

Tempo-spatial Segmentation of Mesh Sequence*

* Submission to Computers & Graphics (Elsevier), Nov. 2012

PhD student: Guoliang LUO
gluo@unistra.fr

December 6, 2012



Outline

- 1 Motivation
- 2 Related works
- 3 Objectives
- 4 Tempo-spatial segmentation of mesh sequence
 - Temporal segmentation
 - Spatial segmentation
 - Tempo-spatial cluster graph
- 5 Results
- 6 Conclusions
- 7 Future works

Motivation

'Facial-expression' data obtained from motion capture:

Applications

- Compression.
- Shape query.
- Motion recognition.
- ...

Segmentation on the mesh sequence provides a solution to the above applications.

Related works

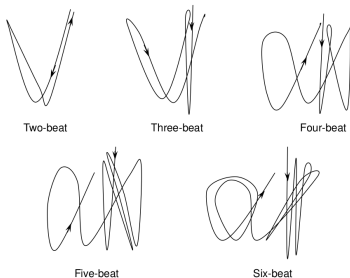
Temporal segmentation / Spatial segmentation

On video

- [Wang et al.]'01

On pose data

- [Fod et al.]'02
- [Barbic et al.]'04



[Wang et al.]'01

Related works

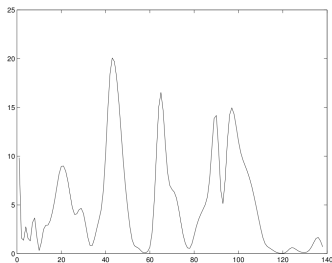
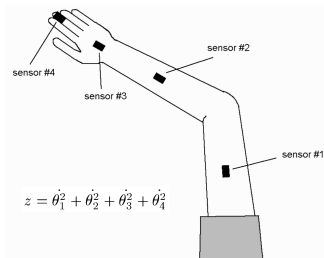
Temporal segmentation / Spatial segmentation

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Sum of squares of angular velocity. [Fod et al.]'02

Related works

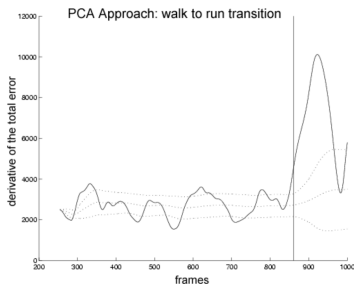
Temporal segmentation / Spatial segmentation

On video

- [Wang et al.]'01

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- [Barbic et al.]'04



Reconstruction errors. [Barbic et al.]'04

Related works

Temporal segmentation / Spatial segmentation

Spectral clustering

- [Sattler et al.]'05
- [Kalafatlar et al.]'10
- *Entire sequence*

Region growing

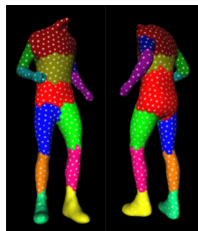
- [Lee et al.]'06
- Per-frame based

Learning

- [Kalogerakis et al.]'10
- [Benhabiles et al.]'11
- Ground-truth sets
- Not dynamic mesh



(c) [Sattler et al.]'05



(d) [Kalafatlar et al.]'10

Related works

Temporal segmentation / Spatial segmentation

Spectral clustering

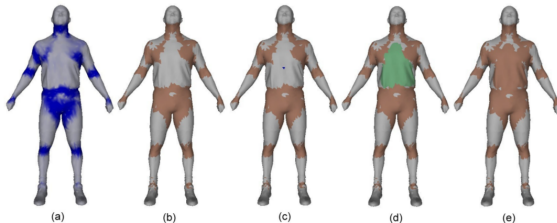
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[Lee et al.]'06

Related works

Temporal segmentation / Spatial segmentation

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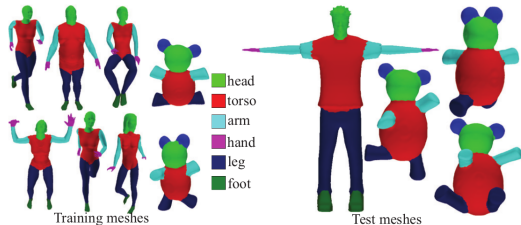
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Region growing

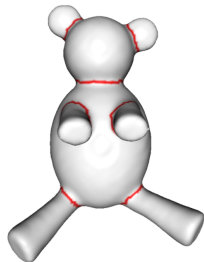
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(e) [Kalogerakis et al.]'10

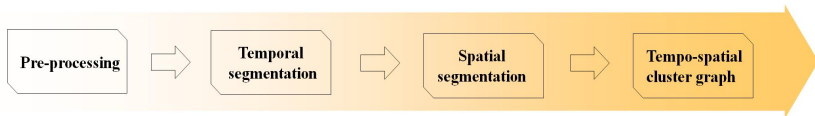


(f) [Benhabiles et al.]'11

Objectives

- Temporal segmentation of **mesh sequence**.
- Spatial segmentation within each temporal segment.
- High-level representation of mesh sequence.

Tempo-spatial segmentation of mesh sequence



Overview of our approach.

Temporal segmentation

- Maximizing within-segment frame affinities.

Spatial segmentation

- Deformation based.

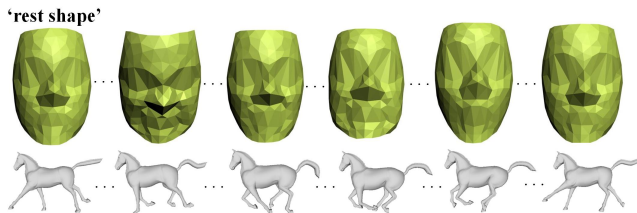
Tempo-spatial cluster graph

- Devising a high-level representation of mesh sequence.

Pre-processing



- Input data

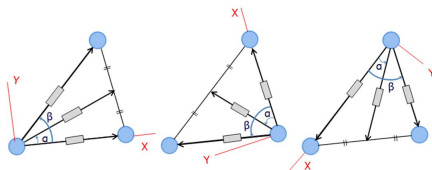


- Deformation feature descriptor: Triangle-based strain
- Geodesic distance:
 - ▶ Triangle pair
 - ▶ Averaging 9-pair of vertex-distance

Pre-processing



- Input data
- Deformation feature descriptor: Triangle-based strain



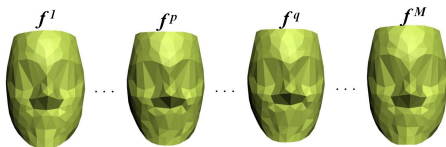
Triangle-based strain approximated by using linear gage rosettes.[Seo et. al]'12

- Geodesic distance:
 - ▶ Triangle pair
 - ▶ Averaging 9-pair of vertex-distance

Frame affinity



Frame affinity $A_f(p, q)$, $p, q = 1, \dots, M$:



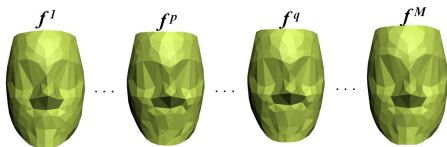
$$\mathbf{s}^p = (s_1^p, \dots, s_N^p)^T, \quad \mathbf{s}^q = (s_1^q, \dots, s_N^q)^T$$
$$A_f(p, q) = \exp(-0.5\delta_t^2 \|\mathbf{s}^p - \mathbf{s}^q\|_{L_2}^2)$$

- M : Number of frames,
- N : Number of triangles,
- s_i^p : The strain of the i -th triangle in the p -th frame.

Frame affinity



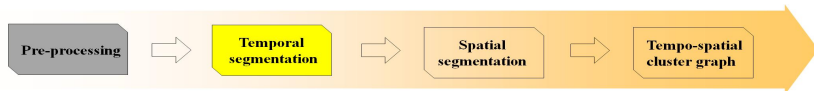
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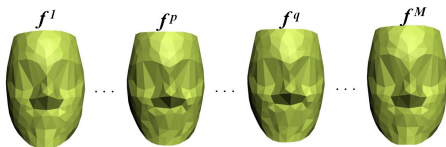
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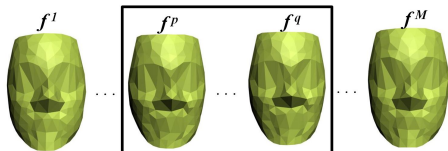
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- M : Number of frames,
- N : Number of triangles,
- s_i^p : The strain of the i -th triangle in the p -th frame.

Average frame affinity



Average frame affinity $A_s(p, q)$ within subsequence $[p, q]$:



$$A_s(p, q) = \frac{\sum_{m=n+1}^q \sum_{n=p}^{q-1} A_f(n, m)}{(q-p+1) \cdot (q-p)/2}, p < q.$$

Average frame-affinity matrix

Pre-processing



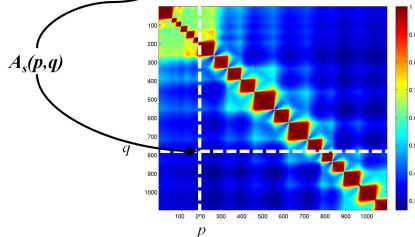
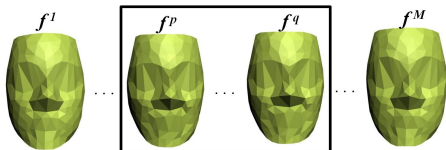
Temporal segmentation



Spatial segmentation

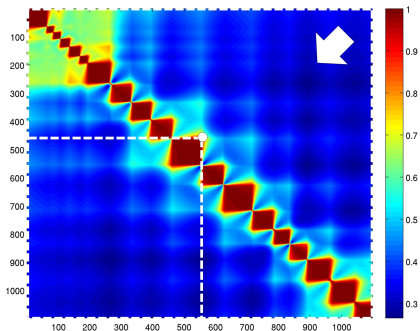
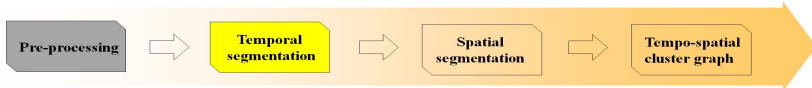


Tempo-spatial cluster graph



An example of $A_s(p, q)$ in an average frame-affinity matrix.

Temporal segmentation



(g) Average frame-affinity matrix.

Algorithm 1: $TempSeg(I_B, A_s, I_h, I_t)$

Init: $I_B = [], I_h = 1, I_t = M, A_s$

$L = I_t - I_h + 1$

for $l = L$ to 1 **do**

for $p = 1$ to $L - l + 1$ **do**

$A_{s-sub}(p) = A_s(p, p+l-1)$

end for

$[A_{s-max} \ p] = \max(A_{s-sub})$

if $A_{s-max} > \rho_0$ **then**

$I_B = [I_B \ p]$

$q = p + l - 1$;

$TempSeg(I_B, A_s, I_h, p-1)$

$TempSeg(I_B, A_s, q+1, I_t)$

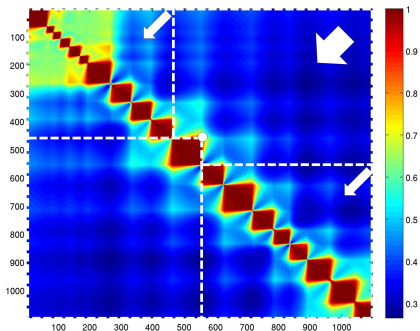
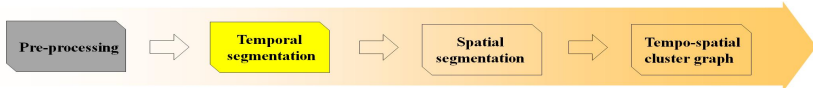
Break

end if

end for

Return: I_B

Temporal segmentation



(i) Average frame-affinity matrix.

Algorithm 1: $TempSeg(I_B, A_s, I_h, I_t)$

Init: $I_B = [], I_h = 1, I_t = M, A_s$

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$TempSeg(I_B, A_s, I_h, p-1)$

$TempSeg(I_B, A_s, q+1, I_t)$

Break

end if

end for

Return: I_B

Temporal segmentation

Pre-processing



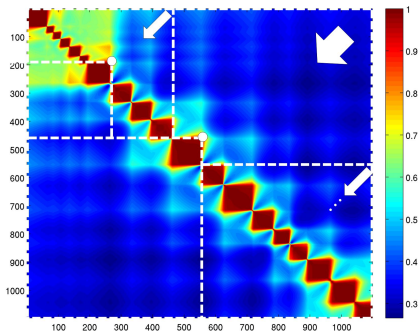
Temporal segmentation



Spatial segmentation



Tempo-spatial cluster graph



(k) Average frame-affinity matrix.

Algorithm 1: $TempSeg(I_B, A_s, I_h, I_t)$

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$TempSeg(I_B, A_s, q+1, I_t)$

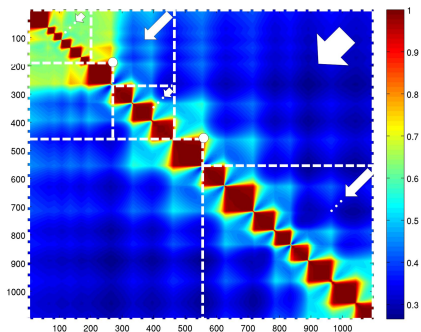
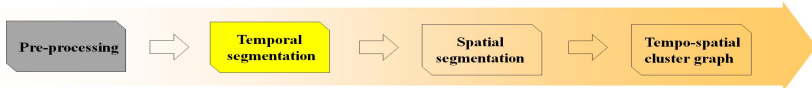
Break

end if

end for

Return: I_B

Temporal segmentation



(m) Average frame-affinity matrix.

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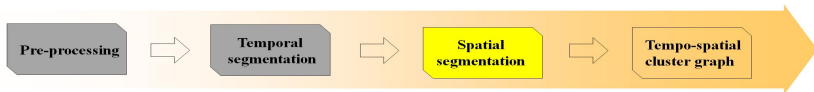
Break

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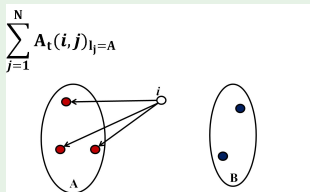
end for

Return: I_B

Initial segmentation



Correlation clustering ([Bagon et. al]'11)



Triangle affinities

$\forall i, j = 1, \dots, N,$

$$dist_G(i, j) \xrightarrow{GKF} A'_t(i, j) \xrightarrow{\text{linearly rescale}} A_t(i, j),$$

where $A'_t(i, j) \in [0, 1]$ and $A_t(i, j) \in [-1, 1]$.

Algorithm 2: Adaptive-label ICM

Init: $l_i = 1, i = 1, \dots, n, L = 1, A_l$

repeat

 for $i = 1$ to n do

 for $l = 1$ to L do

$$A_l = \sum_{j=1}^n A_t(i, j)_{l_j=l}$$

 end for

 if $\forall A_l < 0$ then

$L = L + 1$

$l_i = L$

 else

$$[A_{l_{\max}}, l_{\max}] = \max(A_l)$$

$$l_i = l_{\max}$$

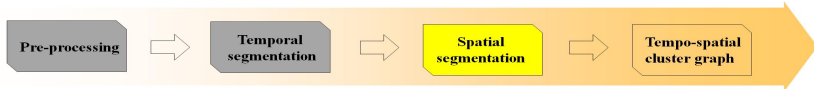
 end if

 end for

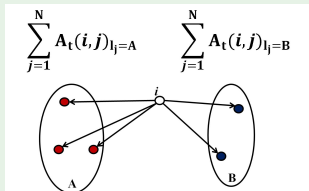
until L is unchanged

return $l_i, i = 1, \dots, n$

Initial segmentation



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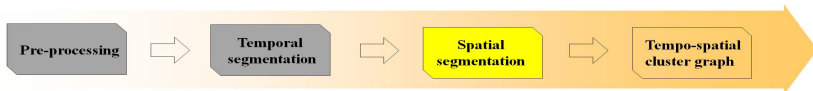
end if

end for

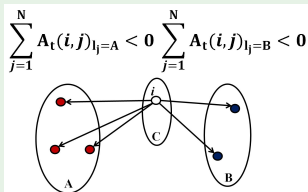
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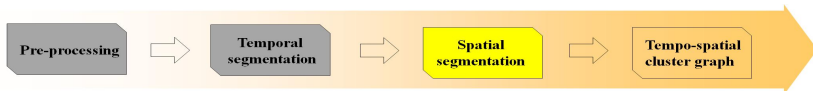
 end if

 end for

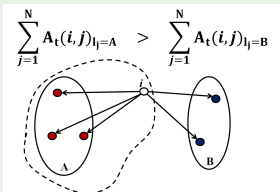
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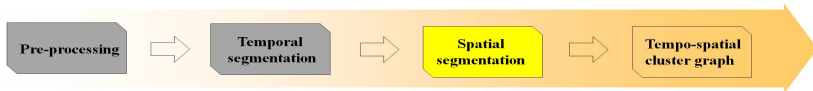
end if

end for

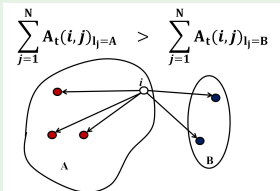
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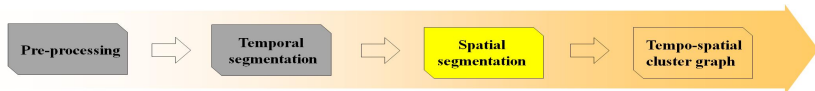
 end if

 end for

until L is unchanged

return $l_i, i = 1, \dots, n$

Deformation-based merging



Initial segmentation



Deformation-based merging

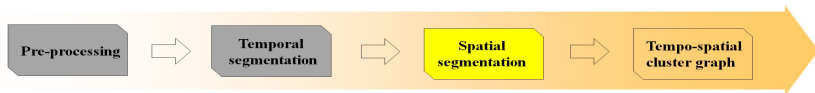
Average deformation of spatial cluster L_c , in the k -th temporal segment,

$$\overline{\text{deform}(c)}^k = \frac{\sum_{p \in [p_k, q_k], l_i = L_c} |s_i^p|}{\alpha_c}.$$

Threshold,

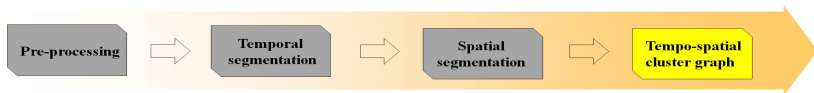
$$\rho_s(k) = \omega \cdot \overline{\text{deform}}^k = \omega \cdot \frac{\sum_{p \in [p_k, q_k]} |s^p|}{\sum_{c=1}^L \alpha_c}.$$

Post-processing



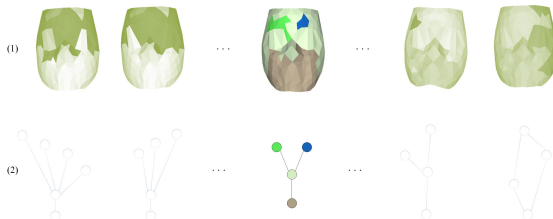
Spatial segmentation on the 10-th temporal segment of 'Facial-expression' animation.

Tempo-spatial cluster graph



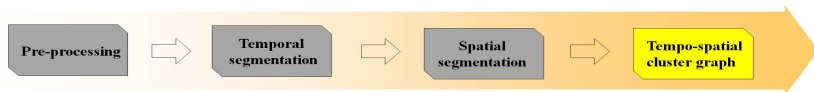
TSCG

- Graph representation
- Relaxed correspondence
- Transfer ratio



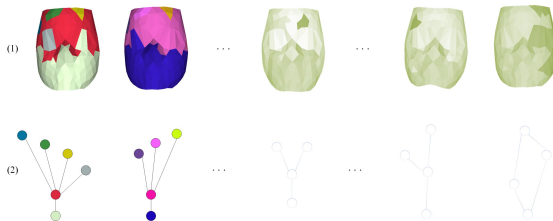
Tempo-spatial cluster graph of the 'Facial-expression' animation.

Tempo-spatial cluster graph



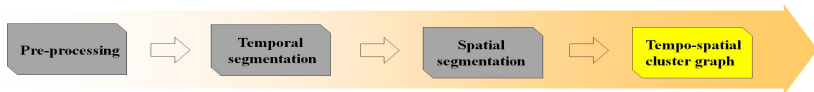
TSCG

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- Transfer ratio



Tempo-spatial cluster graph of the 'Facial-expression' animation.

Tempo-spatial cluster graph



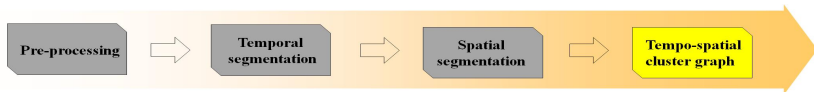
TSCG

- Graph representation
- Relaxed correspondence
- Transfer ratio



Tempo-spatial cluster graph of the 'Facial-expression' animation.

Tempo-spatial cluster graph



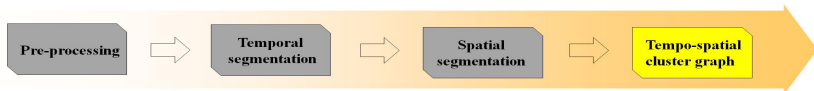
TSCG

- Graph representation
- Relaxed correspondence
- Transfer ratio



Tempo-spatial cluster graph of the 'Facial-expression' animation.

Tempo-spatial cluster graph



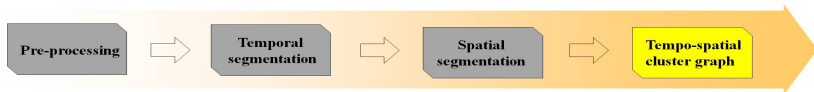
TSCG

- Graph representation
- Relaxed correspondence
- Transfer ratio



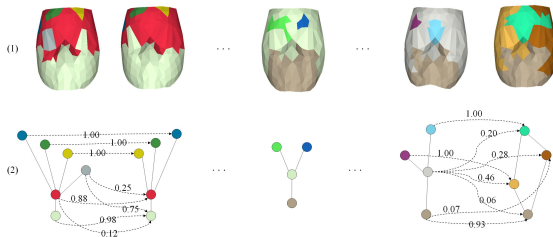
Tempo-spatial cluster graph of the 'Facial-expression' animation.

Tempo-spatial cluster graph



TSCG

- Graph representation
- Relaxed correspondence
- Transfer ratio



Tempo-spatial cluster graph of the 'Facial-expression' animation.

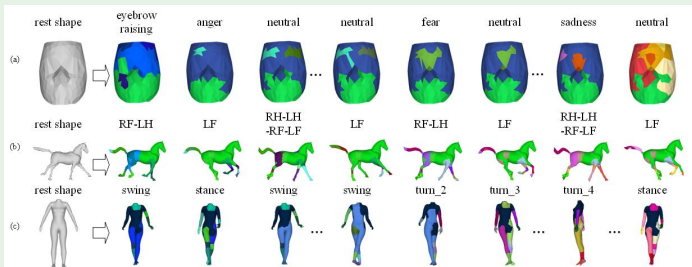
Timing

Data \ Time (sec)	size		Pre-processing	Temporal segmentation	Spatial segmentation
	# triangles	# frames			
Facial expressions	286	1098	7.68	347.15	0.65
Galloping horse	8420	48	572.44	0.26	218.89
Walking woman	8590	279	656.82	11.14	228.64

Segmentation timings of animations.

Results

Tempo-spatial segmentation



(a) 'Facial-expression' animation, (b) 'Gallop-horse' animation (RF: right fore, LF: left fore, RH: right hint, LH: left hint.), (c) 'Walking-woman' animation.

The complete results

Conclusions

- We have introduced a method for temporal segmentation of mesh sequence.
- We develop geometric segmentation of mesh sequence.
- We devise an abstract representation of mesh sequence.
- Our segmentation results faithfully reflect the movements in the given mesh sequence.

Future works

- Improving of the relaxed correspondence algorithm.
- Comparison with other segmentation works.
- Consistent segmentation.
- Shape query.
- Compression of animations.

Acknowledgements

We would like to thank Frederic Larue and Olivier Genevaux for providing us with the facial motion capture data.

This work has been supported by the French national project SHARED (Shape Analysis and Registration of People Using Dynamic Data, No.10-CHEX-014-01).

köszönöm !תודה dĕkuji

mahalo 고맙습니다

thank you

merci 谢谢 *danke*

Ευχαριστώ شڪرا

どうもありがとう *gracias*

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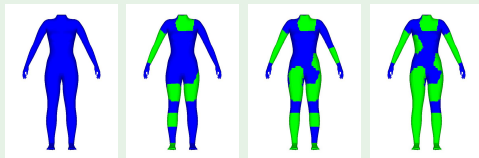
Discussions

Evaluation of δ_s



(o) $\delta_s=0.1$ (p) $\delta_s=0.15$ (q) $\delta_s=0.2$ (r) $\delta_s=0.3$

Evaluation of ω



(s) $\omega=0.3$ (t) $\omega=0.5$ (u) $\omega=0.7$ (v) $\omega=0.9$