A Human Activity Recognition System using HMMs with GDA on Enhanced Independent Component Features

Md. Zia Uddin[1], Deok-Hwan Kim[2], and Tae-Seong Kim[3]
[1]Department of Computer Education, Sungkyunkwan University, Republic of Korea
[2]School of Electronic Engineering, Inha University, Republic of Korea
[3]Department of Biomedical Engineering, Kyung Hee University, Republic of Korea

Abstract: *Human Activity Recognition (HAR) from time-sequential video images is an active research area in various applications such as video surveillance and smart homes nowadays. This paper presents a novel approach of automatic HAR based on Generalized Discriminant Analysis (GDA) on Enhanced Independent Component (EIC) features from binary silhouette information to be used with Hidden Markov Model (HMM) for training and recognition. The recognition performance using GDA on EIC features has been compared to other conventional approaches including Principle Component (PC), EIC and Linear Discriminant Analysis (LDA) on PC features where the preliminary results show the superiority of the proposed approach.*

Keywords: *HAR, EICA, GDA, HMM.*

Received May 13, 2013; accepted September 19, 2014; published online June 26, 2014

1. Introduction

Recently, Human Activity Recognition (HAR) has got considerable interests of many researchers in distinguished research areas due to its potential use in proactive computing [2, 6, 12, 17], which is a technology to proactively anticipate people's necessity in situations such as health-care and take necessary actions. A system that is capable of recognizing various human activities has many significant applications such as video surveillance, human computer interaction and smart home healthcare. The common method for HAR so far is based on video images from where features are extracted and compared with the pre-collected activity features. Thus, useful feature extraction, modelling and recognition play key roles in a HAR system.

Basically, binary silhouettes of various activities are commonly used to represent different human activities [5, 11, 14]. In [11] Principal Component (PC) features from binary silhouettes were utilized for HAR. In this regard, the most common feature analysis technique applied is Principal Component Analysis (PCA). PCA is a second order statistical approach that looks for useful basis for data representation and it usually finds PCs at the reduced dimension of the input. Regarding to HAR, it tries to focus on the global features of the binary silhouettes, which has been actively applied.

However, PCA has limitations of second order statistical analysis, allowing up to decorrelation of data.

Lately, Independent Component Analysis (ICA) has been actively exploited to find statistically independent basis images [1, 7, 8, 9, 14]. In [14], ICA has been applied in HAR successfully to find the local features from binary silhouettes. ICA is a generalization of PCA that finds the statistical independencies of the image features via a blind source separation method considering that the input data is the linear mixture of the sources. Besides, it has been employed successfully for face recognition [9], speech recognition [7] and bioinformatics [8]. Later on, ICA was applied on the selected PC features to generalize the basic ICA and to extract better features than ICA [10]. This method is known as Enhanced Independent Component Analysis (EICA). In [10] EICA was utilized for content-based face image retrieval from a face image database.

A robust discriminant analysis called General Discriminant Analysis (GDA), a nonlinear approach to classify patterns from different classes has recently been used in distinguished applications such as palm print recognition where it significantly outperforms the traditional approaches such as Linear Discriminant Analysis (LDA), which tries to find a classification space to classify the samples of different classes linearly [13, 16]. GDA on EIC features may obtain better discrimination among the binary silhouettes from different activities.

In recent years, many recognition methods have been proposed for HAR. Gavrilla presented a detailed survey on human action recognition [3]. To train and recognize different human activities, Hidden Markov Models (HMMs) have been used successfully in many papers such as [2, 3, 4, 6, 11, 15]. In [11], PC-based silhouette features were applied to train HMMs for recognition. In [15] 2D mesh features of binary silhouettes extracted from video frames were used to recognize several tennis activities in time sequential images using HMM.

In this work, an EICA and GDA-based silhouette feature extraction approach is proposed in combination with HMMs to recognize different human activities. EICA is employed first to focus on the local status of the activity silhouette features of different activities and then extended by GDA to further classify the EIC features for better silhouette feature representation and achieved superior recognition rate over other approaches such as PCA, EICA and LDA on PC features.

2. The Research Methods

The recognition system consists of binary silhouette extraction, feature extraction, activity training and recognition. Figure 1, shows the overall architecture of the proposed activity recognition system.

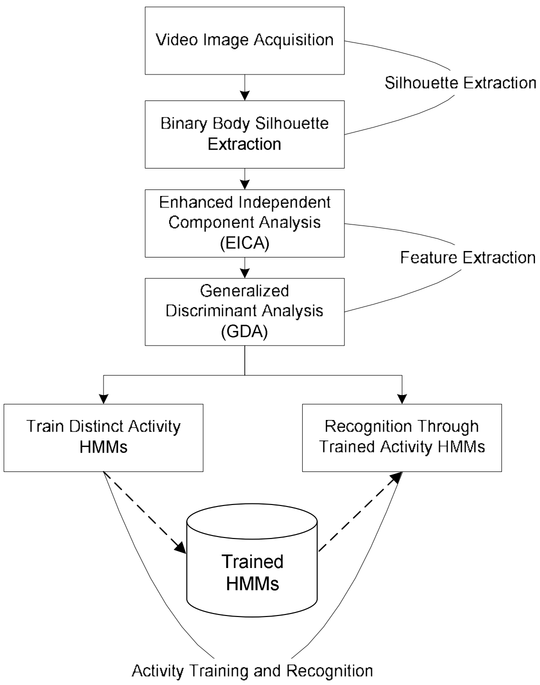
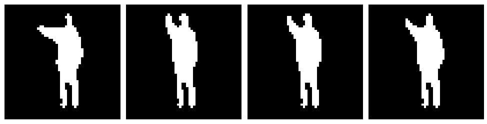


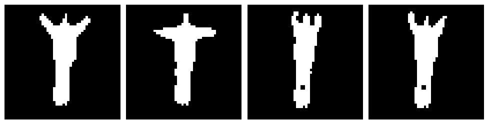
Figure 1. Basic steps of the proposed HAR system.

2.1. Silhouette Extraction

A Gaussian probability distribution is applied to remove the background from a recent activity frame and to extract a human body silhouette from video [14]. To extract the silhouette, the background subtracted difference image is then converted to binary based on a threshold, which is determined experimentally on the basis of subtraction result. Thus, after subtracting the background, the binary silhouettes are extracted from the video frames. Figure 2 shows a sequence of binary silhouettes from an image sequence of right hand waving and both hand waving. Every silhouette is represented as a row vector and before applying feature extraction algorithm on the silhouette images, all the vectors are converted to zero mean.



a) Binary silhouettes from right hand waving activity.



b) Binary silhouettes from both hand waving activity.

Figure 2. Sample binary silhouettes from different activities.

2.2. EICA Feature Extraction

EICA feature extraction method extracts the independent components of activity silhouette images and decomposes the general ICA method into three major steps: Namely whitening, rotations and normalization. Basically, EICA does generalization of ICA by operating it in a reduced PCA space where the dimensionality of the PCA space is determined by focusing on PCs and their corresponding eigevalues. Thus, to improve the generalization performance of ICA, EICA chooses a proper space, where the small-valued trailing eigenvalues are ignored as they represent negligible importance to represent the data in PC space. More specifically, in EICA, ICA is preceded by a PCA dimensionality reduction procedure so that the space dimensionality is reduced before carrying out the ICA whitening step and that is how EICA represents better performance than general ICA in terms of generalization and the computational complexity reduction. Hence, we have adopted EICA in this study to represent local binary silhouette features.

The first step of EICA feature extraction is to apply PCA that computes the eigenvectors of the covariance data matrix. Then, approximation is done using the linear combination of top eigenvectors. Suppose E reflects the original coordinate system onto the eigenvectors where the eigenvector corresponding to the largest eigenvalue indicates the axis of largest variance. So, the eigenvectors corresponding to the largest eigenvalues can be used to define the PCA subspace.

PCA is a popular method to approximate original data in the lower dimensional feature space. The fundamental approach is to compute the eigenvectors of the covariance data matrix c and then approximation is done using the linear combination of top eigenvectors. The covariance matrix c of the v number of sample training silhouette vectors $\tilde{X}$ and the PCs E can be calculated respectively as:

$$c = \frac{1}{v}\sum_{i=1}^{v}\left(\tilde{X}_i \tilde{X}_i^T\right) \tag{1}$$

$$E^T CE = \Lambda \tag{2}$$

Where, E represents eigenvector matrix and Λ diagonal matrix of the eigenvalues. E reflects the eigenvectors (i.e., PCs) where the eigenvector corresponding to the largest eigenvalue represents the axis of highest variance and the next largest one is the second highest variance and so on. As a result, the eigenvalues with values close to zero indicates negligible variance and hence can be ignored. So, the several m eigenvectors E_m corresponding to the largest eigenvalues can be used to define the PC subspace. After applying PCA on human silhouettes of different activities, it produces global features representing frequently moving parts of human body in all activities. Figure 3 shows eight PCA basis images which represent the global body features.

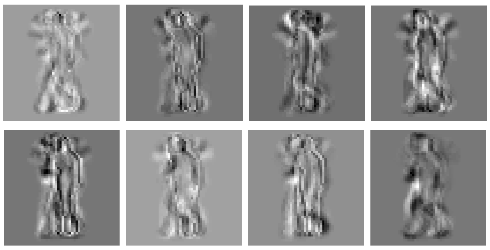


Figure 3. Eight PCs of all the images of the four activities.

The next step is to apply ICA on the PC features. Basically, ICA represents a set of random variables using basis function where the components are statistically independent. If S is a collection of ICA basis images and X a collection of silhouettes then the relation between X and S can be expressed as:

$$X=RS \tag{3}$$

Where, R is a linear mixing matrix. Basically, the ICA algorithm tries to find the unmixing weight matrix W. It focuses on the local feature information rather than global information like PCA. However, before applying ICA, PCA is used here to reduce dimension of total training image data. Thus, ICA algorithm is performed on E_m as:

$$E_m^T = W^{1}S \tag{4}$$

$$X_r = UW^{-1}S \tag{5}$$

Where, U is a projection matrix of silhouettes on E_m and X the reconstructed silhouette images. Figure 4 shows eight ICs from all activity silhouettes after applying EICA. The EICA representation P_i of i^{th} silhouette vector $\tilde{X}_i$ from an activity image sequence is as:

$$P_i = \tilde{X}_i E_m W^{-1} \tag{6}$$

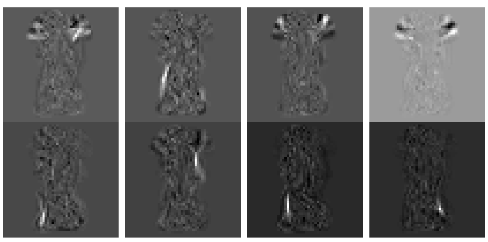


Figure 4. Eight ICs from all activity silhouettes.

2.3. GDA on the EIC Features

GDA is an approach that produces an optimal discriminant function, which maps the input into a classification space. The main idea of GDA is to map the training binary silhouettes into a high dimensional feature space Z by a function as:

$$F : R\text{®}Z, P_i\text{®}Y\left(P_i\right) \tag{7}$$

Assuming that there exists a kernel function $K(P_j, P_i)$ and a map Y that satisfy $K(P_j, P_i)= F(P_j)F(P_j)$. The advantage of GDA is a nonlinear feature space for sample classification that is not separable by linear methods. Basically, Gaussian kernels are used for GDA. The goal of GDA is to maximize the Fisher criterion as:

$$L = \frac{\left|G^T B^F G\right|}{\left|G^T T^F G\right|} \tag{8}$$

Where, B^F and T^F are the between-class and total sample scatter matrices respectively. However, the optimal Discriminant vectors G_{GDA}^T can be achieved via solving the following eigenvalue problem.

$$B^F G = LT^F G \tag{9}$$

Thus, the extracted EICA representation of the silhouettes can be extended by GDA as:

$$D = G_{GDA}^T P \tag{10}$$

Figures 5, 6 and 7 show exemplar plots of 3-D EICA, LDA on EICA and GDA on EICA representations of all the binary silhouette images respectively. Figure 7 shows a better separation among most of the silhouette prototypes of different classes than other approaches.

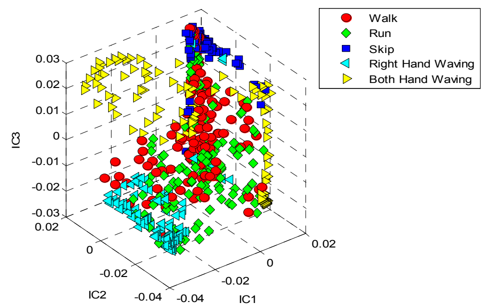


Figure 5. 3-D plot of EIC features of silhouettes of the five activities.

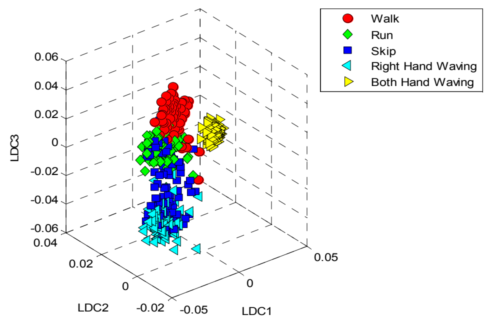


Figure 6. 3-D plot of LDA on the EIC features of silhouettes.

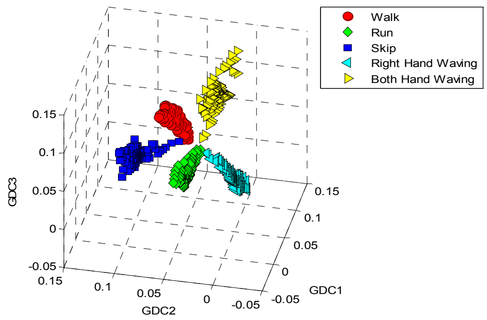
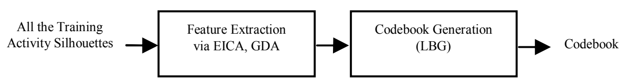


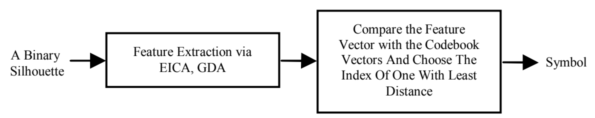
Figure 7. 3-D plot of GDA on the EIC features of silhouettes.

2.4. Codebook Generation for HMM

Each feature vector obtained using GDA on EICA was symbolized before applying to train or recognize by HMM. A codebook of feature vectors can be generated using vector quantization from training vectors. There are two famous vector quantization algorithms: Namely ordinary K-means clustering and Linde, Buzo, and Gray (LBG)'s clustering algorithm [14]. Basically, initial selection of centroids is done first in this regard. In K-means clustering, until a convergence criterion is met, the nearest centroid is found for each sample to assign it to a cluster and compute the center of that cluster again. In LBG, re-computation is performed after assigning all samples to new clusters. Since, LBG follows binary splitting methods, the size of the codebook must be power of two. In K-means, the performance varies based on the selection of the initial random centroids. On the other hand, LBG starts from binary splitting of the centroid of entire dataset, thus there is less variation in its performance. Hence, LBG is chosen in this work for codebook generation. Once a codebook is obtained, index numbers of the codebook vectors are used as symbols to apply on HMM. Figure 8 shows the basic steps of codebook generation using feature vectors of training binary silhouettes and symbol selection for a silhouette (i.e., training or testing) using the generated codebook.



a) Codebook generation.



b) Symbol selection

Figure 8. Steps for codebook generation and symbol selection using codebook.

2.5. HMM for Activity Modeling, Training and Recognition

In learning HMM, the symbol sequences obtained from the training image sequences of distinct activity are used to optimize the corresponding HMM. A generic HMM can be expressed as $H=\{\theta, \pi, A, B\}$ where, θ is collection of possible states, π is the initial probability of the states, A the transition probability matrix and B observation symbols' probability from every state. For N activities, there will be a collection $(H_1, H_2, ..., H_N)$ of N trained HMMs. Let us denote the states in the model by θ and each state at given time t by q. Then, the state transition probability A, the observation symbol probability B and the initial state probability π are defined as:

$$A = \{a_{ij}\}, a_{ij} = Pr(q_{t+1} = \theta_j \mid q_t = \theta_i), 1 \le i, j \le N \tag{11}$$

$$B = \{b_j(O_t)\}, b_j = P(O_t \mid q_t = \theta_j), 1 \le j \le N \tag{12}$$

$$\pi = \{\pi_i\}, \pi_i = Pr(q_1 = \theta_i) \tag{13}$$

In the learning step, we set the variable, $\xi_t(i, m)$, the probability of being in state q_i at time t and state q_m at time $t+1$, to re-estimate the model parameters, and we also define the variable, $\gamma_t(i)$, the probability of being in state q_i at time t as follows:

$$\xi_t(i, M) = \frac{\alpha_t(i) a_{iM} b_M(O_{t+1}) \beta_{t+1}(M)}{P(O \mid H)} \tag{14}$$

$$\gamma_t(i) = \sum_{M=1}^{N} \xi(i, M) \tag{15}$$

Where, $\alpha_t(i)$ means the forward variables and $\beta_t(i)$ the backward variables such as:

$$\alpha_{t+1}(M) = \left[\sum_{i=1}^{N} \alpha_t(i) a_{iM}\right] b_M(O_{t+1}) \tag{16}$$

$$\beta_t(i) = \sum_{M=1}^{N} a_{iM} b_M(O_{t+1}) \beta_{t+1}(i) \tag{17}$$

Now, let us estimate the updated parameters A, B of the HMM as follows:

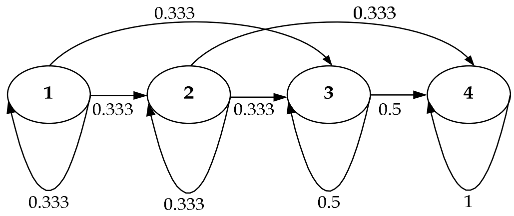
$$\bar{a}_{iM} = \frac{\sum_{t=1}^{T-1} \xi_t(i, M)}{\sum_{t=1}^{T-1} \gamma_t(i)} \tag{18}$$

$$\bar{b}_M(k) = \frac{\sum_{\substack{t=1 \\ O_t=k}}^{T-1} g_t(i)}{\sum_{t=1}^{T-1} g_t(i)} \tag{19}$$

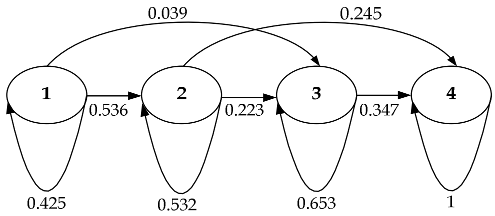
Where, $\bar{a}_{iM}$ is the estimated transition probability from the state i to the state M and $\bar{b}_M(k)$ the estimated observation probability of symbol k from the state M. Figure 9 shows the structure and transition probabilities of a walking HMM before and after training.

To test an activity image sequence, the obtained discrete observation symbol sequence O is used to determine the proper model by means of highest likelihood computation of all trained activity HMMs as:

$$Actvitiy = \arg \max_{k=1}^{N} (Pr(O \mid H_k)) \tag{20}$$



a) A HMM structure.



b) A trained HMM.

Figure 9. HMM structure and a walking HMM after training.

3. Experimental Results

To compare EICA-GDA with the conventional feature extraction methods, all the methods were implemented with HMMs to recognize five different human activities: Namely walking, running, skipping, Right Hand Waving (RHW) and Both Hand Waving (BHW). Fifteen and forty video image sequences of variable lengths were applied for training and recognition of the activities respectively. The videos for HAR were collected from the activity databases utilized in [4].

In the case of PCA, the eigenvectors were computed, among which 100 were selected to train the HMMs. As shown in Table 1, the recognition rate using the PCA method is 61.50%, very poor recognition rate. Then, EICA was employed to extract the ICs from the dataset. Since the EICA applies ICA on the PC feature space, 100 ICs were obtained to apply for training activity HMMs. Table 2 shows the recognition result of 80% using the EIC features.

Furthermore, PCA-LDA was performed for the comparison study and it achieved the recognition rate of 77% as shown in Table 3. The result of EICA method in Table 2 shows the improved recognition rate than the result of PCA and PCA-LDA. Then, LDA on the EIC features were applied with HMMs and achieved the total mean recognition rate of 87% as shown in Table 4. Later on, GDA is applied on the the PC features and obtained better results (i.e., 79.50%) than PCA-LDA as shown in Table 5. Finally, GDA was applied on the EIC features that show the superior performance over all the approaches (i.e., 95%) as shown in Table 6.

Table 1. Confusion matrix using PCA.

Activity	Walk	Run	Skip	RHW	BHW
Walk	60	15	20	5	0
Run	2.50	65	27.50	0	0
Skip	25	17.50	57.50	0	0
RHW	5	0	0	60	35
BHW	0	0	5	30	65
Mean	61.50				

Table 2. Confusion matrix using EICA.

Activity	Walk	Run	Skip	RHW	BHW
Walk	**80**	17.50	2.50	0	0
Run	5	**80**	15	0	0
Skip	5	17.50	**77.50**	0	0
RHW	0	5	0	**82.50**	12.50
BHW	0	2.50	0	17.50	**80**
Mean	**80**				

Table 3. Confusion matrix using PCA-LDA.

Activity	Walk	Run	Skip	RHW	BHW
Walk	**75**	12.50	10	2.50	0
Run	12.50	**77.50**	10	0	0
Skip	5	15	**77.50**	2.50	0
RHW	7.50	0	0	**80**	12.50
BHW	0	0	7.50	17.50	**75**
Mean	**77**				

Table 4. Confusion matrix using EICA-LDA.

Activity	Walk	Run	Skip	RHW	BHW
Walk	**90**	7.50	2.50	0	0
Run	2.50	**82.50**	15	0	0
Skip	5	10	**82.50**	2.50	0
RHW	0	0	0	**90**	10
BHW	0	2.50	0	7.50	**90**
Mean	**87**				

Table 5. Confusion matrix using PCA-GDA.

Activity	Walk	Run	Skip	RHW	BHW
Walk	**80**	15	2.50	2.50	0
Run	10	**80**	10	0	0
Skip	7.50	17.50	**75**	0	0
RHW	5	0	0	**82.50**	12.50
BHW	0	7.50	0	12.50	**80**
Mean	**79.50**				

Table 6. Confusion matrix using EICA-GDA.

Activity	Walk	Run	Skip	RHW	BHW
Walk	**95**	7.50	0	0	0
Run	0	**95**	5	0	0
Skip	0	10	**90**	0	0
RHW	0	0	0	**97.50**	2.50
BHW	0	0	0	2.50	**97.50**
Mean	**95**				

Thus, during the experiments, the recognition performance achieved using EICA-GDA was higher than other feature extraction approaches such as PCA, EICA, PCA-LDA, EICA-LDA, GDA, and PCA-GDA. However, EICA-LDA produces the improved recognition rates in HAR but, does not produce sufficient recognition performance. Due to the nonlinear separation capability of GDA, EICA-GDA shows its superiority over the conventional feature extraction methods in this work by achieving the highest recognition rate. Figure 9 shows the recognition rates of different feature extraction approaches regarding to HAR where the proposed method (i.e., EICA-GDA) outperforms the others.

The proposed HAR system worked fast as the recognition process requires simple matrix multiplications for EICA, GDA and HMM for testing a binary silhouette sequence though the training process was a little time-consuming due to EICA-GDA feature space construction using the entire training silhouette activity database. Besides, to capture the human activity videos, we utilized normal RGB camera, which is very cheap and hence indicating to an inexpensive HAR system. The proposed system can also be applied in real time if an efficient background subtraction can be applied to extract clear and smooth silhouettes from noisy backgrounds.

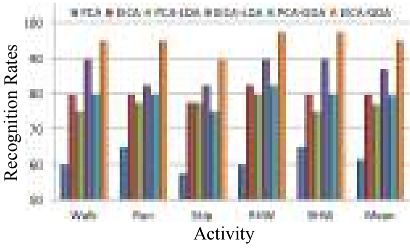


Figure 10. Recognition performance of different approaches applied for HAR.

4. Conclusions

A robust approach has been proposed here for HAR using GDA on EIC features of binary silhouettes in combination with HMM. The proposed approach shows superior performance in recognition rate than other conventional methods. For more robust activity recognition, stronger local features with time-sequential recognition model can be analyzed for various smart environments.

Acknowledgements

This work was supported in part by the Industrial Strategic Technology Development Program, (10043977, Development of a Sustainable and Practical Wellness System using Emotion Mechanism and Smart Media for the Elderly) funded by the Ministry of Knowledge Economy (MKE, Korea) and in part by the MSIP(Ministry of Science, ICT and Future Planning), Korea, under the C-ITRC (Convergence Information Technology Research Center) support program (NIPA-2014-H0401-14-1003) supervised by the NIPA(National IT Industry Promotion Agency) and in part by Key Research Instit ute Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2010-0020163).

References

[1] Bartlett S., Lades M., and Sejnowski J., "Independent Component Representations Recognition," *in Proceedings of the SPIE Symposium on Electronic Imaging: Science and Technology, Human Vision and Electronic Imaging III*, San Jose, California, pp. 528-539, 1998.

[2] Fernández-Caballero A. and Rodríguez-Sánchez M., "Human Activity Monitoring by Local and Global Finite State Machines," *Expert Systems with Applications*, vol. 39, no. 8, pp. 6982-6993, 2012.

[3] Gavrila D., "The Visual Analysis of Human Movement: A Survey," *Computer Vision and Image Understanding*, vol. 73, no. 1, pp. 82-98, 1999.

[4] Gorelick L., Blank M., Shechtman E., Irani M., and Basri R., "Actions as Space-time Shapes," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol., 29, no. 12, pp. 2247-2253, 2007.

[5] Jalal A., Uddin Z., Kim T., and Kim S., "Recognition of Human Home Activities via Depth Silhouettes and ℜ Transformation for Smart Homes," available at: http://www.csheb.org/PDF/5th/25.%20Ahmad20 Jalal.pdf, last visited 2012.

[6] Kokkinos M., Doulamis D., and Doulamis D., "Local Geometrically Enriched Mixtures for Stable and Robust Human Tracking in Detecting Falls," *International Journal of Advanced Robotic Systems*, vol. 10, pp. 1-13, 2013.

[7] Kwon W. and Lee W., "Phoneme Recognition using ICA-based Feature Extraction and Transformation," *Signal Processing*, vol. 84, no. 6, pp. 1005-1019, 2004.

[8] Lee I. and Batzoglou S., "Application of Independent Component Analysis to Microarrays," *Genome Biology*, vol. 4, no. 11, pp. 1-22, 2003.

[9] Liu C. and Wechsler H., "Comparative Assessment of Independent Component Analysis for Face Recognition," *in Proceedings of International Conference on Audio and Video Based Biometric Person Authentication*, USA, pp. 22-24, 1999.

[10] Liu C., "Enhanced Independent Component Analysis and its Application to Content Based Face Image Retrieval," *IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics*, vol. 34, no. 2, pp. 1117-1127, 2004.

[11] Niu F. and Abdel-Mottaleb M., "HMM-Based Segmentation and Recognition of Human Activities from Video Sequences," *in Proceedings of the IEEE International Conference on Multimedia and Expo*, Amsterdam, pp. 804-807, 2005.

[12] Rehman A. and Saba T., "An Intelligent Model for Visual Scene Analysis and Compression," *the International Arab Journal of Information Technology*, vol. 10, no. 2, pp. 126-136, 2013.

[13] Shen L., Bai L., and Fairhurst M.," Gabor Wavelets and General Discriminant Analysis for face Identification and Verification," *Image and Vision Computing*, vol. 25, no. 5, pp. 553-563, 2007.

[14] Uddin Z., Lee J., and Kim S., "Independent Shape Component-Based Human Activity

Recognition via Hidden Markov Model," *Applied Intelligence*, vol. 33, no. 2, pp. 193-206, 2010.

[15] Yamato J., Jun O., and Ishii K., "Recognizing Human Action in Time-sequential Images using Hidden Markov Model," *in Proceedings of IEEE International Conference on Computer Vision and Pattern Recognition*, Champaign, pp. 379-385, 1992.

[16] Yu P., Xu D., and Yu P., "Comparison of PCA, LDA and GDA for Palm Print Verification," *in Proceedings of International Conference on Information, Networking and Automation*, Kunming, pp.148-152, 2010.

[17] Yun S., Choi T., Kim M., and Song B., "Intention Reading from a Fuzzy-Based Human Engagement Model and Behavioural Features," *International Journal of Advanced Robotic Systems*, vol. 9, pp- 1-10, 2012.

Md. Zia Uddin received his PhD degree in biomedical engineering from Kyung Hee University, South Korea. Currently, he is working as an Assistant Professor at the Department of Computer Education of Sungkyunkwan University (SKKU) of South Korea. His researches are focused on computer vision, image processing, and pattern recognition.

Deok-Hwan Kim received the MS and PhD degrees in computer engineering from Korea Advanced Institute of Science and Technology. Currently, he is a professor in the School of Electronic Engineering at Inha University, Korea. His research interests include embedded systems, storage systems, multimedia system and bio-inspired systems.

Tae-Seong Kim received the BS degree in biomedical engineering from the University of Southern California in 1991, MS degrees in biomedical and electrical engineering from USC in 1993 and 1998 respectively and PhD in biomedical engineering from USC in 1999. After his postdoctoral work in cognitive sciences at the University of California, Irvine in 2000, he joined the Alfred E. Mann Institute for Biomedical Engineering and Department of Biomedical Engineering at USC as a Research Scientist and Research Assistant Professor. In 2004, he moved to Kyung Hee University in Korea where he is currently a Professor in the Biomedical Engineering Department. His research interests have spanned various areas of biomedical imaging including Magnetic Resonance Imaging (MRI), functional MRI, E/MEG imaging, DT-MRI, transmission ultrasonic CT and magnetic resonance electrical impedance imaging. Lately, he has started research work in proactive computing at the u-Lifecare Research Center where he serves as Vice Director. he has published more than 50 peer reviewed papers and 100 proceedings and holds 3 international patents. He is a member of IEEE, KOSOMBE and Tau Beta Pi and listed in Who's Who in the World '09-'10.