A Real Time 3D Foot Pose Estimation using silhouette based 2.5D database

Ho-Geun Song and Ha-Sung Koo

***Abstract*—**This paper proposes a real time 3D foot pose estimation method using silhouette based 2.5D database. Shape descriptor for 3D pose estimation should be chosen to hold robustness for geometrical transformations, and to require short processing time. To reduce processing time, total 13,500 silhouette-based foot image database is built and meta information which involves 3D pose and feature vectors of the foot image is appended to the database. And we proposed a modified Centroid Contour Distance whose size of the feature space is small and performance of pose estimation is better than the others. In order to analyze performance of the proposed descriptor, we evaluate time and spatial complexity with retrieval accuracy, and then compare with the previous methods. According to the result of our experiment, proposed descriptor has only 63 feature values. It is about 20% of the average spatial complexity. Furthermore, our method takes about 0.00296 seconds to extract feature values. It is about 86% of the average time complexity. The results show that the proposed descriptor is more effective than the previous methods on feature extraction time. Finally, if we estimate retrieval accuracy as a reciprocal of the average error, then the proposed method improves about 36% of the average retrieval accuracy in comparison with the other methods. The experimental results show that the proposed descriptor is more effective than the previous methods on feature extraction time and pose estimation accuracy.

***Keywords*—**Shape descriptor, Pose estimation, Image retrieval, 3D foot pose, and Silhouette based database

I. Introduction

An application for human body tracking needs motion analysis technology, and is used in the field of special effects in cinema, game, animation and perceptual interface, etc[1]. The motion tracking technology should be robust within the given environment conditions and fast for real time processing.

Shape descriptors for many applications such as human motion tracking, human pose estimation, object recognition and augmented reality are active research themes in the content-based image retrieval systems [1][2][3][4]. The related researches have recently studied to estimate 3D object pose from the 2.5D database when a 2D shape is given to the system[5].

The 2D shape descriptor of a 3D object is indexed for the database with object pose information especially for real-time system[6]. This dimensionality reduction provides following benefits:

(1) Lower storage requirements : each image is reduced to a compact feature vector.

(2) Increased efficiency : the training data can be processed more rapidly.

(3) Reduced sensitivity to noise : features capture the most informative shape characteristic while ignoring irrelevant details[6].

Moreover, this allows us to cancel out difficulties for the previous methods which require time consuming initialization, tracking and geometrical computation. However those systems require not only fast processing scheme for real time process but also accurate decision capacity for real applications.

A shape is an important clue to represent projected images of a 3D object. In particular, silhouettes as projected images are insensitive to variations in surface such as color and texture, and encode a great deal of information to help recover 3D poses[1]. However, the projected shape depends on occlusion, noise, and other environmental changes as well as geometrical distortions [7][8][9][10]. For that reason, the shape descriptor for 3D application should be chosen to hold robustness for those geometrical transformations and to require short processing time when the object shape is retrieved from database.

In general, shape descriptor is divided into two categories, e.g. region-based and contour-based approach. The region-based approach is available for both all single connected regions and multiple regions, and whose retrieval time is fast with noise robustness. However, they show poor performance for some distorted object. The contour-based method represents an external closed shape of 2D object. The approaches are robust for some distortion, but sensitive to noise. The methods include Chain-code, Centroid contour distances (CCD), Fourier descriptor, B-spline, and Shape contexts, etc [14][15][16][17][18].

Therefore this paper proposes the effective shape descriptor for 3D foot pose estimation. To reduce processing time, silhouette-based foot image database is built and meta information which involves the 3D pose of the foot is appended to the database. And we proposed a modified Centroid Contour Distance whose size of the feature space is small and performance of pose estimation is better than the others. In order to analyze performance of the descriptor, we evaluate time and spatial complexity with retrieval accuracy, and then compare with the previous methods.

Experimental results show that the proposed descriptor is more effective than the previous methods on feature extraction time and pose estimation accuracy.

II. Foot features and its Related works.

It is needed to understand the structures and the features of human foot before our studies. A human foot consists of 28 bony segments which are surrounded with various types of ligaments and muscles. Toe joints are so short that scope of its movement is limited as compared with finger joints. Furthermore, its outer shape is covered by socks and footwear in general. All this make us difficult to describe the foot and its pose[10]. Therefore, a shape descriptor for the 3D foot pose estimation should be chosen to hold effectiveness and sensitivity for those geometrical foot features.

As a related works, Christopher et al. estimated 3D pose of spine using projected 2D shape of the vertebra and used its information in 3D medical object registration[19]. A. Tresadern et al. search a database of training silhouette examples for the task of human pose estimation[6]. And those of dimensionality reduction are effective and alternative methods that estimate 3D pose of an object in real time application systems.

Therefore we propose the effective shape descriptor for 3D foot pose estimation whose size of the feature space is small and performance of pose estimation is better than the previous methods. And silhouette-based foot image database with 3D pose information is built for the proposed descriptor.

In order to verify the efficiency of our method, we choose typical 6 shape descriptors, e.g. Chain Code, Hu Moments, Binary Sequences, Axis Projection and Shape Context.

For the purpose of comparing the descriptors with ours under same condition as much as possible, we normalize each descriptor to have certain size when an object scale is vary.

A. Chain code[14]

Chain code is a lossless compression algorithm for monochrome images. Chain coding is based on the idea that we follow the outer edge of the object and store the direction in which we are travelling. The directions are calculated as 4 or 8 neighborhood directions in general.

The chain code is of the same length as the perimeter of the object, which in many cases are too long. Therefore, in our experiment, we normalize the code length by total 360 codes.

And the code is highly dependent on the starting point. To reduce this dependency and to perceive the rotational changes of shape, we always start at the top of left sided contour point.

Therefore, our normalization and the restriction of start point make the code invariant to size, but variant to rotation.

B. Hu Invariant Moments[6]

Hu invariant moments are used for the geometric and statistical definition of an image. They are computed from normalized central moments up to order three and are shown below. :

$$
\begin{aligned}
\Phi_1 &= \mu_{20} + \mu_{02} \\
\Phi_2 &= (\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2 \\
\Phi_3 &= (\mu_{30} - 3\mu_{03})^2 + (3\mu_{21} - \mu_{03})^2 \\
\Phi_4 &= (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2 \\
\Phi_5 &= (\mu_{30} - 3\mu_{12})(\mu_{30} + \mu_{12})[(\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2] \\
&\quad + (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03})[(3\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] \\
\Phi_6 &= (\mu_{20} - \mu_{02})[(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] \\
&\quad + 4\mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03}) \\
\Phi_7 &= (3\mu_{21} - \mu_{03})(\mu_{30} + \mu_{12})[(\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2]
\end{aligned} \tag{1}
$$

The Hu Moments are invariant under translation, changes in scale, and also rotation. The first one is analogous to the moment of inertia around the image's centroid, where the pixels' intensities are analogous to physical density. The last one is skew invariant, which enables it to distinguish mirror images of otherwise identical images.

As showed above, the moments need only 7 features to describe an object. Therefore there is no need to normalize the size of it in our experiment.

C. Binary Sequence[12]

A Binary Sequence(BS) is a sequence of *N* bits, and defined as 1 or 0 when a pixel is in the object region or not.

The binary sequence for an arbitrary *m* x *n* image, *I(x,y)*, can be represented as :

$$
BS[I_i]_{i=1\cdots N} = \begin{cases} 1, & \text{if } I_i \in object\ regrion \\ 0, & otherwise \end{cases} \tag{2}
$$

, where I_i is the *ith* pixel value of the image and *N* is the total number of pixel of the image, i.e. *N*= *m* x *n*.

The descriptor allows us to define an object shape with easy and fast, but the size of this descriptor depends on image size. Therefore, in our experiment, we resize an image to 16 x 16 image, and then estimate the sequences to make the length of the BS as 256 sequences.

D. Axis Projection[13]

Axis projection method accumulates vertical pixels of an image on x-axis and horizontal pixels on y-axis respectively to describe spatial distribution of a shape with related axis. Given an m x n image, $I(x,y)$, projected feature value X, Y for the x- and y-axis can be defined as :

$$X[x] = \sum_{x=0}^{m-1} I(x,y)$$
$$Y[y] = \sum_{y=0}^{n-1} I(x,y) \tag{3}$$

However, the axis projection depends on the size of an image also. Therefore, we normalize the m x n image to 128 x 128 image, and then obtain 256 feature values for every image.

E. Shape Contexts [18]

The basic idea of shape context is to pick n points on the contours of a shape. For each point p_i on the shape, consider the $n - 1$ vectors obtained by connecting p_i to all other points. The set of all these vectors is a rich description of the shape localized at that point but is far too detailed. So, for the point p_i, the coarse histogram of the relative coordinates of the remaining $n - 1$ points,

$$h_i(k) = \#\{q \neq p_i : (q - p_i) \in bin(k)\} \tag{4}$$

is defined to be the shape context of p_i. The bins are normally taken to be uniform in log-polar space. The Shape Contexts are empirically demonstrated to be robust to deformations, noise, and outliers.

For our experiment, we choose 16 sample points on the contours and set the number of angular bins to 8, while each bin is divided by 3 in log-polar space.(See Fig. 1) As a result, we can obtain total 384 features as a shape context of a foot image.

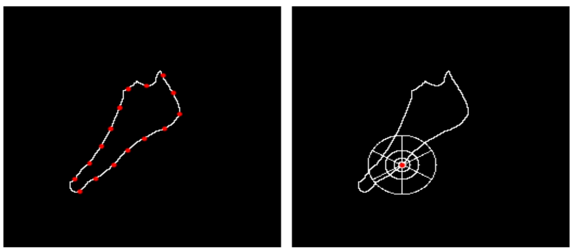


Fig. 1 Shape context extraction from foot image

III. Proposed Method

Proposed shape descriptor for 3D foot pose estimation has three groups of feature value whose size of the feature space is small and performance of pose estimation is better than the previous methods.

A. Centroid Contour Distance

When contour points $P(p_1,p_2,p_3,\ldots,p_n)$ of an object and the coordinate set of the P , $f(x,y)$, are given, centroid of the object $C(X_c,Y_c)$ is defined as :

$$X_c = \sum_x \sum_y f(x,y)x / \sum_x \sum_y f(x,y) \tag{5}$$

$$Y_c = \sum_x \sum_y f(x,y)y / \sum_x \sum_y f(x,y) \tag{6}$$

If we consider r as distance between the centroid C and arbitrary contour point p' at angle α , we can define the set of distance $R(r_1,r_2,\ldots r_{360})$ from each α as shown in Fig. 2. Then the set R is defined as Centroid Contour Distance(CCD).

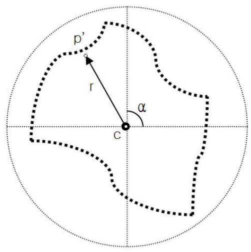


Fig.2 Centroid contour distance

B. Angular segmentation for refinement.

As we described above, the CCD has 360 distance feature values for an object. However, we can reduce the number of the features because of its discrete, local and redundant characteristics in digital images.

When we divide entire 360 angular region A by arbitrary angle α', number of the angular bin is $m=360/\alpha'$.

Therefore, angular bin set A is defined as :

$$A = \{ A_1, A_2, A_3, \ldots A_m\} \tag{7}$$

where m is the number of the bins. (Fig. 3)

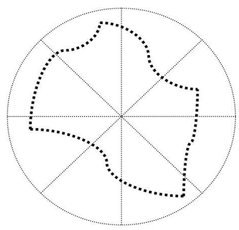


Fig. 3 Angular segmentation, when α'=45°

C. Adjacent Area Distance

On the basis of above definition, we need to describe an object shape as its relational features effectively. Because 2D shape of foot has no prominent geometrical features and the distribution over relative positions is a robust, compact, and highly discriminative descriptor.

First of all, as shown in Fig. 4, we accumulate difference of corresponding distance r for each adjacent angular bin. It called as Adjacent Area Distance(AAD) and defined as :

$$AAD_i = \sum_{j=0}^{q} \left\| A_j^i - A_j^{next} \right\|, i = 0,1,\cdots,p \tag{8}$$

where p represents the number of angular bins and q describes grouping size of the bins, angle α'.

The AAD is one of statistical features that stand for relative variance of the CCD features within the local area. Therefore, if an object has regular shape with small relative variance, the AAD shows small value. Otherwise, e.g. irregular shape, the AAD shows large one.

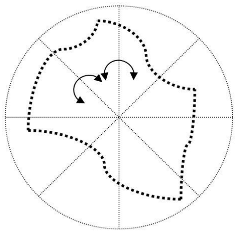


Fig. 4 Adjacent Area Difference

D. Symmetric Area Distance

In spite of advantage of the AAD, it does not represent global feature of an object. In other words, we need to discriminate between variances with large and small feature value.

Therefore, we accumulate difference of corresponding distance r for each symmetric angular bin as shown in Fig. 5. And it called Symmetric Area Distance(SAD) and defined as :

$$SAD_i = \sum_{j=0}^{q} \frac{\left\| A_j^i - A_j^{symmetric} \right\|}{1 + A_j^i - A_j^{symmetric}}, i = 0,1,\cdots,p' \tag{9}$$

where p' is a half of number of angular bins, q describes grouping size of the bins, and adding number 1 in denominator is a minimum constant to avoid dividing by zero, respectively.

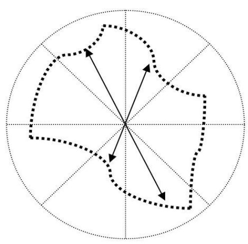


Fig. 5 Symmetric Area Difference

E. Self-Area Accumulation

Both AAD and SAD are relational feature values to describe the shape of an object. However, the shape of an object should be represented by the feature itself.

Therefore, distance r for each angular bin is accumulated and defined as :

$$SAA_i = \sum_{j=0}^{q} A_j^i, i = 0,1\cdots,p \tag{10}$$

where p denotes the number of angular bins and q represents the grouping size, as stated above.

In this paper, we set the grouping size of the bin to 20 for AAD and SAD, and define the size as 10 for SAA. Then number of AAD, SAD and SAA are 18, 9 and 36, respectively. As a result, the proposed shape descriptor has total 63 feature values for an object while the CCD has 360 values.

IV. Experimental Conditions and the Results

In order to analyze performance of the proposed descriptor, we evaluate time and spatial complexity with retrieval accuracy, and then compare with the previous methods.

A. Experimental Environment

Our experiments are performed on IBM personal computer with Pentium 4 Dual core 3.2 Ghz CPU and 2GB memory. And we write a program with Visual Studio 2005.

Total flow of our experiment is as followed. First, when a query foot image is given, feature distances between the query and each database image are calculated. Second, we select a database image whose feature values are approximately matched with the query image among the candidate images. Third, 3D pose of query foot image is estimated by using the meta information in the database. (Fig. 6)

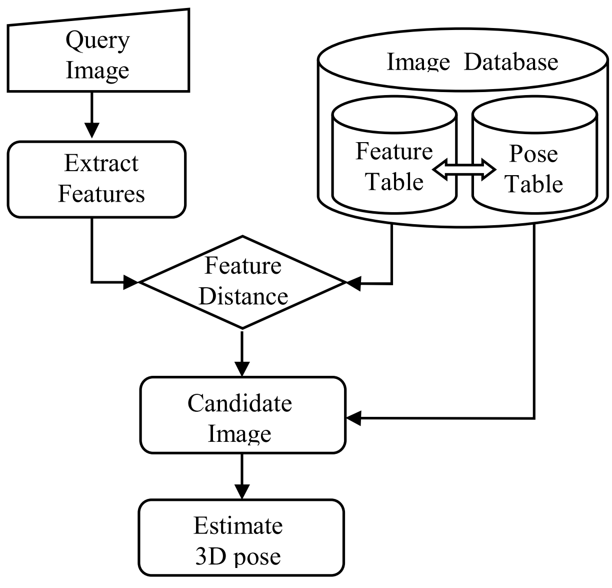


Fig. 6 Overall flowchart

B. Database for Foot Pose Estimation

To reduce the processing time, silhouette-based foot image database is built and additional information is appended to the database. The additional information includes not only 3D pose of the foot but also pre-estimated proposed feature values.

For this, we make 3D foot model as in Fig. 7, and create total 13,500 silhouette based foot image database as shown in Fig. 8. Each rotational scope of 3D axis and the unit angle for the rotation when we make the database are explained in Table 1.

The rotational scope and the unit angle are defined experimentally so that we can design the database to effectively represent the 3D pose of foot model. Each rotational angle of the model when we make the silhouette images is used to represent the 3D pose of the foot, and feature values of the silhouettes are estimated for all database images before it is appended to the database.

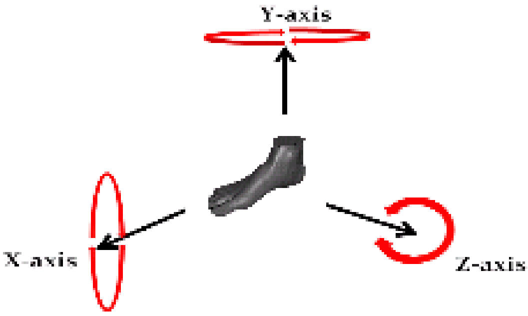


Fig. 7 3D foot model and its 3D axis

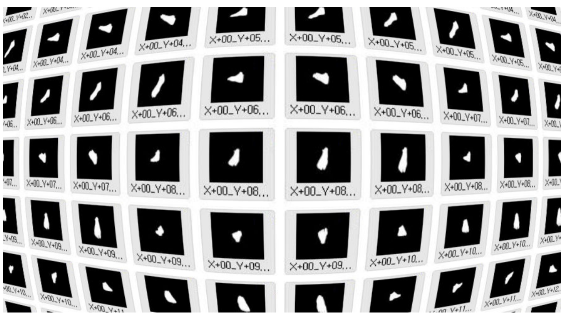


Fig. 8 Foot Database image

Table 1. Scope of axis rotation

Axis	Classified number	Scope of axis rotation (unit angle)
X	20	$-40^\circ \sim +40^\circ$ (every 4°)
Y	45	$0^\circ \sim 180^\circ$ (every 4°)
Z	15	$-30^\circ \sim +30^\circ$ (every 4°)

C. Create a Query Image

A query image is created by capturing still image from CCD camera, and uniform background within the image is removed by using the Blue screen technique. Then we make use of its color information to segment foreground foot region, and morphological filter to cover up defects and inner holes caused by some noise, e.g. illumination, shadow and reflection. (Fig.9)

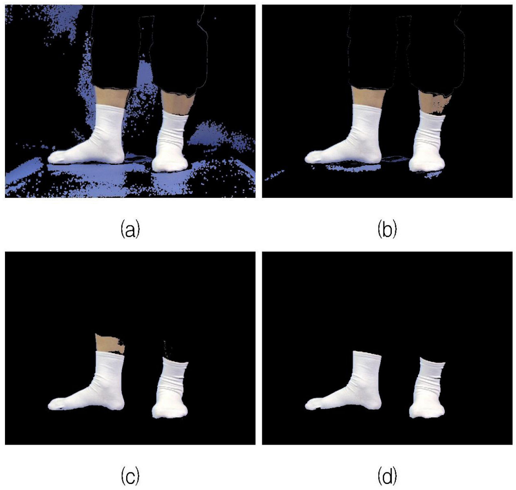


Fig.9 Creation of query image

D. Spatial and Time Complexity

In order to analyze the performance of our method, we choose and compare with typical 6 shape descriptors, namely Chain Code, Hu Moments, Binary Sequences, Axis Projection and Shape Context.

In our experiment, spatial complexity is defined as total number of the shape feature. This complexity is proportional to number of operation when the system estimates the similarity between query and model image. Therefore it has a big impact on real time processing.

Table 2 shows the spatial complexities for each shape descriptor. Except the Hu moment and the proposed method, we can obtain 323 features for average spatial complexity. As mentioned above, proposed descriptor has only 63 feature values. It is about 20% of the average spatial complexity. Therefore our descriptor can save more time for estimating of feature distance between query and model image than the other descriptors.

Table 2. Spatial complexity

Descriptor	Feature number
Chain Code	360
Hu Invariant Moments	7
Binary Sequences	256
Axis Projection	256
Shape Contexts	384
Proposed method	63

On the other hand, time complexity is defined as overall time for extracting the shape feature values. This complexity also includes time interval for pre-processing of the features.

Table 3 reveals the time complexities for each descriptor. Our method takes about 0.00296 seconds to extract feature values. And it is about 86% of the average time complexity.

The smaller time complexity we have for a shape, the faster we can retrieve candidate images from database. Because the time complexity stands for constant time when we extract feature values of the query and then retrieve candidate images from database with the descriptor.

Therefore, the results show that the proposed descriptor is more effective than the previous methods on feature extraction time.

Table 3. Time complexity

Descriptor	Extraction time
Chain Code	0.000861
Hu Invariant Moments	0.008119
Binary Sequences	0.001504
Axis Projection	0.001815
Shape Contexts	0.036798
Proposed method	0.002960

E. *Retrieval Accuracy*

Retrieval accuracy is estimated as followed.

First of all, we select 100 query images from database arbitrarily, and compute feature distance between the query and the 13,500 database images, respectively. The feature distance is given as:

$$Dist\ (F_n, F_n^k) = \sum_{i=0}^{n} \left| F_i - F_i^k \right| \qquad (11)$$

,where F_n and F_n^k are feature vectors for query image and the *kth* database image, respectively, and *n* is the length of a shape feature vector. Second, 10 candidate database images are chosen in ascending order of the distance for all the query images. Third, average pose estimation errors of the candidate images are recorded for each 3D axis.

Table 4 shows the estimation errors for each and every descriptor and 3D axis. In Table 4, Rank(2) denotes average error of pose estimation with two candidate images in ascending order of feature distance, and Rank(5) and Rank(10) are also defined in the same way of Rank(2).

In Table 4, proposed method has a smallest estimation error for every 3D axis than any other methods, while Chain Code has the maximum error.

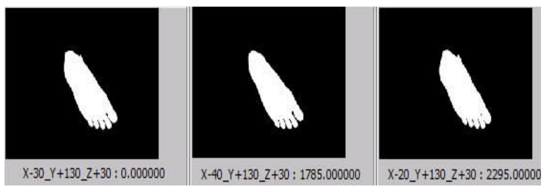
In the case of Shape Context, if we choose more number of sample points on the contours and increase the number of angular bins in log-polar space, then we could obtain more precise descriptions of the foot images. However, it also causes to increase the degree of spatial/time complexity. Therefore we find difficulty in real-time processing with the Shape Context.

As a result, if we estimate retrieval accuracy as a reciprocal of the average error, then the proposed method improves about 36% of the average retrieval accuracy in comparison with that of other methods.

In Fig. 10, retrieved three candidate images are arranged in ascending order of its estimation errors for every descriptor.

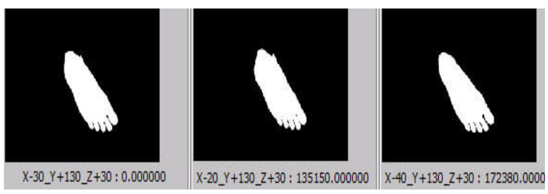
Table 4. Retrieval accuracy

Descriptor	axis	average error of pose estimation		
		Rank(2)	Rank(5)	Rank(10)
Chain Code	x-axis	11.5	25.5	6
	y-axis	17	27.8	6.4
	z-axis	20.5	29.6	7.9
Hu Moment	x-axis	5.5	15	2.5
	y-axis	10.8	29.2	5.6
	z-axis	12.7	36.8	6.7
Binary Sequences	x-axis	3	3.5	0
	y-axis	6.6	7.6	0.8
	z-axis	*9.5*	*10.1*	*1.4*
Axis Projection	x-axis	3	3.5	0
	y-axis	8	8.6	1
	z-axis	12.1	11.8	2.4
Shape Contexts	x-axis	3	4	0.5
	y-axis	6.2	8.6	1.2
	z-axis	8.4	11.6	2.4
Proposed method	x-axis	2.5	2.5	0
	y-axis	5.6	5.8	0.2
	z-axis	7.9	8.3	0.9



(a) Moment

(b) Binary string



(c) Axis Projection

(d) Chain Code

(e) Shape Context

(f) Proposed method

Fig. 10 Retrieval result

V. CONCLUSIONS

Shape descriptor for 3D application should be chosen to hold robustness for geometrical transformations, and to require short processing time. To reduce processing time, total 13,500 silhouette-based foot image database is built and meta information which involves the 3D pose of the foot is appended to the database. And we propose the effective shape descriptor for 3D foot pose estimation.

In order to analyze performance of the proposed descriptor, we evaluate time and spatial complexity with retrieval accuracy, and then compare with the previous methods. According to the result of our experiment, proposed descriptor has only 63 feature values. It is about 20% of the average spatial complexity. Furthermore, our method takes about 0.00296 seconds to extract feature values. It is about 86% of the average time complexity. The results show that the proposed descriptor is more effective than the previous methods on feature extraction time. Finally, if we estimate retrieval accuracy as a reciprocal of the average error, then the proposed method improves about 36% of the average retrieval accuracy in comparison with the other methods.

The experimental results show that the proposed descriptor is more effective than the previous methods on feature extraction time and pose estimation accuracy.

REFERENCES

[1] A. Agarwal and B. Triggs, Recovering 3D Human Pose from Monocular Images, IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 28, No. 1, 2006

[2] J. K. Aggarwal and Q. Chai, Human Motion Analysis: A review, Computer Vision and Image Understanding, Vol. 73, No. 3, pp. 428-440, 1999.

[3] A. Veeraraghavan, A. K. Roy-Chowdhury and R. Chellappa, Matching Sequences in Video with Applications in Human Motion Analysis, IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 27, No. 12, pp.1896-1909, 2005

[4] A. O. Balan, L. Sigal, M. J. Black, J. E. Davis and H. W. Haussecker, Detailed Human Shape and Pose form Images, International Conference on Computer Vision and Pattern Recognition, pp.73-80, 2007.

[5] Chen, J L and Stockman, Indexing to 3D model aspects using 2D contour features, Proceedings of IEEEE Conference on Computer Vision and Pattern Recognition, San Francisco, 913-920.

[6] P. Tresadern and I. Reid, An Evaluation of Shape Descriptors for Image Retrieval in Human Pose Estimation, The 18th British Machine Vision Conference, Vol. 2, pp. 800-809, 2007.

[7] D. Zhang and G. Lu, Review of Shape Representation and Description Techniques, Pattern Recognition, Vol. 37, pp. 1-19, 2004.

[8] J. T, Cheung, M. Leung, A. K. Fan and Y. B, Three-dimensional Finite Element Analysis of The Foot During Standing-A Material Sensitivity Study, Journal of Biomechanics, Vol. 38, pp. 1045-1054, 2005.

[9] W. J. Wang and R. H. Crompton, Analysis of the Human and Ape Foot During Bipedal Standing with Implications for The Evolution of The Foot, Journal of Biomechanics, Vol. 37, pp.1831-1836. 2004.

[10] J. T-M. Cheung and M. Zhang, Finite Element Modeling of the Human Foot and Foot Wear, ABAQUS User's Conference, pp. 145-159, 2006.

[11] W.Y. Kim, Y.S.Kim, A region-based shape descriptor using Zernike moments, Signal Process. Image Communication. 16, 2000 95–102.

[12] B. G. Prasad, K. K. Biswas and S.K. Gupta, Region based image retrieval using integrated color, shape &location index, Computer Vision and Image Understanding, Vol. 94, pp. 193-233, 2004

[13] D.H. Kwon and T.H Yi, Image retrieval considering shape information of projection vector, Journal of Korea Information Science, vol.28, pp. 651-656, 2001

[14] Herbert Freeman, Computer processing of line-drawing images, Computing Surveys, Vol. 6, No. 1, pp. 57-97, 1974

[15] Z. Wang, Z. Chi and D. Feng, Shape based leaf image retrieval, IEE Proceedings of Image and Signal Processing, Vol. 150, No.1, pp. 34-43, 2003.

[16] P.J. van Otterloo, A Contour-Oriented Approach to Shape Analysis, Prentice-Hall International (UK) Ltd, Englewood Cliffs, NJ, pp. 90–108. 1991

[17] M. Sonka, V. Hlavac, R. Boyle, Image Processing, Analysis and Machine Vision, Chapman & Hall, London, UK, NJ,1993

[18] G. Mori, S. Belongie and J. Malik, Efficient Shape Matching using Shape Context, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 27, No. 11, pp. 1832-1837, 2005

[19] C.M.Christopher, A.F.Kamal, T.B.Sebastian and B.B.Kimmia, 2D-3D registration based on shape matching, Proceedings of Mathermatical Method in Biomedical Image Analysis, pp.198-203, 2000

Ho-Geun Song
Prof. Song received his B.S degree from Department of Electronic Engineering, ChungAng University, Korea, in 1991 and his M.S and Ph.D degrees from Graduate School of ChungAng University, Korea,in 1993 and 1997, respectively. Since 1996, he has been a faculty member of the Hanseo University in Korea, where he is now a professor at the Department of Computer and Information Engineering, and holding the position of Infomation Technology Officer at Information Technology Service Center in Hanseo University since 2007. His current research interests are Digital image processing, Contents-based image/video retreival, 3D image processiong, 3D object recognition, Digital image forengics, etc.

Ha-Sung Koo
Ha-Sung Koo graduated from Kwangwoon University in Korea in 1989 with an Electrical Engineering degree. He received MS degree and Ph.D. form Kwangwoon University in Electrical Communication department in 1995. He is Associate Professor of Computer and Information Engineering at Hanseo University, and his research interests include machine vision, pattern recognition and 3D image processing.