# Topology Dictionary with Markov Model for 3D Video Content-Based Skimming and Description

Tony Tung Takashi Matsuyama

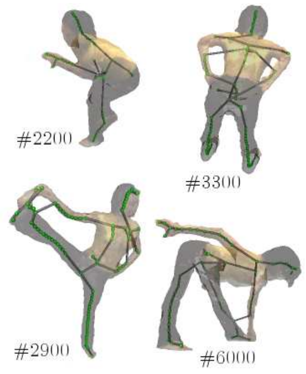
Graduate School of Informatics, Kyoto University, Japan

Presented by Dimitrios Makris

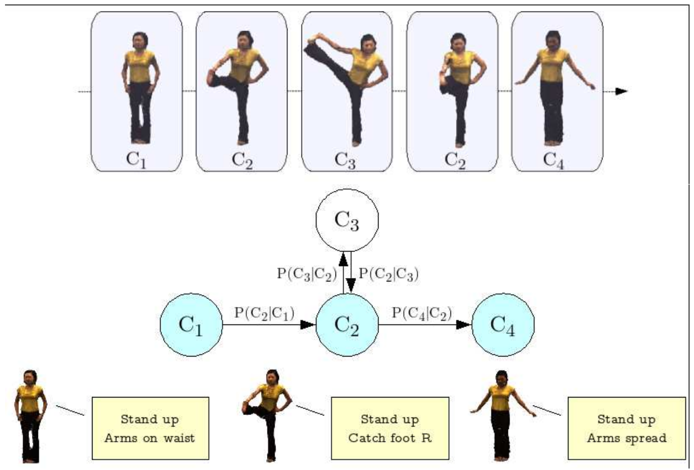
# Why did I select the paper?

- Looking for a method that:
  - Simplify graphs
  - Match graphs
  - Use graphs for the purposes of activity recognition

# Applications

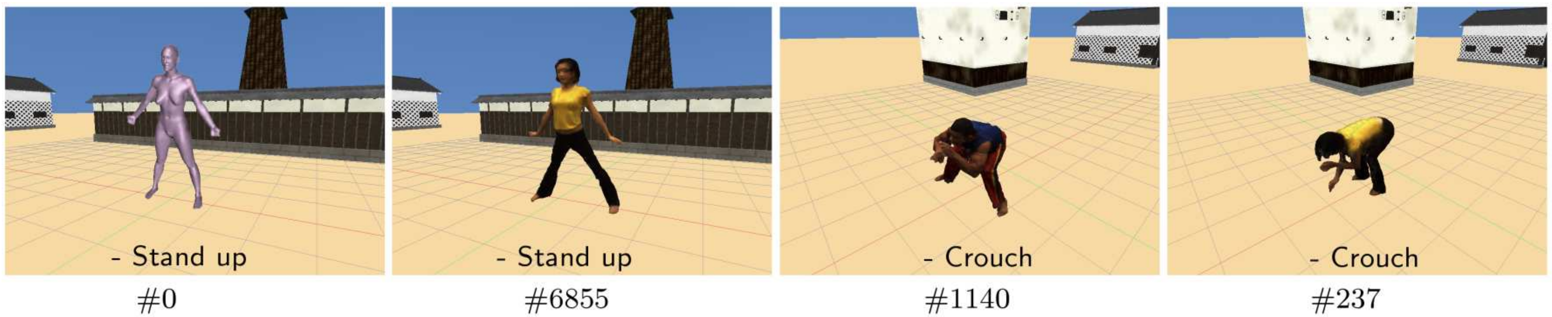



- Topological representation of human body pose (CVPR2007)




- 3D Compression

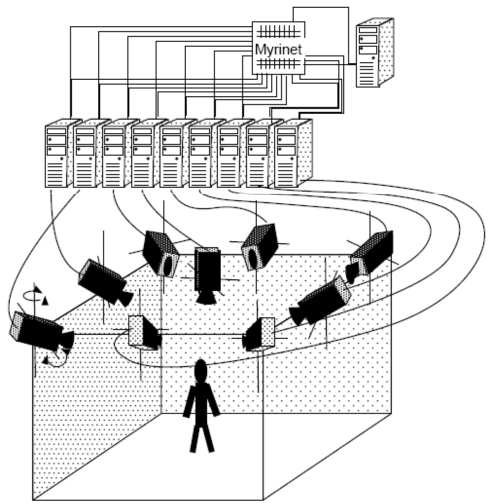
- 3D Action Recognition



# Pre-processing (CVPR2007)

- Synchronous recording from multiple cameras
- Object volume extraction using shape-from-silhouette method
- 3D mesh estimation by fitting a 3D deformable model (3D snake)

  ... graphical representation of 3D triangular mesh with vertices expressed in Cartesian coordinates



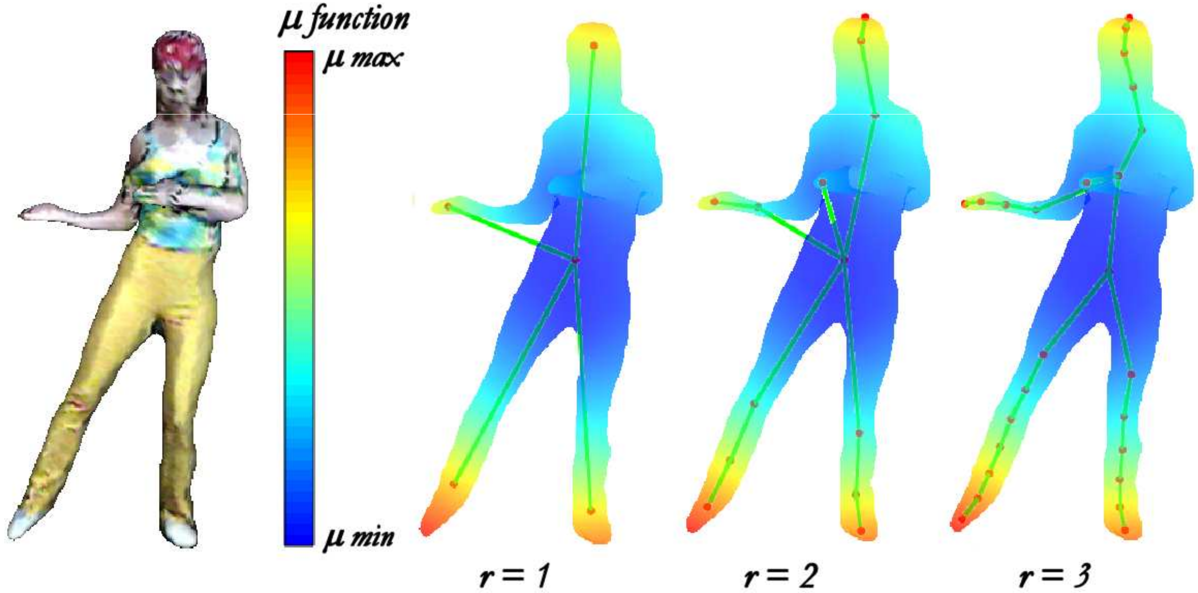
# Reeb Graph

- Morse function $\mu(\mathbf{v})$ and its normalised version $\mu_N(\mathbf{v})$ are defined based on the geodesic distance $g(\mathbf{v},\mathbf{p})$ along the 3D mesh.

$$\mu(\mathrm{v}) = \int_{\mathrm{p} \in S} g(\mathrm{v}, \mathrm{p}) dS \quad \text{and} \quad \mu_N(\mathrm{v}) = \frac{\mu - \mu_{\min}}{\mu_{\max} - \mu_{\min}}$$

# Multi-resolution RG

- $\mu_N(\mathbf{v})$ is subdivided into $2^r$ intervals ($r \in [1..R]$: level of resolution)




(a) 3D model. (b) Reeb graphs.

# Augmented RG

$\mathbf{Up_N(n)}$ : the number of neighbor nodes linked to $n$ and belonging to the next upper $\mu$ interval,

$\mathbf{Down_N(n)}$ : the number of neighbor nodes linked to $n$ and belonging to the next lower $\mu$ interval,

$\mathbf{Up_E(n)} \in \{0, 1\}$ : a flag telling if $n$ is a "maximal" terminal node ($Up_E(n) = 1$) or not ($Up_E(n) = 0$),

$\mathbf{Down_E(n)} \in \{0, 1\}$ : a flag telling if $n$ is a "minimal" terminal node ($Down_E(n) = 1$) or not ($Down_E(n) = 0$).

- if $Up_N(n) = 0$ then $n$ is a "maximal" terminal node, $Up_E(n) = 1$ and $Down_E(n) = 0$,
- if $Down_N(n) = 0$ then $n$ is a "minimal" terminal node, $Up_E(n) = 0$ and $Down_E(n) = 1$,
- if $Up_N(n) = Down_N(n) = 0$ then the graph at maximal resolution $R$ is represented by one unique root node and $Up_E(n) = Down_E(n) = 1$.

# Augmented MRG

- At each lower lever r<R, topological features are iteratively added for each node m:
  - $Up_N(m) = \sum_{n \in \{children\ of\ m\}} Up_N(n)$,
  - $Down_N(m) = \sum_{n \in \{children\ of\ m\}} Down_N(n)$,
  - $Up_E(m) = \sum_{n \in \{children\ of\ m\}} Up_E(n)$,
  - $Down_E(m) = \sum_{n \in \{children\ of\ m\}} Down_E(n)$.
- and in addition:
  - if $n$ is a terminal node then we set $Up_N(n) = 0$ and $Down_N(n) = 0$,

# Example of aMRG (CVPR 2007)

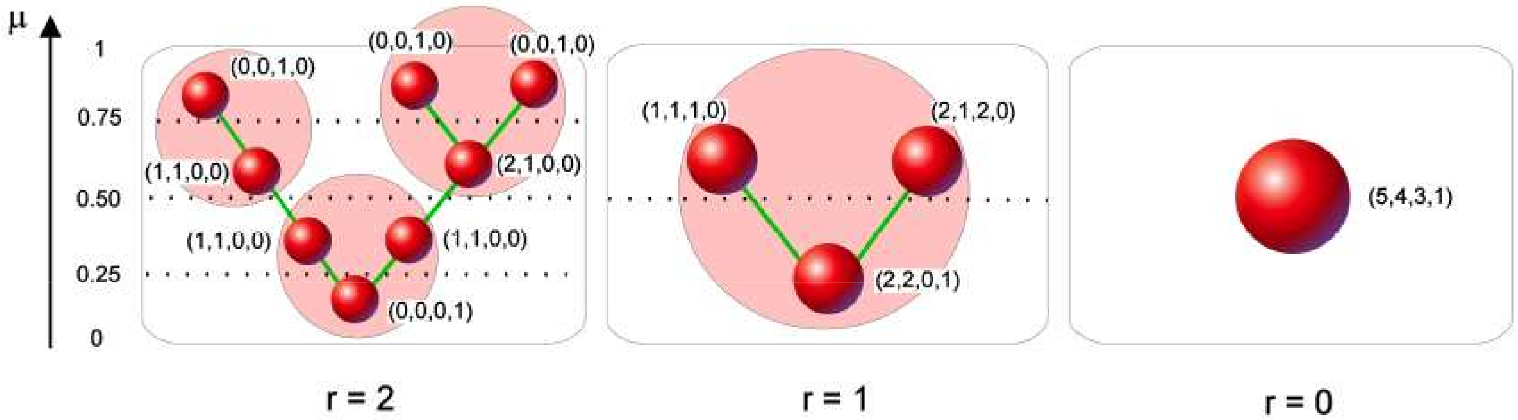



Figure 4. **Topological attributes.** Left: at resolution level $r = 2$, attributes $(Up_N, Down_N, Up_E, Down_E)$ are introduced to describe the local topology of each node. Middle: at lower level of resolution $r = 1$, topological information is cumulated. Right: at root ($r = 0$) all the topological attributes are cumulated. The embedded values characterize the global shape of the descendant subgraphs.

# Similarity Function (IJSM2005)

- Similarity function between two models (graphs) by:

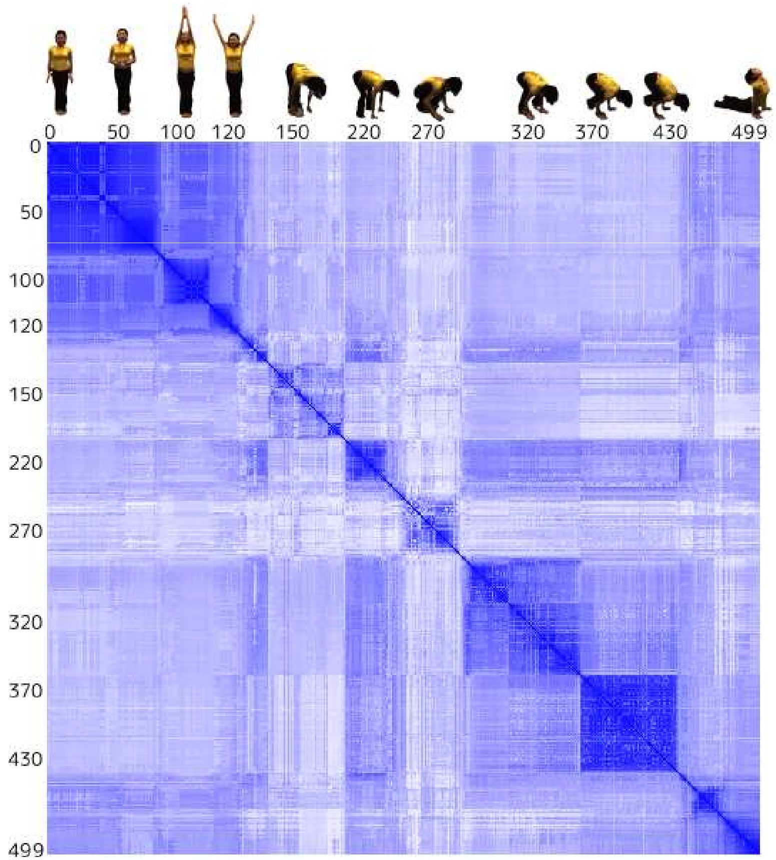
$$\mathrm{SIM}(M,N) = \sum_{r=0}^{R} \sum_{(m,n)\in\mathcal{C}_r} \mathrm{sim}(m,n)$$

- Where $C_r$ is the set of topologically consistent nodes and sim(m,n) is defined as:

$$sim(m,n) = \sum_{i=0}^{N_f} \lambda_i d_i'(f_i(m), f_i(n)).$$

# Topology Dictionary: Clustering

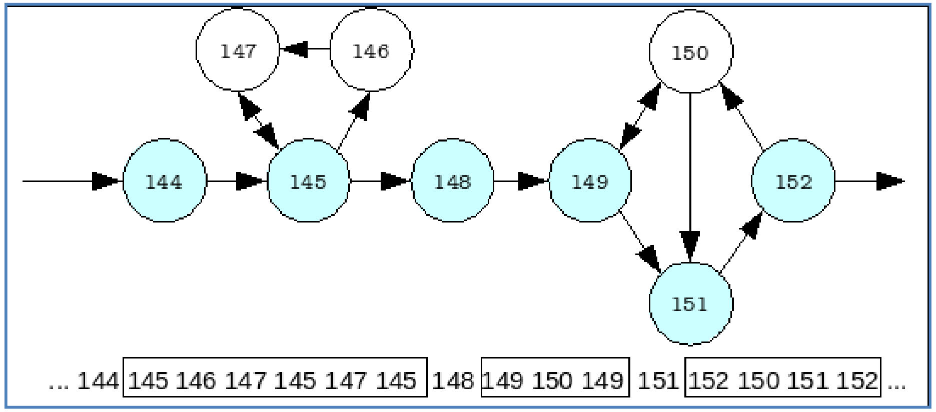
- Cluster similar poses according to SIM(m,n)



# Topology Dictionary: Probabilistic Graph Structure

Markov Model:

- Clusters → States of MM
- Simple statistics to estimate the initial probabilities $P(c_i)$ of states $c_i$ and the transition probabilities $w_{ij}=P(c_j|c_i)$.



# Topology Dictionary: (Manual) Cluster Annotation