

# Motion Recognition Based on Fuzzy WP Feature Extraction Approach

Keun-Chang Kwak

**Abstract**—This paper is concerned with motion recognition based fuzzy WP(Wavelet Packet) feature extraction approach from Vicon physical data sets. For this purpose, we use an efficient fuzzy mutual-information-based WP transform for feature extraction. This method estimates the required mutual information using a novel approach based on fuzzy membership function. The physical action data set includes 10 normal and 10 aggressive physical actions that measure the human activity. The data have been collected from 10 subjects using the Vicon 3D tracker. The experiments consist of running, seating, and walking as physical activity motion among various activities. The experimental results revealed that the presented feature extraction approach showed good recognition performance.

**Keywords**—Motion recognition, fuzzy wavelet packet, Vicon physical data.

## I. INTRODUCTION

ONE of difficulties in applying to context-aware computer applications is to develop the algorithms that can detect context from noisy and often ambiguous sensor data. One facet of the user's context is physical activity. The previous works have been discussed physical activity recognition using acceleration or a fusion of acceleration and other data modalities. Bao [1] has developed and evaluated to detect physical activities from data acquired using five small biaxial accelerometers worn simultaneously on different parts of the body. The acceleration data set was collected from 20 subjects without researcher supervision or observation. The features were computed on 512 sample windows of acceleration data with 256 samples overlapping between consecutive windows. The feature computation includes DC feature, energy, frequency-domain entropy, and correlation features for activity recognition. Theodoridis [2] has compared QA(quadraple)-TSK(Takagi-Sugeno-Kang) fuzzy model with evolutionary decision trees towards nonlinear action pattern recognition. The performance statistics have been used for remote surveillance within a smart environment incorporating an ubiquitous 3D marker based tracker which acquires the time series data streams, whereas activity recognition statistics have generated through an off-line process. Recently, Reiss [3] have introduced a new benchmarked data set for activity monitoring. This data set was recorded from 18 activities performed by 9 subjects, wearing 3 IMUs (inertial measurement units) and an HR (heart rate) monitor. From the segmented 3D-acceleration data, various signal features were calculated in both time and

frequency domain (mean, variance, energy), and normalized mean and gradient was calculated on the heart rate data. The classifier has been used the well-known ones such as C4.5 and boosted C4.5 decision tree, Bagging C4.5 decision tree, Naïve Bayes and KNN.

On the other hand, many applications of the fast wavelet transform and WP (Wavelet Packet) have been reported in signal processing and compression as well as pattern recognition. Wavelets divide data into different frequency components, whereby each component may be studied at a resolution matched to its scale. In this sense, wavelet transforms have the important and useful abilities of detecting and recognizing stationary, nonstationary or transitory characteristics of the signal including abrupt change, spikes, drifts, and trends. Li [4] has used fuzzy wavelet packet based feature extraction method and its application to biomedical signal classification such as magnetic resonance spectra. The extraction algorithm constructs fuzzy sets of features via fuzzy clustering to assess their discriminatory effectiveness. Wang [5] has used optimal wavelet packet using Davies-Bouldin criterion managed to outperform the fuzzy wavelet packet when classifying biomedical signals.

In this paper, we shall use fuzzy WP(Wavelet Packet) feature extraction approach from Vicon physical data sets. This approach is based on an efficient fuzzy mutual-information-based WP transform for feature extraction [6]. Furthermore, this method estimates the required mutual information using a novel approach based on fuzzy membership function. The physical action data set used in this paper includes 10 normal and 10 aggressive physical actions that measure the human activity. The data have been collected from 10 subjects using the Vicon 3D tracker [7]. Here the experiments are performed by three activities (running, seating, and walking) as physical activity motion among this benchmark data set.

The material of this paper is organized into following fashion. In section 2, we describe fuzzy WP feature extraction approach. In section 3, we perform the experimental setup and results. Finally the conclusions and comments are given in section 4.

## II. FUZZY WP FEATURE EXTRACTION

In this section, we describe fuzzy WP feature extraction approach for motion recognition. Fast wavelet transform leads to a dyadic pyramidal implementation using filter banks and the corresponding Mallat algorithm with multiresolution analysis. Fast wavelet transform develops the two channel filter banks through which the signal is split into two subspaces,  $V$  and  $W$ , which are orthonormally complementary to each other, with  $V$

K. C. Kwak, is with the Department of Control, Instrumentation, and Robot Engineering, Chosun University, Gwangju, Korea (e-mail: kwak@chosun.ac.kr).

being the space that includes the low frequency information. Compared to the fast wavelet transform, WP not only decomposes the approximation coefficients, but also the detail coefficients. In contrast to fast wavelet transform, WP offers a broader range of possibilities for alternative signal decompositions [4].

The WP compression procedure involves four steps [8].

[Step1] Decomposition

For a given wavelet, compute the wavelet packet decomposition of signal  $X$  at level  $N$ .

[Step 2] Computation of the best tree

For a given entropy, compute the optimal wavelet packet tree. Of course, this step is optional. The graphical tools provide a Best Tree button for making this computation quick and easy.

[Step 3] Thresholding of WP coefficients

For each packet except for the approximation, select a threshold and apply thresholding to coefficients.

[Step 4] Reconstruction

Compute wavelet packet reconstruction based on the original approximation coefficients at level  $N$  and the modified coefficients.

The fuzzy WP feature extraction algorithm used in this paper involves the following steps [6]. Given a training data set consisting of labeled original signals,

[Step 1] For each labeled original signal, perform a full WP decomposition to the maximum level  $J$ . For all  $j=0,1,\dots, J$  and  $k=0,1,2,\dots,2^j-1$ , construct features according to logarithmic operator. This operator is applied to normalize the distribution of the generated feature.

[Step 2] Construct the associated fuzzy sets and compute the fuzzy entropies and mutual information. Then calculate  $F(\Omega_{j,k})$  according to  $I(C;f_i)/H(f_i)$ , where  $\Omega_{j,k}$  is the subspace representing each of the features.

[Step 3] Determine the optimal WP decomposition  $X^*$ , being the one that corresponds to the maximum value of  $F$ .

[Step 4] In descending order, sort the subspaces by  $F$ ,  $\Omega=\{\Omega(1), \Omega(2),\dots, \Omega(1)\}$ .

[Step 5] Move first element in  $\Omega$  to  $X^*$ .

[Step 6] If  $\Omega(k)$  is an ascendant or descendant of  $\Omega(j1)$ , remove  $\Omega(k)$  from  $\Omega$ .

[Step 7] If  $\Omega=0$ , stop, Otherwise go to Step 3 and continue.

[Step 8] The set  $X$  is the final WP decomposition.

### III. EXPERIMENTAL RESULTS

We used The physical action data set including 10 normal and 10 aggressive physical actions that measure the human activity. The data have been collected from 10 subjects using the Vicon 3D tracker. Here the experiments were performed by only three activities (running, seating, and walking) as physical activity motion among this benchmark data set to confirm the effectiveness of fuzzy WP feature extraction approach. Seven male and three female subjects, who have experienced aggression in scenarios. Throughout 20 individual experiments, each subject had to perform ten normal and ten aggressive

activities. Regarding the rights of the subjects involved, ethical regulations have been followed based on the code of ethics of the British psychological society, which explains the ethical legislations to conduct statistical experiments using human subjects. Each experimental trial has been taken separately for each physical activity. The duration of each activity was approximately 10 seconds per subject, which corresponds to a time series of 3000 samples, with a sampling frequency of 200Hz. Within this performance time, approximately 15 action trajectories were extracted counting in average 15 normal, and 15 aggressive actions. Fig. 1 visualizes the configuration setting showing an actor's action performance in a 3D environment, captured by Vicon [2]. Figs 2~4 show the 27 sensor values captured by Vicon for seating, running, and walking motion, respectively. As shown in the figures, the sensor values of seating motion consist of flat values in comparison to running and walking motions. We performed fuzzy WP feature extraction for each motion from multisignal sensor values. Here, we used level 3, window size 256, spacing of the windows 32, sampling frequency 256. Utilizing a window size of 256 at 32 increments features are extracted from the WP tree. We assumed 3 decomposition levels ( $J=3$ ). Fig. 5 shows feature values with  $63 \times 405$  size for running motion. Figs. 6~8 show the mean of feature values ( $1 \times 405$ ) for seating, running, and walking motions, respectively.

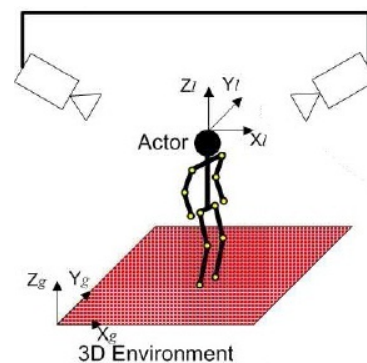


Fig. 1 Ubiquitous Vicon cameras environments

Table I lists the Euclidean distance for each motion. As listed in Table, we could find the fact that the fuzzy WP feature extraction approach showed good performance for medicinal sensor values. This approach used in this paper was developed to extract the most relevant features required to classify several motions. We have plans to extend other motions such as bowing, clapping, handshaking, hugging, jumping, standing, and waving motion.

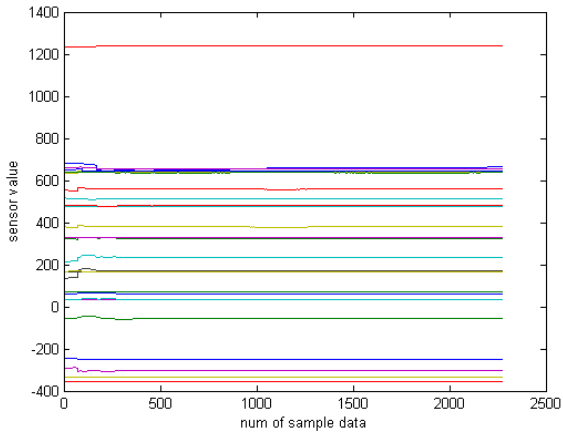


Fig. 2 Sensor values of seating motion

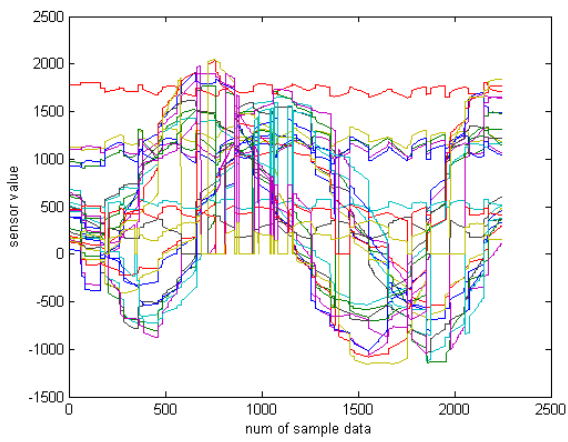


Fig. 3 Sensor values of running motion

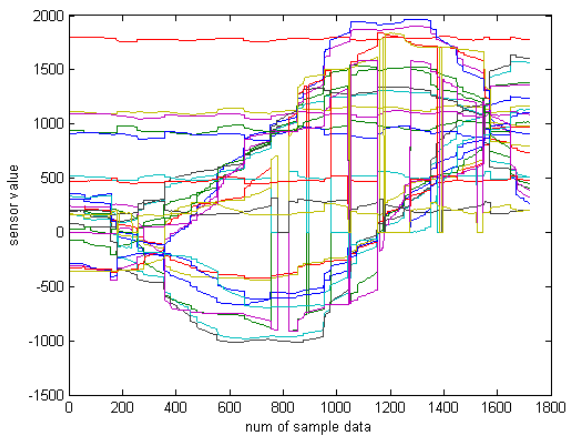


Fig. 4 Sensor values of walking motion

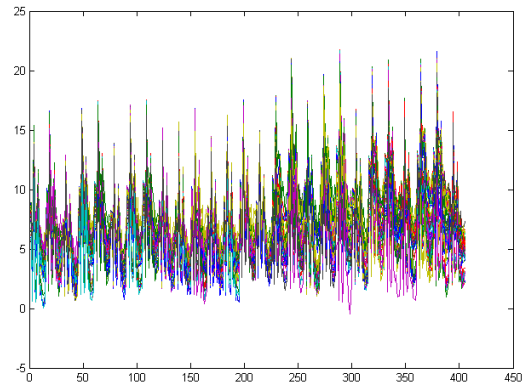


Fig. 5 Feature values of running motion (63x405)

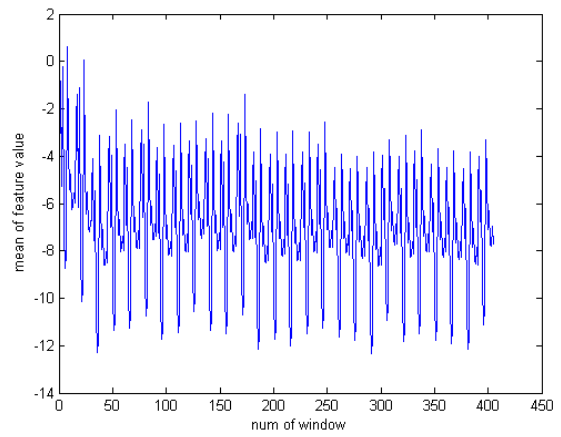


Fig. 6 Mean of feature values for seating motion

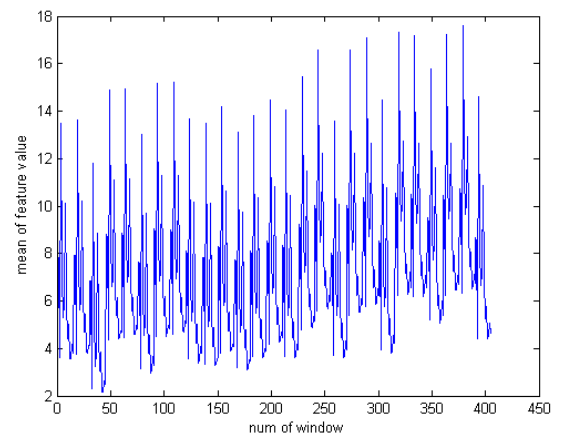


Fig. 7 Mean of feature values for running motion

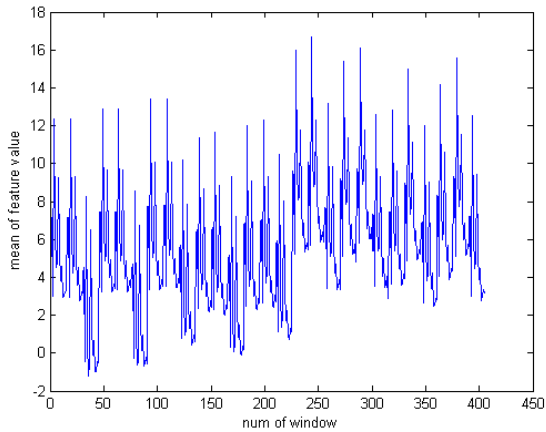


Fig. 8 Mean of feature values for walking motion

TABLE I  
EUCLIDEAN DISTANCE FOR EACH MOTION

	Seating1	Running1	Walking1
Seating 1	-	14.12	12.44
Seating2	1.50	12.67	10.99
Seating 3	1.17	14.58	12.90
Running1	14.12	-	1.73
Running2	13.75	1.23	1.37
Running3	14.81	0.91	2.37
Walking1	12.44	1.73	-
Walking2	12.58	1.53	0.75
Walking3	12.58	1.53	0.75

#### IV. CONCLUSION

We developed the motion recognition method based on fuzzy WP feature extraction approach from multisignal Vicon data set. This method estimated the required mutual information using a novel approach based on fuzzy membership function. The experimental results revealed that the presented method showed good effectiveness and performance regarding some motion activities. For future research, we are planning to extend various motion activities and study the advanced feature extraction method.

#### ACKNOWLEDGMENT

This work was supported by the Ministry of Knowledge Economy (MKE), Rep. of Korea, under the IT R&D program supervised by the Korea Evaluation Institute of Industrial Technology (KEIT) (10041627).

#### REFERENCES

- [1] L. Bao and S. S. Intille, "Activity recognition from user-annotated acceleration data", *Lecture Notes in Computer Science* 3001, Springer-Verlag, pp. 1-17, 2004.
- [2] T. Theodoridis, A. Agapitos, H. Hu, and S. M. Lucas, A QA-TSK Fuzzy Model versus Evolutionary Decision Trees Towards Nonlinear Action Pattern Recognition, *IEEE International Conference in Information and Automation (ICIA-2010)*, June 20-23, 2010, pp. 1813-1818.
- [3] A. Reiss and D. Stricker, "Introducing a new benchmarked dataset for activity monitoring," *The 16<sup>th</sup> IEEE International Symposium on Wearable Computers (ISWC)*, 2012, pp.108-1092.
- [4] D. Li, W. Pedrycz, N. J. Pizzi "Fuzzy wavelet packet based feature extraction method and its application to biomedical signal classification", *IEEE Trans. on Biomedical Engineering*, Vol. 52, No. 6, pp.1132-1139, 2005.
- [5] G. Wang, Z. Wang, W. Chen, and J. Zhuang, "Classification of surface EMG signals using optimal wavelet packet method based on Davies-Bouldin criterion," *Medical and Biological Engineering and Computing*, Vol. 44, No. 10, pp.1741-1744, 2006.
- [6] R. N. Khushaba, S.Kodagoda, S. Lai, and G. Dissanayake, "Driver drowsiness classification using fuzzy wavelet-packet-based feature extraction algorithm", *IEEE Trans. on Biomedical Engineering*, Vol. 58, No. 1, pp. 121-131, 2011.
- [7] <http://archive.ics.uci.edu/ml/datasets>
- [8] <http://www.mathworks.com> , Wavelet toolbox