Key-Frame Extraction for 3D Human Motion Sequence Segmentation

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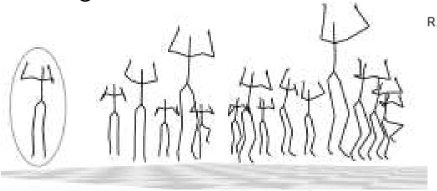
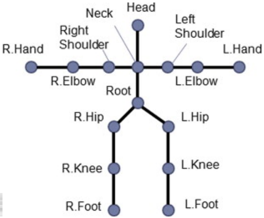
3D Human Motion Capture

- Employment
  - motion simulation and exposition - avatar graphics
  - content-based retrieval in motion database
  - biomechanical analysis - gait disorders detection, rehabilitation
  - generating new motion instances

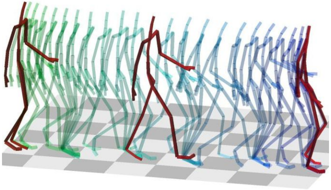




- 3D data capturable via Microsoft Kinect or on-body sensors
- Human motion in the form of a sequence of body poses
- Pose characterised by 3D coordinates of selected body points and time
- Various extractable features
  - joint angles, their velocity or acceleration
  - body points' distances
  - relational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

Key-Frames

- Key-frames are time frames of motion sequence extracted according to specific sampling strategy.

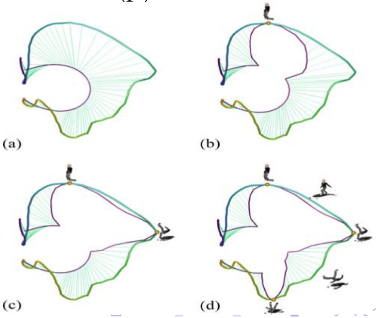


- Purposes
  - compression of motion data
  - motion retrieval
  - motion sequence segmentation
- Two base key-frame sampling strategies
  - uniform - each two consecutive key-frames of equal time difference
  - adaptive - respect to motion sequence (extremal poses, turnover, etc.)
- Approaches to key-frame extraction - Assa, Műller, Gong, Xiao, Liu

Assa

Assa - curve averaging

- Pose consists of skeletal joints and their associated aspects: (1) positions, (2) angles, (3) velocity, (4) angular velocity
- x_a^f - value of aspect a in frame f
- High-dimensional curve x_a^f ($4\times\#$joints) is reduced by RMDS algorithm to a curve $C(f)$ of 5-8 dimensions
- Point p in $C(p)$ is projected onto average curve $\overline{C}(p)$
- $r_p = |C(p) - \overline{C}(p)|$ - distance at point p
- Iterative key-frame extractor algorithm:
  1. add p_i of maximum r_{p_i} to key-frames
  2. modify $\overline{C}(p)$ to touch $C(p)$



#Műller

Műller - genetic learning

- $F = (F_1, \ldots, F_f)$ - set of f relational features
- F-segment of data stream D represented by matrix $M_F[D]$
- Example: $F = (F_{LeftKneeBent}, F_{RightKneeBent})$, $K = 5$ F-segments

$$M_F[D] = \begin{pmatrix} 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 1 \end{pmatrix}$$

- error tolerant $(0/1 \rightarrow *)$ motion class patterns $X \in \{0, 1, *\}^{f \times K}$
- $V_k \subseteq \{0, 1\}^f$ - subset of alternative feature vectors = fuzzy set
- $T^{+/-}$ - set of positive/negative training F-motions
- Individual described by element of T^+ and submatrix of $M_F[D]$
- Mutations: change element of T^+, change row or column of $M_F[D]$
- Optimization in terms of recall and performance of fuzzy query $V(X) = (V_1, \ldots, V_K)$

Gong, Xiao, Liu

Gong - local-motion energy extremes

- θ_l^a - angle between limb l and axis a
- $\psi = [cos(\theta_1^x), cos(\theta_1^y), cos(\theta_1^z), \ldots, cos(\theta_{12}^x), cos(\theta_{12}^y), cos(\theta_{12}^z)]$ - pose
- $E_i = |\psi_i - \psi_{i-1}|^2$ - energy in i-th frame of pose ψ_i
- Key-frames are frames i of extremal E_i

Xiao - angle extremes

- $\theta_i^{(l)}$ - angle between limb bone l and central bone in frame i
- Key-frames are frames i such that $\exists l \in \{1, \ldots, 8\} : \theta_i^{(l)}$ is extremal

Liu - cluster centroids

- r_{lxi} - rotational parameter of lhip/rhip/chest in axis x/y/z in frame i
- $F_i = [r_{lxi}, r_{lyi}, r_{lzi}, r_{rxi}, r_{ryi}, r_{rzi}, r_{cxi}, r_{cyi}, r_{czi}]$ - frame
- σ_i - i-th cluster of frames clustered by weighted Euclidean distance
- Key-frames are frames i closest to centroid of σ_i

The Goal

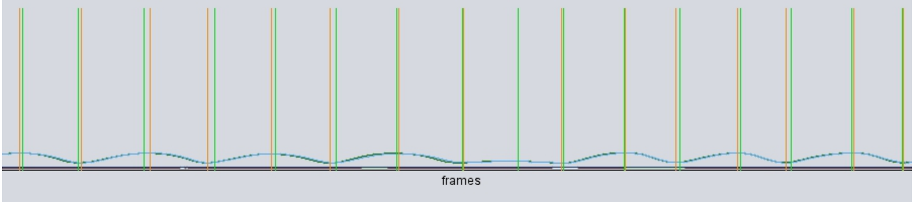
Key-Frame Extraction for 3D Human Motion Sequence Segmentation

- Soon-to-be paper
- Database: CMU Motion Capture Database
- Extracted features: distance signals of selected pairs of body points, angle signals of selected joints
- Key-frame sampling strategy: adaptive, local extremes with additional criteria (neighbourhood, weight)
- Evaluation against ground truth: recall, precision, F-measure, ratio between ground truth and algorithmically selected key-frames
- Evaluation against current approaches: evaluation against identical ground truth in all aspects, evaluation of flexibility and performance

Current State and Future Vision

We have:

- extracted distance and angle signals as motion features
- defined ground truth over 5 motion sequences
- implemented an algorithm that extracts key-frames according to given sampling strategy
- recall and precision of 50-70% (hit within 20-frames neighbourhood)



We continue with:

- evaluation against current approaches
- hierarchical motion segmenter

Questions?

Thank you for attention.

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