We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,900
Open access books available

186,000
International authors and editors

200M
Downloads

154
Countries delivered to

Our authors are among the
TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us? Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

14

Silhouette-based Human Activity Recognition Using Independent Component Analysis, Linear Discriminant Analysis and Hidden Markov Model

Tae-Seong Kim and Md. Zia Uddin
Kyung Hee University, Department of Biomedical Engineering
Republic of Korea

1. Introduction

In recent years, Human Activity Recognition (HAR) has evoked considerable interest in various research areas due to its potential use in proactive computing (Robertson & Reid, 2006; Niu & Abdel-Mottaleb, 2004; Niu & Abdel-Mottaleb, 2006). Proactive computing is a technology that proactively anticipates peoples' necessity in situations such as health-care or life-care and takes appropriate actions on their behalf. A system capable of recognizing various human activities has many important applications such as automated surveillance systems, human computer interaction, and smart home healthcare systems. The most common method for activity recognition so far is based on video images from which features are extracted and compare with the pre-defined activity features. Hence, effective feature extraction, modeling, learning, and recognition technology play vital roles in a HAR system.

In general, binary silhouettes (i.e., binary shapes or contours) of various human activities are commonly employed to represent different human activities (Niu & Abdel-Mottaleb, 2004; Niu & Abdel-Mottaleb, 2006; Yamato et al., 1992). In (Niu & Abdel-Mottaleb, 2004) and (Niu & Abdel-Mottaleb, 2006), Principal Component (PC) of binary silhouette features were applied for view invariant human activity recognition. In (Yamato et al., 1992), 2-D mesh features of binary silhouettes extracted from video frames were used to recognize several tennis activities in time sequential images. In (Cohen & Lim, 2003), the authors used a view independent approach utilizing 2-D silhouettes captured by multiple cameras and 3-D silhouette descriptions with Support Vector Machine (SVM) for recognition. In (Carlsson & Sullivan, 2002), a silhouette matching key frame based approach was proposed to recognize forehand and backhand strokes from tennis video clips. In addition to the binary silhouette features, motion features have also been used in HAR (Ben-Arie et al., 2002; Nakata, 2006; Niu & Abdel-Mottaleb, 2004; Niu & Abdel-Mottaleb, 2006; Robertson & Reid, 2006; Sun et al., 2002). In (Ben-Arie et al., 2002), the authors proposed multi-dimensional indexing to recognize different actions represented by velocity vectors of major body parts. In (Nakata, 2006), the authors applied the Burt-Anderson pyramid to extract useful features consisting

of multi-resolutional optical flows to recognize human activities. In (Niu & Abdel-Mottaleb, 2004) and (Niu & Abdel-Mottaleb, 2006), the authors augmented the optical flow motion features with the PC-based binary silhouette features to recognize different activities. In (Robertson & Reid, 2006), the authors described human action with trajectory information (i.e., position and velocity) and a set of local motion descriptors. In (Sun et al., 2002), the authors used affine motion parameters and optical flow for activity recognition.
Regarding fore-mentioned features so far, the most common feature extraction technique applied in video-based human activity recognition is Principal Component Analysis (PCA) (Niu & Abdel-Mottaleb, 2004; Niu & Abdel-Mottaleb, 2006). PCA is an unsupervised second order statistical approach to find useful basis for data representation. It finds PCs at the optimally reduced dimension of the input. For human activity recognition, it focuses on the global information of the binary silhouettes, which has been actively applied. However, PCA is only limited to second order statistical analysis, allowing upto decorrelation of data. Lately, a higher order statistical method called Independent Component Analysis (ICA) is being actively exploited in the face recognition area (Bartlett et al., 2002; Kwak & Pedrycz, 2007; Yang et al., 2005) and has shown superior performance over PCA. It has also been utilized successfully in other fields such as speech recognition (Kwon & Lee, 2004) and functional magnetic resonance imaging signals (Mckeown et al., 1998) but rarely on HAR.
Various pattern classification techniques are applied on the features in the reduced dimensional space for recognition from the time sequential events. Among them, Hidden Markov Models (HMM) have been used effectively in many works (Nakata, 2006; Niu & Abdel-Mottaleb, 2006; Niu & Abdel-Mottaleb, 2004; Sun et al., 2002; Yamato et al., 1992). In (Nakata, 2006) and (Sun et al., 2002), the authors utilized optical flows to build HMMs for recognition. In (Niu & Abdel-Mottaleb, 2004) and (Niu & Abdel-Mottaleb, 2006), the authors applied binary silhouette and optical flow motion features in combination with HMM. In (Yamato et al., 1992), the binary silhouettes were employed to develop distinct HMMs for different activities.
In this chapter, we present a novel approach utilizing independent binary silhouette-component and HMM for HAR (Uddin et al., 2008a; Uddin et al., 2008b). ICA is used for the first time on the activity silhouettes obtained from the activity video to extract the local features rather than global features produced by PCA. With the extracted features, HMM, a strong probabilistic tool to encode the time sequential information is employed to train and recognize different human activities from video. The IC-feature based approach shows better performance in recognition over PC features. In addition, the IC-features are further enhanced by Linear Discriminant Analysis (LDA) by finding out the underlying space that better discriminates the features of different activities, which leads further improvement in the recognition rate of HAR.

2. Methodology of the HMM-based Recognition System

Our recognition system consists of binary silhouette extraction, feature extraction, vector quantization, modeling, and recognition via HMM. The feature extraction is done over the extracted silhouettes from the activity video frames. The extracted features are then vector quantized by means of vector quantization to generate discrete symbol sequences for HMM for training and recognition. Fig. 1 shows the basic procedures of the silhouette feature-based activity recognition system using HMM.

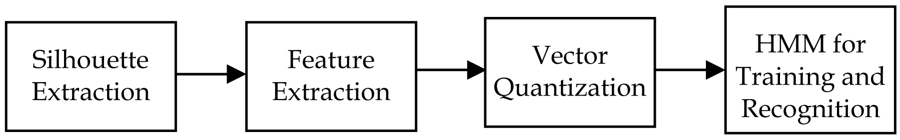


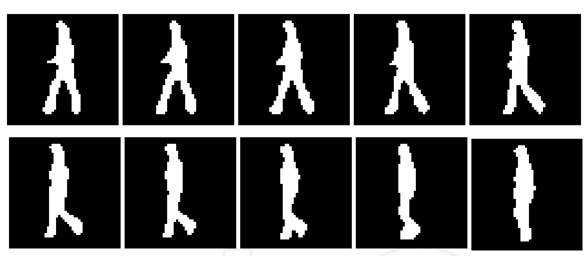
Fig. 1. Silhouette-based human activity recognition system using HMM.

2.1. Silhouette Extraction

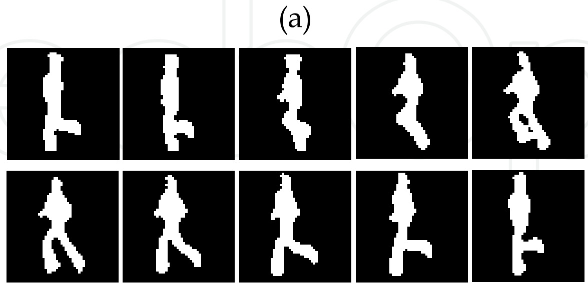
A simple Gaussian probability distribution function is used to remove background from a recent frame and to extract a Region of Interest (ROI). To extract the ROI, the background subtracted difference image is converted to binary using a threshold that is experimentally determined on the basis of subtraction result. Fig. 2 shows a generation of ROI from a sample frame and Fig. 3 a couple of sequences of generalized ROIs for walking and running.

(a) (b) (c)

Fig. 2. (a) A Background image, (b) a frame from a walking sequence, and (c) a ROI indicated with the rectangle.



(a)



(b)

Fig. 3. Generalized ROIs or silhouettes from image sequences of (a) walking and (b) running.

To apply feature extraction on human activity binary silhouettes, every normalized ROI image is represented as a row vector in a raster scan fashion where the dimension of the vector is equal to the number of pixels in the entire image. Some preprocessing steps are necessary before applying a feature extraction algorithm on the images. The first preprocessing step is to make all the training vectors as zero mean. Then the feature extraction algorithm is applied on the zero mean input vectors.

2.2. Feature Extraction Using PCA

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 Q and then approximation is done using the linear combination of top eigenvectors. The covariance matrix of the sample training image vectors and the PCs of the covariance matrix can be calculated respectively as

$$Q = \frac{1}{T}\sum_{i=1}^{T}(\tilde{X}_i \tilde{X}_i^T) \tag{1}$$

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

where E represents the matrix of orthonormal eigenvectors and Λ diagonal matrix of the eigenvalues. E reflects the original coordinate system onto the eigenvectors where the eigenvector corresponding to the largest eigenvalue indicates the axis of largest variance and the next largest one is the orthogonal axis of largest one indicating second largest variance and so on. Usually, the eigenvalues that are close to zero values carry negligible variance and hence can be excluded. So, the several m eigenvectors corresponding to the largest eigenvalues can be used to define the subspace. Thus the full dimensional silhouette image vectors can be easily represented in the reduced dimension.

However, PCA is a second order statistics-based analysis to represent global information such as average faces or eigenfaces in the case of face recognition. After applying PCA on human silhouettes of different activities, it produces global features representing frequently moving parts of human body in all activities. Fig. 4 shows 30 basis images after PCA is applied on 600 images of four activities: namely walking, running, right hand waving, and both hand waving. The basis images are the resized form of eigenvectors and normalized in gray scale. Fig. 5 shows top 150 eigenvalues corresponding to the first 150 eigenvectors where 600 silhouette image vectors are considered for PCA.

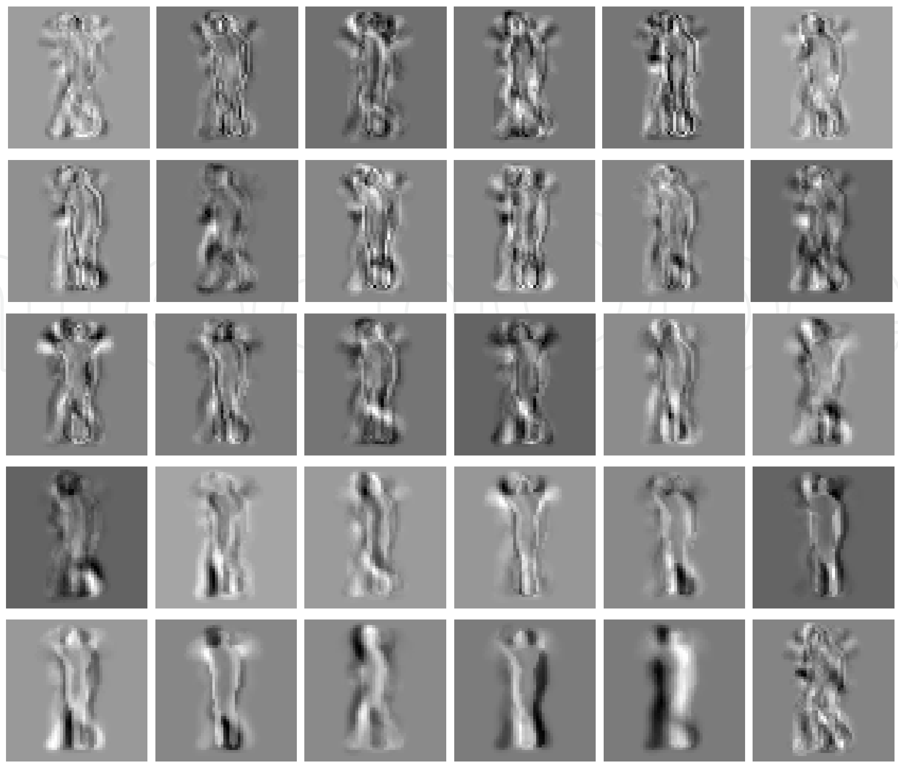


Fig. 4. Thirty PCs of all the images of the four activities.

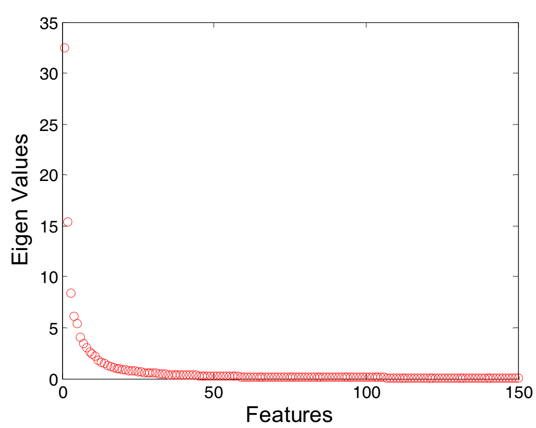


Fig. 5. Hundred and fifty top eigenvalues of the training silhouette images of the four activities.

2.3. Feature Extraction Using ICA

ICA finds the statistically independent basis images. The basic idea of ICA is to represent a set of random observed variables using basis function where the components are statistically independent. If S is collection of basis images and X is collection of input images then the relation between X and S is modeled as

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

where M represents an unknown linear mixing matrix of full rank.

An ICA algorithm learns the weight matrix W, which is inverse of mixing matrix M. W is used to recover a set of independent basis images S. The ICA basis image focuses on local feature information rather than global information as in PCA. ICA basis images show the local features of the movements in activity such as open or closed legs for running. Fig. 6 shows 30 ICA basis images for all activities. Before applying ICA, PCA is used to reduce the dimension of the image data. ICA is performed on E_m as follows.

$$S = WE_m^T \tag{4}$$

$$E_m^T = W^{-1}S \tag{5}$$

$$X_r = VW^{-1}S \tag{6}$$

where V is projection of the images X on E_m and X_r the reconstructed original images. The independent component representation I_i of i^{th} silhouette vector $\tilde{X}_i$ from an activity image sequence can be expressed as

$$I_i = \tilde{X}_i E_m W^{-1}. \tag{7}$$

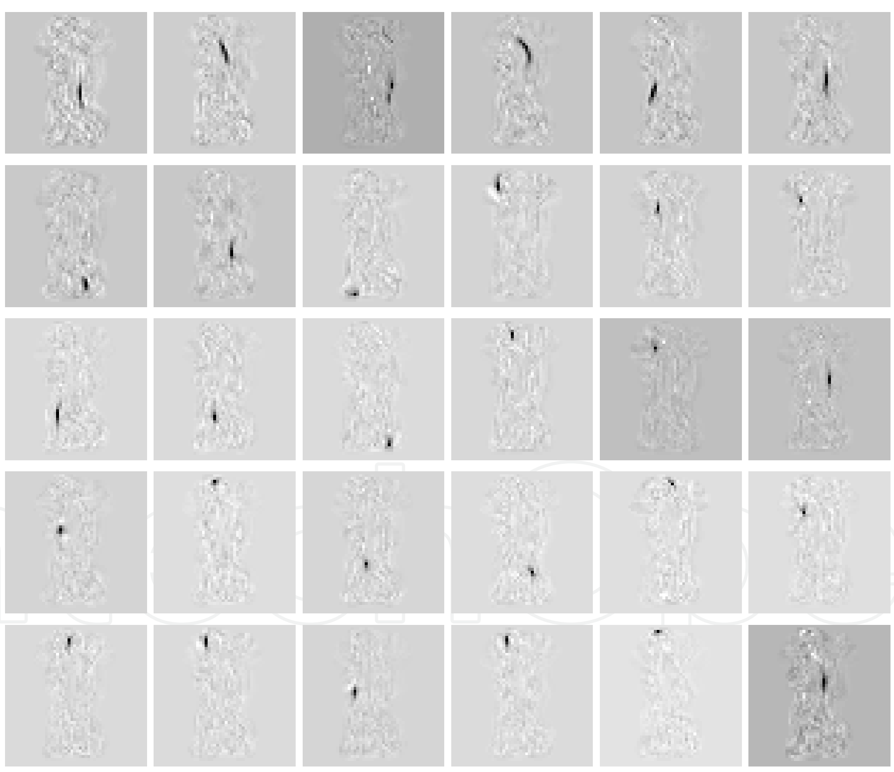


Fig. 6. Thirty ICs of all the images of the four activities.

2.4. Feature Extraction Using LDA on the IC Features

LDA produces an optimal linear discriminant function which maps the input into the classification space based on which the class identification of the samples can be decided

(Kwak & Pedrycz, 2007). The within scatter matrix, S_W and the between scatter matrix, S_B are computed by the following equations:

$$S_B = \sum_{i=1}^{c} G_i (\overline{m_i} - \overline{\overline{m}})(\overline{m_i} - \overline{\overline{m}})^T \tag{8}$$

$$S_W = \sum_{i=1}^{c} \sum_{m_k \in C_i} (m_k - \overline{m_i})(m_k - \overline{m_i})^T \tag{9}$$

where G_i is the number of vectors in i^{th} class C_i. c is the number of classes and in our case, it represents the number of activities. $\overline{\overline{m}}$ represents the mean of all vectors, $\overline{m_i}$ the mean of the class C_i and m_k the vector of a specific class. The optimal discrimination matrix D_{LDA} is chosen from the maximization of ratio of the determinant of the between and within class scatter matrix as

$$D_{LDA} = \arg \max_{D} \frac{\left| D^T S_B D \right|}{\left| D^T S_W D \right|} \tag{10}$$

where D_{LDA} is the set of discriminant vectors of S_W and S_B corresponding to the $(c-1)$ largest generalized eigenvalues λ and can be obtained via solving

$$S_B d_i = \lambda_i S_W d_i. \tag{11}$$

The LDA algorithm looks for the vectors in the underlying space to create the best discrimination among different classes. Thus the extracted ICA representations of the binary silhouettes of different activities can be extended by LDA. The feature vectors using LDA on the IC features can be represented as

$$F_i = I_i D_{LDA}^T. \tag{12}$$

Fig. 7 shows the 3-D representation of the binary silhouette features after applying on three ICs that are chosen on the basis of top kurtosis values. Fig. 8 demonstrates the 3-D plot of LDA on the IC features of the silhouettes of four classes where 150 ICs are taken. Fig. 8 shows a good separation among the representation of the silhouettes of different classes.

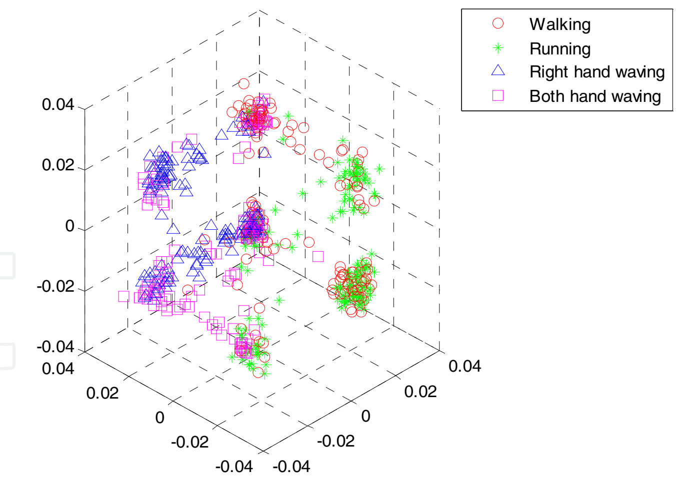


Fig. 7. 3-D plot of the IC features of 600 silhouettes of the four activities.

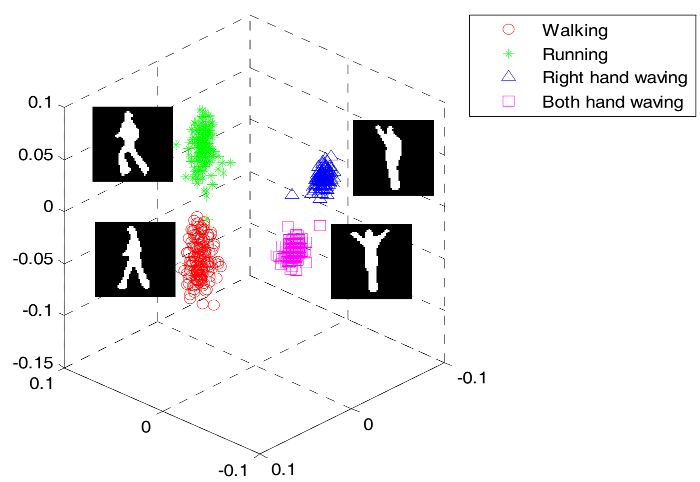


Fig. 8. 3-D plot of the LDA on the IC features of 600 silhouettes of the four activities.

2.5. Vector Quantization

We symbolize the feature vectors before applying them to train or recognize by HMM. An efficient codebook of vectors can be generated using vector quantization from the training vectors. In our experiment, we have used two vector quantization algorithms: namely ordinary K-means clustering (Kanungu et al., 2000) and Linde, Buzo, and Gray (LBG)'s clustering algorithm (Linde et al., 1980). In both of them, first initial selection of centroids is obtained. In the case of K-means clustering, until a convergence criterion is met, for every sample it seeks the nearest centroid, assign the sample to the cluster, and compute the center of that cluster again. However, in the case of LBG, recomputation is done after assigning all samples to new clusters. In LBG, initialization is done by splitting the centroid of whole dataset. It starts with the codebook size of one and recursively splits into two codewords. After splitting, optimization of the centroids is done to reduce the distortion. Since it follows the binary splitting method, the size of the codebook must be power of two. In the case of K-means, the overall performance varies due to the selection of the initial random centroids. On the contrary, LBG starts from splitting the centroid of entire dataset, thus there is less variation in its performance.

When a codebook is designed, the index numbers of the codewords are used as symbols to apply on HMM. As long as a feature vector is available then index number of the closest codeword from the codebook is the symbol for that replace. Hence every silhouette image is going to be assigned a symbol. If there are K image sequences of T length then there will be K sequences of T length symbols. The symbols are the observations, O. Fig. 9 shows the codebook generation and symbol selection from the codebook using the IC features.

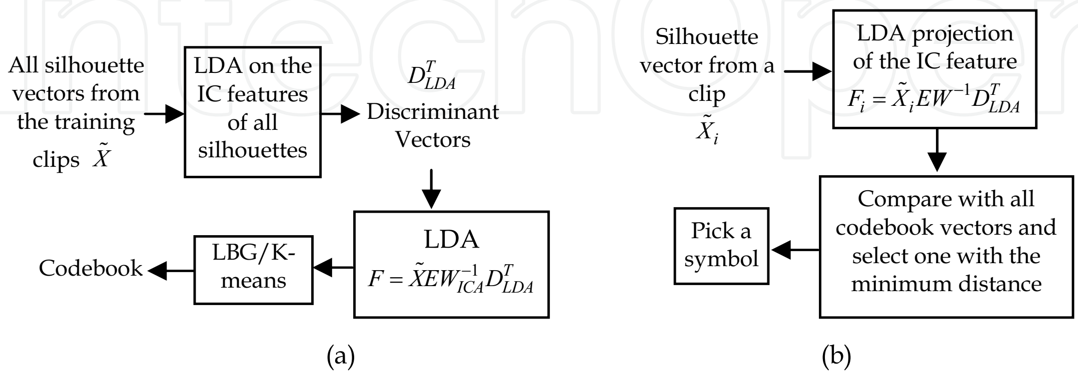


Fig. 9. Steps for (a) codebook generation and (b) symbol selection using LDA on the IC features.

2.6. HMM for Activity Modeling, Training, and Recognition

HMM has been applied extensively to solve a large number of problems including speech recognition (Lawrence & Rabiner, 1989). It has been adopted in the human activity research field as well in (Niu & Abdel-Mottaleb, 2004; Niu & Abdel-Mottaleb, 2006; Yamato et al., 1992; Nakata, 2006; Sun et al., 2002). Once human activities are represented in features then HMM can be applied effectively for human activity recognition as it is a most suitable technique for recognizing time sequential feature information. Silhouette features are converted to a sequence of symbols that are corresponding to the codewords of the codebook obtained by vector quantization. In learning HMM, the symbol sequences obtained from the training image sequences of distinct activity are used to optimize the corresponding HMM. Each activity is represented by a distinct HMM. In recognition, the symbol sequence is applied to all HMMs and one is chosen that gives the highest likelihood.
An HMM is a collection of finite states connected by transitions. Every state is characterized by two types of probabilities: namely transition probability and symbol observation probability. A generic HMM can be expressed as $H = \{\Xi, \pi, A, B\}$ where Ξ denotes possible states, π the initial probability of the states, A the transition probability matrix between hidden states where state transition probability a_{ij} represents the probability of changing state from i to j, and B observation symbols' probability from every state where the probability $b_j(O)$ indicates the probability of observing the symbols O from state j. If the number of activities is N then there will be a dictionary $(H_1, H_2, ..., H_N)$ of N trained models. We used the Baum-Welch algorithm for HMM parameter estimation (Iwai et al., 1997) according to (13) to (16).

$$\xi_t(i,j) = \frac{\alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{\sum_{i=1}^{q} \sum_{j=1}^{q} \alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)} \tag{13}$$

$$\xi_t(i,j) = \frac{\alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)}{\sum_{i=1}^{q} \sum_{j=1}^{q} \alpha_t(i) a_{ij} b_j(O_{t+1}) \beta_{t+1}(j)} \tag{14}$$

$$\hat{a}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T} \gamma_t(i)} \tag{15}$$

$$\hat{b}_j(d) = \frac{\sum_{\substack{t=1 \\ O_t = d}}^{T-1} \gamma_t(j)}{\sum_{t=1}^{T} \gamma_t(j)} \tag{16}$$

where $\xi_t(i, j)$ is the probability of staying in a state i at time t and a state j at time $t+1$. $\gamma_t(i)$ represents the probability of staying in the state i at time t. α and β are the forward and backward variables respectively. $\hat{a}_{ij}$ represents the estimated transition probability from the state i to the state j and $\hat{b}_j(d)$ the estimated observation probability of symbol d from the state j. q is the number of states in the model.
Four-state left-to-right HMM was chosen for each activity. In the case of observation matrix B, the possible number of observations from every state is the number of codebook vectors. Fig. 10 shows the transition probabilities of a walking HMM before and after training with the codebook size of 32. To test a sequence O, the appropriate HMM is one that gives the highest likelihood. The likelihood of the sequence O at time t for an HMM H can be represented as

$$P(O \mid H) = \sum_{i=1}^{q} \alpha_t(i). \tag{17}$$

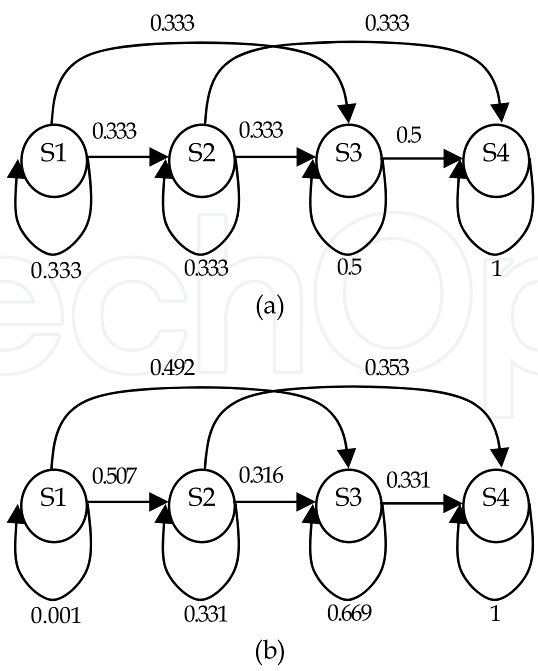


Fig. 10. A walking HMM (a) before and (b) after training.

3. Experiments and Discussion

In our silhouette-based recognition approaches, we used two different kinds of inputs: namely binary (Uddin et al., 2008a) and depth (Uddin et al., 2008b). The binary silhouette pixels contain a flat distribution of the intensity (i.e., 0 or 1). On the contrary, the depth silhouette contains variable pixel intensity distribution based on the distance of human body parts to the camera.

3.1. Recognition Using Binary Silhouettes

We recognized four activities using the IC features of the binary silhouettes through HMM: namely walking, running, right hand waving, and both hand waving. Every sequence consisted of 10 images. A total of 15 sequences from each activity were used to build the feature space. Thus, the whole database consisted of a total of 600 images. After applying ICA and PCA, 150 features were taken in the feature space.

We further extended the IC features by LDA for more robust feature representation. Thus, several tests were performed with different features using LBG with the codebook size of 32 where LDA on the IC features showed superior recognition rate. A total of 160 sequences were used for testing the models. Table 1 lists the recognition results using the different features: namely PCA, LDA on the PC features, ICA, and LDA on the IC features.

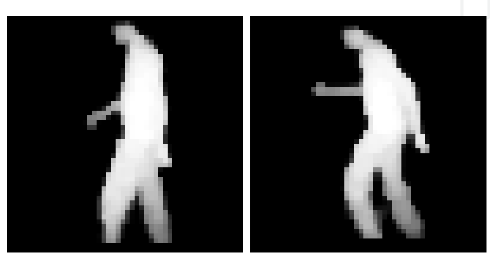
Approach	Activity	Recognition Rate	Mean	Standard Deviation
PCA	Walking	100%	87.26	8.90
	Running	82.5		
	RHW*	80		
	BHW**	88		
LDA on the PC features	Walking	100	89.87	8.37
	Running	87.5		
	RHW	80		
	BHW	92		
ICA	Walking	100	96.13	4.48
	Running	92.5		
	RHW	100		
	BHW	92		
LDA on the IC features	Walking	100	99.5	1
	Running	100		
	RHW	100		
	BHW	98		

*RHW=Right Hand Waving **BHW=Both Hand Waving

Table 1. Recognition result using different feature extraction approaches on the binary silhouettes.

3.2. Recognition Using Depth Silhouettes

Basically, binary silhouettes reflect only the silhouette contour information. On the other hand, regarding the depth-based silhouettes, pixel values are set based on the distance to the camera and hence can represent more activity information than binary. Fig. 11 shows a sample depth image of walking and running respectively where the near parts of human body from the camera have brighter pixel intensity values than the far ones. Thus, the depth silhouettes can represent the human body better than binary by differentiating the major body parts by means of different intensity values based on the distance to camera (Uddin et al., 2008b). In this work, we employed LDA on the IC features of the depth silhouettes to recognize six different activities (i.e., walking, running, skipping, boxing, sitting up, and standing down) through HMM and obtained much improvement over the binary silhouette-based approach using the same feature extraction technique. The recognition results using both the binary and depth silhouette-based approaches are shown in Table 2.



(a) (b)

Fig. 11. Sample depth silhouette of (a) walking and (b) running.

Features	Activity	Recognition Rate with HMM	Mean	Standard Deviation
LDA on the IC features of the binary silhouettes	Walking	84	91.33	8.17
	Running	96		
	Skipping	88		
	Boxing	100		
	Sitting	84		
	Standing	100		
LDA on the IC features of the depth silhouettes	Walking	96	96.67	4.68
	Running	96		
	Skipping	88		
	Boxing	100		
	Sitting Up	100		
	Standing Down	100		

Table 2. Recognition result using LDA on the IC features of the binary and depth silhouettes.

4. Conclusion

In this chapter, we have presented novel approaches for binary and depth silhouette-based human activity recognition using ICA and LDA in combination with HMM. LDA on the binary IC feature-based approach outperforms PCA, ICA, and LDA on the PC feature-based approaches, achieving 99.5% recognition rate for the four activities. Using depth silhouettes, the recognition further improves from 91.33% to 96.67% in the overall recognition of the six different activities.

5. Acknowledgement

This work was supported by the MKE (Ministry of Knowledge Economy), Korea, under the ITRC (Information Technology Research Center) support program supervised by the IITA (Institute of Information Technology Advancement) (IITA 2008-(C1090-0801-0002)).

6. References

Bartlett, M.; Movellan, J. & Sejnowski, T. (2002). Face Recognition by Independent Component Analysis, *IEEE Transactions on Neural Networks*, Vol., 13, pp. 1450-1464.

Ben-Arie, J.; Wang, Z.; Pandit, P. & Rajaram, S. (2002). Human Activity Recognition Using Multidimensional Indexing, *IEEE Transactions on Pattern Analysis and Machine Intelligence Archive*, Vol., 24(8), pp. 1091-1104.

Carlsson, S. & Sullivan, J. (2002). Action Recognition by Shape Matching to Key Frames, *IEEE Computer Society Workshop on Models versus Exemplars in Computer Vision*, pp. 263-270.

Cohen, I. & Lim, H. (2003). Inference of Human Postures by Classification of 3D Human Body Shape, *IEEE International Workshop on Analysis and Modeling of Faces and Gestures*, pp. 74-81.

Iwai, Y.; Hata, T. & Yachida, M. (1997) Gesture Recognition Based on Subspace Method and Hidden Markov Model, *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 960-966.

Kanungu, T.; Mount, D. M.; Netanyahu, N.; Piatko, C.; Silverman, R. & Wu, A. Y. (2000). The analysis of a simple k-means clustering algorithm, *Proceedings of 16th ACM Symposium On Computational Geometry*, pp. 101-109.

Kwak, K.-C. & Pedrycz, W. (2007). Face Recognition Using an Enhanced Independent Component Analysis Approach, *IEEE Transactions on Neural Networks*, Vol., 18(2), pp. 530-541.

Kwon, O. W. & Lee, T. W. (2004). Phoneme recognition using ICA-based feature extraction and transformation, *Signal Processing*, Vol., 84(6), pp. 1005–1019.

Lawrence, R. & Rabiner, A. (1989). Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition, *Proceedings of the IEEE*, 77(2), pp. 257-286.

Linde, Y.; Buzo, A. & Gray, R. (1980). An Algorithm for Vector Quantizer Design, *IEEE Transaction on Communications*, Vol., 28(1), pp. 84–94.

Mckeown, M. J.; Makeig, S.; Brown, G. G.; Jung, T. P.; Kindermann, S. S.; Bell, A. J. & Sejnowski, T. J. (1998) Analysis of fMRI by decomposition into independent spatial components, *Human Brain Mapping*, Vol., 6(3), pp. 160–188.

Nakata, T. (2006). Recognizing Human Activities in Video by Multi-resolutional Optical Flow, *Proceedings of International Conference on Intelligent Robots and Systems*, pp. 1793-1798.

Niu, F. & Abdel-Mottaleb M. (2004).View-Invariant Human Activity Recognition Based on Shape and Motion Features, *Proceedings of the IEEE Sixth International Symposium on Multimedia Software Engineering*, pp. 546-556.

Niu, F. & Abdel-Mottaleb, M. (2005). HMM-Based Segmentation and Recognition of Human Activities from Video Sequences, *Proceedings of IEEE International Conference on Multimedia & Expo*, pp. 804-807.

Robertson, N. & Reid, I. (2006). A General Method for Human Activity Recognition in Video, *Computer Vision and Image Understanding*, Vol., 104(2), pp. 232 - 248.

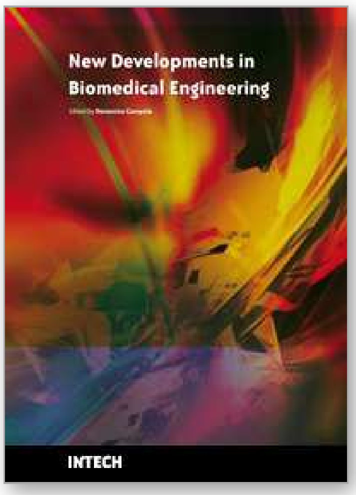
Sun, X.; Chen, C. & Manjunath, B. S. (2002). Probabilistic Motion Parameter Models for Human Activity Recognition, *Proceedings of 16th International Conference on Pattern recognition*, pp. 443-450.

Yamato, J.; Ohya, J. & Ishii, K. (1992). Recognizing Human Action in Time-Sequential Images using Hidden Markov Model, *Proceedings of IEEE International Conference on Computer Vision and Pattern Recognition*, pp. 379-385.

Yang, J.; Zhang, D. & Yang, J. Y. (2005). Is ICA Significantly Better than PCA for Face Recognition?. *Proceedings of IEEE International Conference on Computer Vision*, pp. 198-203.

Uddin, M. Z.; Lee, J. J. & Kim T.-S. (2008a) Shape-Based Human Activity Recognition Using Independent Component Analysis and Hidden Markov Model, *Proceedings of The 21st International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*, pp. 245-254.

Uddin, M. Z.; Lee, J. J. & Kim, T.-S. (2008b). Human Activity Recognition Using Independent Component Features from Depth Images, *Proceedings of the 5th International Conference on Ubiquitous Healthcare*, pp. 181-183.



New Developments in Biomedical Engineering
Edited by Domenico Campolo

ISBN 978-953-7619-57-2
Hard cover, 714 pages
Publisher InTech
Published online 01, January, 2010
Published in print edition January, 2010

Biomedical Engineering is a highly interdisciplinary and well established discipline spanning across engineering, medicine and biology. A single definition of Biomedical Engineering is hardly unanimously accepted but it is often easier to identify what activities are included in it. This volume collects works on recent advances in Biomedical Engineering and provides a bird-view on a very broad field, ranging from purely theoretical frameworks to clinical applications and from diagnosis to treatment.

How to reference
In order to correctly reference this scholarly work, feel free to copy and paste the following:

Tae-Seong Kim and Zia Uddin (2010). Silhouette-based Human Activity Recognition Using Independent Component Analysis, Linear Discriminant Analysis and Hidden Markov Model, New Developments in Biomedical Engineering, Domenico Campolo (Ed.), ISBN: 978-953-7619-57-2, InTech, Available from: http://www.intechopen.com/books/new-developments-in-biomedical-engineering/silhouette-based-human-activity-recognition-using-independent-component-analysis-linear-discriminant

INTECH
open science | open minds

InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China
Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

© 2010 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License, which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.