Shape Profile Matching and Its Applications

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***Abstract*—The focus of this paper is on the development of a novel cross correlation technique for shape matching between two similar objects. The shape profile is derived from the curvature of the object profile. The cross correlation technique is applied to the shape profile of the two image objects to evaluate their similarity. An application of the shape profile technique is presented in the context of pose detection of human models from image sequences or videos. To extract the feature points on the human model, a number of human motion templates are constructed with designated feature points on each of the human motion profiles. The human model feature extraction procedure is divided into two steps, including: (1) pre-process and construction of motion templates, and (2) extraction of feature points. The best matched template image pairs and best fitted feature points are identified by evaluating the cross correlation coefficient of the corresponding shape profiles. The proposed method is demonstrated by experimental results.**

Index Terms- shape profile; feature matching; pose detection

I. INTRODUCTION

Shape matching and feature extraction found many applications in computer vision and computer graphics. The purpose of this paper is to present a novel method for shape matching and feature extraction using a cross correlation technique. This paper provides a robust technique to match two similar 2D profiles and to extract the feature points in the target object profile, with reference to the corresponding specified feature points in a template object profile. An interesting application of human pose detection from image sequences is shown as an example.

In feature extraction, methods such as a rule-based approach [9, 12, 23], kinematic-based method [5, 10], and shape matching method [4, 6, 14, 18, 22] are commonly adopted. In the rule-based approach, a set of rules is pre-defined to extract the feature points using geometry relationships. However, this is more applicable to a designated object configuration. It is difficult to use the method for extracting features from the same class objects with slightly different shape, such as human models with different posture. Besides the rule-based approach, successful results were presented using kinematics in feature extraction from motion sequences [10]. However, manual initialization is commonly required in defining the feature points on the first frame for every extraction process which causes inconvenience. Compared with the above methods, shape matching technique is more flexible and self initialization could be achieved.

The shape matching processes can be classified into two levels, namely the global shape matching and local shape matching. Global shape matching refers to the comparison of the overall shape of an object which deals with shape similarity. Local shape matching refers the matching of a pair of points in two similar shapes which deals with feature correspondence.

Common shape matching methods include shape distribution [11], shape context [4], and curvature scale space [18]. Reference [11] applied the shape distribution method to meshed and faceted representations and used the membership classification distribution as the basis for a shape classification histogram. Reference [4] used shape context method to represent each point in the object as the relative vector of each point on an object relative to all remaining points, in an L_2 Euclidean metric. This leaded to an efficient representation of characteristics histograms useful for shape comparison. This method gives reasonable good performance in shape matching and feature correspondence but it suffers from high computational cost. The curvature scale space method in [17, 18] took advantage of connectivity between contour points and the shape of object is represented by a graph of the parametric positions of the curvature extreme points of extreme curvature on the contour, however only curvature extreme points can be extracted. Besides using curvature as a measure for matching, Reference [15] proposed to use integral invariant for measurement due to its robustness to noise. However, it is shown in [14] that curvature based method can achieve more accurate results, with suitable parameter for filtering.

Through the comparison of above solutions, we conclude that these existing methods almost pay attentions to either one

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part, global or local shape matching. However, the approach presented in this paper which combining the conventional Fourier descriptor techniques first developed in the seventies in [20, 25] and the advantage of the curvature scale space method [17, 24] caters for both global and local shape matching. The cross correlation technique is used to improve the shape matching procedure and is extended to cover the feature extraction process. It is applied to feature extraction from video clips of human motion sequence to facilitate the construction of human models.

II. SHAPE PROFILE MATCHING

Using the shape profile approach, the curvature along the external contour of a segmented object in an image is first evaluated. The approach takes advantage of the geometric invariant property of freeform objects of the same semantic feature model class [2] and the curvature profile is exploited to determine the feature correspondence. The feature extraction procedure is divided into two main steps:

1) Shape matching by cross correlation: In the first phase, templates objects are specified and the shape of the template objects and image sequence objects are firstly compared. The frame with the best match to a template object is selected from the image sequence.

2) Feature extraction by feature correspondence: In the second phase, feature correspondence is performed by extracting the point on the image object which best corresponds to the feature point on the template.

In the shape profile approach, the shape ξ of the object segmented from the video frame is first represented by a finite set of its discrete closed silhouette profile points. This is achieved using common region based segmentation followed by a simple edge linking algorithm [21] giving the silhouette profile $P = \{p(i) = (x(i), y(i)) \mid i = 1,\ldots, n)\}$ of n points. Normalized arc length parameterization on the profile P is adopted, and the profile can be represented as $P = \{p(u) \mid u \in [0, 1]\}$, $p(u) \in R^2$.

A. *Shape Curvature Profile*

In the shape profile approach, the shape profile is represented by the curvature $k(u)$ along the contour using the following equation:

$$k(u) = \frac{\dot{x}(u) \times \ddot{y}(u) - \ddot{x}(u) \times \dot{y}(u)}{\left[\dot{x}(u)^2 + \dot{y}(u)^2\right]^{\frac{3}{2}}} \qquad (1)$$

The curvature profile ψ along the contour of ξ is

$$\psi(\xi) = \{k(u) \mid u \in [0, 1]\}.$$

Due to the quantization error in the silhouette extraction process, the window-based method [3] is adopted to smooth out the noise.

To label the curvature of the contour, a signed curvature is adopted with positive value indicating convexity and vice versa. This eliminates the ambiguity of the curvature representation in view of its scalar property. Examples of the shape representation of the shape descriptor are shown in Fig. 1.

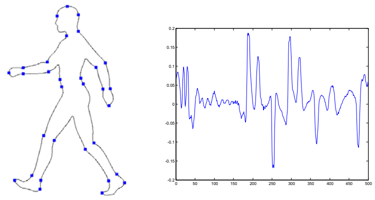


Figure 1. Shape profile of a moving object

B. *Shape Matching by Cross Correlation*

An object, represented by the curvature profile or shape profile, is evaluated on shape similarity with the anther object using the cross correlation technique [19]. The definition of the shape similarity is given as follow:

Definition. Given two shapes ξ_1 and ξ_2, ξ_1 is similar to ξ_2 if and only if ξ_1 can achieve a strong cross correlation with ξ_2 by a sequence of translation, scaling and rotation operations.

In the current approach, let the two shapes each represented by the shape profile $\psi(\xi_1)$ and $\psi(\xi_2)$. The similarity between ξ_1 and ξ_2 is measured using the cross correlation coefficient defined by

$$C(\xi_1, \xi_2) = \frac{\sum_{u\in[0,1]} (k_1(u) - \bar{k}_1)(k_2(u+v) - \bar{k}_2)}{\sqrt{\sum_{u\in[0,1]} (k_1(u) - \bar{k}_1)^2} \sqrt{\sum_{u\in[0,1]} (k_2(u+v) - \bar{k}_2)^2}} \qquad (2)$$

where $\bar{k}$ is the average of the curvature k, and v the phase shift between two shape profiles in the curvature parametric space representing the profile of the two shapes. The higher the correlation, the higher is the similarity between the two shapes. Special attention must be paid to the circular object. In this case $k - \bar{k} = 0$ and we set 0/0 = 1.

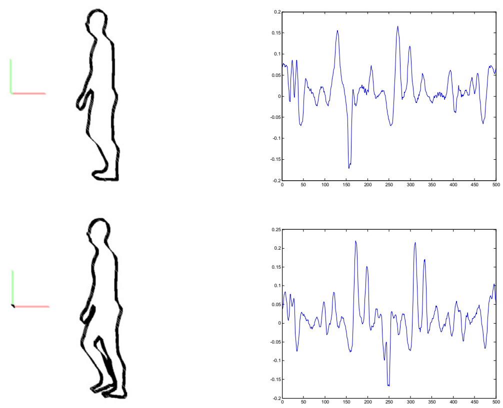


Figure 2. Similarity of two shape profiles

	1	2	3	4	5	6	7	8	9	10
ξ_1	0.070	-0.010	0.075	0.001	0.071	-0.065	0.040	-0.025	0.020	-0.030
ξ_2	0.060	0.010	0.058	0.050	0.056	-0.075	0.025	-0.010	0.010	-0.010
	11	12	13	14	15	16	17	18	19	20
ξ_1	0.150	-0.170	0.020	-0.020	0.030	0.005	-0.070	0.005	-0.035	-0.060
ξ_2	0.050	-0.020	0.070	-0.010	0.010	-0.070	-0.170	-0.080	-0.040	-0.060

Table 1. Sampling Results of two shape profiles

C. *Shape Matching by Statistical Method*

With the defined shape profile, we propose a new statistical method about shape matching. In statistics, there is a universal method named Kullback-Leibler divergence [26]. However, the measure is non-symmetric and unbounded. So, we use Jensen-Shannon divergence *L* to overcome this limitation. The *L* is defined as:

$$L(\xi_1,\xi_2) = D(\frac{\xi_1+\xi_2}{2}) - \frac{D(\xi_1)+D(\xi_2)}{2} \quad (3)$$

where $D(\xi_1) = -\int \psi(\xi_1)\log_2 \psi(\xi_1) d\xi_1$ is the differential entropy. The smaller $L(\xi_1,\xi_2)$ is, the less different between the two shapes are. The Jensen-Shannon divergence is a very useful method to discriminate two shape distributions and have a perfect symmetry.

For example, there are two shape profiles named ξ_1 and ξ_2 in Fig. 2.

At first, we obtain 20 key points and the corresponding value *k (u)* by sampling, Table 1 shows the result. Then we use (3) to calculate the D and L. Note that *k (u)* has some negative values, so the shape profile must be moved up 0.2 units to ensure that all values are positive. With the modified $D'(\xi) = -\sum \psi(\xi)\log_2 \psi(\xi)$, we compute the dissimilarity of the two shape profiles shown in Table 2. We find that the matching rate between ξ_1 and ξ_2 is up to 92.5%.

$D'(\xi_1)$	8.973
$D'(\xi_2)$	8.833
$D'(\frac{\xi_1+\xi_2}{2})$	8.978
$L(\xi_1,\xi_2)$	0.075

Table 2. Matching Results

III. Feature Extraction

In the current approach, the feature extraction process is formulated as a feature correspondence problem. The problem can be defined as: Given two similar shapes ξ_1 and ξ_2, determine the "best" corresponding feature point $q_v \in \xi_2$ that matches a feature point $p_u \in \xi_1$. The feature extraction process is divided into two steps: *1) Shape profile for feature point extraction; 2) Feature point correspondence and extraction.*

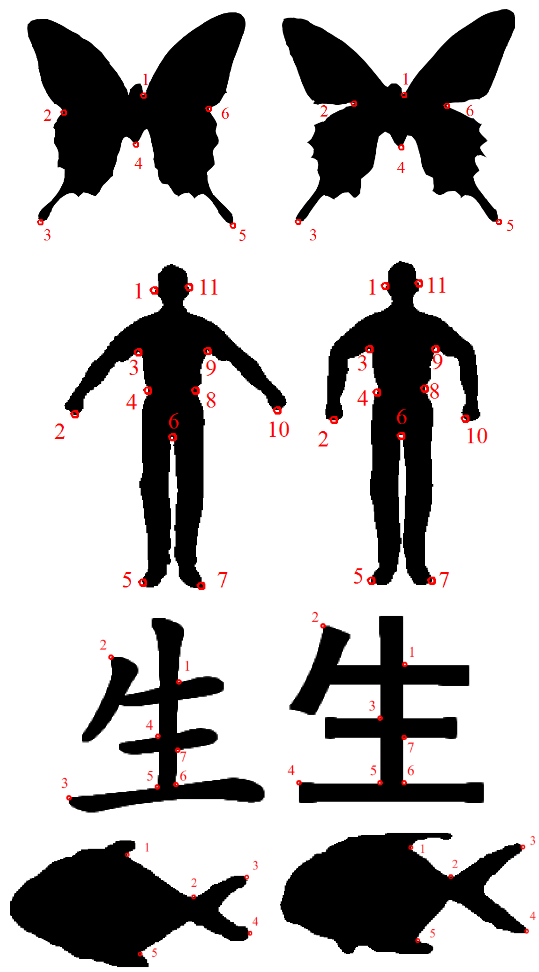


Figure 3. The feature correspondence by indices of two pairs of objects: one is for butterfly and the other is for human with different pose. Note that misalignment occurs at the Chinese font “sheng” when all the local features are similar.

A. *Shape Profile for Feature Extraction*

Using a template shape consisting of point $p_{u0} \in \xi_1$ with parametric value u_0, the shape profile for feature point extraction is defined as:

$$\psi(p_{u0}) = \{c(u)k(u) \mid u \in [u_0 - w, u_0 + w], k(u) \in \xi_1\} \quad (4)$$

where w is the half-width of the filtering window and $c(u)$ is a contribution function:

$$c(u) = \begin{cases} \left[\left(\dfrac{u-u_0}{w}\right)^2 - 1\right]^2, & |u-u_0| < w \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

The feature point extraction from the shape profile ξ_1 depends on the curvature sequence within the filtering window. This is consistent with the observation that, curvature is influenced more by neighboring points than by remote points in the profile [4]. The contribution function is added to the shape profile in equation (4) to address the provided local sensitivity.

B. *Feature Point Correspondence and Extraction*

For each feature point p_u on the template object ξ_1, the shape profile $\psi_{(pu0)}$ of each feature point $p_u \in \xi_1$ is constructed by equation (3). The parametric value $v_0 = u_0 + \gamma$, where γ is the phase shift between the two shape profiles, ξ_1 and ξ_2, is adopted as the initial trial value. The shape profile of the initial trial point $q_{v0} \in \xi_2$ is given as $\psi_{(qv0)} = \{c(v)k(v) \mid v \in [v_0 - w, v_0 + w], k(v) \in \xi_2\}$.

To estimate the degree of similarity between two points $p_{u0} \in \xi_1$ and $q_{v0} \in \xi_2$, the cross correlation coefficient is computed. Similar to the shape similarity, the higher the value of the coefficient means better correspondence between the two points. A neighborhood search is performed after the initial trial to obtain the best matched point. The neighborhood search evaluates the cross correlation of the feature point shape profile against the profile of the template. The best matched point is labeled as the matching feature point in target ξ_2 for the template feature point $p_{u0} \in \xi_1$.

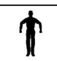
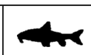
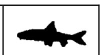
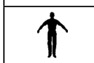
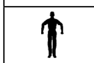
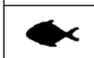
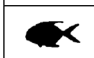
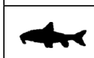
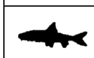
									生	生	力	力				
	1.0	0.94	0.88	0.57	0.22	0.39	0.17	0.22	0.28	0.36	0.39	0.39	0.38	0.25	0.32	0.28
	0.94	1.0	0.88	0.59	0.29	0.40	0.27	0.33	0.37	0.33	0.30	0.33	0.26	0.28	0.44	0.37
	0.88	0.88	1.0	0.60	0.32	0.51	0.29	0.35	0.54	0.45	0.45	0.56	0.36	0.41	0.36	0.37
	0.57	0.59	0.60	1.0	0.87	0.92	0.72	0.74	0.47	0.39	0.28	0.44	0.46	0.36	0.43	0.51
	0.22	0.29	0.32	0.87	1.0	0.96	0.80	0.79	0.32	0.23	0.22	0.25	0.19	0.38	0.37	0.27
	0.39	0.40	0.51	0.92	0.96	1.0	0.77	0.79	0.35	0.29	0.31	0.22	0.22	0.25	0.39	0.46
	0.17	0.27	0.29	0.72	0.80	0.77	1.0	0.99	0.35	0.38	0.39	0.42	0.30	0.26	0.41	0.38
	0.22	0.33	0.35	0.74	0.79	0.79	0.99	1.0	0.34	0.40	0.39	0.39	0.26	0.22	0.42	0.39
生	0.28	0.37	0.54	0.47	0.32	0.35	0.35	0.34	1.0	0.75	0.36	0.46	0.46	0.50	0.49	0.54
生	0.36	0.33	0.45	0.39	0.23	0.29	0.38	0.40	0.75	1.0	0.55	0.55	0.44	0.43	0.46	0.42
力	0.39	0.30	0.45	0.28	0.22	0.31	0.39	0.39	0.36	0.55	1.0	0.73	0.46	0.36	0.50	0.53
力	0.39	0.33	0.56	0.44	0.25	0.22	0.42	0.39	0.46	0.55	0.73	1.0	0.47	0.46	0.41	0.46
	0.38	0.26	0.36	0.46	0.19	0.22	0.30	0.26	0.46	0.44	0.46	0.47	1.0	0.73	0.46	0.54
	0.25	0.28	0.41	0.36	0.38	0.25	0.26	0.22	0.50	0.43	0.36	0.46	0.73	1.0	0.42	0.44
	0.32	0.44	0.36	0.43	0.37	0.39	0.41	0.42	0.49	0.46	0.50	0.41	0.46	0.42	1.0	0.86
	0.28	0.37	0.37	0.51	0.27	0.46	0.38	0.39	0.54	0.42	0.53	0.46	0.54	0.44	0.86	1.0

Figure 4. The similarity ranking between the 16 testing examples

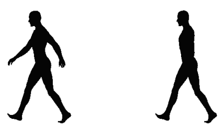
C. *Matching using Shape Profile*

The distinct feature of the proposed technique is to unify the global shape match and local feature correspondence in a single and efficient framework. Some testing examples are shown in Fig. 3. The coefficient of the cross correlation (see equation (2)) gives an overall ranking of the global shape matching as shown in Fig. 4. By applying the same framework with feature point correspondence extraction, the local features between similar objects are related by the same indices as demonstrated in Fig. 3. By using curvature profile, our technique is insensitive to the rigid motion between different subparts of the same object; this makes our method particularly suitable for shape matching and local feature correspondence of articulated objects.

IV. Human Feature Extraction from a Motion Sequence

The feature point extraction from a typical human motion video sequence is used as an application to demonstrate the versatility of the shape profile in shape matching and feature extraction. The feature point extracted from the video frames is used to generate metric constraints for the construction of a human model based on a semantic human model template.

A pre-processing procedure is first performed to set up the templates and to extract the shape profiles. Then feature extraction is conducted on the target object to facilitate the setup of the metric constraints for the human model construction process. A typical example is shown in Fig. 5 This upper part of the figure shows the template samples and the lower part of the figure shows the human motion video sequence.



Templates T_1 and T_2

Image sequence object D_5

Image sequence object D_{11}

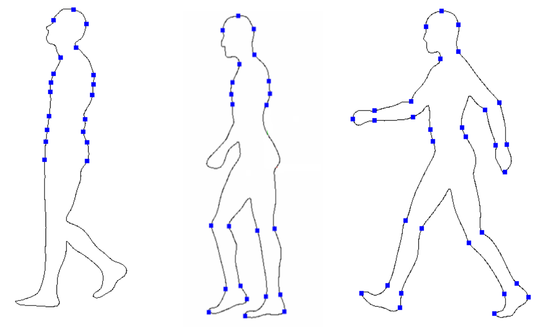
Image sequence object D_{30}

Figure 5. Templates and human motion video sequence

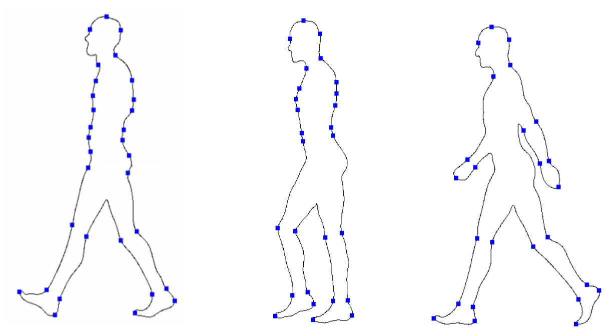
A. *Pre-processing*

The image input for the feature extraction algorithm is in the form of typical video image sequence from any digital camcorder. In the current work, an image sequence with one hundred frames containing the human model is used in the feature extraction process.

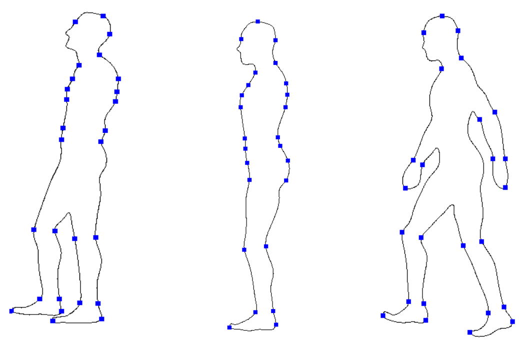
To facilitate the eventual human model construction process, a set of nine human motion templates representing the side view of key walking postures are constructed. These templates are generated using the software Poser. Fig. 6 shows the templates. On each template, a set of feature points is defined with reference to the feature-based human model as depicted in [23] which is shown in Fig. 7. The feature points will be used as the primary information to construct the human model.



Templates 1~3



Templates 4~6

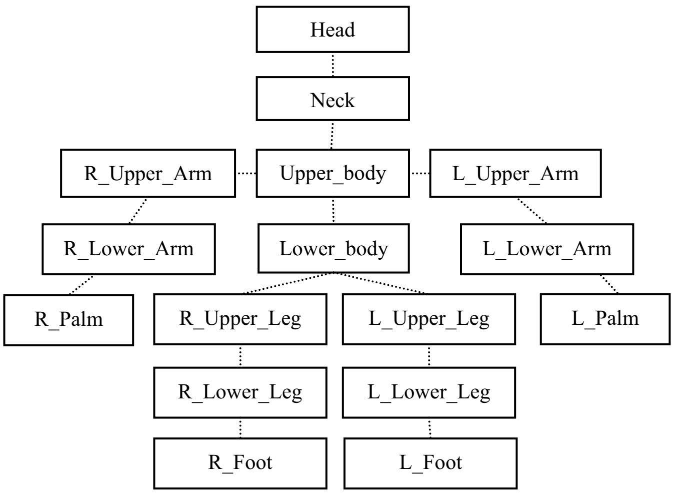


Templates 7~9

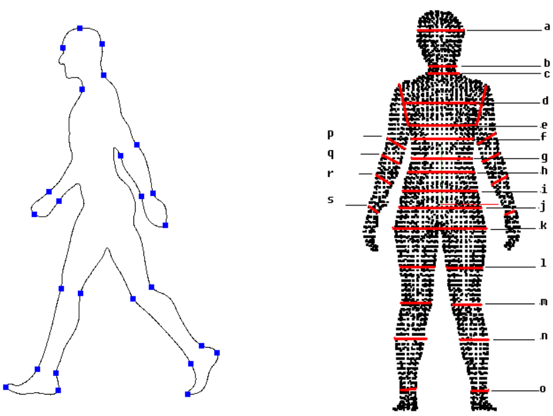
Figure 6. Templates used in the feature extraction from video sequence

Index	Feature Curve
a	Head
b	Neck
c	Neck-base
d	Upper Chest
e	Chest
f	Lower Chest
g	Waist
h	Lower Waist
i	Upper Hip
j	Hip
k	Max Thigh
l	Mid Thigh
m	Knee
n	Mid Calf
o	Below Ankle
p	Upper Arm
q	Elbow
r	Lower Arm
s	Wrist

a) List of feature curves in human model



b) Feature graph for the human model



c) Template 6 d) human model with feature curves

Figure 7. Feature definition on human model and template

The feature points are derived from the set of 184 feature points for constructing the human model [7]. As illustrated in Fig. 7, the specification of feature points on each template follows two basic rules. Firstly, the feature points are defined only on the non-occluded area. Secondly, the feature points are defined on the joint locations. Each joint location in the template is identified by the corresponding curvature maximal point in the neighborhood. This facilitates the search over the shape profile for joint locations in the feature extraction process. It has to be noted that the feature points on the templates are duplicated, which means that a particular feature point on the human model is specified multiple times on the different templates. The duplication provides a means to improve the quality of the feature point matching.

In the preprocessing stage, the shape profiles for the following items are constructed and stored for subsequent processing:

1) the segmented human model from each frame of the input images;

2) the human motion templates;

3) the feature points specified in the human motion templates.

The shape profile of the first four frames of a sample video sequence is shown in Fig. 8. The shape profiles of the first four templates are shown in Fig. 9.

B. *Template-Image Matching using Shape Profile*

In the template selection process, an image best fitted to each template is selected from the image sequence using the shape profile matching scheme. This is determined by picking the image shape profile with the highest cross correlation value against the shape profile of the selected template.

The shape profile matching result is shown in Fig. 10 illustrating the matching process against template T_2. The tabulated result shows that the best match against template T_2 is the input image frame D_{13} with a highest cross correlation value of 0.67. Feature extraction is also conducted on each of the input images and the less correlated images have some of the feature points misplaced. Fig. 11 shows the matching respectively for templates T_1 and T_2 against three different human objects. Feature points are also extracted on each of the images and it can be seen that while the technique can be applied to different human samples, the quality of the extracted feature point varies.

C. *Optimized Feature Point Selection from Images*

To improve the quality of the feature point extraction result, the results from the multi templates approach are evaluated and optimized for the best fitted feature point. For each of the nine human model motion templates, the feature points in the best fit image will be evaluated. Using the shape profile approach, the cross correlation value against each of the feature points in the template is calculated. As the feature points on the templates are duplicated, each feature point has multiple cross correlation values from different template-image matching pairs.

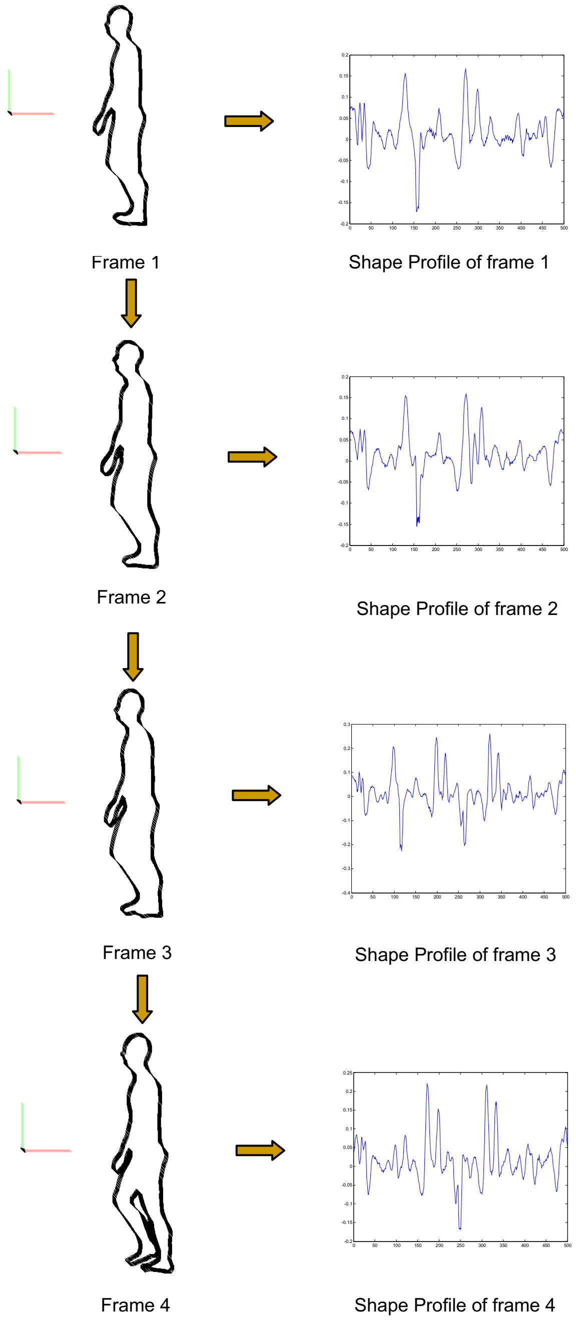


Figure 8. Shape profile representation of the input images

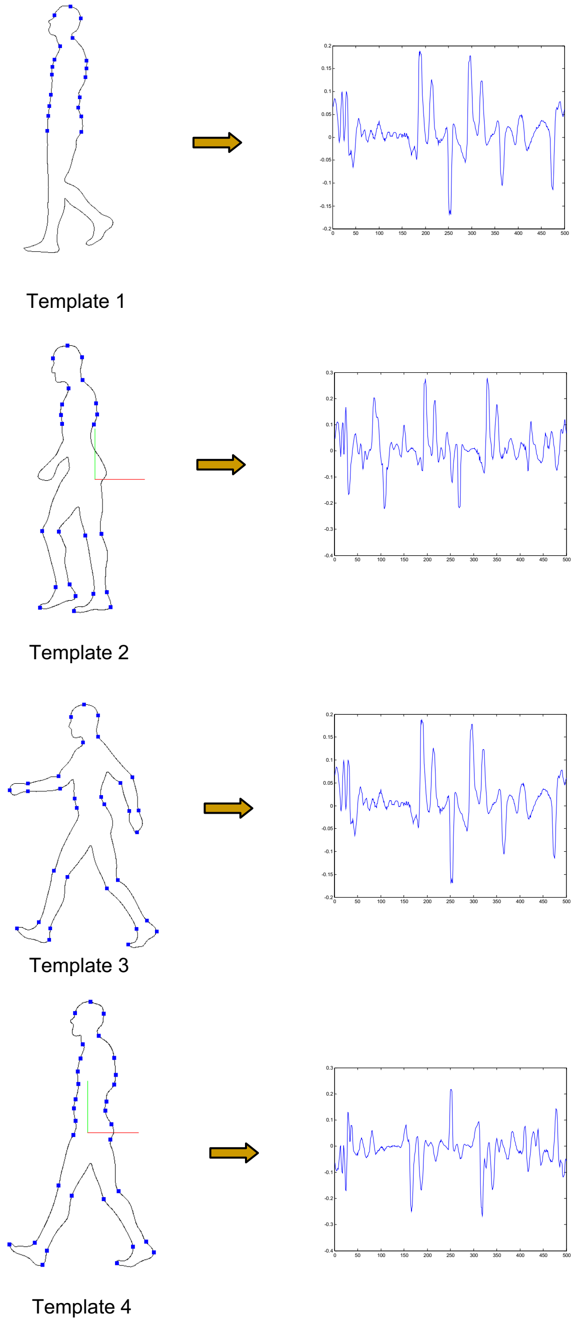
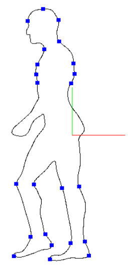


Figure 9. Shape profile for human motion templates

The goal of best feature point selection is to select the best fitted feature point pairs representing the boundary of feature curve for the human model construction. In the example shown in Fig. 12, the red points indicating the location of the chest feature curve are extracted from the template T_1 and template T_2. The best correlated feature point pair is selected for the construction of the feature curve. The average correlation of the feature point pairs in both images are computed by the mean value of the cross correlation coefficients of the two feature points extracted from each of the template. In this case, the template T_1 (Fig. 12a) shows a higher value than that of the template T_2 and is selected for the subsequent human model construction. Fig.12 also shows the two human models by different templates.



Template T_2

Image	Cross-Correlation
$C(T_2,D_1)$	0.26
$C(T_2,D_4)$	0.49
$C(T_2,D_8)$	0.38
$C(T_2,D_{13})$	0.67(Best fit image)
$C(T_2,D_{19})$	0.26

Shape Matching Results forTemplate Selection

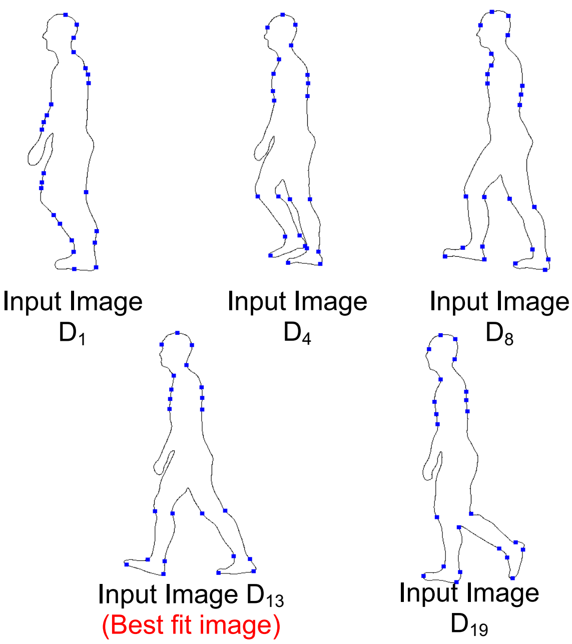


Figure 10. Image Matching against Template T_2

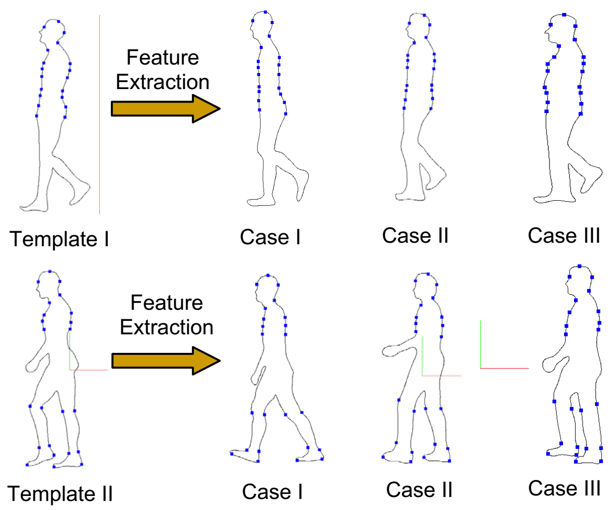
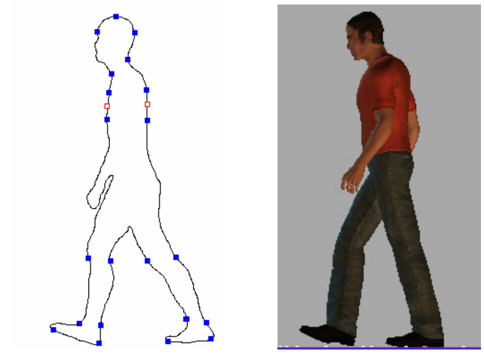
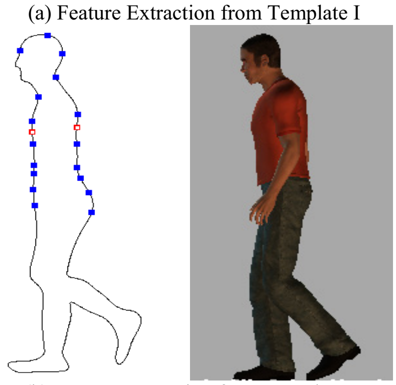


Figure 11. Image Matching against Different Human Objects



(a) Feature Extraction from Template I



(b) Feature Extraction from Template II

Figure 12. Feature Extraction based on Related Feature Point Pair

When getting the two models, we could use software Poser to imitate the human moving from an pose to another. In the Figure 13, there are 10 frames in screen snapshoot of human walking from template T_1 to template T_2.

Figure 13. Human Walking form Template I to Template II

V. CONCLUSION

The paper has presented a novel method for 2D shape matching and feature extraction based on the concept of curvature profile and the cross correction technique. The method is similar to the curvature space method but utilizes the cross correlation technique to provide a unified method which enables global and local shape matching. The method also enables an efficient mapping of the feature points from the template to the segmented object in the target image frame. In shape matching, the phase shift in the cross correlation method can be used to rotationally align the object against the template and the cross correlation coefficient can be used to evaluate the shape similarity. By applying the method locally, the shape profile was shown to be able to map and extract the feature points from the profile at location where the curvature is not high. Future work includes extension of the proposed cross correlation approach to hierarchical shape matching in the framework of [8] and using the statistical method to match shape profile.

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