International Journal of Control, Automation, and Systems (2014) 12(1):202-207
DOI 10.1007/s12555-012-0154-6
ISSN:1598-6446 eISSN:2005-4092
http://www.springer.com/12555

A New Gait Recognition System based on Hierarchical Fair Competition-based Parallel Genetic Algorithm and Selective Neural Network Ensemble

Heesung Lee, Heejin Lee, and Euntai Kim*

Abstract: The recognition of a person from his or her gait has been a recent focus in computer vision because of its unique advantages such as being non-invasive and human friendly. However, gait recognition is not as reliable an identifier as other biometrics. In this paper, we applied a hierarchical fair competition-based parallel genetic algorithm and a neural network ensemble to the gait recognition problem. A diverse set of potential neural networks are generated to increase the reliability of the gait recognition, not only the best ones. Furthermore, a set of component neural networks is selected to build a gait recognition system such that generalization errors are minimized and negative correlation is maximized. Experiments are carried out with the NLPR and SOTON gait databases and the effectiveness of the proposed method for gait recognition is demonstrated and compared to previous methods.

Keywords: Gait recognition, hierarchical fair competition-based parallel genetic algorithm, negative correlation, neural network ensemble, selective neural network ensemble.

1. INTRODUCTION

A person's gait is a characteristic feature that is determined by an individual's weight, limb length, footwear, and posture combined with their characteristic motion [1]. The unique advantages of gait as a biometric are that it is non-invasive, easily acquired at a distance, and can be measured even at low resolution. For these reasons, the recognition of a person from his or her gait has become a recent focus in the computer vision and pattern recognition community. However, gait recognition is not reliable an identifier as other biometrics are [2].

Neural networks can construct nonlinear decision boundaries without prior assumptions about the statistical distribution of input data. In particular, they represent implicit knowledge of the given data. Nevertheless, a single neural network of finite size often loads a particular mapping incompletely and the mapping is often generalized poorly [3]. Even increasing the size and number of hidden layers of the single network does not necessarily improve the mapping. Therefore, neural network ensembles are important as a new direction for the development of high-performance systems [4,5]. The neural network ensemble is a learning paradigm in which a collection of neural networks are trained for a task and the system performance can be significantly improved by combining a number of neural networks [2]. Neural network ensembles have recently gained popularity and have already been successfully applied to various applications. For these reasons, we applied a neural network ensemble to gait recognition in our previous work [6] because although gait recognition is a human-friendly and convenient biometric, it is not yet sufficiently reliable. We previously selected the neural network components based on generalization error for the implementation of the gait recognition system [6]. However, in the context of ensembles, the system diversity has been acknowledged as equally important as generalization ability [7]; we thus proposed a new design method for a neural network ensemble in such a way that the generalization error is minimized while the system diversity is maximized [8]. In this previous work [8], the candidate neural networks for an ensemble are first generated using a hierarchical fair competition-based parallel genetic algorithm (HFC-PGA) [9] to increase the diversity of the networks. Furthermore, each candidate neural network is trained to use an appropriate set of features selected by the HFC-PGA rather than all of them. Finally, once the candidate neural networks have been designed, a set of component neural networks is selected such that the generalization error is minimized while the negative correlation is maximized. Since the negative correlation is beneficial in achieving component diversity, which then translates into a higher classification rate,

Manuscript received April 15, 2012; revised May 7, 2013; accepted August 30, 2013. Recommended by Associate Editor Sungshin Kim under the direction of Editor Young-Hoon Joo.

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (NRF-2013R1A2A2A01015624).

Heesung Lee is with the School of Electrical and Electronic Engineering, Yonsei University, Sinchon-dong, Seodaemun-gu, Seoul 120-749, Korea (e-mail: 4u2u@yonsei.ac.kr).

Heejin Lee is with the Department of Electrical Electronic and Control Engineering, Hankyong National University, Sukjong-dong, Ansung-si, Gyunggi-do 456-749, Korea (e-mail: lhjin@hknu.ac.kr).

Euntai Kim is with the School of Electrical and Electronic Engineering, Yonsei University, Sinchon-dong, Seodaemun-gu, Seoul 120-749, Korea (e-mail: etkim@yonsei.ac.kr).

* Corresponding author.

the proposed method shows an increased effectiveness compared with conventional neural network ensembles [5,6]. Therefore in this paper, the neural network ensemble proposed previously [8] is employed for the gait recognition problem to improve accuracy and reliability.

This paper is organized as follows: In Section 2, we provide a new gait recognition system that includes image preprocessing, gait feature extraction, and recognition methods. In Section 3, the proposed scheme is applied to the NLPR and SOTON gait databases and its effectiveness is demonstrated by comparing it with other methods. Finally, conclusions are outlined in Section 4.

2. GAIT RECOGNITON SYSTEM

2.1. Preprocessing

We first generate silhouette images from the image sequences by background subtraction [10]. A bounding box is then built around the contour of the silhouette and the contour is resized to a fixed size to eliminate scaling effects. Fig. 1 shows examples of the original image, background subtraction image, and normalized silhouette image.

2.2. Feature extraction

We use the motion silhouette images (MSIs) [11] from normalized silhouette images as a gait feature. The MSI is a grayscale image where the pixel intensity represents the temporal motion history of motion of that pixel. It possesses the critical spatial and temporal information and is defined as

$$MSI(x,y,f) = \begin{cases} 255 & \text{if } S(x,y,f)=1 \\ \max[0, MSI(x,y,f-1)-1] & \text{otherwise}, \end{cases} \quad (1)$$

(a) (b) (c)

Fig. 1. Examples of (a) original image (b) background subtraction image (c) normalized silhouette image.

(a) Lateral view (0°). (b) Oblique view (45°). (c) Frontal view (90°).

Fig. 2. Motion silhouette images.

where S is the silhouette image, f is the frame number, and (x, y) are the coordinates of the image. Fig. 2 shows examples of MSIs in lateral, oblique, and frontal views.

Then, for low-dimensional features, principal component analysis (PCA) [12] is employed. The ith MSI is represented by $\mathbf{m}_i \in \Re^q$, where q is the number of MSI pixels. $\mathbf{m}_i$ is projected into the eigenspace by

$$\mathbf{x}_i = \mathbf{P}^T \mathbf{m}_i = [\mathbf{P}_1\ \mathbf{P}_2 \ldots \mathbf{P}_p]^T \mathbf{m}_i, \quad (2)$$

where $\{\mathbf{P}_t \mid t = 1, 2, \ldots, p\}$ is the set of q dimensional eigenvectors of the covariance matrix corresponding to the $p(p \ll q)$ largest eigenvalues. $\mathbf{x}_i$ is the ith low dimensional MSI and $\mathbf{x}_i \in \Re^p$.

2.3. Gait recognition system based on a neural network ensemble

As mentioned above, we proposed a new design method for a neural network ensemble [8] and it is here employed for gait recognition to improve the accuracy and reliability of the gait recognition. Our neural network ensemble design method consists of two phases. In the first phase, the multiple neural networks are trained using HFC-PGA [13] such that each of them comes with an appropriate set of features, optimal structures, and adjusted parameters. In the second phase, a set of components is selected from the multiple neural networks available to build an ensemble

2.3.1 Hierarchical fair competition-based parallel genetic algorithm (HFC-PGA)

System diversity is a very important factor in the context of ensembles [7,8]. A simple genetic algorithm (GA) might therefore not be a good choice for the training of multiple neural networks because

1) premature convergence is likely occur and the algorithm gets trapped in local optima and
2) an individual with the highest fitness dominates the entire population in the last generation [8].

Both cases will make the components similar to each other; making them of limited use when forming an ensemble of networks. The HFC-PGA [13] is employed to address this issue, to decrease the possibility of premature convergence and maintains the diversity of the population of individuals. The HFC model allows the young but promising individuals from early competition to grow up in different populations. In due time, the model lets them join in the cruel competition process. The HFC-PGA has multiple subpopulations organized in a hierarchy, and each subpopulation accommodates individuals within a specified range of fitness [13]. The HFC model maintains multiple different subpopulations, thereby providing diverse solutions, in addition to the best one.

For the first phase, in which the individual neural networks are generated using HFC-PGA, each component neural network is encoded as a chromosome shown in Fig. 3. The chromosome consists of two subchromosomes: one deals with feature selection and the other is aimed at the structural and parametric optimization of the

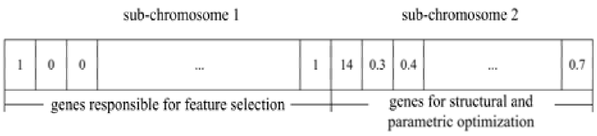

Fig. 3. GA chromosome used in the proposed method.

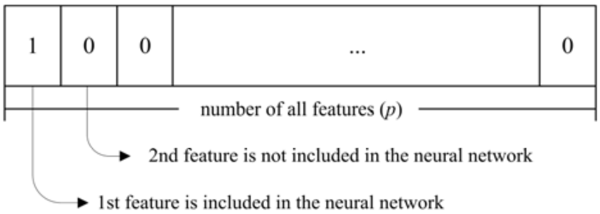

Fig. 4. Feature selection chromosome.

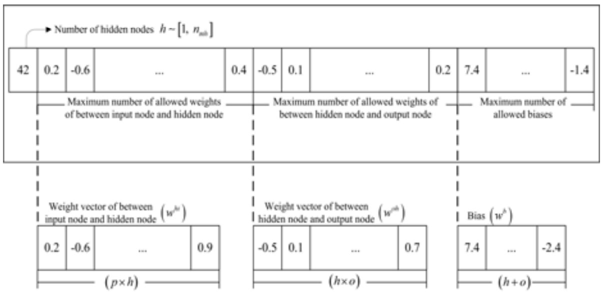

Fig. 5. Genes for the structural and parametric design of the neural network.

neural network. As shown in Fig. 4, the first subchromosome is encoded as a binary string in which each bit is associated with a corresponding feature indicating whether the corresponding feature has been selected ('1') or not ('0'); p indicates the number of features in a low-dimensional MSI.

The second subchromosome represents the structure and parameters of the neural network and is encoded as shown in Fig. 5. In this figure, w^{hi} and w^{oh} indicate the weights between the input and the hidden layers and hidden and output layers, respectively, and w^b represents the bias. p, h, and o indicate the number of input, hidden, and output nodes, respectively. Because p and o are known parameters and h should be determined, it is contained in the chromosome and specified as being between 1 and n_{mh}, where n_{mh} is the maximum number of allowed hidden nodes. Fig. 6 shows an example of the encoding of the neural network for a two-class and four-feature problem. Since there are three selected features and two classes, the neural network has three input nodes, four hidden nodes, and two output nodes, and the lengths of w^{hi}, w^{oh} and w^b are twelve, eight, and six, respectively.

Crossover and mutation are used in HFC-PGA as genetic operators. One-point crossover and bit-flip mutation are used at the subchromosome for feature selection. Arithmetic, simple and heuristic crossovers and uniform and boundary mutations are employed at the second subchromosome. In particular, the number of neurons in the hidden layer is determined by applying the greatest integer function to the corresponding genes.

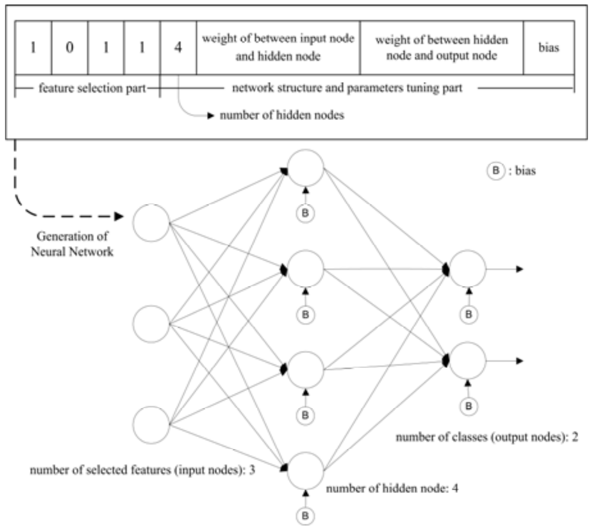

Fig. 6. An example of a neural network representation.

2.3.2 Neural network ensemble

A neural network ensemble is then built by combining the multiple neural networks designed in the previous subsection. To build an efficient ensemble, a set of individual neural networks with uncorrelated errors should be selected while maintaining good generalization capabilities of the ensemble. In other words, the selected individual networks should be diverse among themselves. The negative correlation forces the ensemble to select different individual networks, which learn different parts or focus on different aspects of the training data. Therefore, we select the neural network components based not only on the learning error but also on the correlation among the components [8]. Let us assume that a set of low dimensional MSI pairs

$$\{(\mathbf{x}_i, c_i) \mid i = 1, \cdots, N\}, \quad \mathbf{x}_i \in \Re^p \tag{3}$$

and

$$c_i \in \{1, 2, 3, \cdots, C\} \tag{4}$$

are given, where c_i denotes the label of the associated class.

Theorem 1: Assume that a neural network ensemble with J components is given. If another neural network component is presented and is added to the ensemble, the generalization error of the new ensemble with $J+1$ components $(\hat{E}_{J+1})$ is determined to be in the form

$$\begin{aligned}\hat{E}_{J+1} &= \left(\frac{J}{J+1}\right)^2 \hat{E}_J + \left(\frac{1}{J+1}\right)^2 \\ &\quad \left(2\sum_{j=1}^{J}\left[C_{j(J+1)} - \lambda K_{j(J+1)}\right] + E_{(J+1)}\right) \\ &= \left(\frac{J}{J+1}\right)^2 \hat{E}_J + \left(\frac{1}{J+1}\right)^2 \\ &\quad \left(2\sum_{j=1}^{J+1}\left[C_{j(J+1)} - \lambda K_{j(J+1)}\right] - E_{(J+1)}\right),\end{aligned} \tag{5}$$

where $E_{(J+1)}$ is the error of the $J+1$th neural network component, λ is the controllable variable, and C_{jt} and K_{jt} are defined as

$$C_{jt} = \sum_{i=1}^{N}\sum_{k=1}^{C}\left[\left(f_j^k(\mathbf{x}_i)-y_i^k\right)\left(f_t^k(\mathbf{x}_i)-y_i^k\right)\right] \tag{6}$$

and

$$K_{jt} = \sum_{i=1}^{N}\sum_{k=1}^{C}\sum_{r=1}^{J}\left[\left(f_j^k(\mathbf{x}_i)-f_r^k(\mathbf{x}_i)\right)\left(f_t^k(\mathbf{x}_i)-f_r^k(\mathbf{x}_i)\right)\right], \tag{7}$$

where $f_j^k : \Re^p \to [0,1]$ indicates the kth output of the jth neural network and $\mathbf{y}_i = (y_i^1 \;\; y_i^2 \;\; \cdots \;\; y_i^C)$ is the target representation of c_i. The proof of Theorem 1 can be found in our previous work [8]. The decision regarding whether a new neural network component should be added to the ensemble or not is accomplished with the recursive error equation (5) in Theorem 1, because the error of the new ensemble with $J+1$ components can be computed by combining the errors of the ensemble with J components and $J+1$th neural network component. If $\hat{E}_{J+1} < \hat{E}_J$, the $(J+1)$th neural network component should be added. However, if $\hat{E}_{J+1} \geq \hat{E}_J$, the $(J+1)$th neural network component should be discard. Therefore according to this error recursive equation, we can decide whether we will add the new neural network component to the ensemble and obtain a superior ensemble for the given problems.

3. EXPERIMENTAL RESULTS

3.1. NLPR database

To show the effectiveness of the suggested method and its applicability to gait recognition, we use the NLPR database [14] for our experiments. This database is widely used to benchmark algorithms in gait recognition and is also known as the CASIA gait database. A digital camera fixed on a tripod captured gait sequences on two different days in an outdoor environment was used to construct NLPR database. All subjects walked along a straight-line path at free cadences in three different views with respect to the image plane: lateral (0°), oblique (45°) and frontal (90°) views. Fig. 7 shows example images of the three different views.

The database includes twenty subjects, and each subject has four sequences for each viewing angle: two sequences in one direction and two in the reverse direction. The database thus includes a total of 20×4×3 = 240 gait sequences. In this experiment, the twenty principal components for the MSI images are used and the leave-one-out cross validation to show the general performance of the algorithm. The parameter values used in the evolutionary optimization are summarized in Table 1.

The forty independent neural networks are built by hierarchical neural network evolution. The neural network components are then selected based on the proposed method and used to build an ensemble. We show the performance of the proposed method at three viewing angles in terms of cumulative match scores (CMS) summarized in Table 2 where the rank K means that a test sample is considered correctly classified if any of the top K matches are correct. It can be seen that the recognition accuracy of rank 1 is more than 91% for all three angles. We show the performance of the proposed method and compare it to that of existing gait recognition methods in Table 3.

The proposed method provides better performance than the other gait recognition systems. From the tables, it can be seen that a neural network ensemble is a good choice for gait recognition because it makes gait a more reliable biometric.

(a) Lateral (0°) view.

(b) Oblique (45°) view.

(c) Frontal (90°) view.

Fig. 7. Examples.

Table 1. Evolution optimization parameters.

Parameter	Value
Crossover rate	0.60
Mutation rate	0.05
Population size	40
Negative correlation coefficient	0.50
Maximum size of the hidden layer	100
Number of subpopulations	4

Table 2. Results of the proposed methods.

	Rank 1 (%)	Rank 5 (%)	Rank 10 (%)
lateral	97.50	100.00	100.00
blique	96.25	100.00	100.00
frontal	91.25	98.75	100.00

Table 3. Comparison of several algorithms on the NLPR database in the lateral view.

Methods	Rank 1	Rank 5	Rank 10
Lee *et al*. [15]	87.50	98.75	100.00
Phillips *et al*. [16]	78.75	91.25	98.75
Wang *et al*. [14]	82.50	100.00	100.00
Kale *et al*. [17]	82.50	92.50	96.25
Zhang *et al*. [18]	84.60	89.40	95.10
Hong *et al*. [19]	91.25	96.25	98.75
Lee *et al*. [6]	91.25	98.75	100.00
Proposed method	97.50	100.00	100.00

Table 4. Results of the proposed method.

Rank	Correct Classification Rate (%)
Rank 1	98.45 (0.45)
Rank 5	98.90 (0.45)
Rank 10	99.56 (0.51)

Table 5. Comparison of several algorithms of the SOTON database.

Methods	Correct Classification Rate (%)
Boyd *et al*. [21]	85.80
Chen *et al*. [22]	86.56
Chen *et al*. [23]	87.59
Lam *et al*. [24]	88.95
Bazin *et al*. [25]	92.70
Veres *et al*. [26]	96.67
Lee *et al*. [2]	96.43
Proposed method	98.45

3.2. SOTON database

In this subsection, we employ the larger SOTON database [20] to make a generalized statement concerning the validity of the proposed method in gait recognition. It consists of more than 100 subjects. The gait sequences of each subject in the SOTON database are divided into four subsets. Three subsets are used for training and the remaining one is used for testing. We make four independent runs and compute the performances of the proposed algorithm. Table 4 gives the average correct classification rates (CCR) for the four runs using the proposed method. The numbers in the parentheses indicated the standard deviation of four runs.

In Table 5, the performance of the proposed method is compared with those of previous methods for the SOTON database. The performances of the previous methods are directly cited from previous research [2,21-26]. It can be observed from Table 5 that our gait recognition system demonstrates a significant performance improvement over previous methods, thereby, increasing the reliability of gait recognition systems.

4. CONCLUSION

Gait recognition is unreliable compared with other biometrics such as face, iris, and finger-print recognition. To solve this problem, we apply a neural network ensemble and HFC-PGA to gait recognition in order to obtain a high recognition accuracy. HFC-PGA is employed to generate the diverse individual neural networks. The neural network components are then selected in such a way that the generalization error is minimized and the correlation among components is negative. The experiments performed with the NLPR and SOTON databases show the performance of the proposed method, demonstrating that it outperforms other variable gait recognition methods available in the literature.

REFERENCES

[1] H. Lee, S. Hong, I. F. Nizami, and E. Kim, "A noise robust gait representation: Motion Energy Image," *International Journal of Control Automation and Systems*, vol. 7, no. 4, pp. 638-643, August 2009.

[2] H. Lee, S. Hong, and E. Kim, "Neural network ensemble with probabilistic fusion and its application to gait recognition," *Neurocomputing*, vol. 72, pp. 1557-1564, March 2009.

[3] S. Cho, "Pattern recognition with neural networks combined by genetic algorithm," *Fuzzy Sets and Systems*, vol. 103, pp. 339-347, April 1999.

[4] H. Lee, S. Hong, and E. Kim, "A new genetic feature selection with neural network ensemble," *International Journal of Computer Mathematics*, vol. 86, no. 7, pp. 1105-1117, July 2009.

[5] L. Hansen and P. Salamon "Neural network ensembles," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 12, pp. 333-342, 1992.

[6] H. Lee, S. Hong, and E. Kim, "An efficient gait recognition based on a selective neural network ensemble," *International Journal of Imaging Systems and Technology*, vol. 18, no. 4, pp. 237-241, October 2008.

[7] K.-J. Kim and S.-B. Cho, "Evolutionary ensemble of diverse artificial neural networks using speciation," *Neurocomputing*, vol. 71, no. 7-9, pp. 1604-1608, 2008.

[8] H. Lee, E. Kim, and W. Pedrycz, "A new selective neural network ensemble with negative correlation," *Applied Intelligence*, vol. 37, pp. 488-498, December 2012.

[9] J. Choi, S. Oh, and W. Pedrycz, "Structural and parametric design of fuzzy inference systems using hierarchical fair competition-based parallel genetic algorithms and information granulation," *International Journal of Approximate Reasoning*, vol. 49, pp. 631-648, 2008.

[10] T. Horpraser, D. Harwood, and L. Davis, "A statistical approach for real-time robust background subtraction and shadow detection," *Proc. International Conference on Computer Vision*, 1999.

[11] T. Lam and R. Lee "A new representation for human gait recognition: motion silhouettes image (MSI)," *Proc. International Conference on Biometric*, pp. 612-618, 2006.

[12] H. Lee, S. Hong, and E. Kim, "An efficient gait recognition with backpack removal," *EURASIP Journal on Advances in Signal Processing*, vol. 2009, Article ID 384384, p. 7, 2009.

[13] J. Choi, S. Oh, and W. Pedrycz, "Identification of fuzzy models using a successive tuning method

with a variant identification ratio," *Fuzzy Sets and Systems*, vol. 159, pp. 2873-2889, 2008.
[14] L. Wang, T. Tan, H. Ning, and W. Hu, "Silhouette analysis-based gait recognition for human identification," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 25, pp. 1505-1518, 2003.
[15] L. Lee and W. Grimson, "Gait analysis for recognition and classification," *Proc. International Conference on Automatic Face and Gesture Recognition*, pp. 155-162, 2002.
[16] P. Phillips, S. Sarkar, I. Robledo, P. Grother, and K. Bowyer, "Baseline results for challenge problem of human ID using gait analysis," *Proc. International Conference on Automatic Face and Gesture Recognition*, pp. 137-142, 2002.
[17] A. Kale, N. Cuntoor, B. Yegnanarayana, A. N. Rajagopalan, and R. Chellappa, "Gait analysis for human identification," *Proc. International Conference on Audio- and Video-Based Biometric Person Authentication*, pp. 706-714, 2003.
[18] E. Zhang, J. Lu, and G. Duan, "Gait recognition via independent component analysis based on support vector machine and neural network," *Proc. International Conference on Advances in Natural Computation*, pp. 640-649, August 2005.
[19] S. Hong, H. Lee, K.-A. Toh, and E. Kim, "Gait recognition using multi-bipolarized contour vector," *International Journal of Control, Automation, and Systems,* vol. 7, no. 5, pp. 799-808, October 2009.
[20] J. Shutler, M. Grant, M. Nixon, and J. Carter, "On a large sequence-based human gait database," *Proc. International Conference on Recent Advances in Soft Computing*, pp. 66-71, 2002.
[21] J. Boyd, "Synchronization of oscillations for machine perception of gaits," *Computer Vision and Image Understanding*, vol. 96, pp. 35-59, 2004.
[22] S. Chen and Y. Gao, "Stride history image: a new feature representation for pedestrian identification," *Proc. IEEE Workshop on Signal Processing Systems*, pp. 543-547, October 2007.
[23] S. Chen, W. Huang, T. Ma, and L. Dong, "Towards feature fusion for human identification by gait," *Proc. 4th International Conference on Image and Graphics*, pp. 678-682, August 2007.
[24] T. H. W. Lam, R. S. T. Lee, and D. Zhang, "Human gait recognition by the fusion of motion and static spatio-temporal templates," *Pattern Recognition*, vol. 40, no. 9, pp. 2563-2573, September 2007.
[25] A. Bazin and M. Nixon, "Gait verification using probabilistic methods," *Proc. IEEE Workshop on Applications of Computer Vision*, pp. 60-65, 2005.
[26] G. V. Veres, L. Gordon, J. N. Carter, and M. S. Nixon, "What image information is important in silhouette-based gait recognition?," *Proc. IEEE Conference on Computer Vision and Pattern Recognition*, vol. 2, pp. 776-782, July 2004.

Heesung Lee received his B.S., M.S., and Ph.D. degrees in Electrical and Electronic Engineering from Yonsei University, Seoul, Korea, in 2003, 2005, and 2010, respectively. He is currently a Managing Researcher of Image Sensing Lab. in Samsung S1 Co., Ltd. His current research interests include computational intelligence, visual surveillance, pattern recognition, biometrics, and neural networks.

Heejin Lee received his B.S., M.S., and Ph.D. degrees in Electronic Engineering, from Yonsei University, Seoul, Korea, in 1987, 1989, and 1998, respectively. He was a Researcher in Daewoo Telecom Ltd., Seoul, Korea, from 1989 to 1993. He is currently a Professor in the Dept. of Electrical, Electronic and Control Engineering, Hankyong National University, Gyeonggi-do, Korea. His current research interests include fuzzy control theory, fuzzy application system, adaptive and robust control, robotics and automation.

Euntai Kim received his B.S., M.S., and Ph.D. degrees in Electronic Engineering from Yonsei University, Seoul, Korea, in 1992, 1994, and 1999, respectively. He was a full-time lecturer with the Department of Control and Instrumentation Engineering, Hankyong National University, Gyeonggi-do, Korea from 1999 to 2002. Since 2002, he has been with the faculty of the School of Electrical and Electronic Engineering, Yonsei University, where he is currently a Professor. He was a visiting researcher at Berkeley Initiative in Soft Computing, UC at Berkeley, Berkeley, CA, USA. His current research interests include computational intelligence and statistical machine learning and their application to intelligent robot, vehicle, and machine vision.