, training, and symbolization with the help of linear support vector machine. The examination of our recognition results based on feature extraction strategy show that our model excels others in terms of accuracy and computation time. The proposed system should be considered as a recommendation for systems involving human behavior recognition i.e. kindergarten, elderly at old-age houses and patients with Parkinson diseases.

***Keywords*— feature extractions, human behavior understanding, pattern recognition, wearable devices**

I. Introduction

The most recent advancements in detector/sensor are making residential (i.e., home, apartments, etc.) and non-residential (i.e., office, hospitals, educational institutes, etc.) buildings securer in pursuit of improving human life style [1]. By and large, these innovations either in vision sensing field or even in wearable sensors have revolutionized the health-related [2] industries in specific [3, 4]. Such monitoring sensors are applicable to several practical applications such as security systems, entertainment, user authentication, 3D games, healthcare and pedestrian motion [5-9]. For the reliable video [10] and imaging data analysis of human behaviors, depth [11] camera and bumblebee cameras [12] are largely used to get more relevant information about the subject. In attempt to adapt the environment, these sensors limit the subject's movement [13] to an extent and more complex issues i.e., privacy because they can't be carried to private places such as bedrooms etc. Alongside, these vision sensors which might be used cautiously. On the other hand, wearable sensors i.e. accelerometers, gyroscopes, electrocardiogram and magnetometers [14] offer more in-depth analysis of motion primitives with less power consumption and importantly taking care of the privacy issues [15, 16]. Especially, accelerometers have got prominence in fields involving motion but its importance in the field of patient behavior recognition, activity recognition and gait pattern detection is gaining more strength. With the ability to measure motion across three dimensions [17], it allows extraction of more complex features [18-20] which can later be classified into different behaviors.

For the enhancement of life in expectancy and medication services, researcher adopted different feature extraction and processing strategies with wearable sensor data to achieve significance in behavior recognition. H. Mizuno *et al.* [21], introduced a motion and positional feature extraction methodology for human body and applied discriminating techniques. But complex behaviors got neglected due to the complexity associated with multiple sensors data analysis. C. Zhu *et al.* [22] formulated a Bayesian network model which encompassed Laplace smoothing and likelihood estimation algorithm for the analysis of inconsistency associated with more than one body worn sensor in a smart environment. B. Bruno *et al.* [23] employed Gaussian mixture model to study accelerometer signals as a combination of gaussian components and used them in congruence with feature identity algorithm to segregate motion primitives. S. Eisa *et al.* [24] presented a comparative behavior classification system using decision trees and fuzzy logic with the help of attached sensor and recognize different behaviors.

In this paper, we have put forward a model that encompasses the human movements in the form of relevant hierarchical features extracted from an accelerometer sensor. The proposed model passes the data through three different phases i.e. elimination of unwanted signal components, hierarchical feature extraction with symbolization and classification between different behaviors. The process starts with the denoising of signal with the help of 3rd order median filter. The raw processed signals are further used to extracted meaningful features to help classifier to draw a clear-cut boundary between different behaviors. Hierarchical features are employed which include signal magnitude, min/max components, mean and standard deviation. These features are then symbolized and arranged in feature vectors. Lastly, signals are classified into behaviors with linear support vector machine. To test the validity of model, two universally accepted accelerometer datasets Human Motion Primitives (HMP) and WISDM datasets are used to measure accuracy against other state-of-the-art methods.

The organization of this paper being proposed is as follows: Section II is descriptive towards overall architecture involving noise reduction, robust feature extraction and segregating classifier for the system under proposition. Section III delineates datasets and post experiment results

978-1-5386-9355-1/18/$31.00 ©2018 IEEE
DOI 10.1109/FIT.2018.00026

along with classifier description. Section IV, finally summaries the paper with a conclusion.

II. System Design

A. Proposed System Architecture

The proposed recognition model encompasses the pre-processing phase as a most significant part towards obtaining more trustable signal coordinates. The noise in the signal is dealt with the help of median filter where 3rd order median filter is used for the removal of exaggerated signal peaks [26-28]. After sanitizing the signals, we proposed features that can represent behaviors in the form of differentiated feature vectors. These features processed variation detection in both orientation and temporal form to assist the later stages of the system i.e. classification. While, symbolization algorithm defines jurisdiction for each behavior on the basis of proposed hierarchical features. Fig. 1 shows the whole structure of the proposed model.

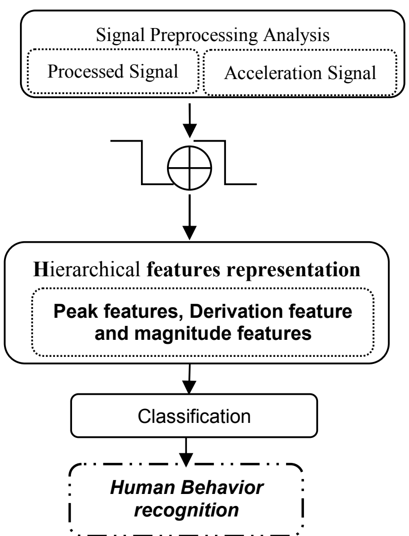

Fig. 1. Overall proposed flow for behavior recogniton system using hierarchical features

B. Data processing and Noise reduction

Noise is an unwanted component of the data which may have entered the system due to transition from one state to another or may be due to the hardware issues. However, its compensation is important before data could be used for further processing. During pre-processing phase, the proposed model uses a median filter [29-31] so that the actual signal contents are retained with very minimal loss of information [32]. Fig 2. Show the plotted noisy and filtered signal for each signal component *x, y, z* individually.

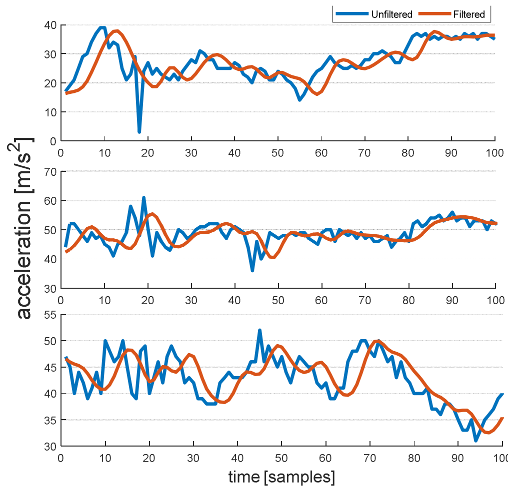

Fig. 2. A comparison of raw and sanitized signal components. (a) unfiltered and filtered *x* signal component (b) processed and unprocessed *y* signal component (c) noisy and denoised *z* signal component

C. Hierarchical Features Representation

Feature representation and extraction is an important phase of a system because it would later act as an input to the classifier. The more relevant and cohesive in nature the features, the lesser misclassified results would be obtained. Proposed model includes five signal coordinates features for human behavior recognition [33-35]. A diagrammatic relationship between features is shown in Fig. 3.

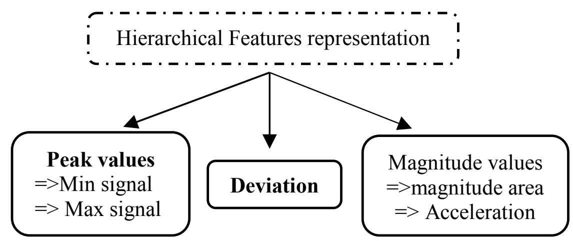

Fig 3. Statistically dependent feature represented as hierarchical features representation

1) Magnitude signal feature

The magnitude signal feature is combined effect of each signal component at i^{th} position [36, 37] in the sample taken as;

$$Sig(mag) = \sqrt{x^2_i + y^2_i + z^2_i} \tag{1}$$

where $x_{(i)}$ is the actual point value of signal x, as is the same for $y_{(i)}$ and $z_{(i)}$ of each windowing signal [38-40].

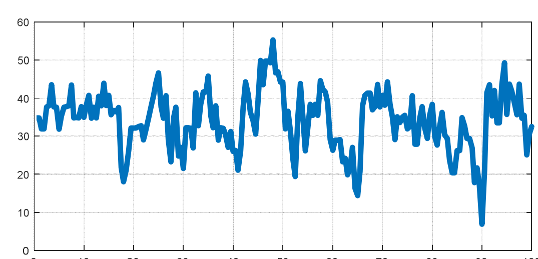

Fig. 4. The instantaenous magnitude involving *x*, *y*, and *z* components of accelerometer

2) Min signal feautre

Behaviors involving less inter-sample variation and less energy can be filtered out with the help of min signal feature *Sig(min$_e$) as;*

$$Sig(min_e) = \min(e(p < Q_s)) \tag{2}$$

where, e is the proxy for signal coordinates i.e. x, y, and z, while p accounts for the current value of the signal under consideration and Q_s provides quartile values having negative peak [41]. Fig. 5 elicits the min signal value taken from actual signal component (i.e. blue line).

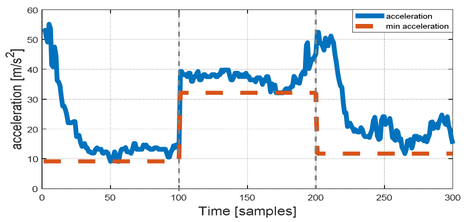

Fig 5. The 1D profile of the combined signals as actual signal acceleration and its respective min values of walk, brush teeth and Use telephone.

3) Max signal feautre

Max signal feature is the indicator of the maximum energy signal in the sample under consideration. With the behavior being rigorous in nature, the peak would act as a good discriminator among other less rigorous behaviors [42, 43]. A visual depiction is shown in Fig. 6, taken from *walk, brush teeth* and *use telephone*.

$$Sig(max_e) = \max(e(p < Q_e)) \tag{3}$$

where Q_e is the 0.9th quartile of the signal component, having value greater than the 90% of data is considered as positive noise.

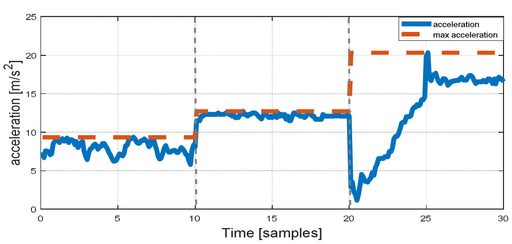

Fig 6. The ID signal structure representing the max signal component in walk, brush teeth and use telephone different behaviors.

4) Standard deviation feature

Standard deviation (SD) feature is a measure of dispersion which helps in discovery of dispersion pattern around the mean [44, 45]. SD as a mathematical function of mean and each signal component is presented in eq (4).

$$Sig(std) = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n-1}} \tag{4}$$

Individual description of each parameter is as follows: X_i is the whole signal component taken one at a time with $\bar{X}$ as mean of the whole data and n is the size of sample [46, 47].

In Fig. 7, the relative position of actual signal w.r.t to its mean is shown.

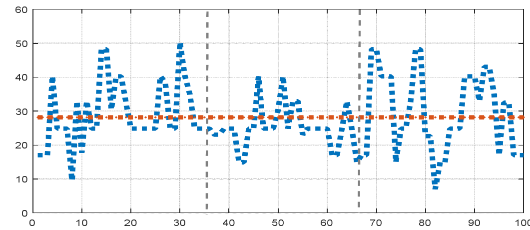

Fig. 7. The disperion of signal values aroound the mean using 1D plot

5) Signal Magnitude Area feature

The signal magnitude area *Area(mag)* is a measure of the area of signal covers just like integration does for a curve. In eq. (5), the derivation involves usage of all three signal components *x, y, z.* It is used to measure the subject's overall impact of behavior [48, 49] and is a good measure of inactive and active phase transition between behaviors.

$$Area(mag) = \sum_{i=1}^{n} x_i + \sum_{i=1}^{n} y_i + \sum_{i=1}^{n} z_i \tag{5}$$

where x_i, y_i, and z_i are placeholders for *x, y,* and *z* signal components of the accelerometer, respectively.

D. Classification Among Different Behaviors

To discriminate between the data components, a mathematical model which can draw clear distinction is inevitable [50-52]. To support the above argument, we needed to have an optimal margin-based classifier with lesser complexity as linear support vector machine [53]. SVM being a binary classifier offers multi-class classifier with the combination of multiple one versus one classifier [54]. Due to the robustness of imbalanced datasets, one-versus-one svm [55, 56] has been applied for training and testing. We used decision function [57, 58] having two possible values to compare the different behavior classes [59] as;

$$Decision = sign(\sum_{i=1}^{\dim} w_i x_i + b) \tag{6}$$

where w_i defines the slope associated with the hyper plane, while x_i accounts for feature vector. The factor b is a biasing factor for proper data distribution. To achieve multiclass classification, one-versus-one strategy was used between the behaviors (see Fig. 8).

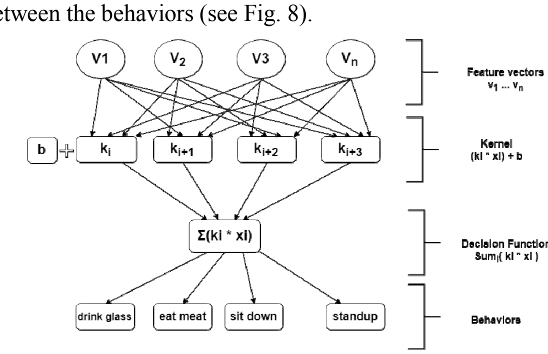

Fig 8. One-versus-one linear support vector machine structure for behavior prediction

III. Experimental Results

For the validation of the proposed recognition system, two renowned publicly available datasets were used i.e. HMP recognition dataset [23] and WISDM dataset [25]. The proceeding subsection further describes the datasets and the results of applying proposed novelty on these datasets, respectively. Lastly, these results have been compared against up-to-dated recognizer models.

A. Dataset Descriptions

The HMP dataset [23] embodies motion data taken from acceleration measuring device i.e. accelerometer. This motion data is further symbolized in 14 different behaviors i.e. *brush teeth*, *climb stairs*, *comb hair*, *descend stairs*, *drink glass*, *eat meat*, *eat soup*, *getup bed*, *lie-down bed*, *pour water*, *sit-down chair*, *standup chair*, *use telephone* and *walk*. A group of volunteers (i.e., both male and female) aging between 19-81 are used to gather different behaviors motion data via wrist worn accelerometer. The accelerometer used in this experiment had a capturing sensitivity ranging from -1.5 to 1.5. Furthermore, these raw triaxial signals are encoded ranging from 0 to 63 to make it more readable.

Second dataset being considered in this paper is WISDM dataset [25] having 6 behaviors including; *sitting*, *standing*, *walking*, *jogging*, *upstairs* and *downstairs*. The pre-installed accelerometer in mobile phone is used for gathering signal coordinates in a laboratory environment with a sampling rate of 50 Hz. Data across each row is divided as behavior type, timestamp, and accelerometer signals.

B. Experimental Evaluation of HMP Recognition dataset

The proposed system was evaluated over all 14 behaviors using extracted hierarchical features. With linear support machine as a classifier; an accuracy of 74.02% was achieved.

Moreover, a comparison of proposed method against state-of-the-art methods [23] is embodied in Table I.

TABLE I. Comparative study of state-of-the-art methods and proposed strategy on accuracy produced using HMP dataset

Types of Behaviors	Mahalanobis Distance [23]	Proposed methods
CS	38.3	94.11
DG	90.91	88.23
GB	88.89	85.29
PW	93.33	100
SD	95	81.81
SU	0	82.35
W	35.71	82.35

CS = Climb stairs, DG = Drink glass, GB = Get up bed, PW = Pour water, SD = Sit down chair, SU = Standup chair, W = walk.

C. Experimental Evaluation of WISDM dataset

The same proposed model was applied over WISDM dataset and a mean accuracy of 82.77% was achieved for six different behaviors using extracted hierarchical features and linear SVM. Table II mentioned about the comparison results with existing methods.

TABLE II. Results of applying proposed methodoly versus state-of-the-art strategies on WISDM dataset

Methods	Recognition Accuracy (%)
Star with out learning [62]	23.4
ISAR [63]	75.21
Star with learning [62]	77.29
Proposed hierarchical features	**82.77**

IV. Conclusion

In this paper, our proposition for accelerometer based human behavior recognition has been presented to expedite the recognition process with in an acceptable range of accuracy in indoor/outdoor environments. The system encapsulates initial data processing for the raw signals having signal magnitude computation along with hierarchical features extraction. These features produced competent results and also proved to be less costly in terms of computational expenses. With above points, we can conclude that our proposed model can work better than state-of-the-art model in terms of accuracy and efficiency.

Future effort in this domain will be focused towards bringing more relevant features to the hierarchical set of features i.e. angular displacement and environment discovery etc. Furthermore, we would have plan towards making our own annotated behavior dataset which would involve more sophisticated behaviors such as workplace, patients, sports and home routines in real environments.

Acknowledgment

This research is supported by the Basic Research Business, Dubai, under the "Innovative Ecosystem Development Scheme" (Grant No. GRSUP32830) cooperated with the DITH (Digital Information and Tele-health Department).

References

[1] P. Chung and C. Liu, "A daily behavior enabled hidden Markov model for human behavior understanding," Pattern Recognition, vol. 41, no. 5, pp. 1572–1580, 2008.

[2] A. Jalal and M. Zeb, "Security and QoS optimization for distributed real time environment," in Proc. of CIT Conference, Japan, pp. 369-374, Oct 2007.

[3] J. Wang, Z. Liu, J. Chorowski, Z. Chen, and Y. Wu, "Robust 3d action recognition with random occupancy patterns," in Proc. European Conf. Computer Vision, pp. 872–885, 2012.

[4] A. Jalal, Y.-H. Kim, Y.-J. Kim, S. Kamal and D. Kim, "Robust human activity recognition from depth video using spatiotemporal multi-fused feature," Pattern recognition, vol. 61, pp. 295-308, 2017.

[5] F. Farooq, A. Jalal, L. Zheng, "Facial expression recognition using hybrid features and self-organizing maps", in proc. of ICME, pp. 409-414, July 2017.

[6] V. Blanz, and T. Vetter, "Face recognition based on fitting a 3D morphable model," IEEE Transaction on Pattern analysis and machine intelligence, vol. 25(9), pp. 1063-1074, 2003.

[7] A. Jalal, and S. Kamal, "Real-time life logging via a depth silhouette-based human activity recognition system for smart home services," in Proceedings of AVSS, Korea, pp. 74-80, Aug 2014.

[8] A. Jalal and M. Zeb, "Security enhancement for e-learning portal," Journal of computer science and network security, pp. 41-45, 2008.

[9] A. Jalal and S. Kim, "The mechanism of edge detection using the block matching criteria for the motion estimation," in Proceedings of HCI Conference, Korea, pp. 484-489, Jan 2005.

[10] S. Kamal and A. Jalal, "A hybrid feature extraction approach for human detection, tracking and activity recognition using depth sensors," Arabian Journal for science and engineering, 2016.

[11] B. Saghafi, D. Rajan and W. Li, "Efficient 2D viewpoint combination for human action recognition," Pattern analysis and application, vol. 19, no. 2, pp. 563-577, 2016.

[12] A. Jalal, S. Lee, J. Kim and T. Kim, "Human activity recognition via the features of labeled depth body parts," in Proceedings of ICOST, Italy, pp. 246-249, 2012.

[13] A. Farooq, A. Jalal and S. Kamal, "Dense RGB-D map-based human tracking and activity recognition using skin joints features and self-organizing map," KSII transactions on internet and information systems, vol. 9, pp.1856-1869, 2015.

[14] W. Xu, M. Zhang, A. Sawchuk, and M. Sarrafzadeh, "Co-recognition of human activity and sensor location via compressed sensing in wearable body sensor networks," in Proc. 2012 Ninth International Conf. Wearable and Implantable Body Sensor Networks, pp. 124-129, 2012.

[15] A. Jalal, S. Kamal and D. Kim, "Depth Silhouettes Context: A new robust feature for human tracking and activity recognition based on embedded HMMs," in *Proc. IEEE URAI*, pp. 294-299, 2015.

[16] A. Jalal and Y. Kim, "Dense depth maps-based human pose tracking and recognition in dynamic scenes using ridge data," in Proc. IEEE Conf. AVSS, pp. 119-124, 2014.

[17] K. Buys, C. Cagniart, A. Baksheev, T.-D. Laet, J. D. Schutter and C. Pantofaru, "An adaptable system for RGB-D based human body detection and pose estimation," Journal of visual communication and image representation, vol. 25, no.1, pp. 39-52, 2014.

[18] M. Mehmood, A. Jalal, and Hawke A. Evans, "Facial Expression Recognition in Image Sequences Using 1D Transform and Gabor Wavelet Transform," IEEE ICAEM, 2018.

[19] A. Jalal, Y. Kim and D. Kim, "Ridge body parts features for human pose estimation and recognition from RGB-D video data," in Proc. of the IEEE ICCCNT, July 2014.

[20] A. Jalal and A. Shahzad, "Multiple facial feature detection using vertex modeling structure," in Proceedings of ICL, pp. 1-7, Sep 2007.

[21] H. Mizuno, H. Nagai, K. Sasaki, H. Hosaka, C. Sugimoto, K. Khalil and S. Tatsuta, "Wearable sensor system for human behavior recognition (First report: Basic architecture and behavior prediction method)," in Proc. of the IEEE Conference on solid-state sensors, actuators and Microsystems, pp. 435-438, June 2007.

[22] C. Zhu, W. Sheng and M. Liu, "Wearable sensor-based behavioral anomaly detection in smart assisted living systems," IEEE Transactions on automation science and engineering, vol. 12, no. 4, pp. 1225-1234, 2015.

[23] B. Bruno, F. Mastrogiovanni, A. Sgorbissa, T. Vernazza and R. Zaccaria, "Analysis of human behavior recognition algorithms based on accleration data," in Proc. of the IEEE ICRA, 2013.

[24] S. Eisa and A. Moreira, "A behaviour monitoring system (BMS) for ambient assisted living," Sensors, vol. 17, no. 9, pp. 1-24, 2017.

[25] J. R. Kwapisz, G. M. Weiss and S. A. Moore, "Activity recognition using cell phone accelerometers," in 4th workshop on knowledge discovery from sensor data, pp. 1-9, 2010.

[26] A. Jalal and S. Kim, "Algorithmic implementation and efficiency maintenance of real-time environment using low-bitrate wireless communication," in Proceedings of SEUS, Korea, April 2006.

[27] A. Jalal, N. Sharif, J. T. Kim, and T.-S. Kim, "Human activity recognition via recognized body parts of human depth silhouettes for residents monitoring services at smart homes," Indoor and Built Environment, vol. 22, no. 1, pp. 271-279, 2013.

[28] A. Jalal and I. Uddin, "Security architecture for third generation (3G) using GMHS cellular network," in IEEE ICET, pp. 74-79, 2007.

[29] G. Zhengyang and Z. Le, "Improved adaptive median filter," in IEEE ICCIS, pp. 44-46, 2014.

[30] A. Jalal, J. Kim and T. Kim, "Development of a life logging system via depth imaging-based human activity recognition for smart homes," in Proceedings of SHB, Korea, pp. 91-95, Oct 2012.

[31] A. Jalal, Y. Kim, S. Kamal, A. Farooq and D. Kim, "Human daily activity recognition with joints plus body features representation using kinect sensor," in Proceedings of ICIEV, pp. 1-6, 2015.

[32] D. Tuan, X. Ma, Y. Liu, S. Yan and C. Hao, "Statistical modeling of additive noise and random drift for triaxial rate gyros and accelerometers," in Proceedings of IEEE ICICA, pp. 308-313, 2016.

[33] A. Jalal, S. Kamal and D. Kim, "Shape and motion features approach for activity tracking and recognition from Kinect video camera," in Proceedings of WAINA Conference, Korea, pp. 445-450, Mar 2015.

[34] A. Jalal, J. T. Kim, and T.-S. Kim, "Human activity recognition using the labeled depth body parts information of depth silhouettes," in Proceedings ISHB, pp. 1-8, 2012.

[35] Y. Yuan, Z. Miao and S. Hu, "Real-time human behavior recogntion in intelligent environment," in Proceedings of the international conference on Signal processing, pp. 1-4, 2006.

[36] G. Kumar, R. Jithin and D. Shankar, "Feature based steganalysis using wavelet decomposition and magnitude statistics," in Proceedings of the ICACE, pp. 298-300, 2010.

[37] A. Jalal, S. Kamal and D. Kim, "A depth video sensor-based life-logging human activity recognition system for elderly care in smart indoor environments," Sensors, vol. 14, pp. 11735-11759, 2014.

[38] A. Jalal, MZ. Uddin, J. T. Kim, and T. Kim, "Daily Human Activity Recognition Using Depth Silhouettes and R Transformation for Smart Home," in Proceedings ICOST, pp. 25-32, 2011.

[39] A. Jalal, S. Kamal and D. Kim, "Individual detection-tracking-recognition using depth activity images," in Proceedings of URAI, Korea, pp. 450-455, Oct 2015.

[40] A. Jalal, S. Kamal and D. Kim, "Depth map-based human activity tracking and recognition using body joints features and self-organized map," in Proceedings of ICCCNT, China, pp. 1-6, Jul 2014.

[41] D. Arifoglu and A. Bouchachia, "Activity recognition and abnormal behaviour detection with recurrent neural networks," Procedia Computer Science, vol. 110, pp. 86-93, 2017.

[42] A. Jalal, S. Kamal and D. Kim, "Detecting Complex 3D Human Motions with Body Model Low-Rank Representation for Real-Time Smart Activity Monitoring System," KSII, pp. 1189-1204, 2018.

[43] A. Jalal and S. Kim, S, "Advanced performance achievement using multi-algorithmic approach of video transcoder for low bit rate wireless communication," ICGST, Vol. 5(9), pp. 27-32, 2005.

[44] A. Jalal, S. Kamal, A. Farooq and D. Kim, "A spatiotemporal motion variation features extraction approach for human tracking and pose-based action recognition," in Proceedings of ICIEV, pp. 1-6, 2015.

[45] A. Jalal, M. Z. Uddin, J. T. Kim, and T.-S. Kim, "Recognition of human home activities via depth silhouettes and R transformation for smart homes," Indoor and Built Environment, pp. 184-190, 2012.

[46] G. Cabau, M. Buhu and C. Oprisa, "Malware classification based on dynamic behavior" in Proc. of the IEEE ISSNA, pp. 315-318, 2016.

[47] A. Jalal and Y. Rasheed, "Collaboration achievement along with performance maintenance in video streaming," in *Proceedings of the IEEE conference on ICAL*, pp. 1-8, 2007.

[48] S. Kamal, A. Jalal and D. Kim, "Depth Images-based Human Detection, Tracking and Activity Recognition Using Spatiotemporal Features and Modified HMM, *JEET,* pp. 1921-1926, 2016.

[49] A. Jalal, S. Kamal and D. Kim, "Facial Expression recognition using 1D transform features and Hidden Markov Model, JEET, 2017.

[50] G. Liu, X. Zhang and S. Zhou, "Multi-class classification of support vector machines based on double binary tree," in Proc. of the IEEE ICNC, pp. 102-105, Oct. 2008.

[51] A. Jalal, Shaharyar Kamal and Daijin Kim, "Human depth sensors-based activity recognition using spatiotemporal features and hidden markov model for smart environments, Journal of computer networks and communications, vol. 2016, pp. 1-11, 2016.

[52] A. Jalal, S. Kamal, and D. Kim, "A depth video-based human detection and activity recognition using multi-features and embedded hidden Markov models for health care monitoring systems, International Journal of IMAI, vol. 4(4), pp. 54-62, 2017.

[53] K. Kim, K. Jung, S. H. Park and H.-J. Kim, "Support vector machines for texture classification," IEEE transactions on pattern analysis and machine intelligence, vol. 24, no. 12, pp. 1542-1550, 2002.

[54] A. Jalal and S. Kim, "Global security using human face understanding under vision ubiquitous architecture system," World Academy of Science, Engineering, and Technology, Vol. 13, pp. 7-11, 2006.

[55] A. Jalal, S. Kim and B. J. Yun, "Assembled algorithm in the real-time H.263 codec for advanced performance," " in Proceedings of the IEEE workshop on enterprise networking and computing in healthcare industry, pp.295-298, 2005.

[56] A. Jalal, S. Kamal and C. Cecer, "Depth maps-based human segmentation and action recognition using full-body plus body color cues via recognizer engine, JEET, 2018.

[57] A. Jalal, M. Zia and T.-S. Kim, “Depth Video-based Human Activity Recognition System Using Translation and Scaling Invariant Features for Life Logging at Smart Home”, IEEE Transaction on Consumer Electronics, pp. 863-871, 2012.

[58] Z. Abduallah, M. Gaber, B. Srinivasan and S. Krishnaswamy, “Adaptive mobile activity recognition system with evolving data streams,” Neurocomputing, vol. 150, pp. 304-317, 2015.

[59] A. Jalal, M. Mahmood, and M. A. Sidduqi, “Robust spatio-temporal features for human interaction recognition via artificial neural network, IEEE Frontiers of information technology, 2018.

[60] A. Jalal, and S. Kim, "A complexity removal in the floating point and rate control phenomenon," Proc. Korea multimedia society, pp.48-51, 2005.

[61] M. Amara, K. Ghedira, K. Zidi and S. Zidi, "A comparative study of multi-class support vector machine methods for Arabic characters recognition," Proc. IEEE conf. computer systems and applications, pp.1-6, 2015.

[62] Z. S. Abduallah, M. M. Gaber, B. Srinivasan and S. Krishnaswamy, “Adaptive mobile activity recognition system with evolving data streams,” Neurocomputing, vol. 150, pp. 304-317, 2015.

[63] T. Dungkaew, J. Suksawatchon and U. Suksawatchon, “Impersonal smartphone-based activity recognition using the accelerometer sensory data” in Proc. of the IEEE International conference on Information technology, pp. 1-6, Nov. 2017.