Semantically Consistent Human Motion Segmentation

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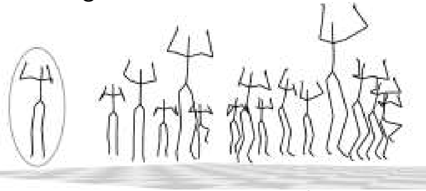
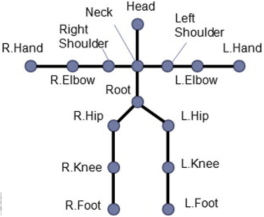
Presentation Outline

1. 3D Human Motion Capture and Representation
2. Key poses
3. Existing approaches to key-pose detection
4. Our purpose of motion segmentation
5. How our method works
6. Results

3D Human Motion Capture and Representation

- Employment
  - Motion simulation and exposition - avatar graphics
  - Content-based retrieval in motion databases
  - Biomechanical analysis - detection of gait disorders, rehabilitation
  - Generating new motion instances

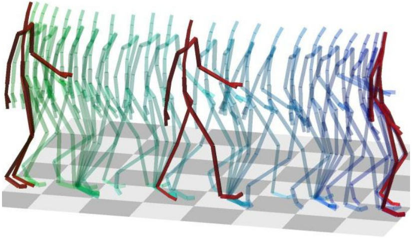




- 3D data capturable via Microsoft Kinect or on-body sensors
- Human motion in the form of a sequence of body poses
- Pose characterised by 3D coordinates of selected body points and time
- Various extractable features
  - Joint angles, angular velocity, acceleration
  - Joint relative distances
  - Relational features

Key poses

- Not all poses are important for us
- We detect key poses - the poses of interest
- Key pose selection according to the purpose

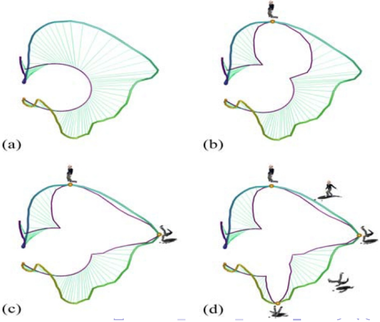


- Purposes
  - Summarization and compression of motion data
  - Motion retrieval
  - Motion sequence segmentation
- Relevant approaches to key-pose detection - Assa, Gong, Xiao

Assa

Assa - based on curve averaging

- Pose described skeletal joints and their associated aspects: (1) positions, (2) angles, (3) velocity, (4) angular velocity
- f_t^a - value of aspect a at time t
- High-dimensional curve f_t^a $(4\times\#\text{joints})$ is reduced by RMDS algorithm to a curve $C(t)$ of 5-8 dimensions
- Point t in $C(t)$ is projected onto a predefined average curve $\overline{C}(t)$
- $r_t = |C(t) - \overline{C}(t)|$ - distance at time t
- Iterative key-pose detection algorithm:
  1. Find pose index t of maximum r_t
  2. Mark the t-th pose as key pose
  3. Modify $\overline{C}(t)$ to touch $C(t)$



Gong

Gong - based on local-motion energy extremes

- Human model consists of 12 limb bones
- Motion features in form of limb bone axis rotations
- $\theta_t^{l,a}$ - angle between limb bone l and axis a at time t
- 36-dimensional pose P_t:

$$[cos(\theta_t^{1,x}), cos(\theta_t^{1,y}), cos(\theta_t^{1,z}), \ldots, cos(\theta_t^{12,x}), cos(\theta_t^{12,y}), cos(\theta_t^{12,z})]$$

- Local-motion energy in pose at time t

$$E_t = |P_t - P_{t-1}|^2$$

- Key poses are the poses P_t of locally extremal E_t

Xiao

Xiao - based on curve simplification

- Human model consists of 8 limb bones
- Motion features in form of limb bone angles
- θ_t^l - angle between limb bone l and central bone at time t
- 8-dimensional pose P_t:

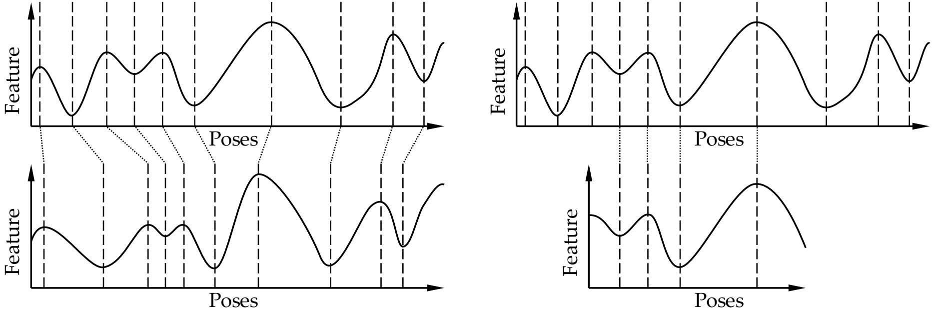
$$[\theta_t^1, \ldots, \theta_t^8]$$

- Key-pose candidates are the poses where any θ_t^l is locally extremal
- Curve is constructed to enclose the key-pose candidates
- LCS (similar to SCS) is applied to this curve to refine key poses

Our Purpose of Motion Segmentation

Our purpose: motion retrieval

- Pose-level indexing - inefficient
- Segment-level indexing
  - Both motion database and query are segmented
  - Segments can be separately analysed, indexed, clustered, or compared
  - Query is searched in the database as a sequence of motion segments
  - Semantic consistency - key poses at semantically equivalent phases



(a) (b)

How Our Method Works

Our - based on changes in body point trajectories

- Database: HDM05 Motion Capture Database - University of Bonn
- Two major steps:
  1. Feature extraction
  2. Pose energy curve construction and analysis

1. Feature extraction

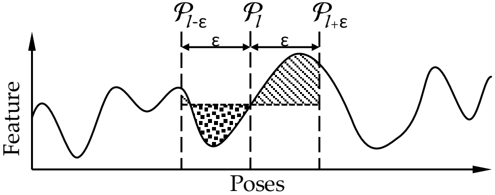
- Relative distances of selected body point pairs:
  1. left hand and right hand
  2. left hand and left foot
  3. right hand and right foot
  4. left knee and right knee
  5. left foot and right foot
- Motion - sequence of poses $\mathcal{M} = (\mathcal{P}_1, \ldots, \mathcal{P}_n)$
- Pose - configuration of features in time $\mathcal{P}_t = (f_t^1, \ldots, f_t^5)$
- f_t^p - relative distance of p-th body point pair at time t

How Our Method Works

2. Pose energy curve construction and analysis

- Energy is determined by pose neighbourhood of radius ϵ
- Feature energy of each feature f_t^p at pose P_t is calculated as

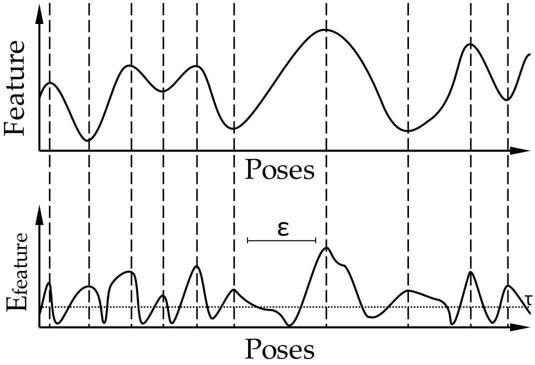
$$E_{feature}(f_t^p) = \sum_{t'=t-\epsilon}^{t+\epsilon} \left(f_t^p - f_{t'}^p\right)$$



- Pose energy of each pose P_t is calculated as

$$E_{pose}(P_t) = \sum_{p=1}^{5} |E_{feature}(f_t^p)|$$

- Pose-energy curve is constructed by concatenating the pose-energy values through the processed motion in chronological order



(c)

- Local maxima greater than a τ threshold of this curve are identified as key poses

Results

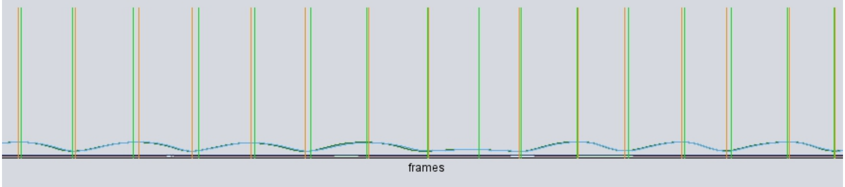
We have:

- Extracted body point distances as motion features
- Manually defined ground truth over 11 motion sequences
- Implemented and tested all methods - our, Assa, Gong, Xiao

Evaluation results:

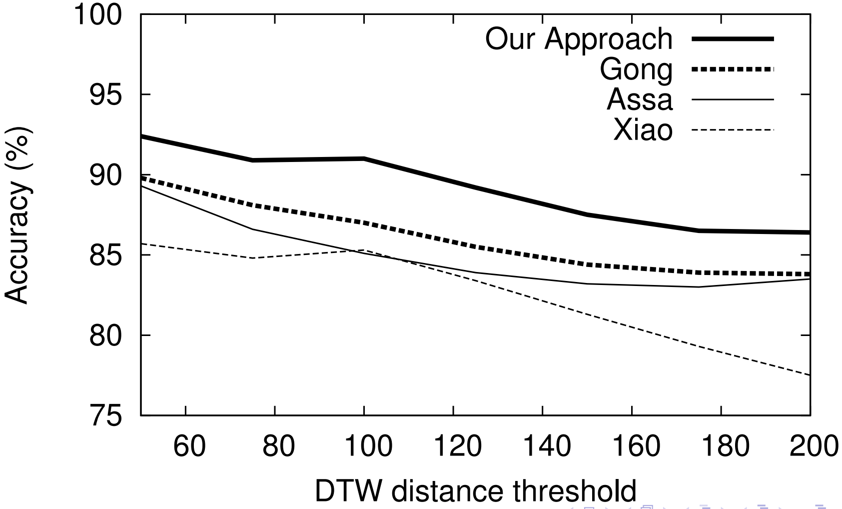
- Evaluation against ground truth: hit within 10-pose neighbourhood

	Recall (%)	Precision (%)	F-measure (%)	Ratio (%)
Our	52.2	46.5	49.2	112.1
Assa	35.2	39.2	37.1	89.7
Gong	92.1	4.6	8.7	2040.8
Xiao	30.7	45.3	36.6	67.7



Results

- Evaluation of semantic consistency of all methods



Questions?

Thank you for attention.

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