SIBGRAPI 2014
XXVII SIBGRAPI CONFERENCE ON GRAPHICS, PATTERNS AND IMAGES

Simplified training for gesture recognition

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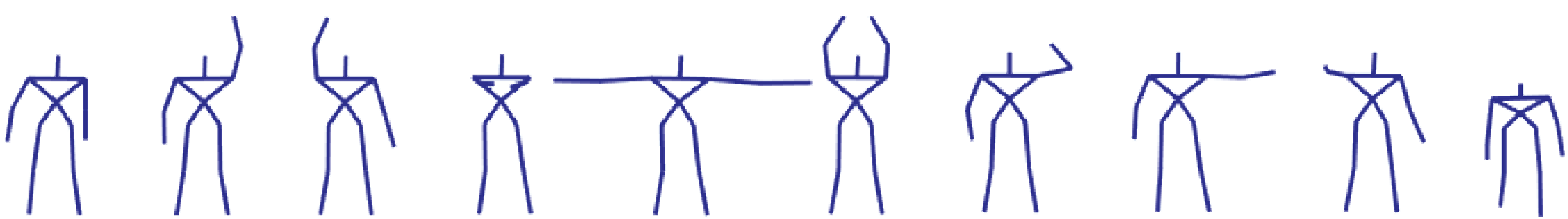
Mathematics, PUC-Rio



Human Gesture Recognition

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Faugeroux et al., 2014

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Simplified training for gesture recognition

Human Gesture Recognition

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Simplified training for gesture recognition

Current Scenario

Popularization of real time depth sensors

Microsoft Kinect Sensor

Development of high quality Natural User Interfaces (NUI)

Current Scenario

Popularization of real time depth sensors

Microsoft Kinect Sensor

Challenges

Gesture are culture specific

Gestures can be performed at different speeds or sequences of poses

Faugeroux et al., 2014

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Gestures can be performed at different speeds or sequences of poses

Solution: learning!

Faugeroux et al., 2014

Learning approaches

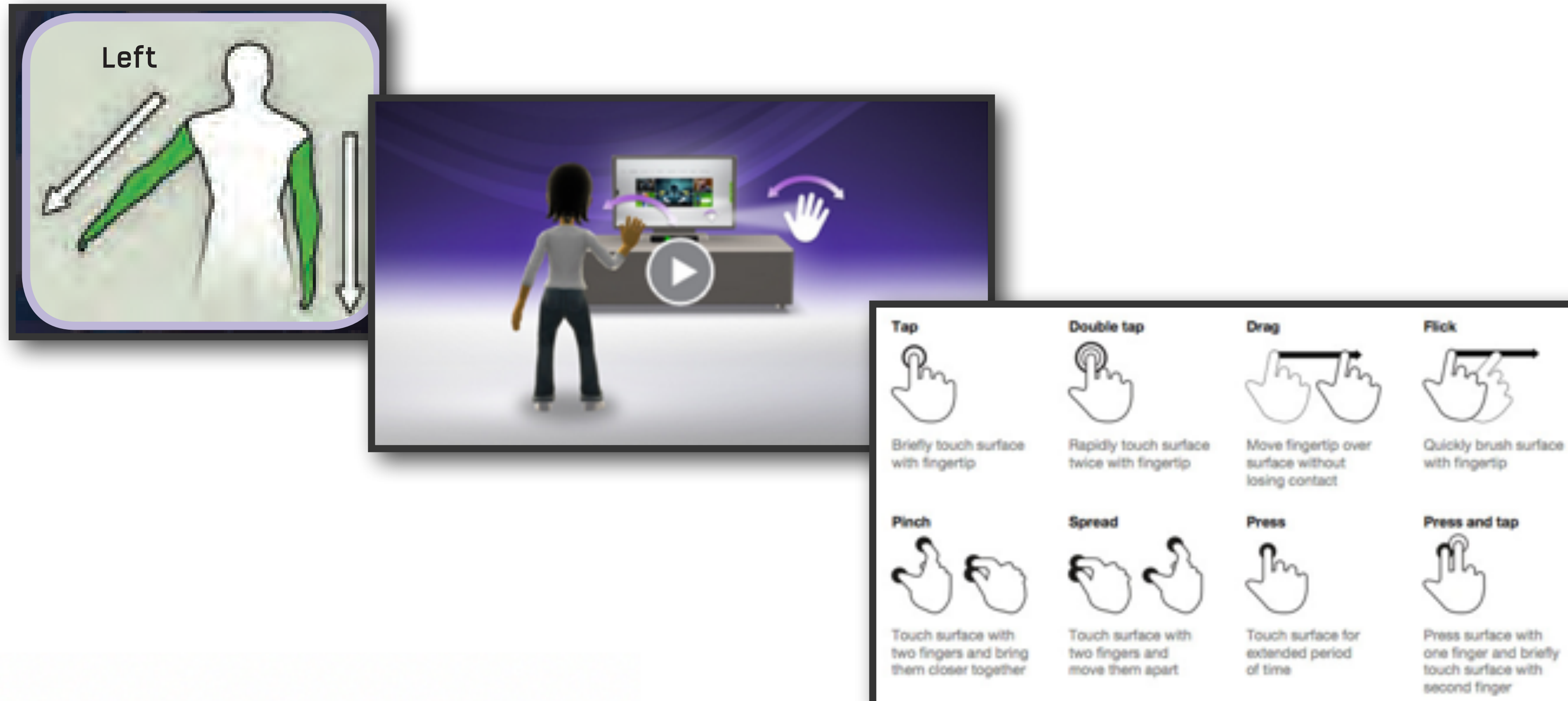
User learns from
the machine

Faugeroux et al., 2014

Simplified training for gesture recognition

Learning approaches

User learns from the machine



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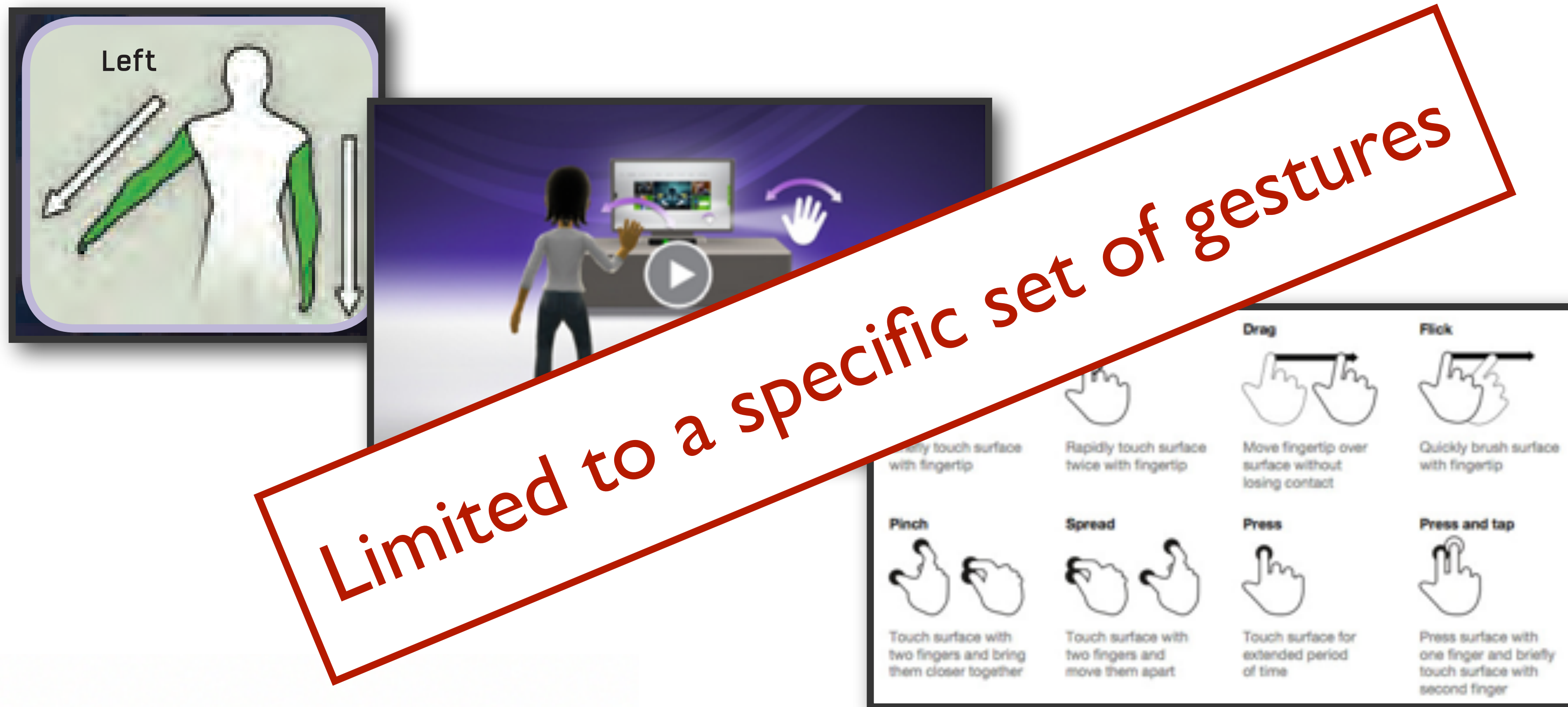

Limited to a specific set of gestures

Faugeroux et al., 2014

Learning approaches

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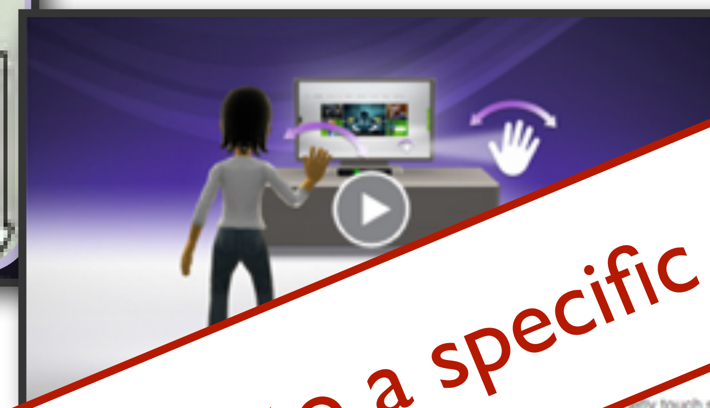

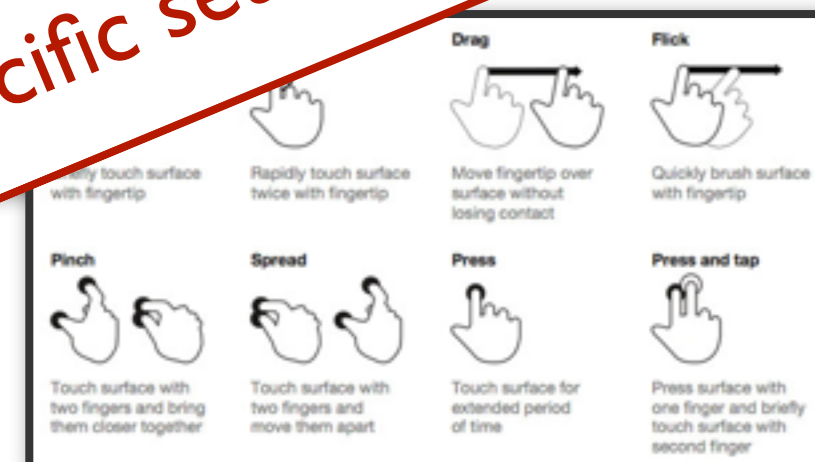

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Machine learns
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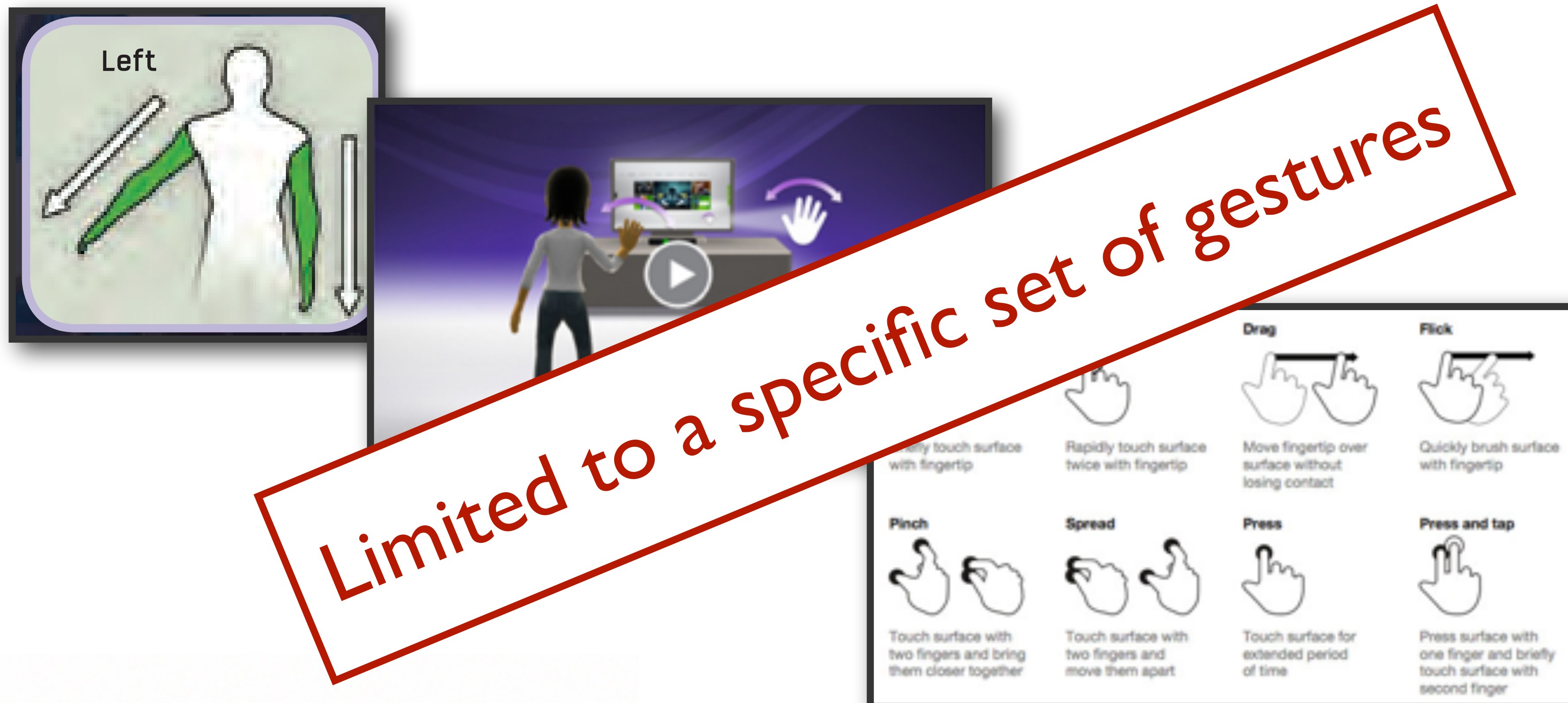

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Machine learns from the user

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Faugeroux et al., 2014

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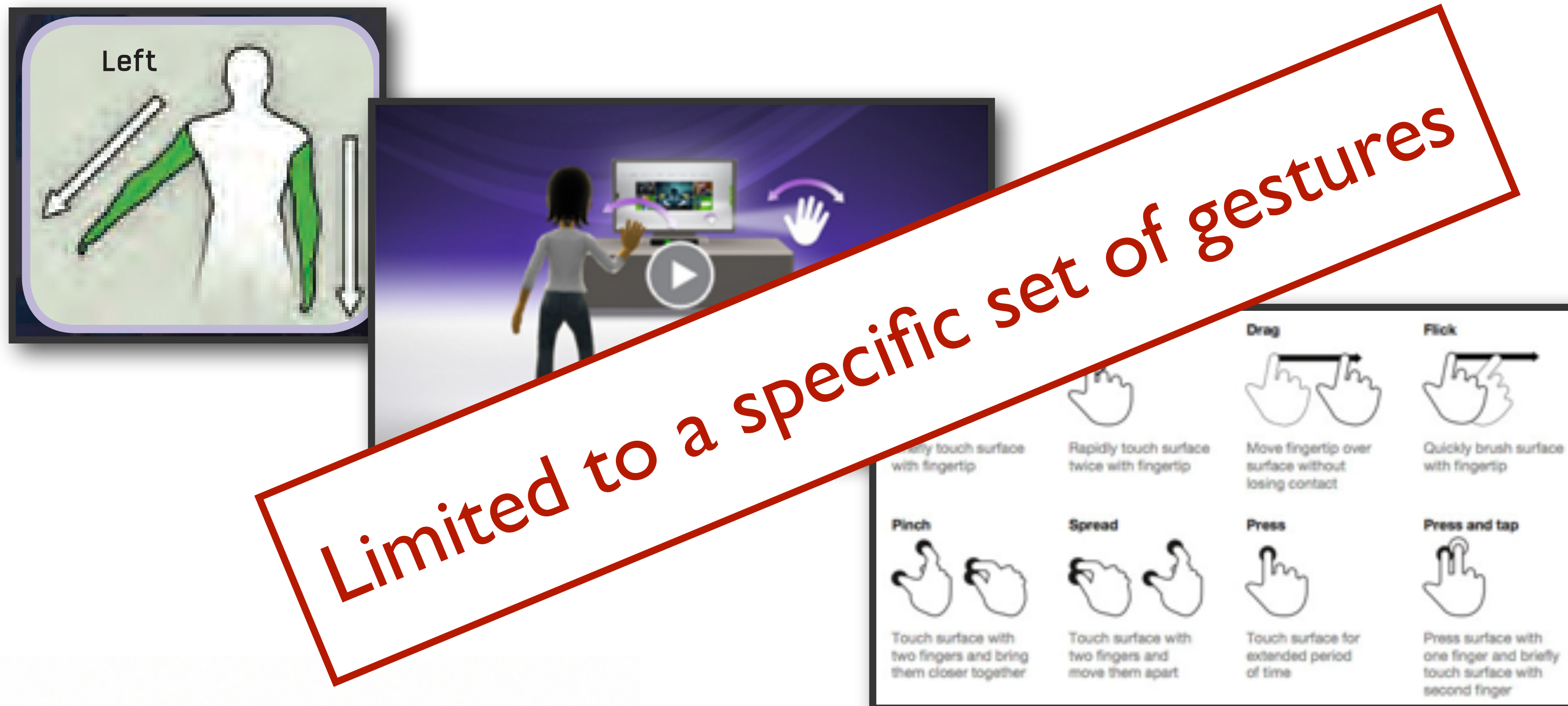

Limited to a specific set of gestures

Requires a training phase: often tedious

Machine learns
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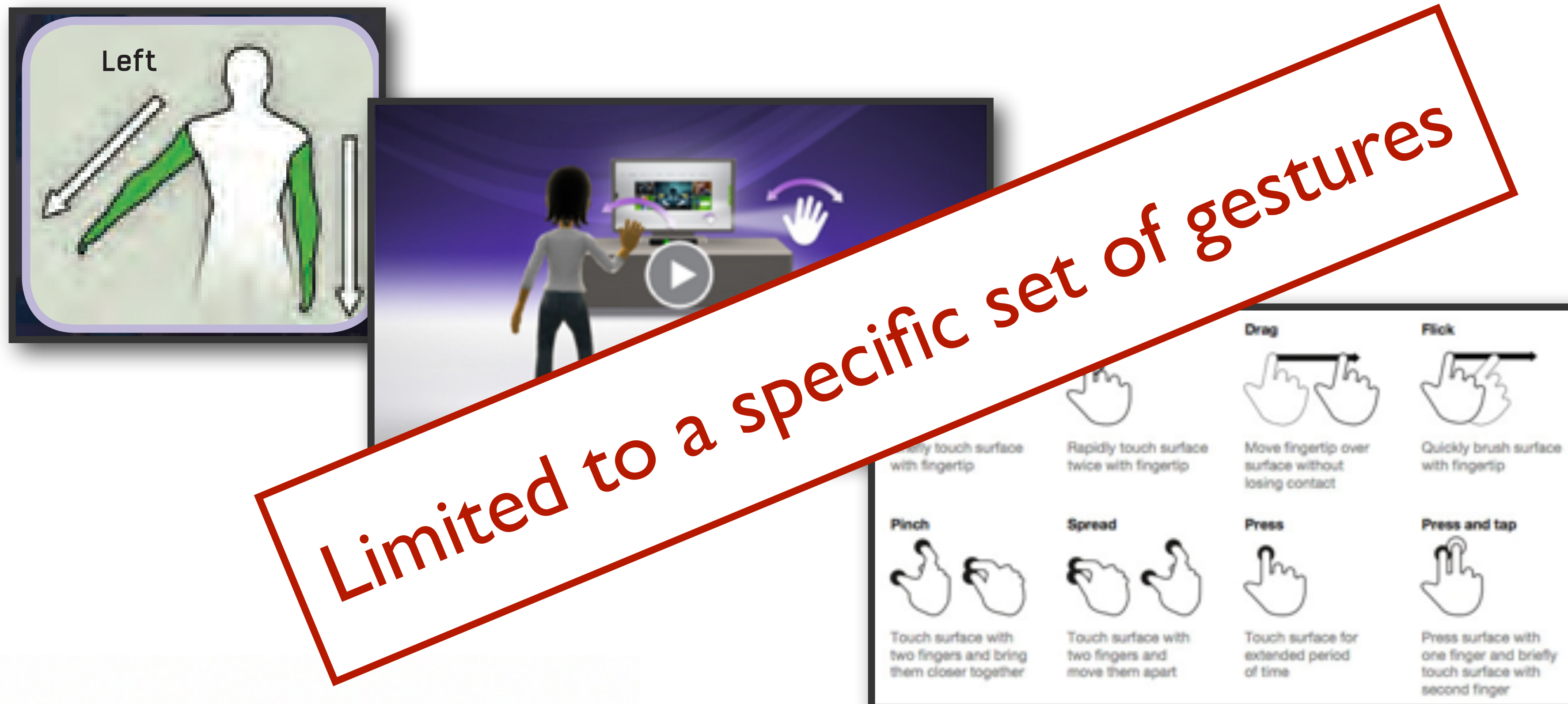

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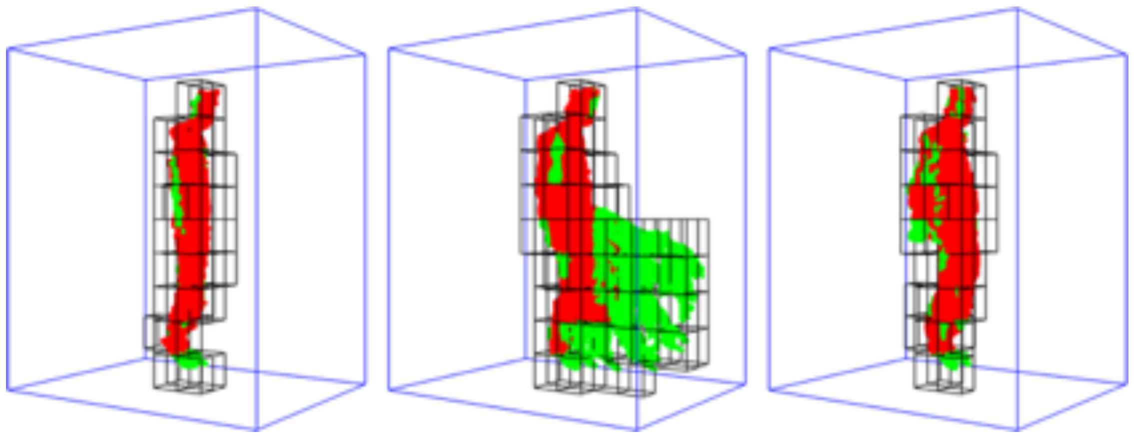
Faugeroux et al., 2014

Related Work: global methods

space-time accumulation / spatio-temporal templates



Vieira *et al* (2014)

Bobick and Davis (2001)

Training phase required for gestures only

Requires more computing resources

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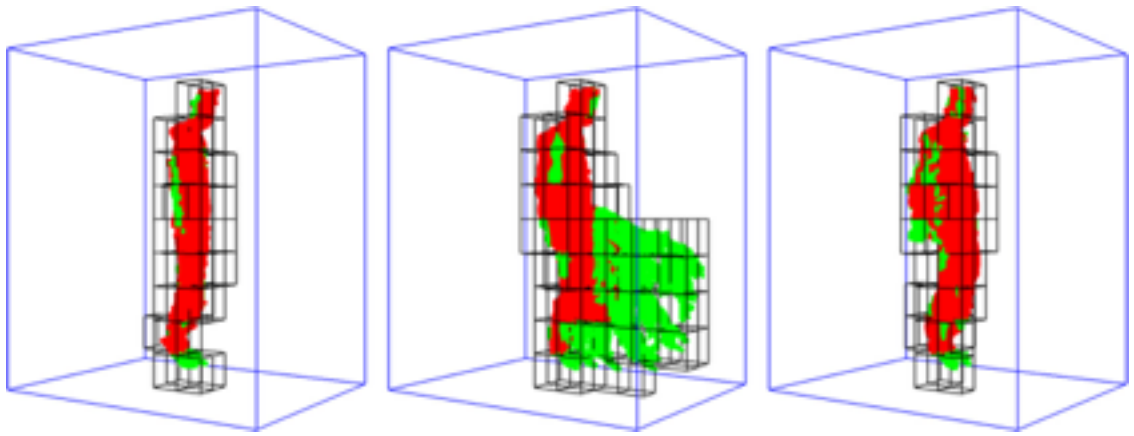
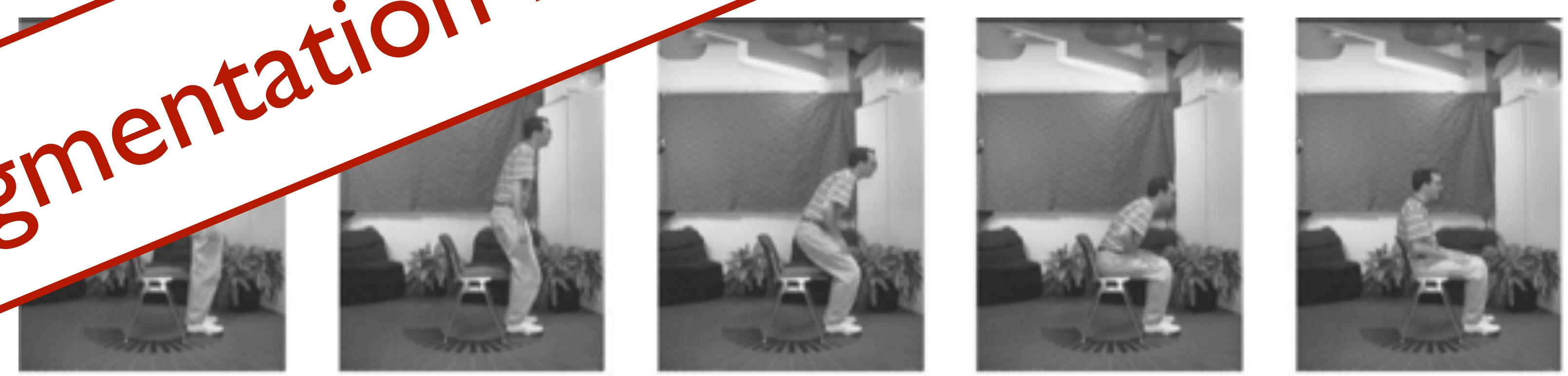


Vieira *et al* (2014)

Gesture segmentation is manual!



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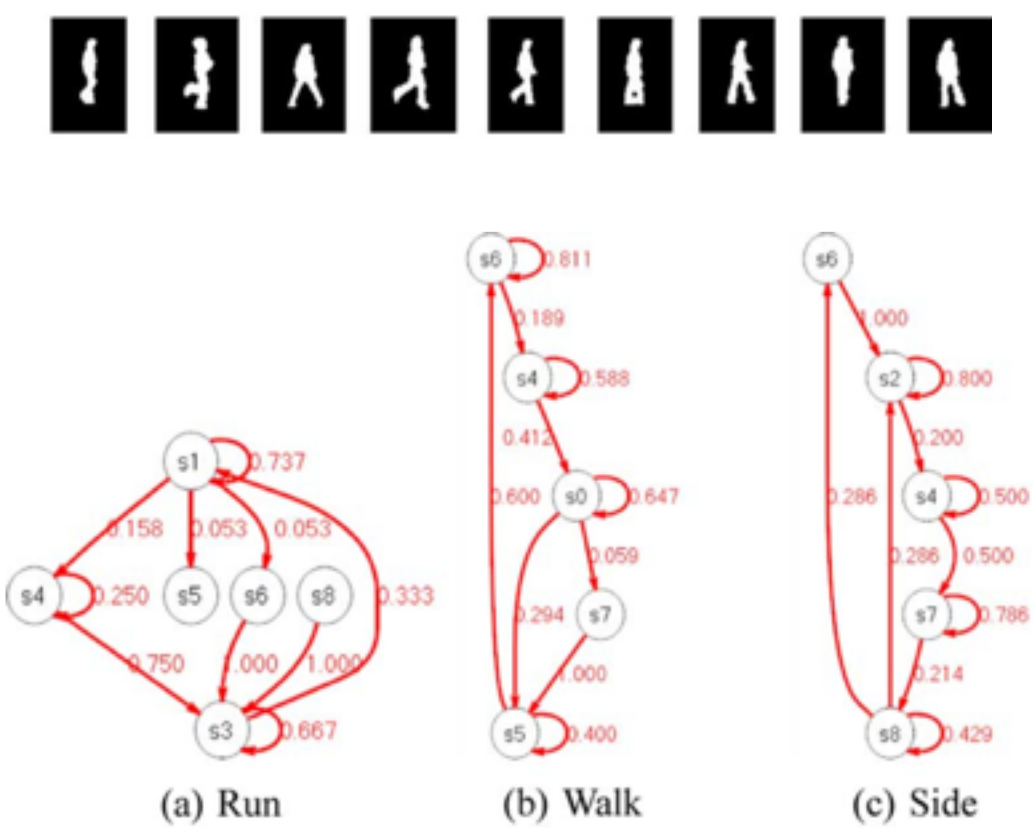
Related Work: local methods

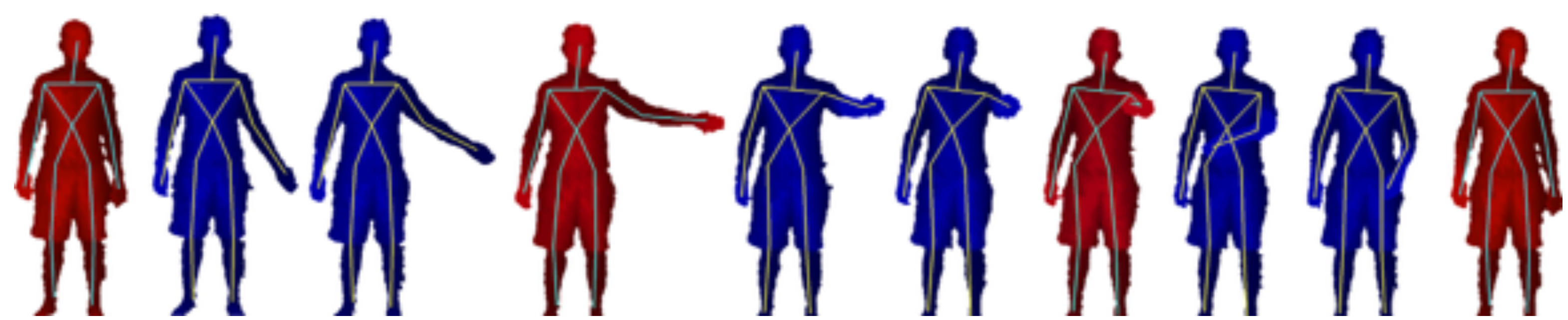
Feature-based: spatiotemporal interest points / **key poses**

salient postures
through clustering



Li *et al* (2008)

manual key pose training



Miranda *et al* (2012)

Extremely fast recognition

Training phase usually required for key pose learning

Discriminativity not considered for trained gestures

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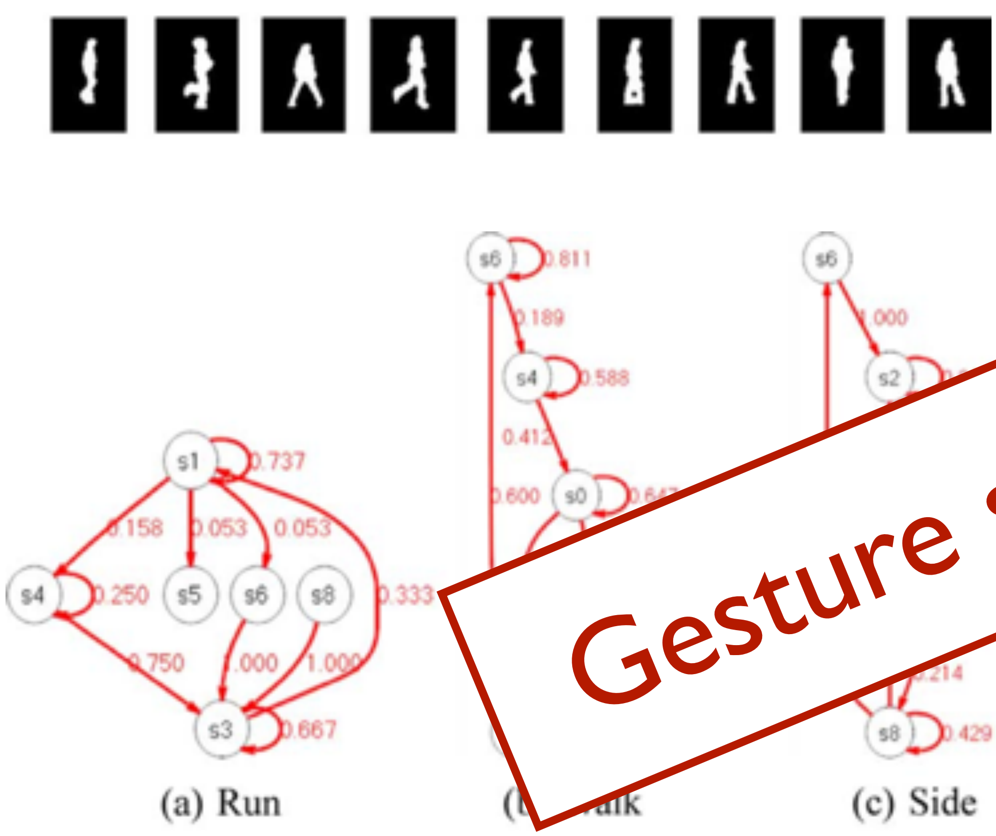

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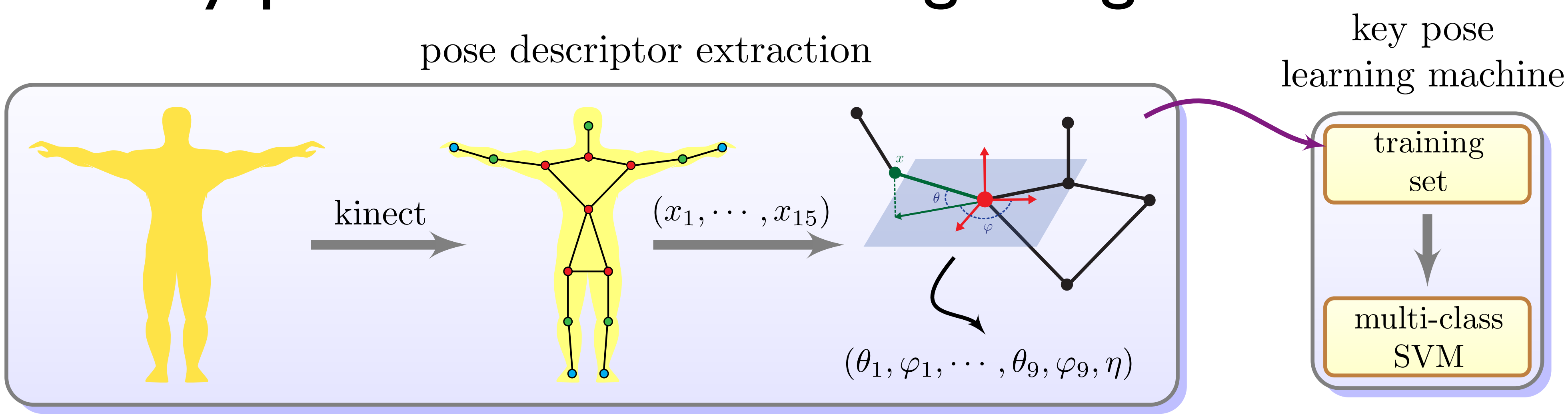
Miranda *et al* (2012) training

1 - manual key pose selection/training using SVMs



Miranda *et al* (2012) training

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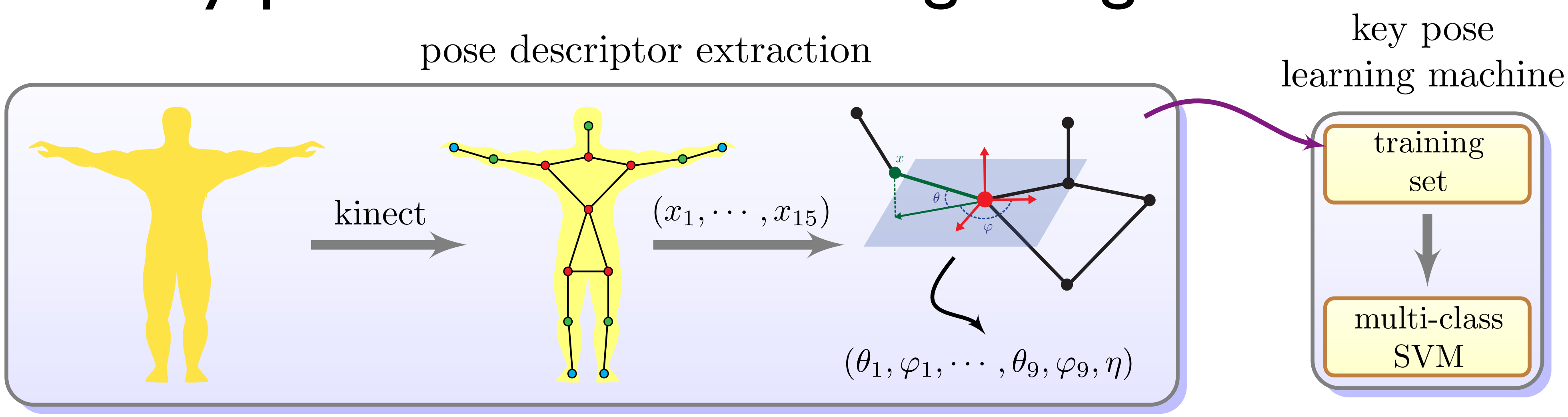
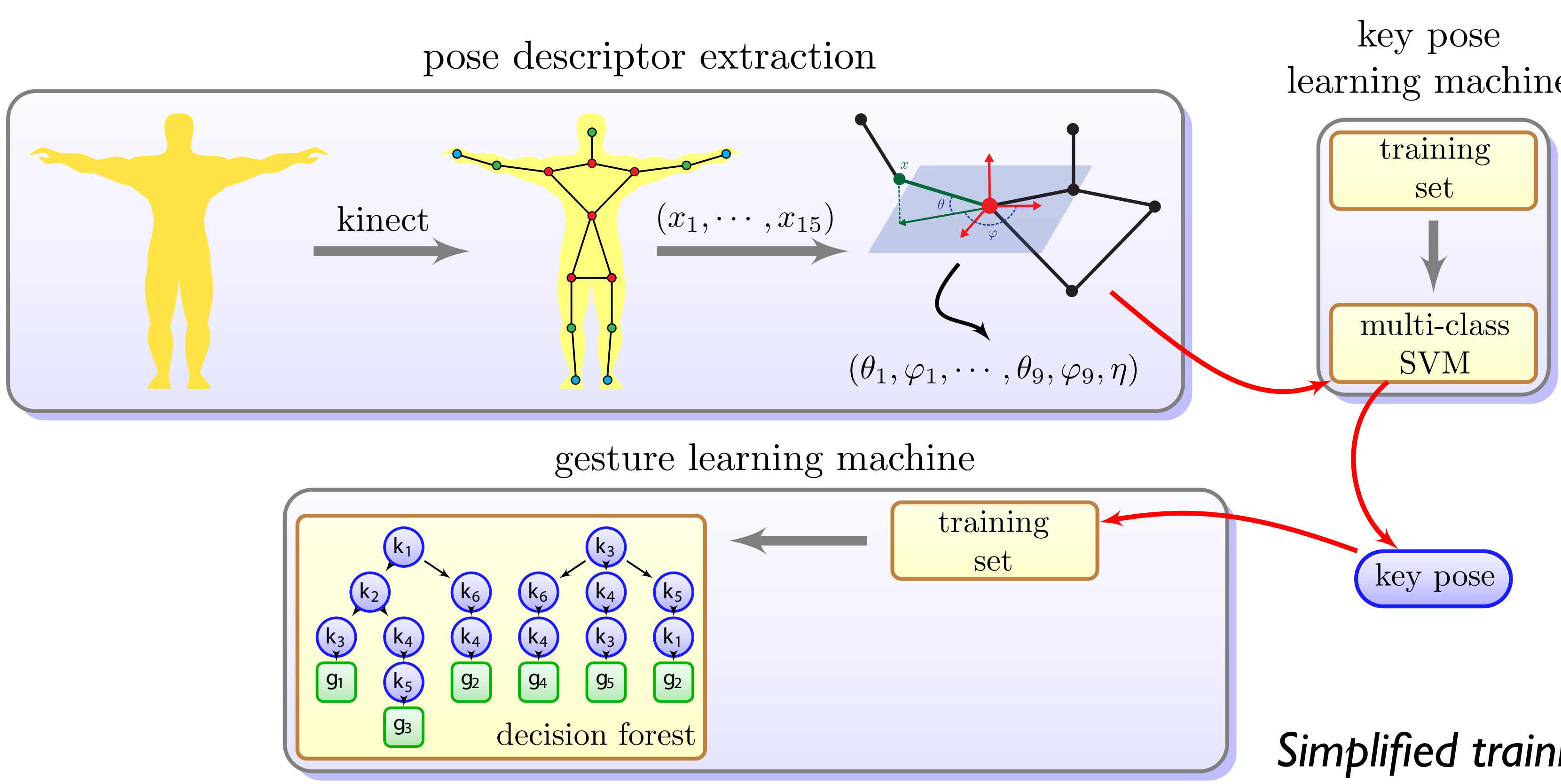


2 - gesture training through key pose detection and decision forests



Faugeroux et al., 2014

Simplified training for gesture recognition

Miranda *et al* (2012) training

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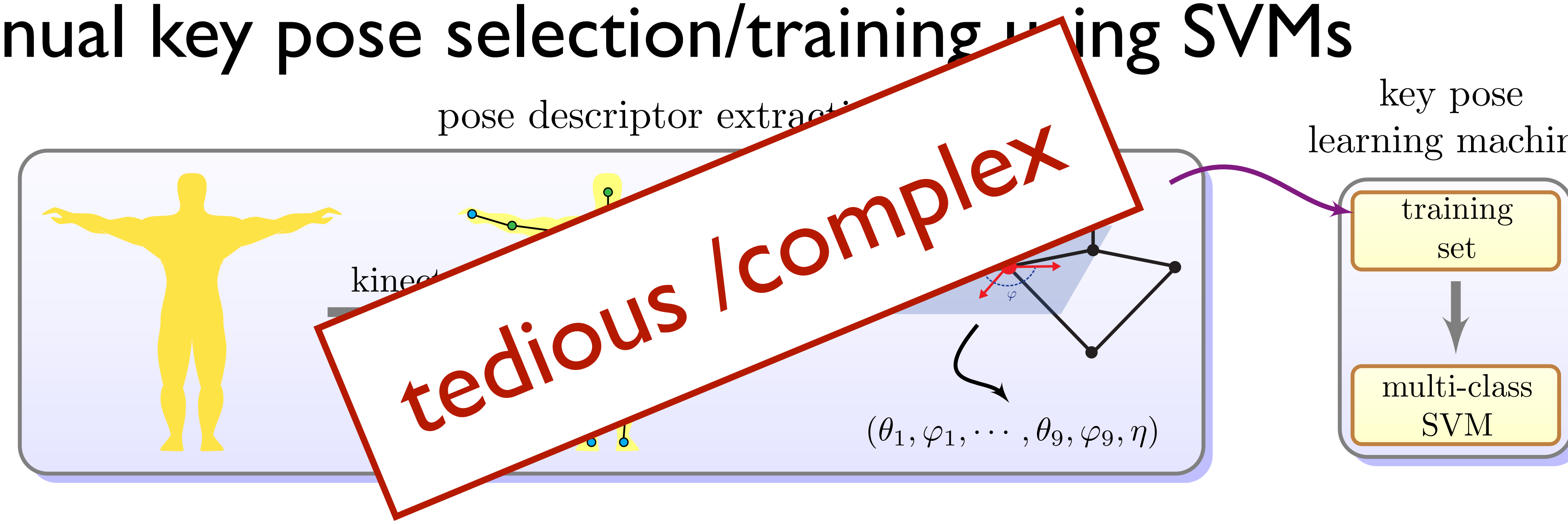

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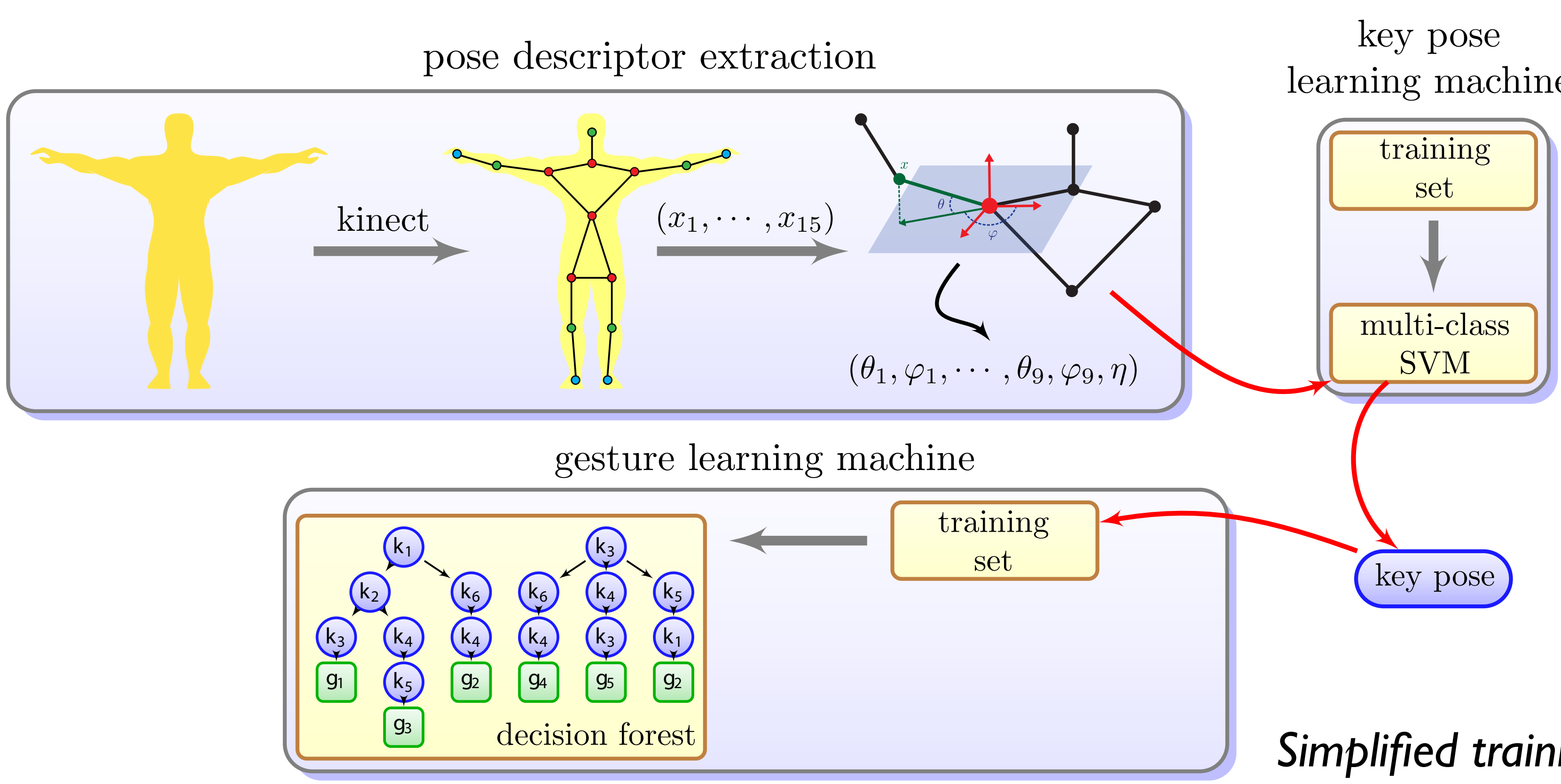
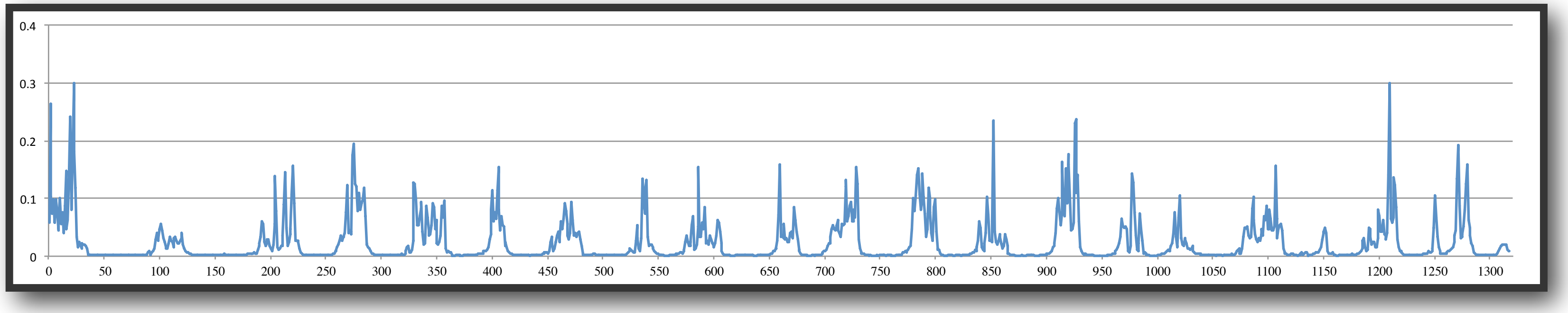


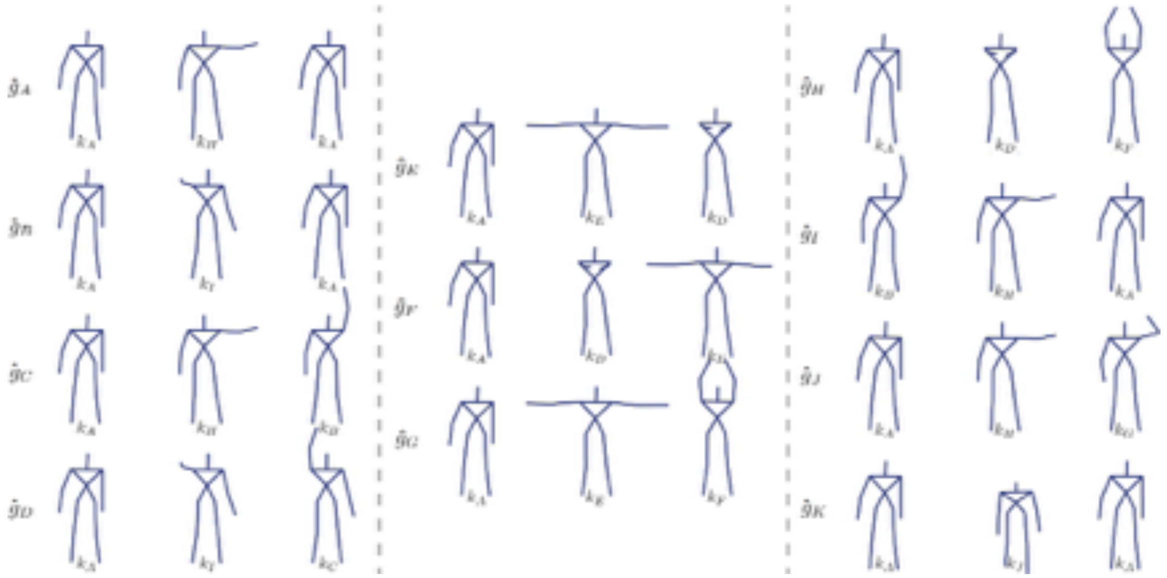
Faugeroux et al., 2014

Simplified training for gesture recognition

Contributions

Automatic gesture segmentation method





Automatic discriminative key pose selection method

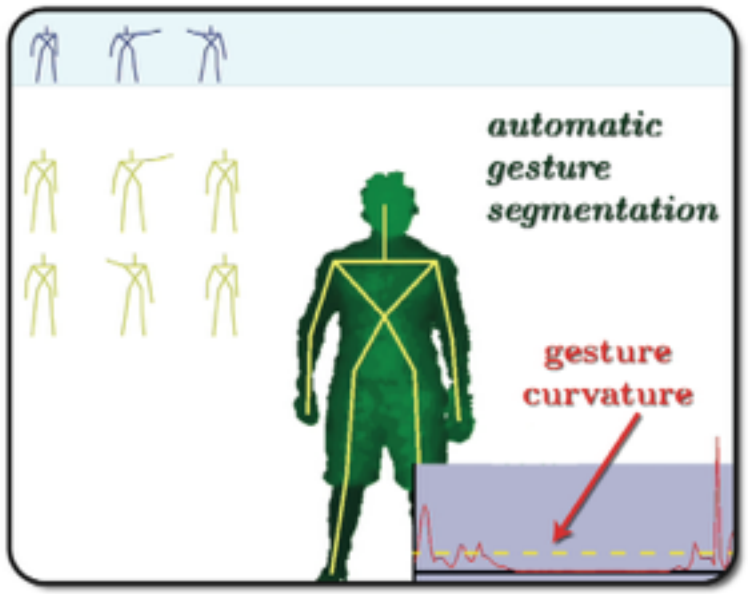
Key pose based: Extremely fast recognition!

Minimal interaction training: single record for all gestures!

Outline

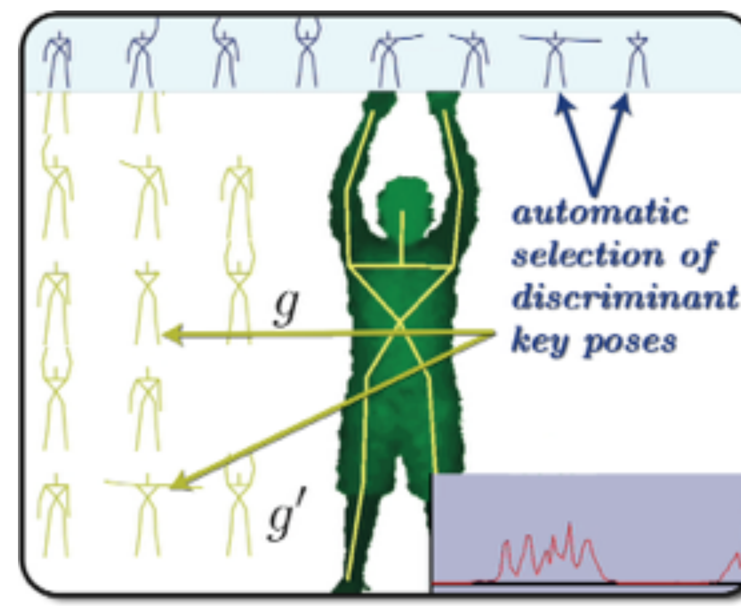
1. Overview
2. Pose representation
3. Gesture segmentation
4. Discriminant key pose selection
5. Gesture identification
6. Experiments

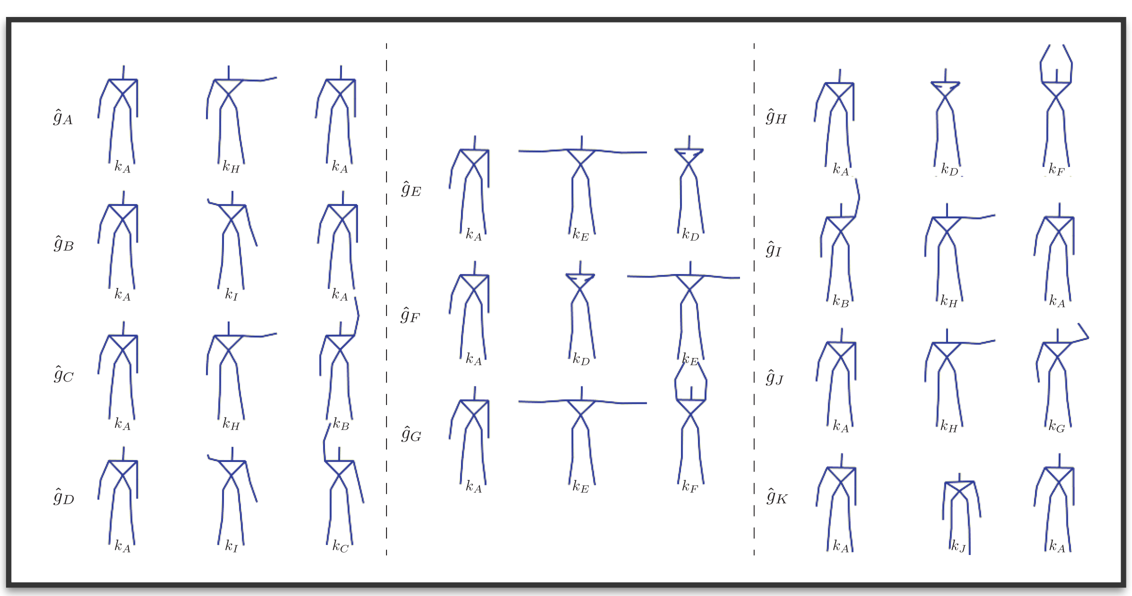
Overview



automatic gesture segmentation

discriminant key pose selection

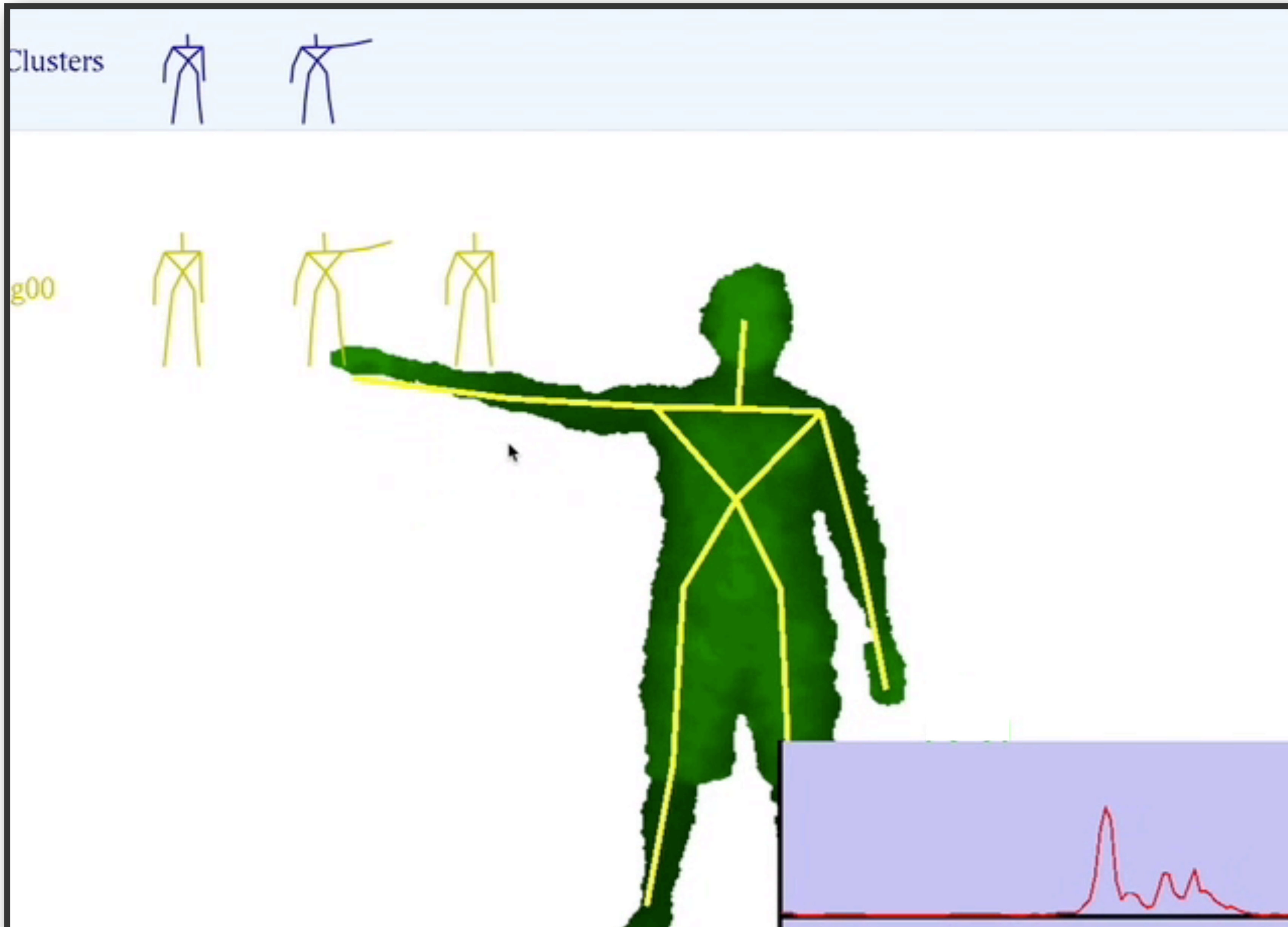




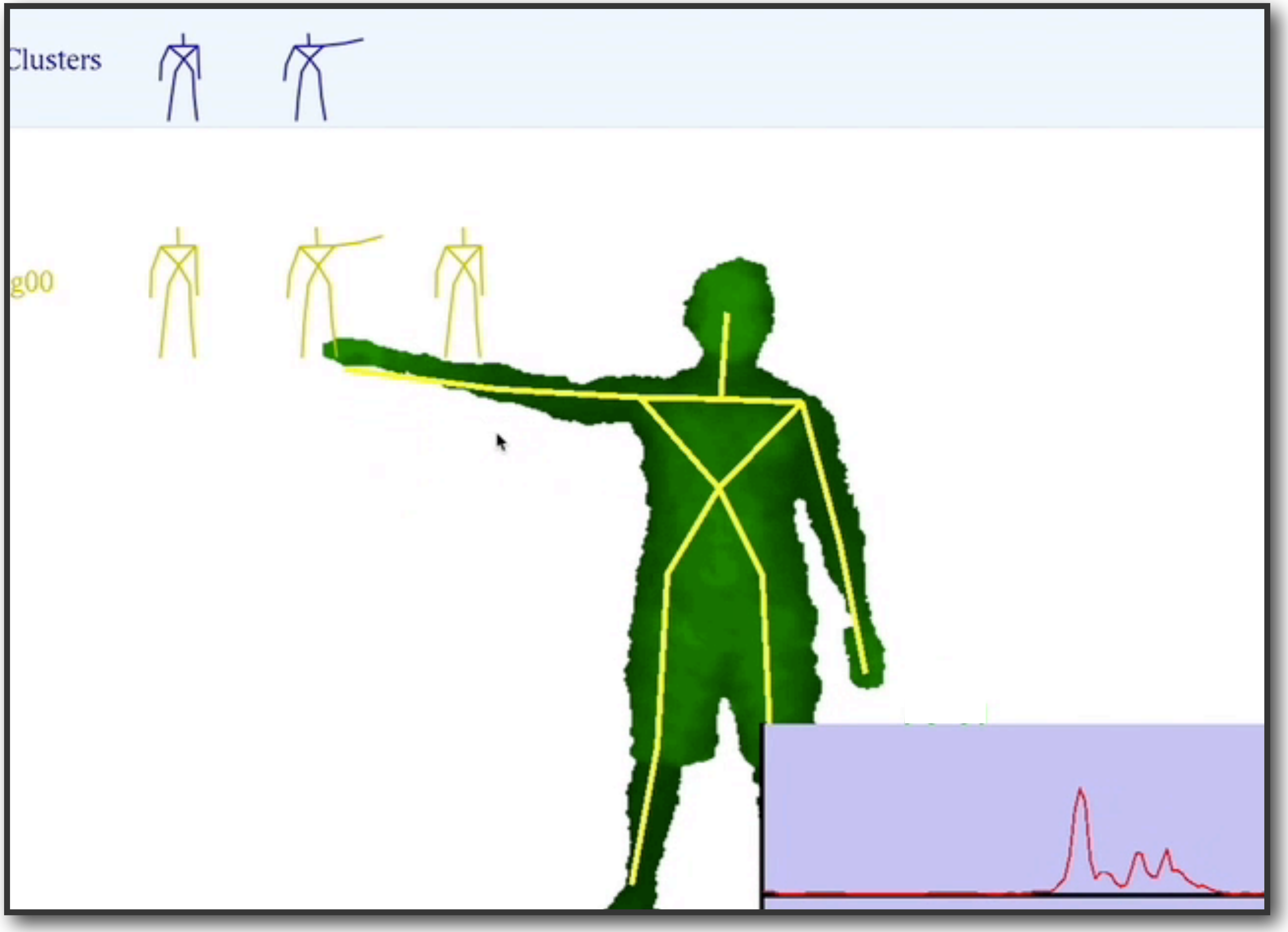
gesture identification

Faugeroux et al., 2014

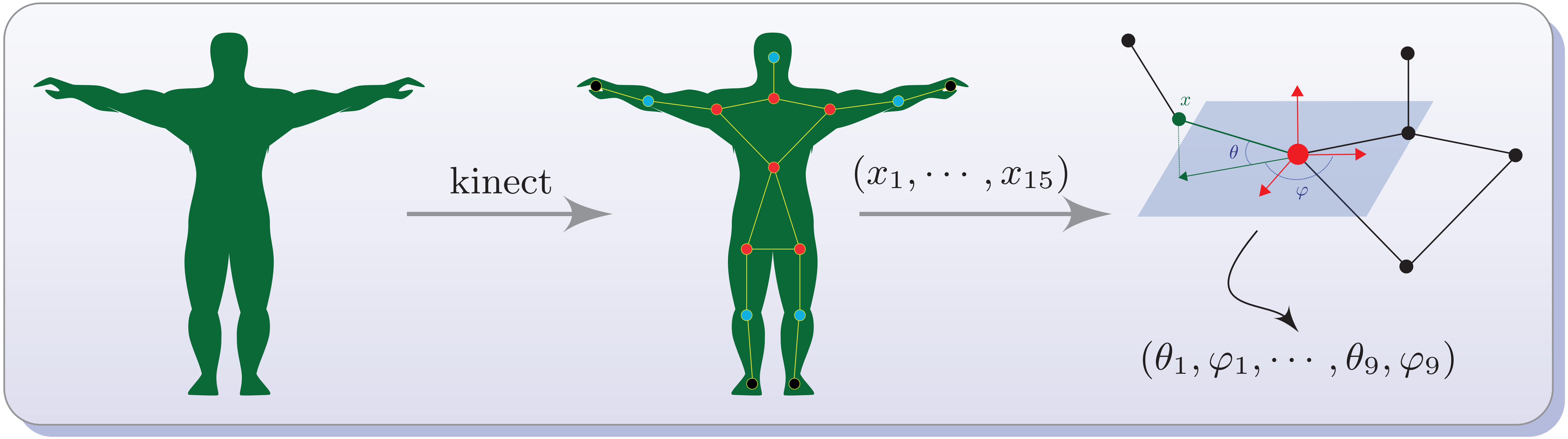
Overview



Overview



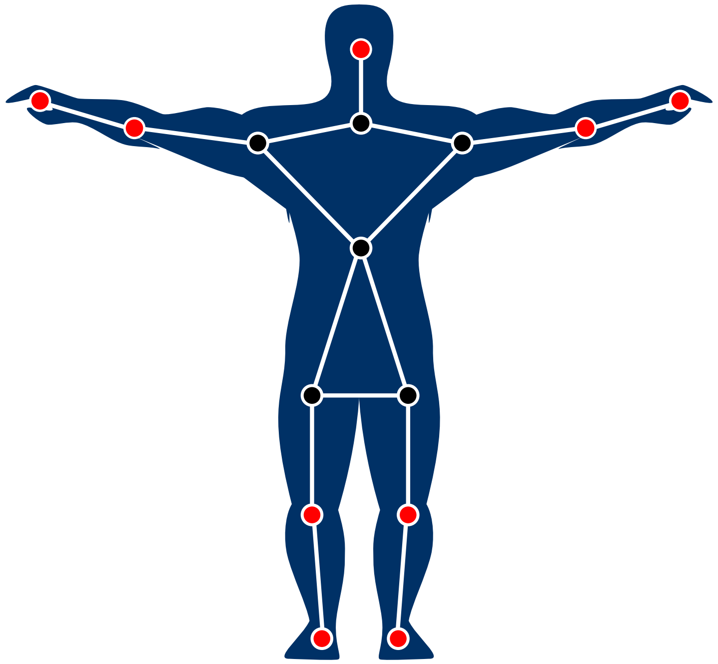
Pose representation



Real-time depth sensing system streaming depth data

OpenNI: public API to extract skeletons at 30fps

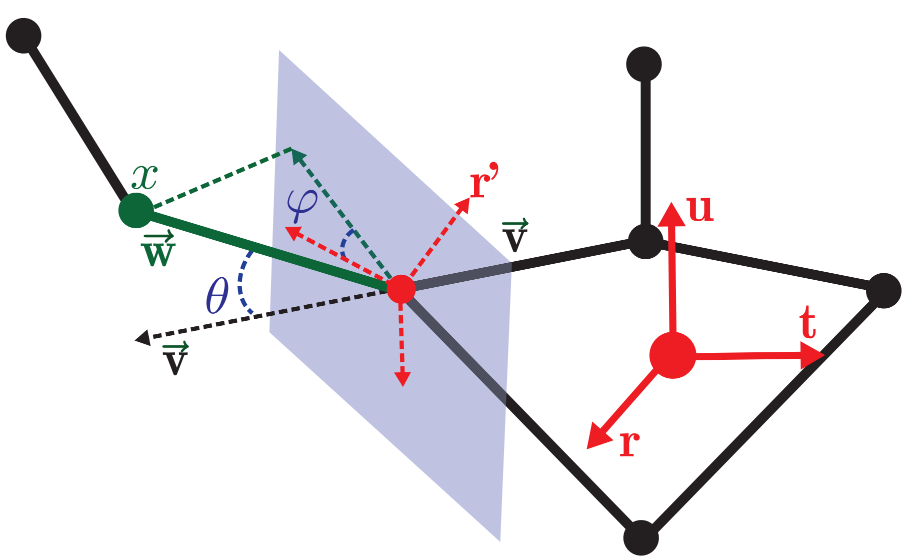
Joint-angle pose descriptor



Miranda *et al* (2012): 9 relevant body joints converted to a list of spherical angles:

$$\text{pose:} \quad p \in \left(\mathbb{S}^2\right)^9$$

$$\text{gesture:} \quad \alpha : I \subset \mathbb{R} \mapsto \left(\mathbb{S}^2\right)^9$$



Faugeroux et al., 2014

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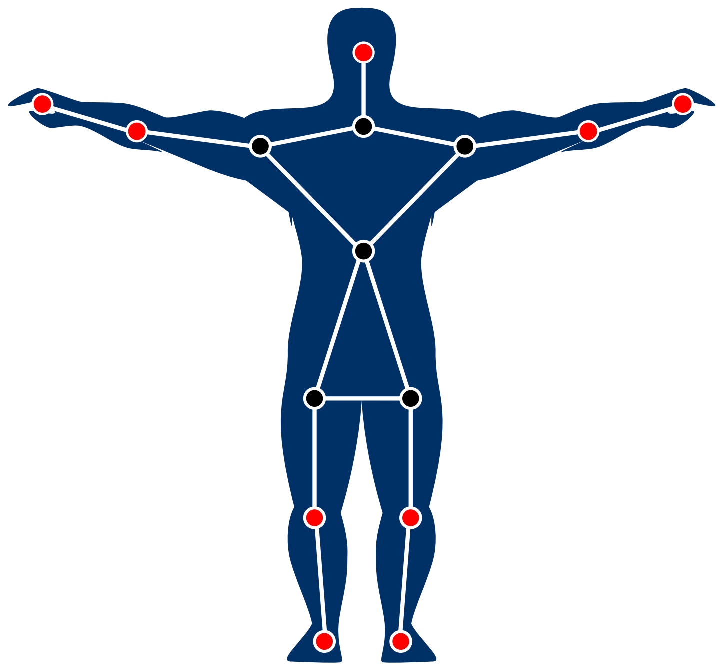

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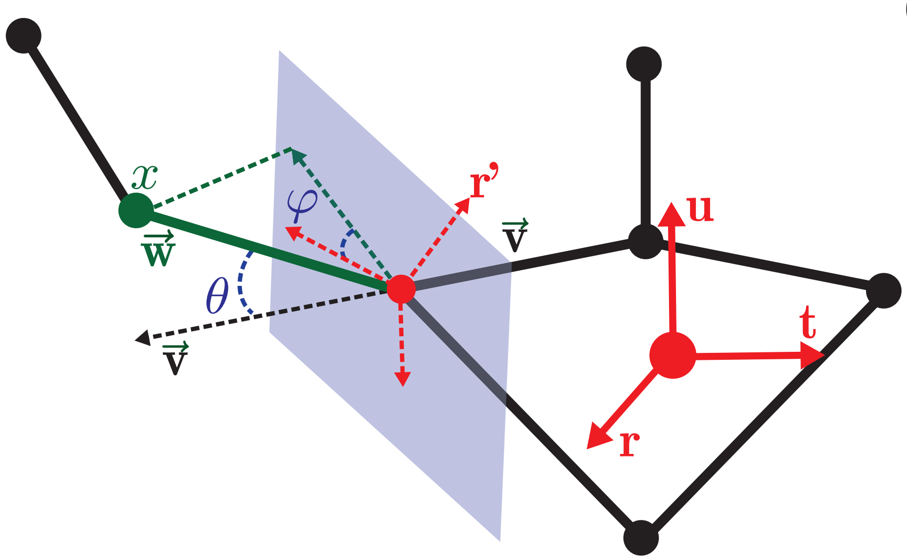

Comparing joints l in distinct poses p and p':

$$\delta(p_l, p_l') = \arccos\left(\sin\theta_l \sin\theta_l' + \cos\theta_l \cos\theta_l' \cos|\varphi_l - \varphi_l'|\right)$$

Faugeroux et al., 2014

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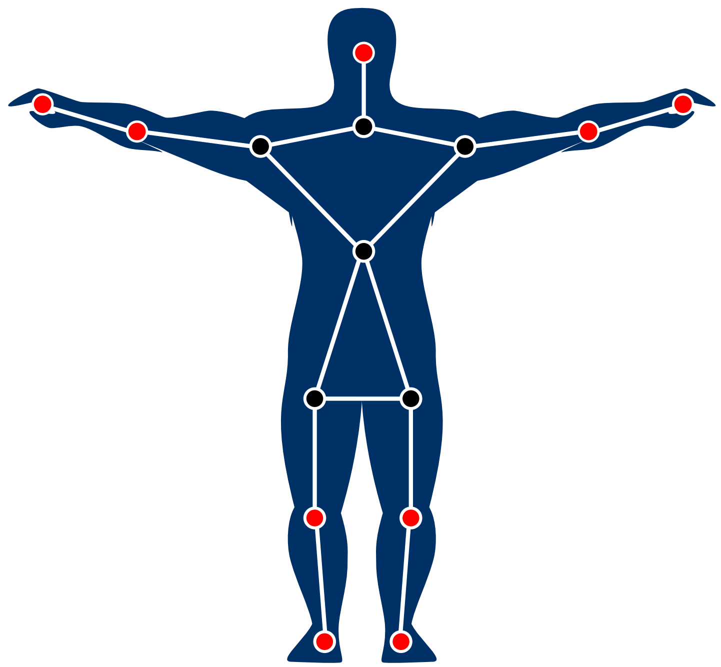

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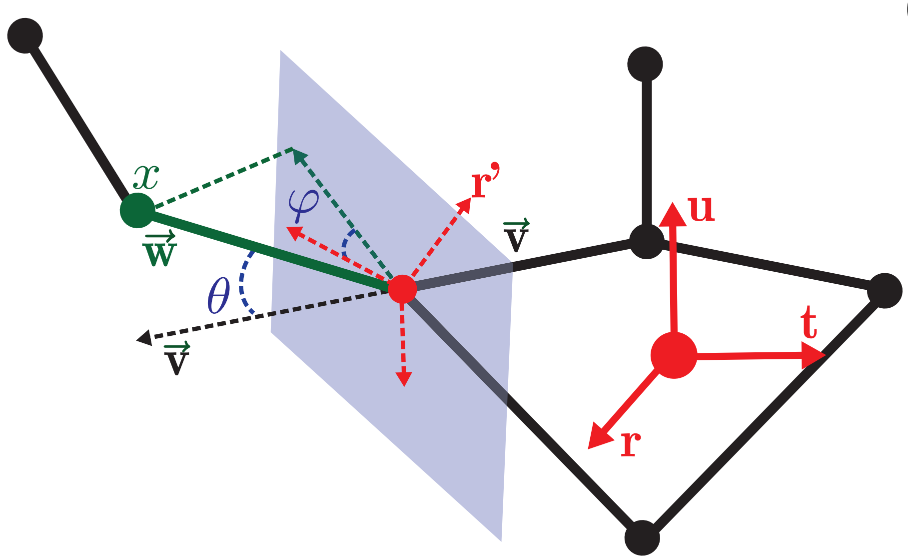

Comparing joints l in distinct poses p and p':

$$\delta(p_l, p'_l) = \arccos\left(\sin\theta_l \sin\theta'_l + \cos\theta_l \cos\theta'_l \cos|\varphi_l - \varphi'_l|\right)$$

Distance between poses:

$$\Delta(p, p') = \sum_{l=1}^{9} \left[\delta\left(p_l, p'_l\right)\right]^2$$

Faugeroux et al., 2014

Gesture segmentation

Objective: avoid usual protocols requirements: neutral pose

Faugeroux et al., 2014

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user inserts small pauses in-between gestures

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depth sensor's random patterns generates rapid skeleton oscillations

Faugeroux et al., 2014

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high curvature of the gesture curve

Faugeroux et al., 2014

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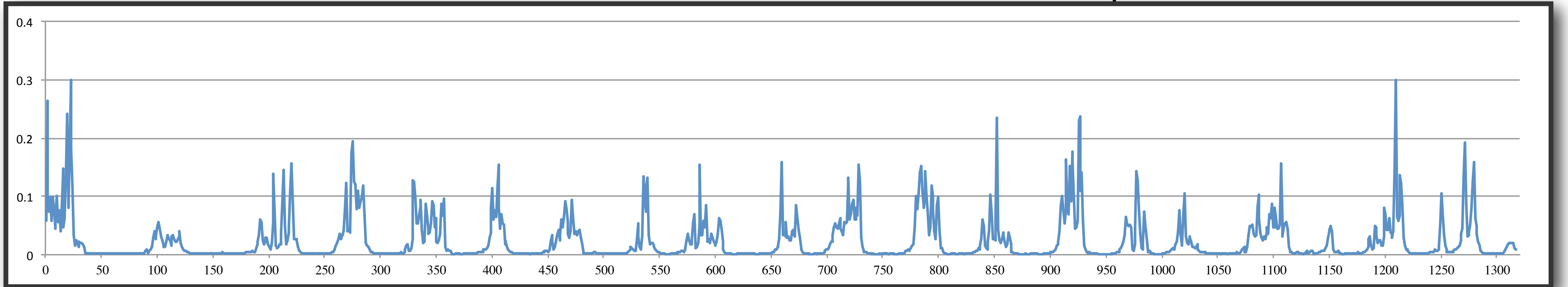
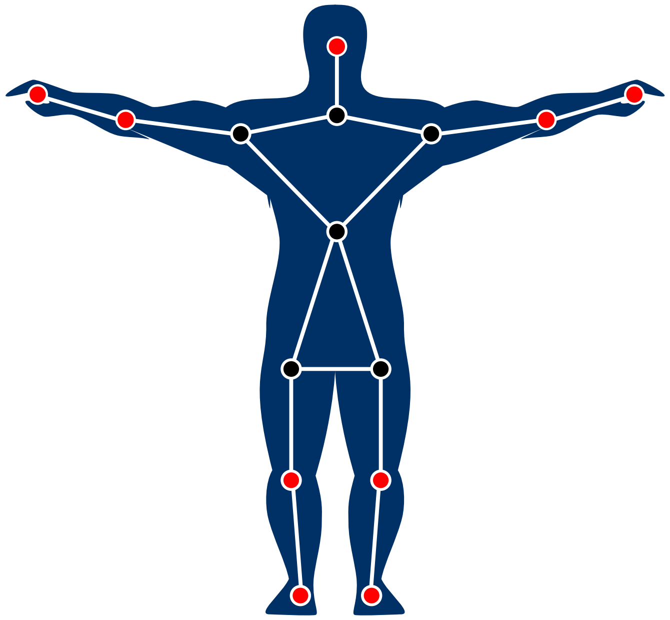


high curvature of the gesture curve

Curvature estimation

$$\alpha : I \subset \mathbb{R} \mapsto \left(\mathbb{S}^2\right)^9$$



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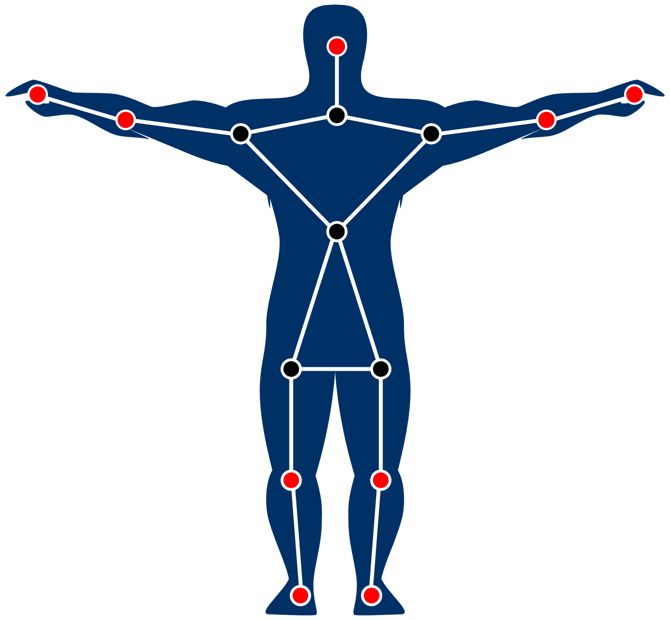

Pose encoded by cartesian coordinates of 9 relevant joints:

$$\alpha\colon I \subset \mathbb{R} \mapsto \mathbb{R}^{27}$$

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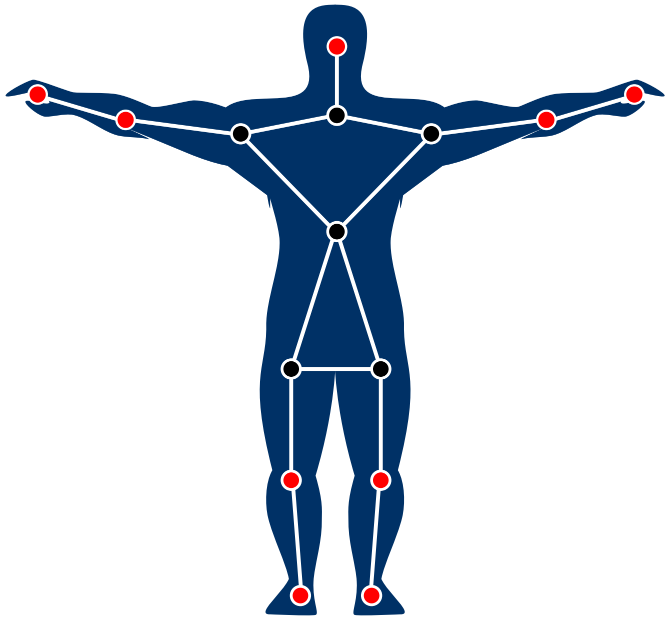

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First curvature:

$$\kappa(t) = \frac{\langle \alpha''(t), \mathbf{e}_2(t) \rangle}{\|\alpha'(t)\|^2}$$

where $\mathrm{e}_2(t)$ points in the direction of the first normal.

Curvature estimation

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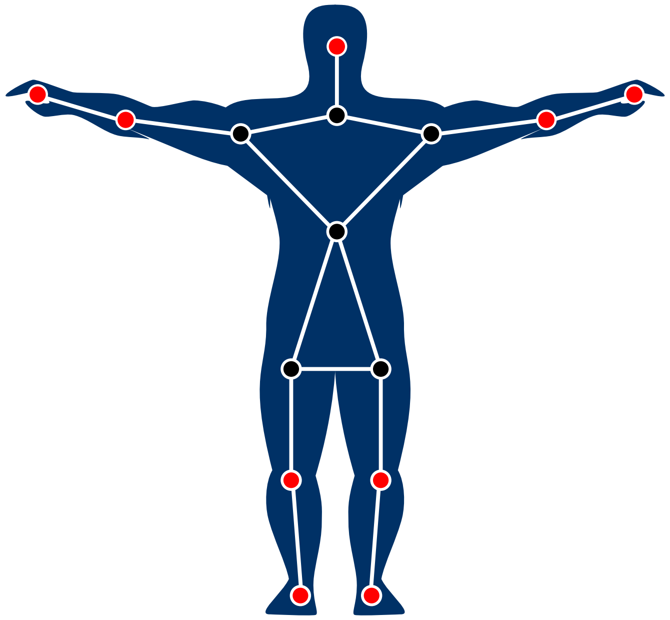

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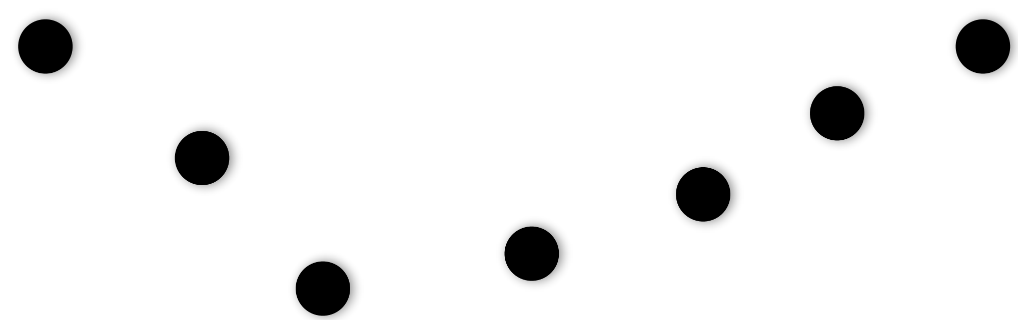
We need to estimate $\alpha'(t)$ and $\alpha''(t)$ in real time!

Parametric curve fitting

Lewiner *et al* (2005): fit a portion of the gesture curve around $\alpha(t)$ to a parabola:

$$\tilde{\alpha}(s) = \alpha(t) + \tilde{\alpha}' \cdot s + \frac{1}{2} \cdot \tilde{\alpha}'' \cdot s^2$$

where $\tilde{\alpha}'$ and $\tilde{\alpha}''$ are estimates for the derivatives $\alpha'(t)$ and $\alpha''(t)$.



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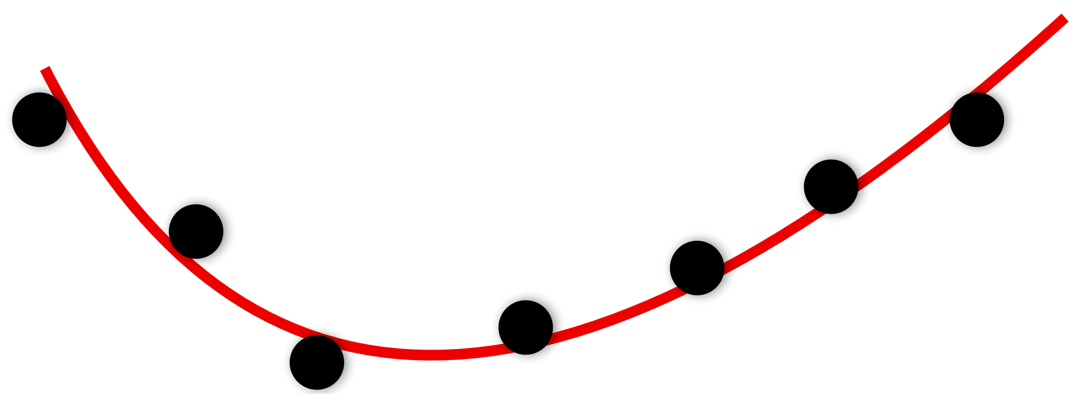

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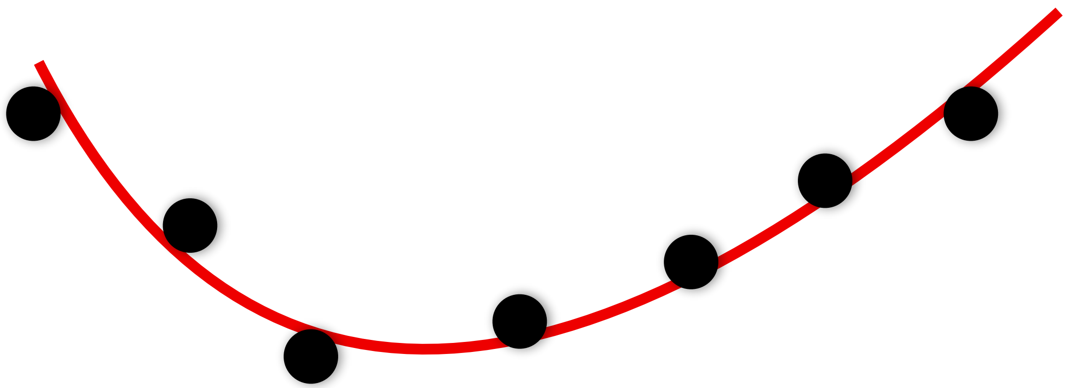
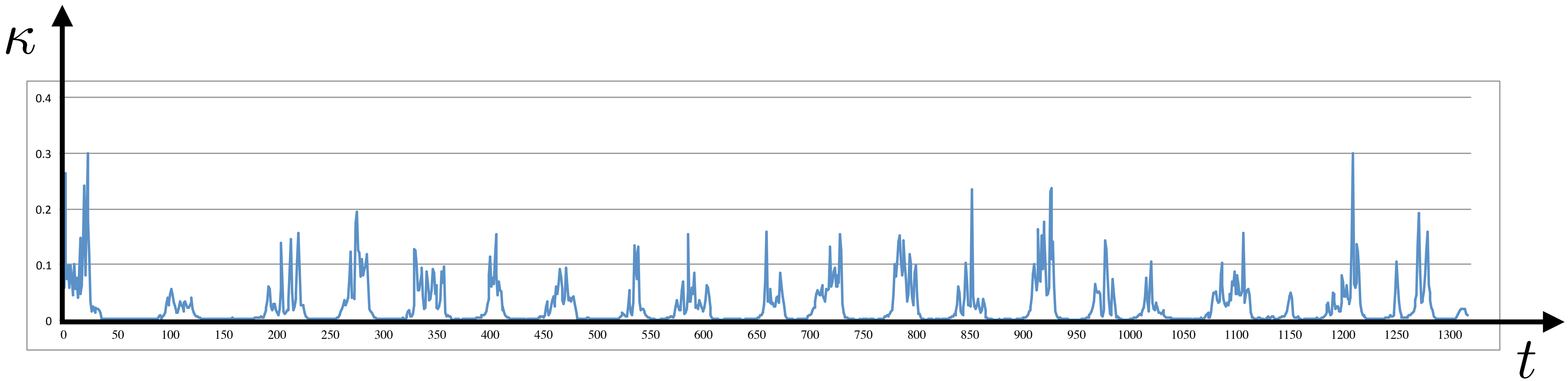


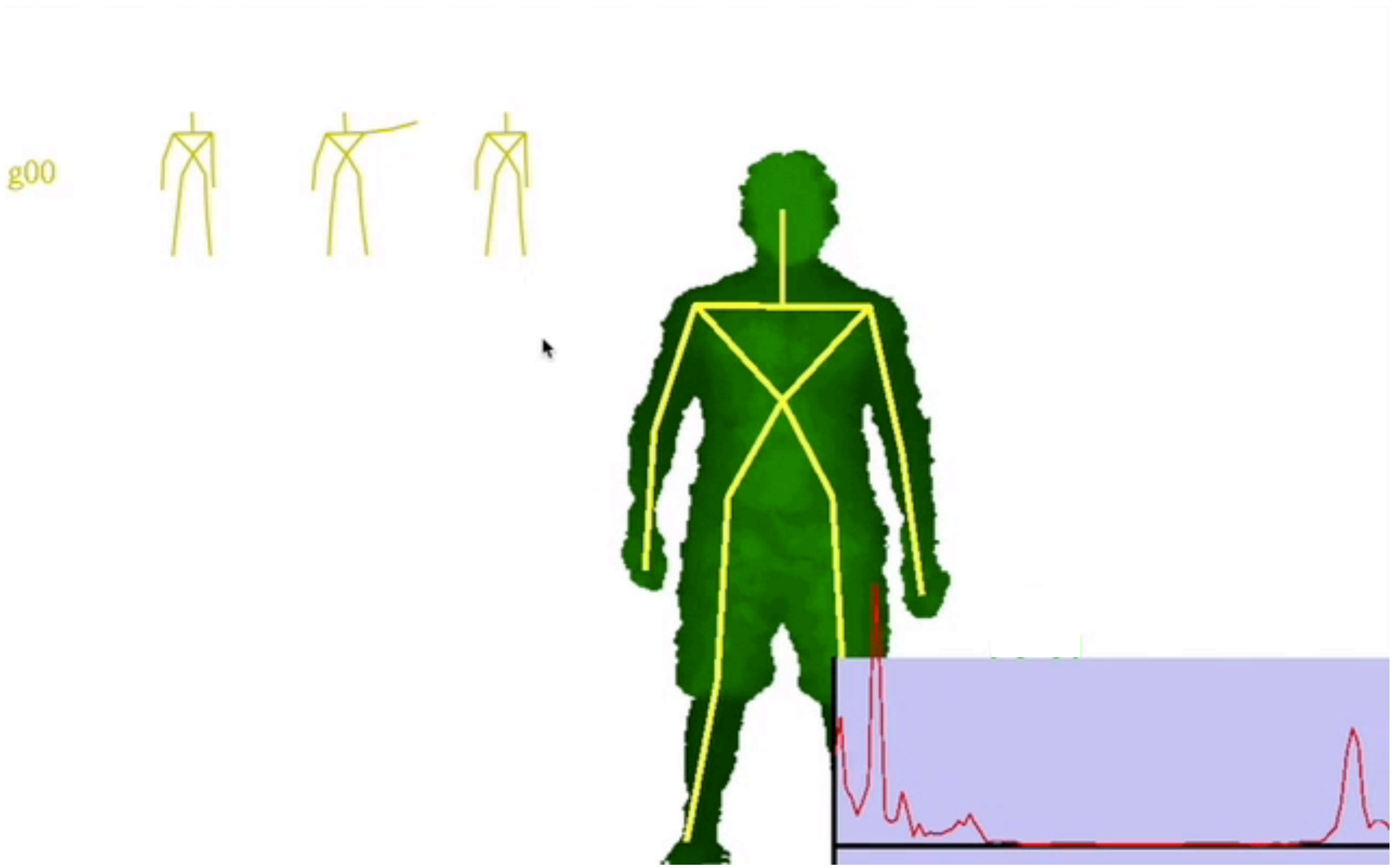
Weighted least squares minimization: fast!

Gesture segmentation



Simple thresholding

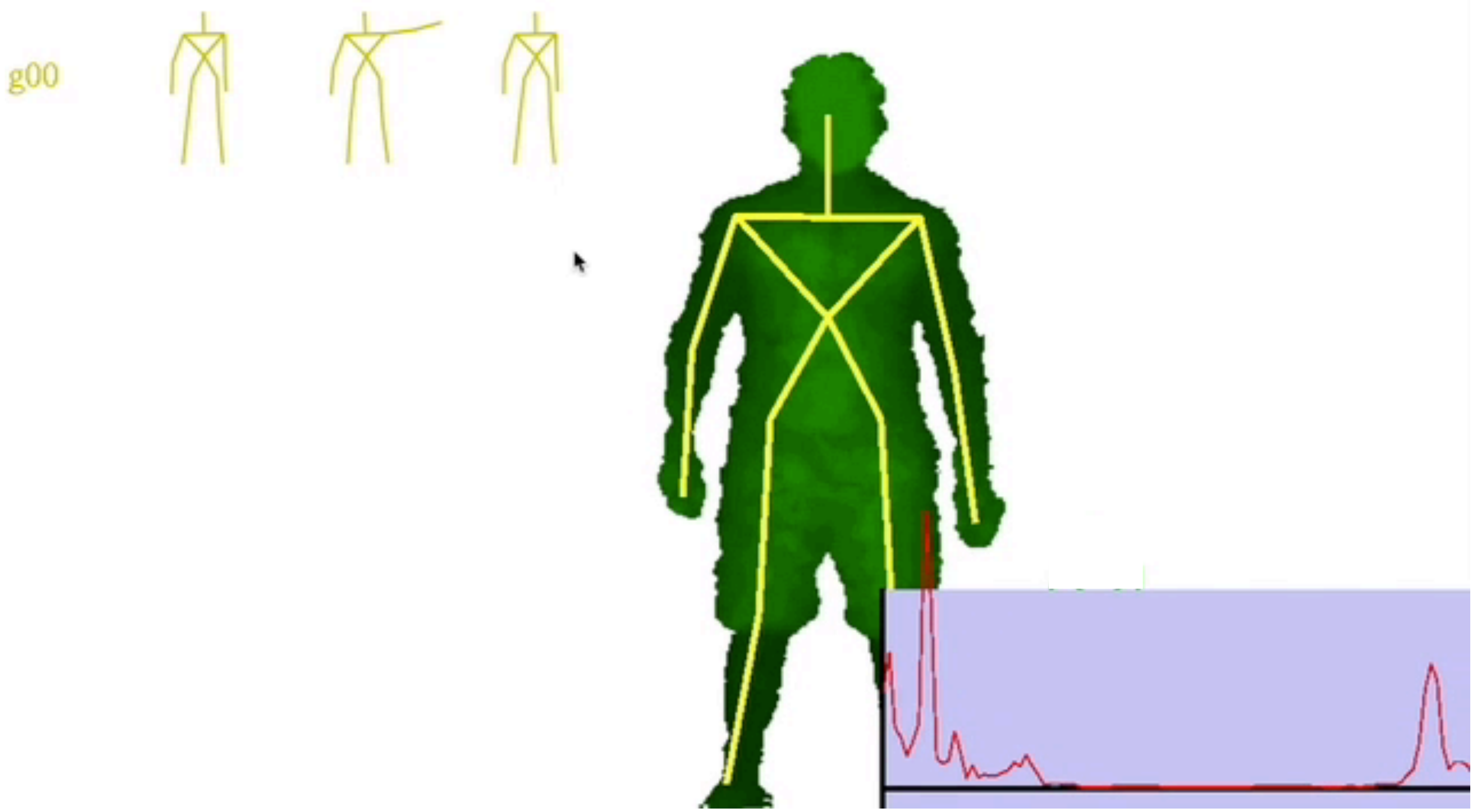
Gesture segmentation



Faugeroux et al., 2014

Simplified training for gesture recognition

Gesture segmentation



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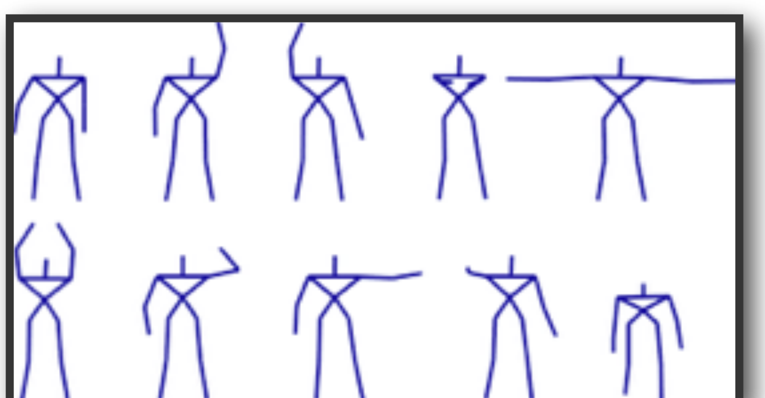
Gesture representation: key poses

Miranda *et al* (2012)

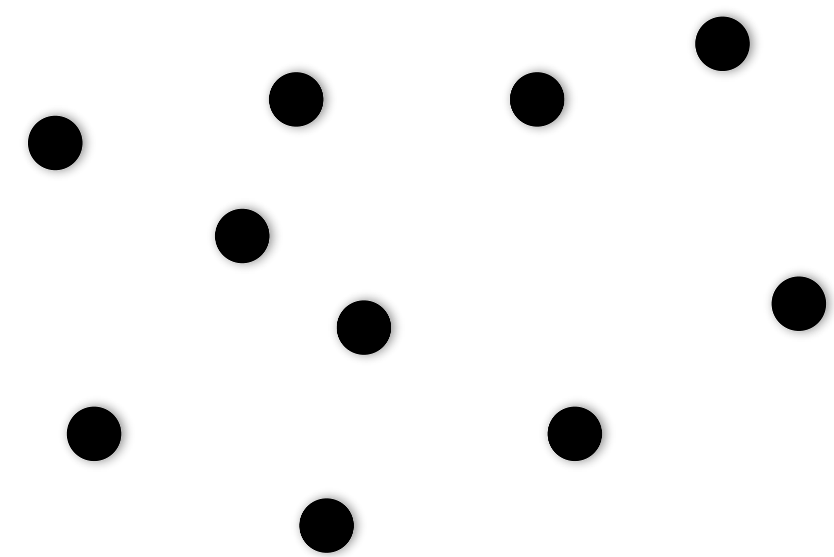


key pose set

$$\mathcal{K} = \{k_1, \ldots, k_n\}$$

gesture

$$g = (p_1, p_2, \ldots)$$



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Faugeroux et al., 2014

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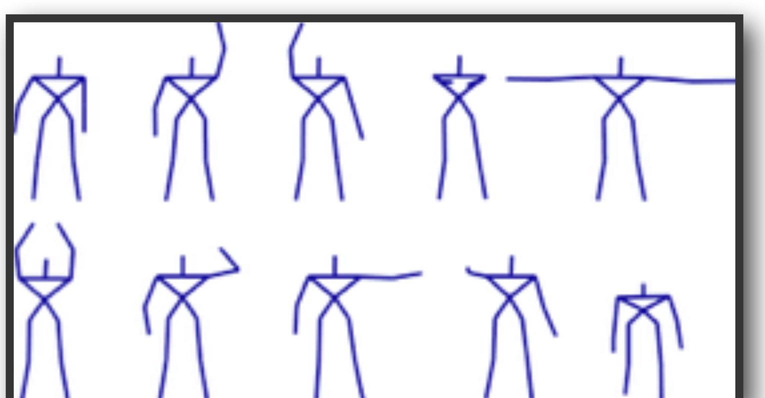

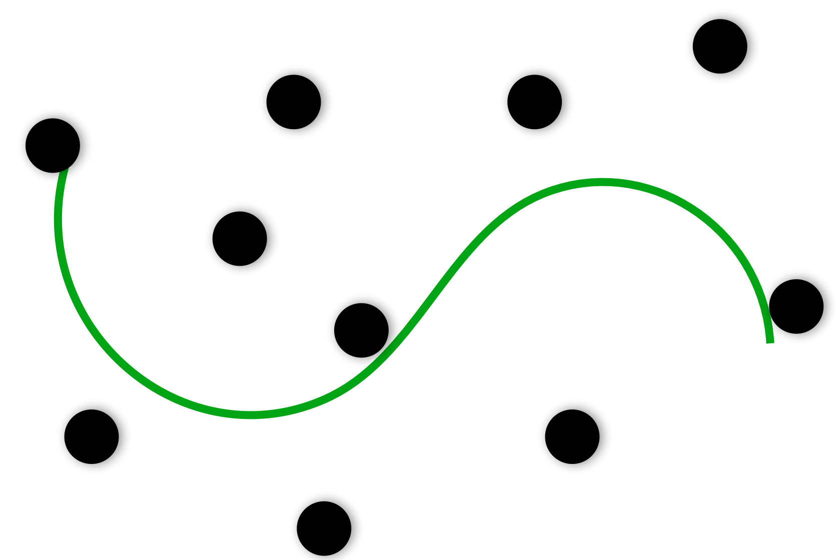

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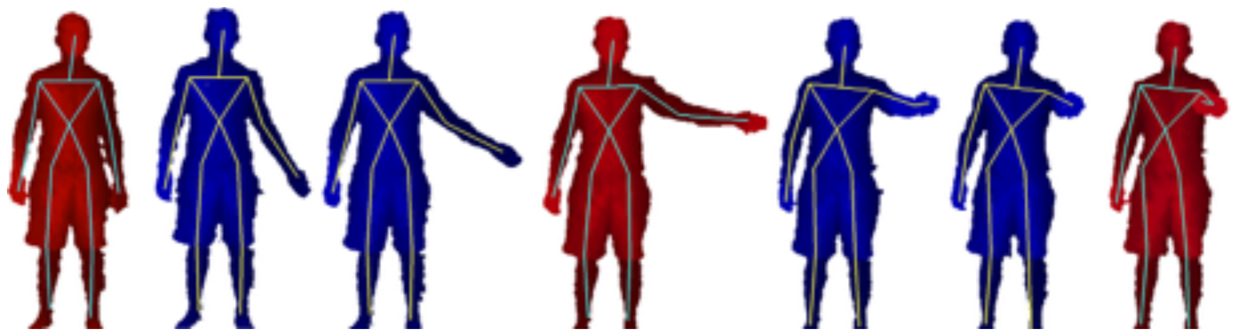
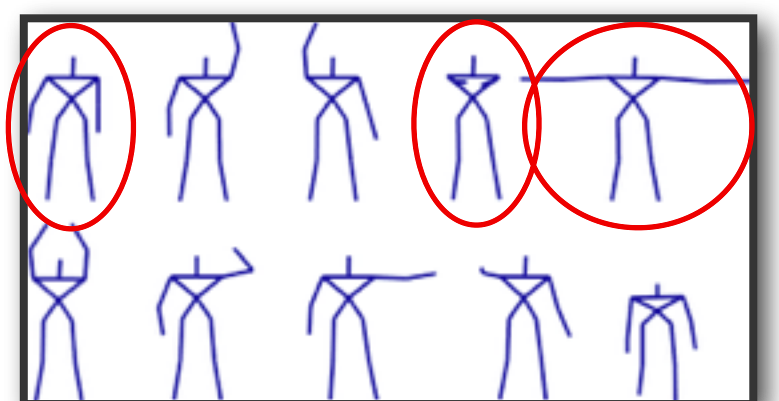


Miranda *et al* (2012)

$$\Delta(p, k_p) < \epsilon \quad ?$$

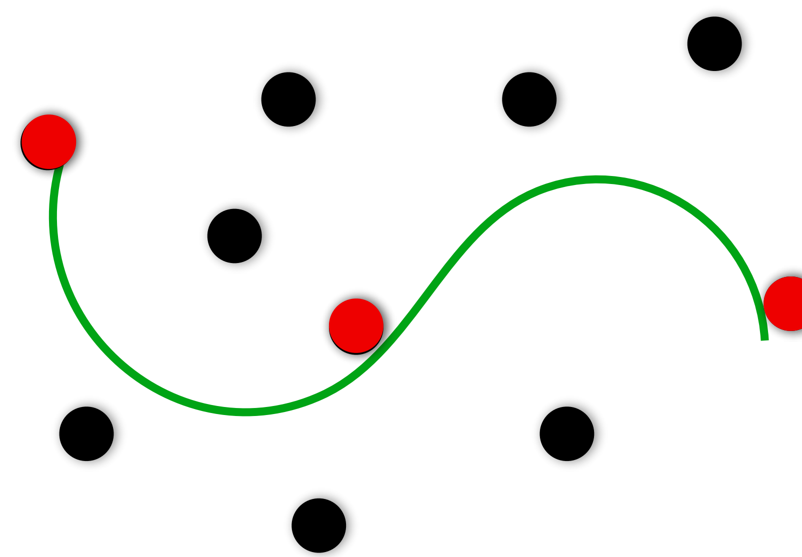


key pose set

$$\mathcal{K} = \{k_1, \ldots, k_n\}$$

gesture

$$g = (p_1, p_2, \ldots)$$



gesture representation

$$\hat{g} = (k_i, k_j, \ldots)$$

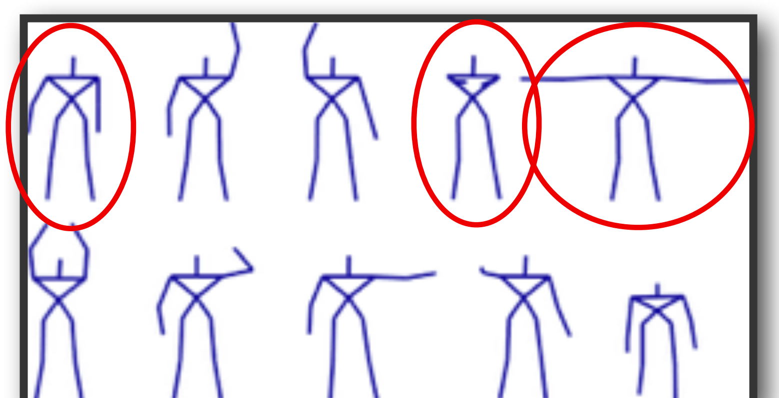
Faugeroux et al., 2014

Gesture representation: key poses

Miranda *et al* (2012)

What is a good key pose set?

$\Delta(p, k_p) < \epsilon \quad ?$



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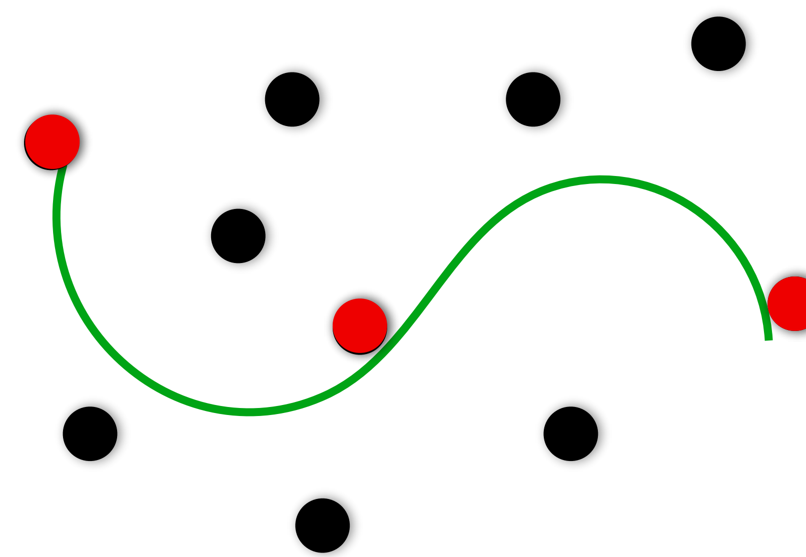

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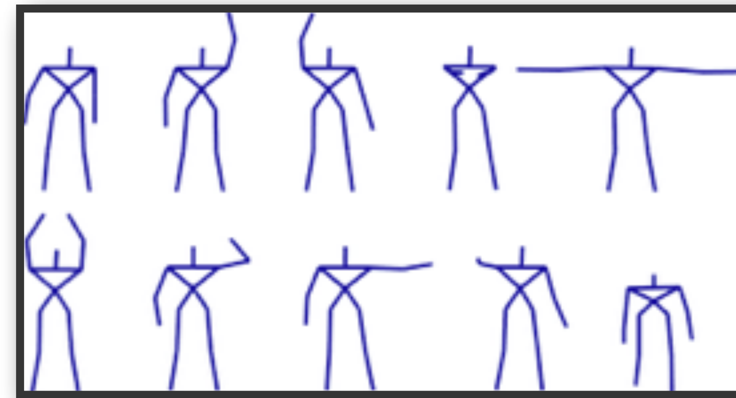
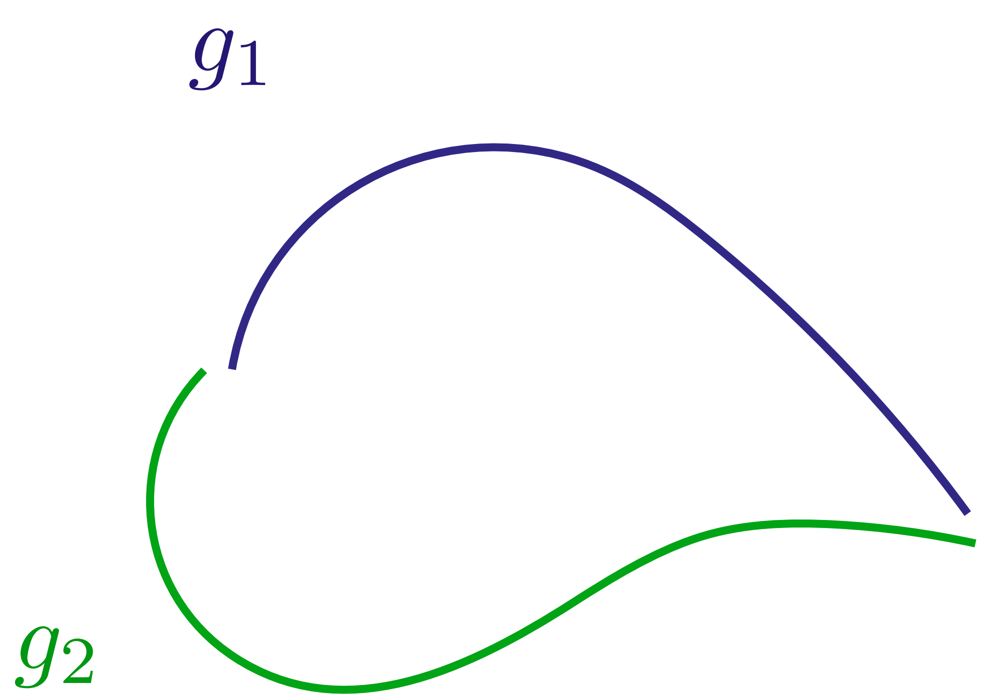
Faugeroux et al., 2014

Ideal key pose set

- ✓ Concise (small)
- ✓ Discriminative (avoid ambiguity)





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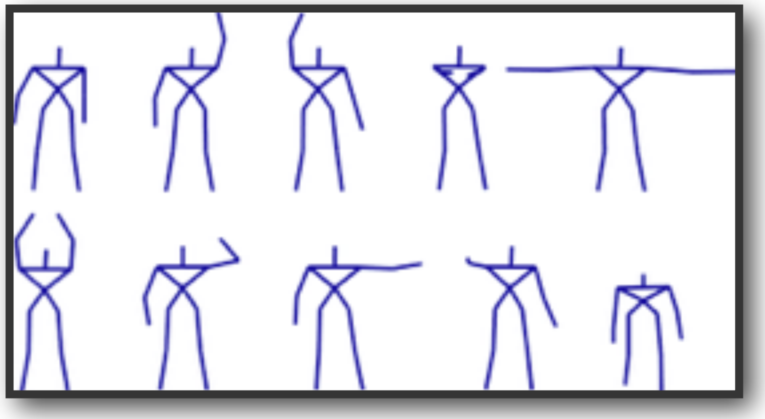

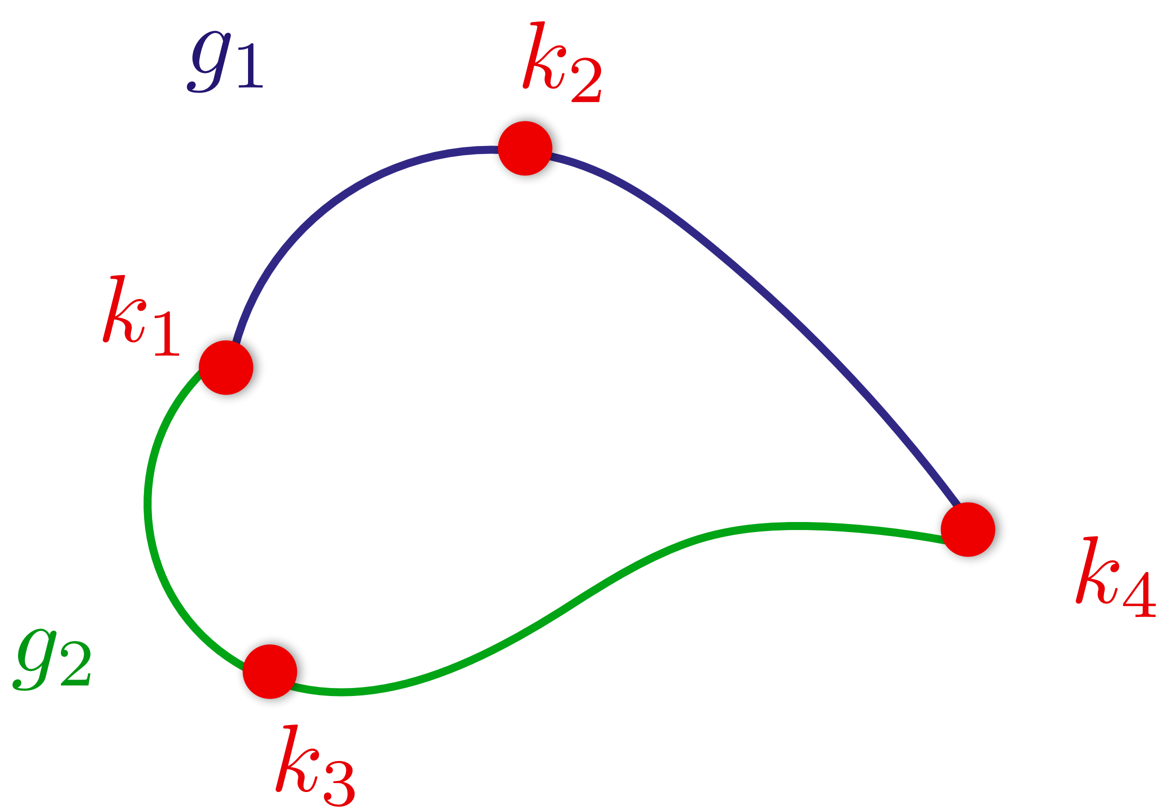

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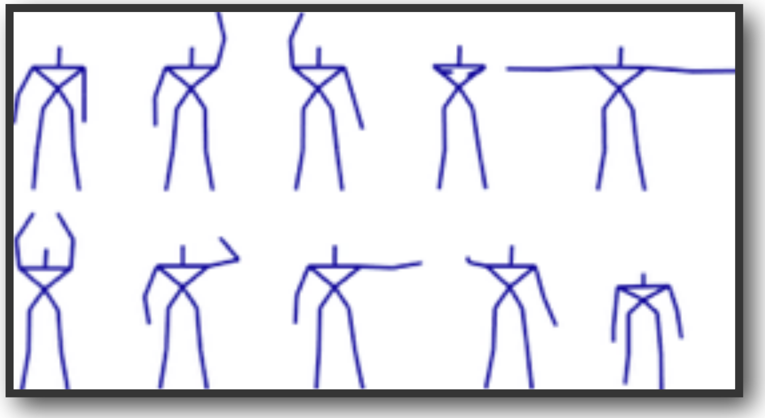

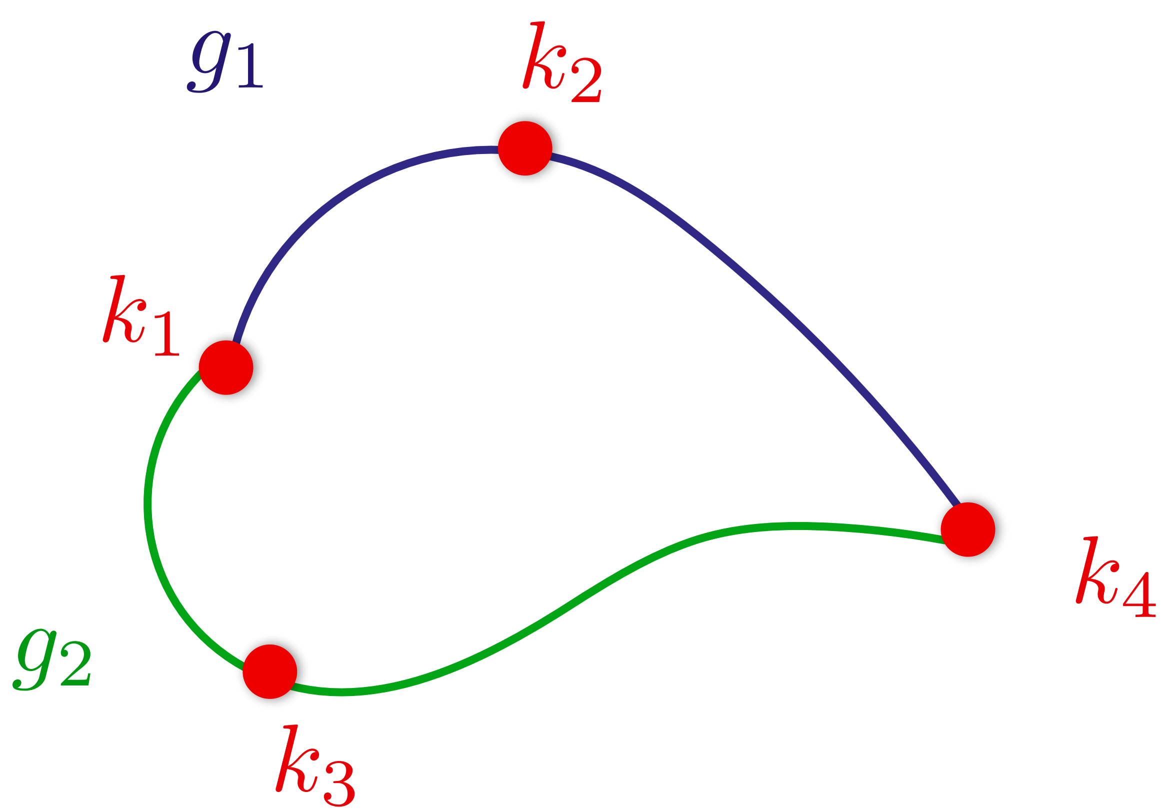

Our solution: adaptive sampling

Building a good key pose set

1 - initial / final gesture poses

k_1 and k_2 must be key poses

Building a good key pose set

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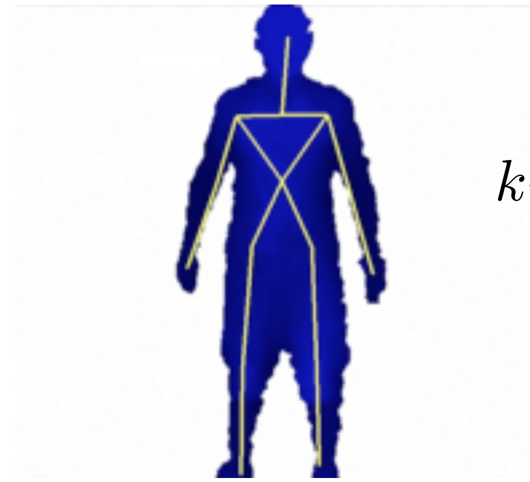
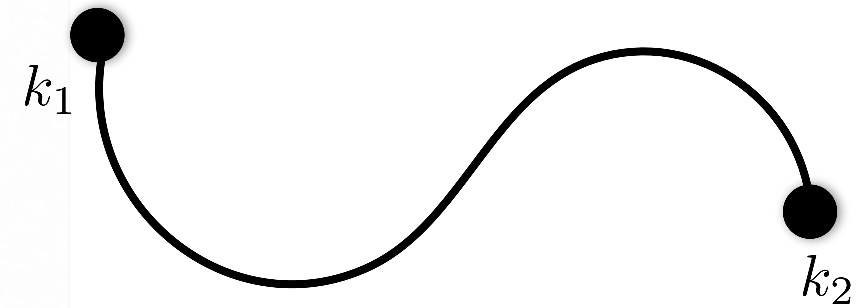
k_1 and k_2 must be key poses





Building a good key pose set

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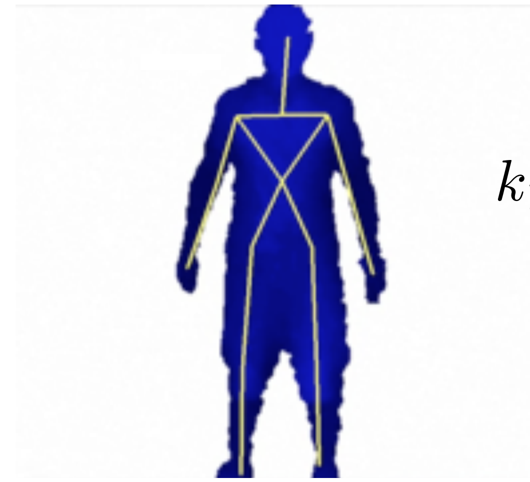
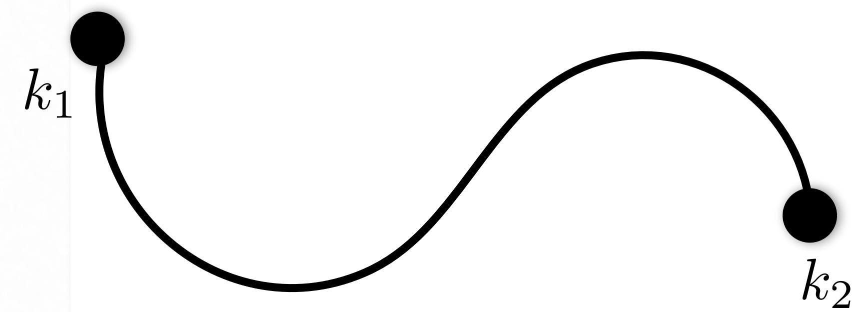
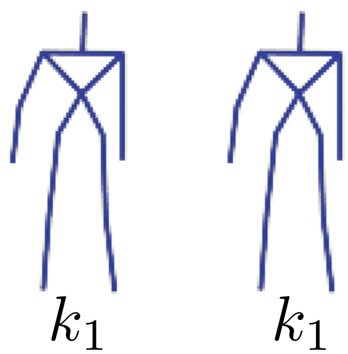




what if initial == final?



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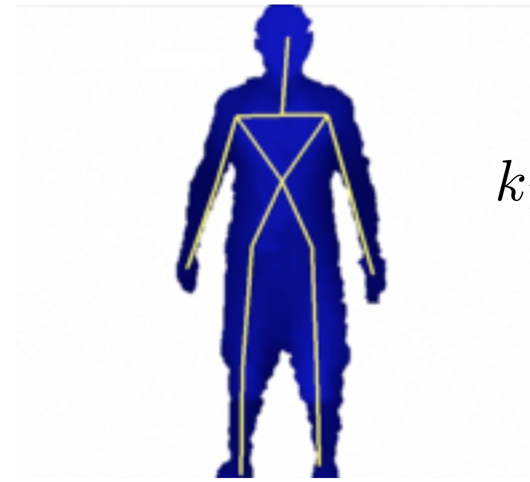

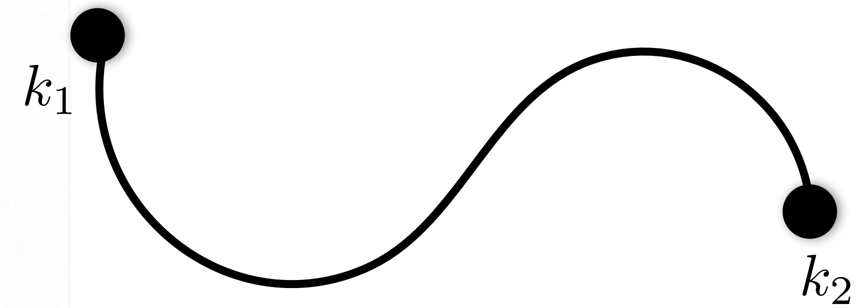

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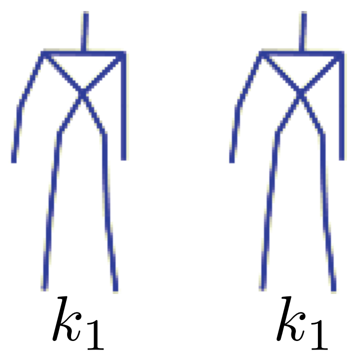

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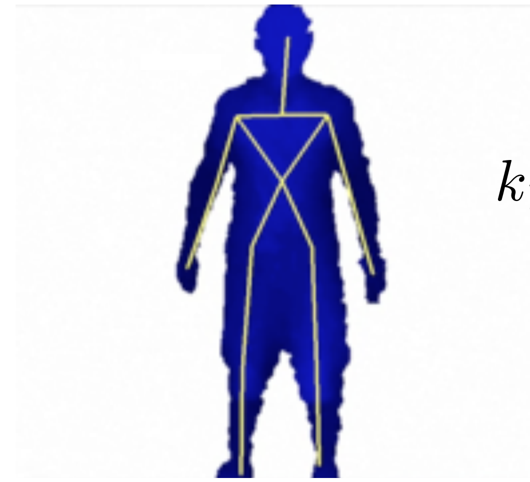

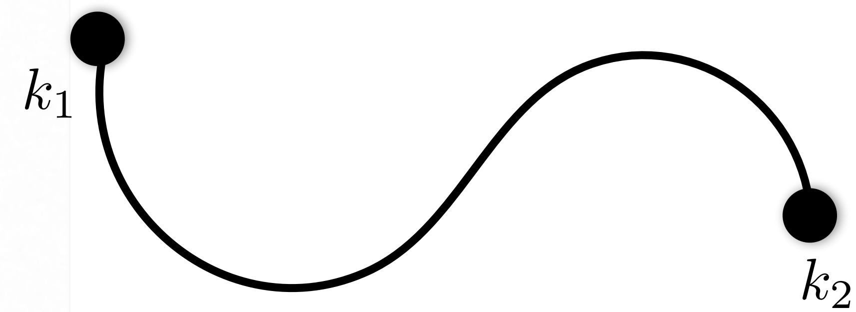

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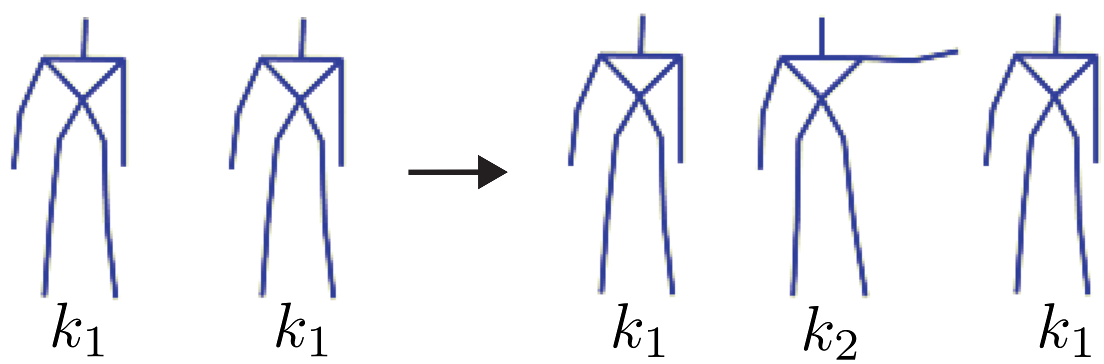
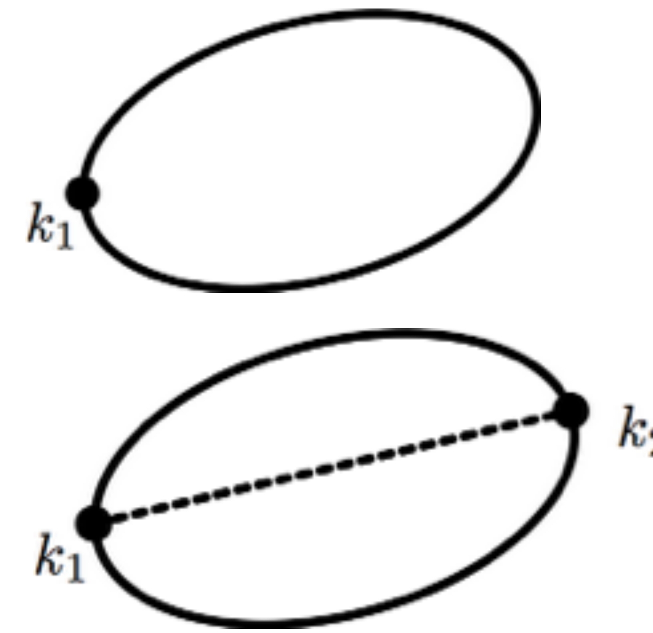


$$\hat{g} = (k_1, k_2, k_1)$$



insert intermediate farthest pose:

$$k_2 = \underset{p \in g}{\operatorname{argmax}} \, \Delta(p, k_1)$$

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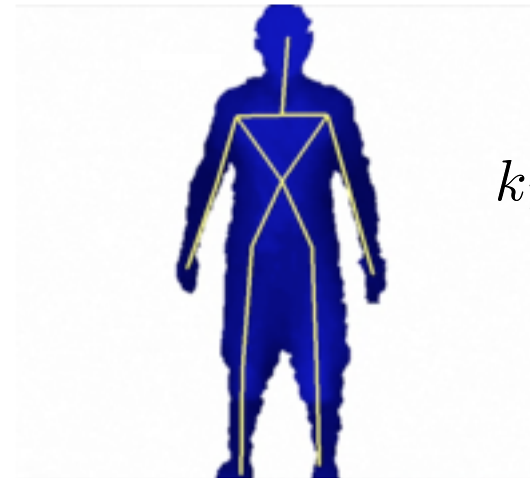

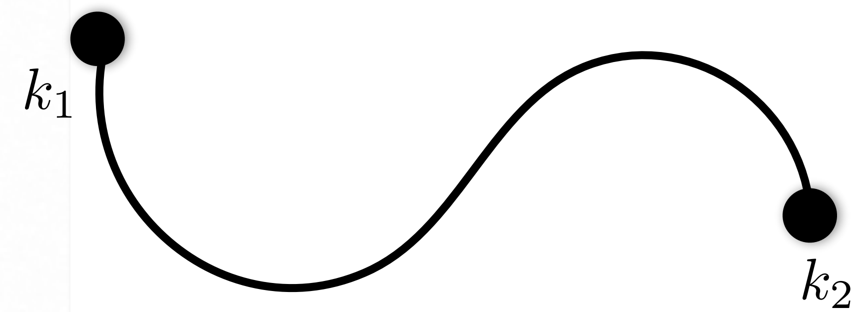

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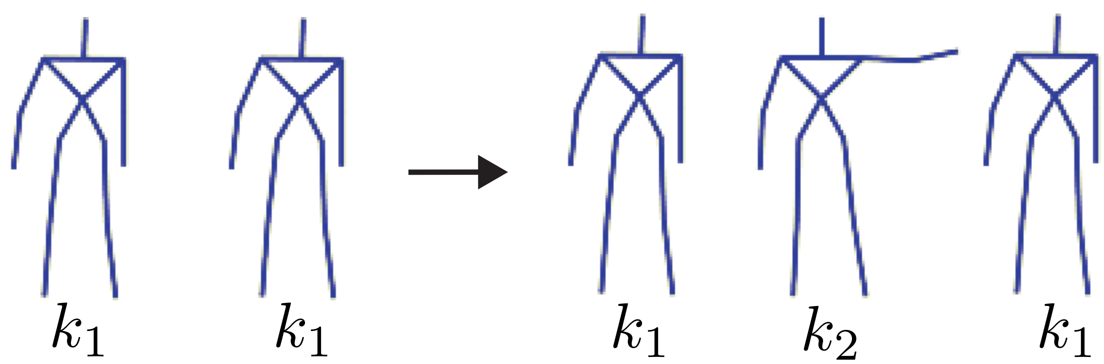
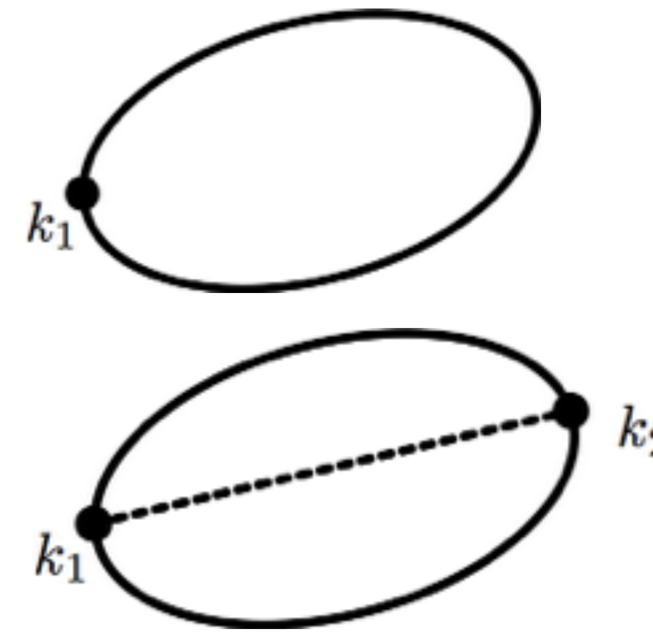




$$\hat{g} = (k_1, k_2, k_1)$$

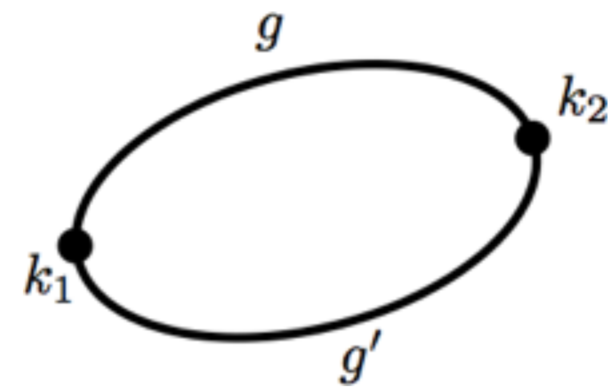
insert intermediate farthest pose:

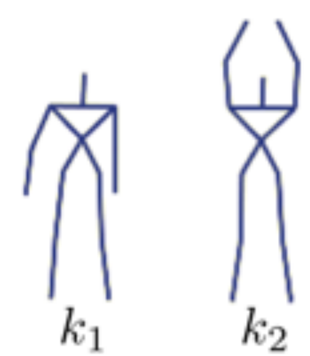
$$k_2 = \underset{p \in g}{\operatorname{argmax}} \, \Delta(p, k_1)$$

if k_1 == k_2 , discard. (static gesture)

Building a good key pose set: Discriminant poses

2 - similar representations for distinct gestures g and g' must be refined.





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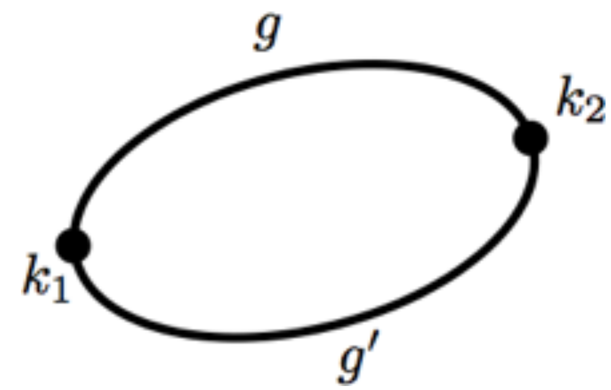

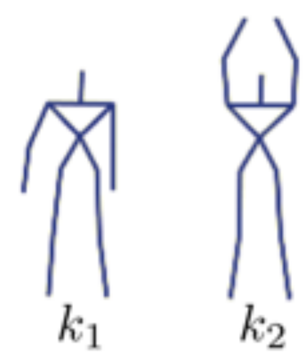

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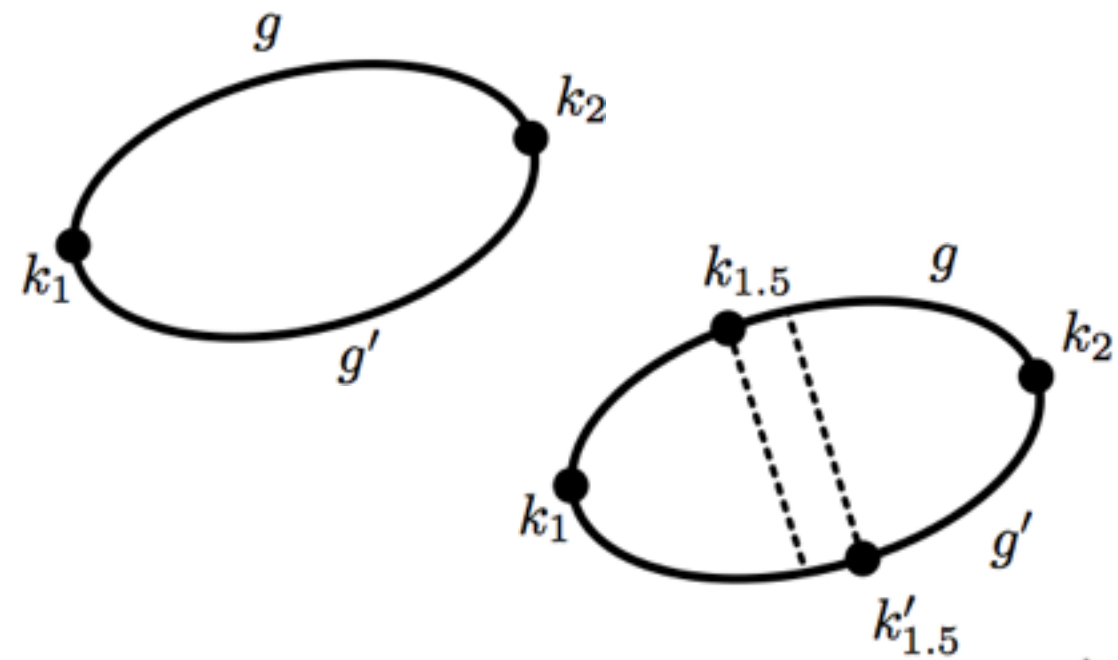
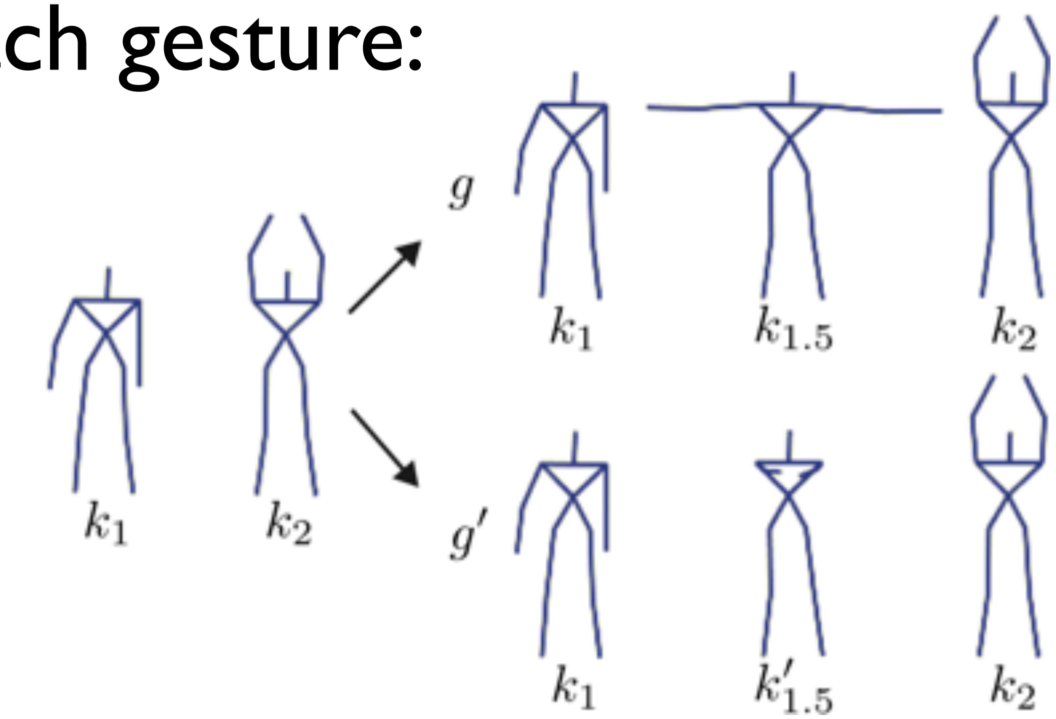


Insert most discriminant pose in each gesture:

$$k_{1+1/2} = \underset{p \in g}{\operatorname{argmax}} \min_{p' \in g'} \Delta(p, p')$$

$$k'_{1+1/2} = \underset{p' \in g'}{\operatorname{argmax}} \min_{p \in g} \Delta(p', p)$$



Faugeroux et al., 2014

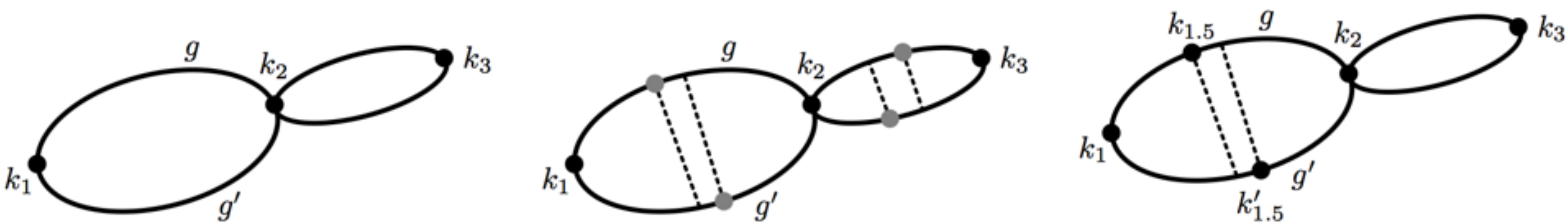
Simplified training for gesture recognition

Discriminant poses: general case

Repeat the process above for every sub-sequence between successive key poses of g and g'

Select the most distinctive pair

$$j = \underset{i}{\operatorname{argmax}} \left\{ \min_{p' \in g'_i} \Delta\left(k_{i+1/2}, p'\right) + \min_{p \in g_i} \Delta\left(k'_{i+1/2}, p\right) \right\}$$



If $\Delta\left(k_{j+1/2}, k'_{j+1/2}\right) < \epsilon$, give gestures identical label.

Iterate until all gestures have different representations

Faugeroux et al., 2014

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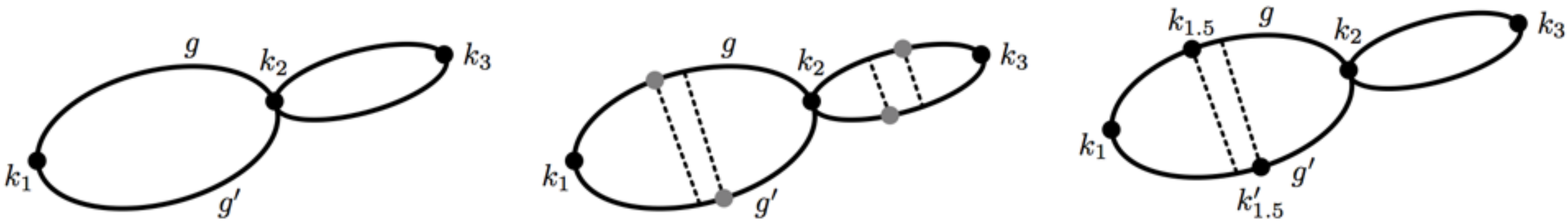

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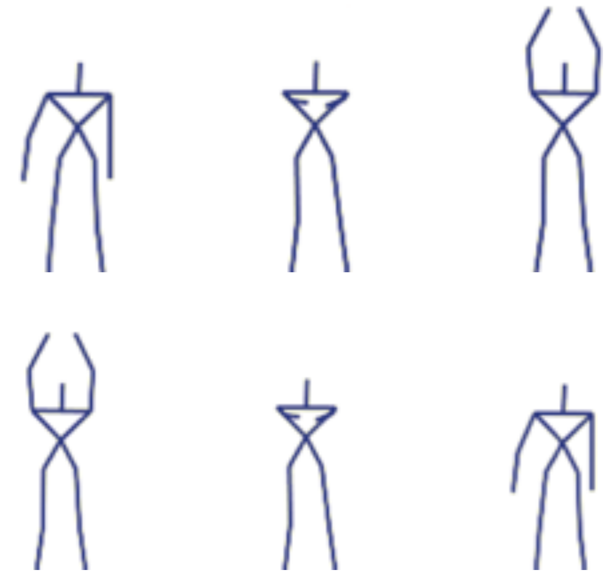
Outline

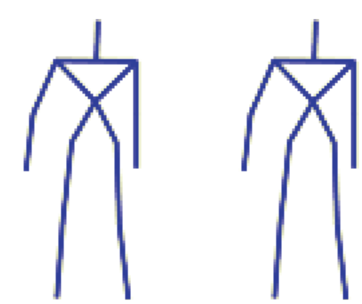
1. Overview
2. Pose representation
3. Gesture segmentation
4. Discriminant key pose selection
5. Gesture identification
6. Experiments

Spurious gesture elimination

Transitions between gestures



Static gestures



Faugeroux et al., 2014

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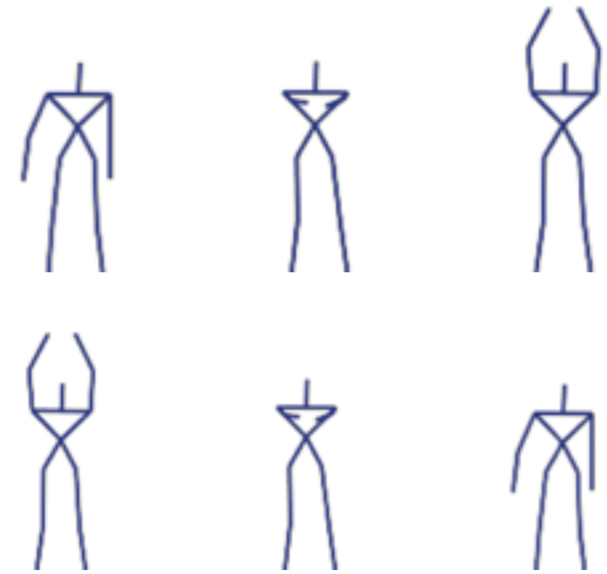

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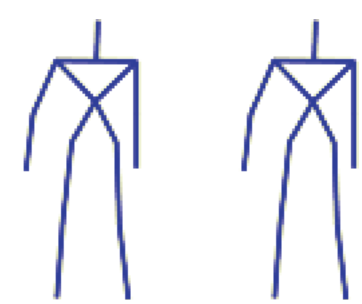

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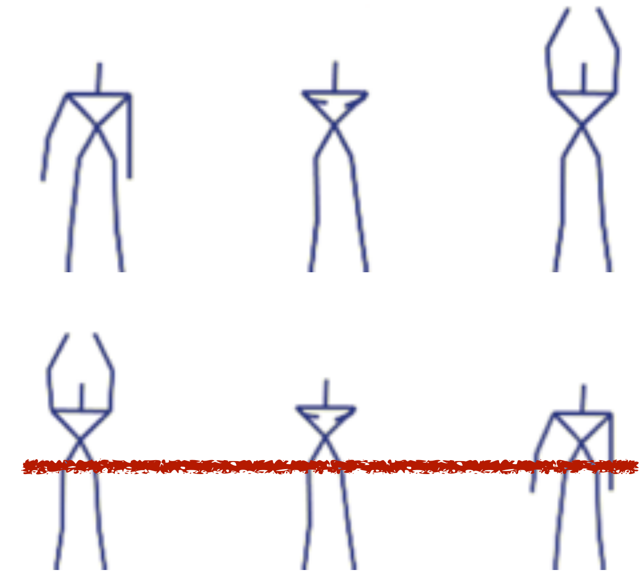

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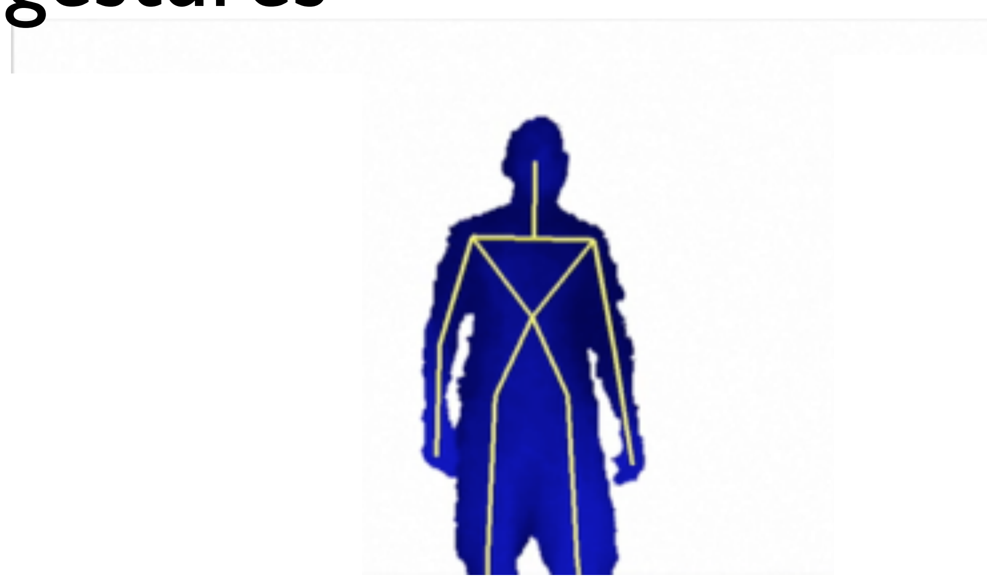

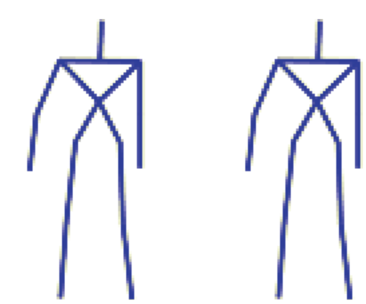

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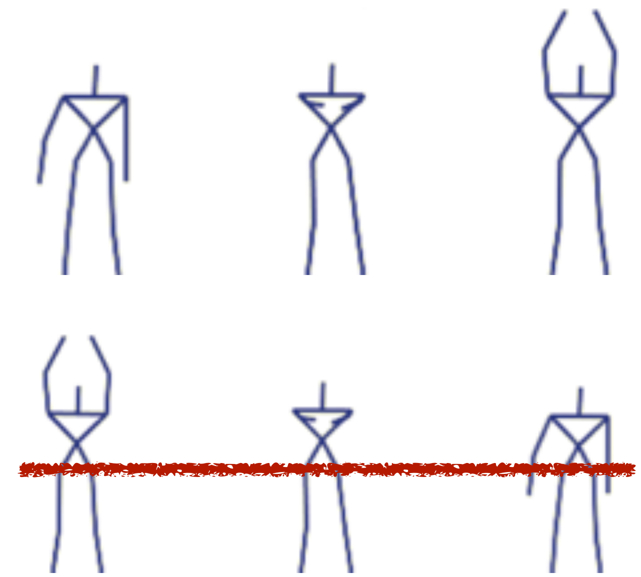

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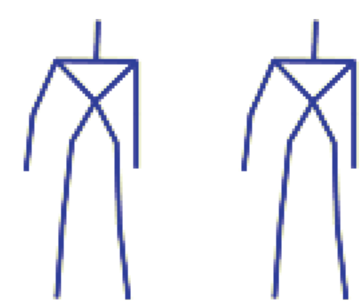

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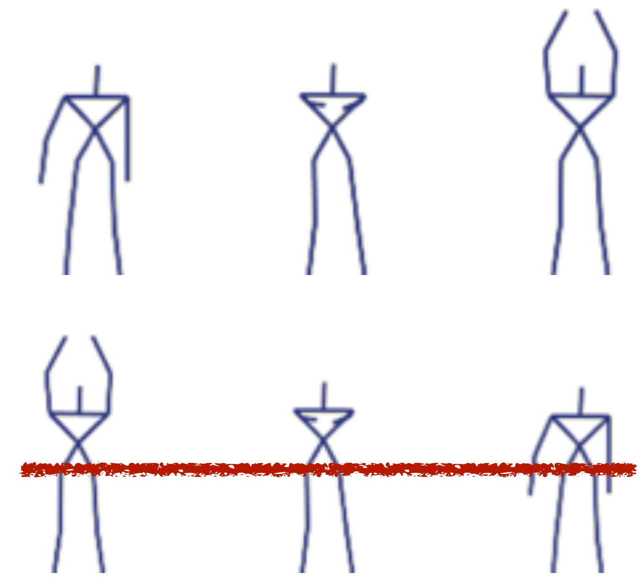

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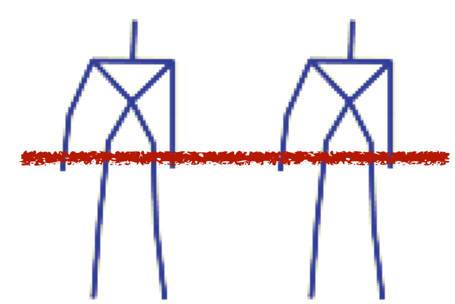
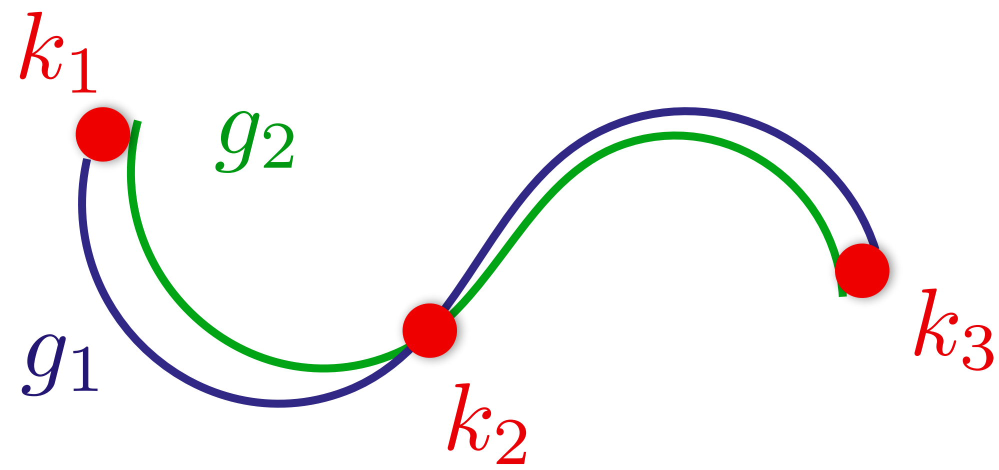


Semiautomatic labeling

Similar gestures confirmation



$$\hat{g}_1 = (k_1, k_2, k_3)$$
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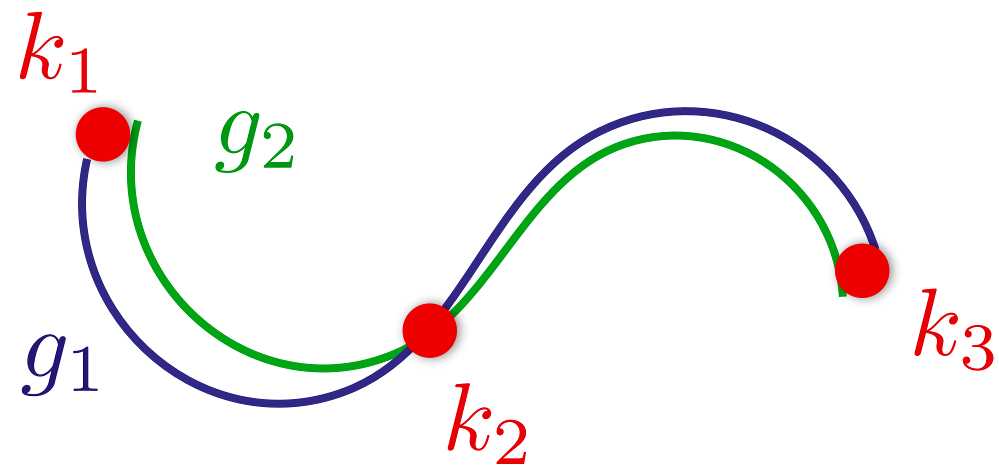
“Is g_1 and g_2 performances of the same gesture?"

Semiautomatic labeling

Similar gestures confirmation



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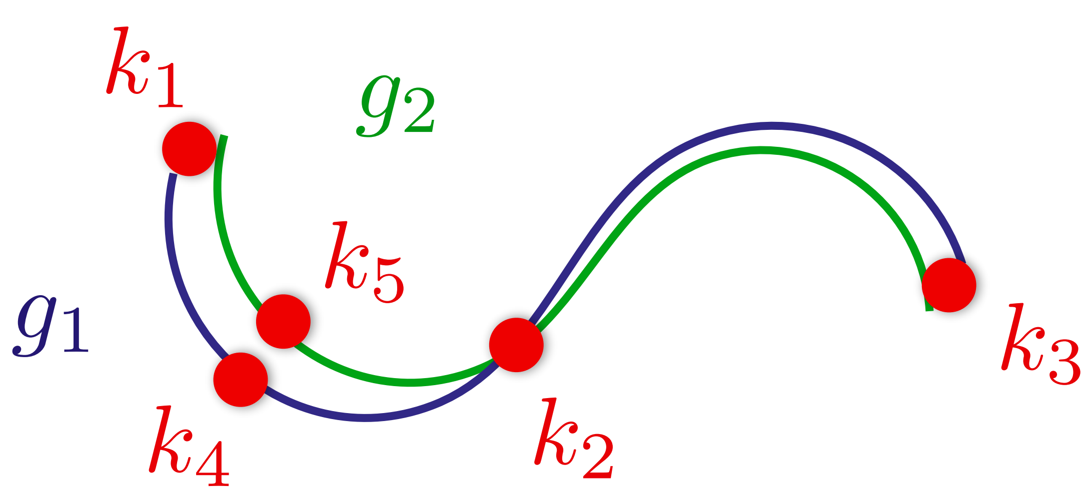
“Is g_1 and g_2 performances of the same gesture?"

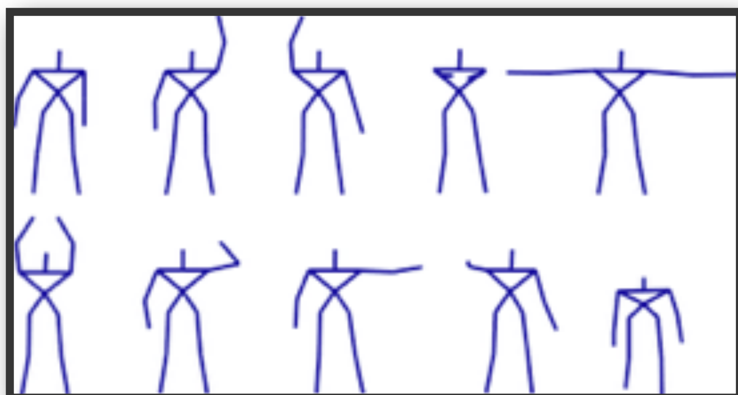
Negative: force key-pose subdivision (ignore ϵ)



$\hat{g}_1 = (k_1, k_4, k_2, k_3)$

$\hat{g}_2 = (k_1, k_5, k_2, k_3)$

Gesture recognition



key pose set

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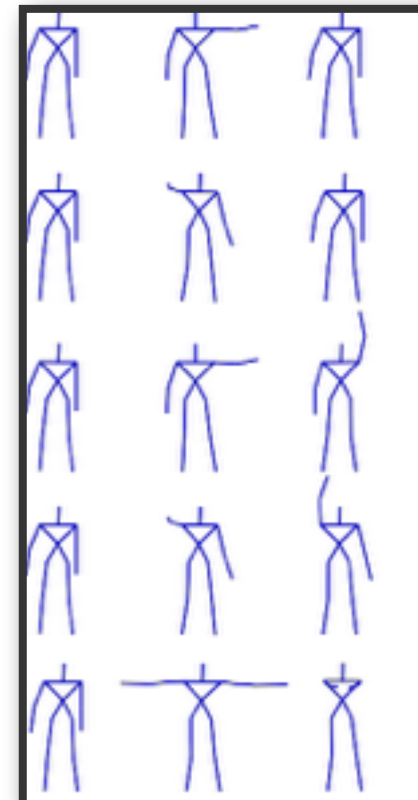

gesture set

$$\mathcal{G} = \{\hat{g_1}, \hat{g_2}, \ldots, \hat{g_m}\}$$

training set

Learning method?

Many alternatives: action graph, decision forests, bag of features, SVM, nearest neighbor classifier,…

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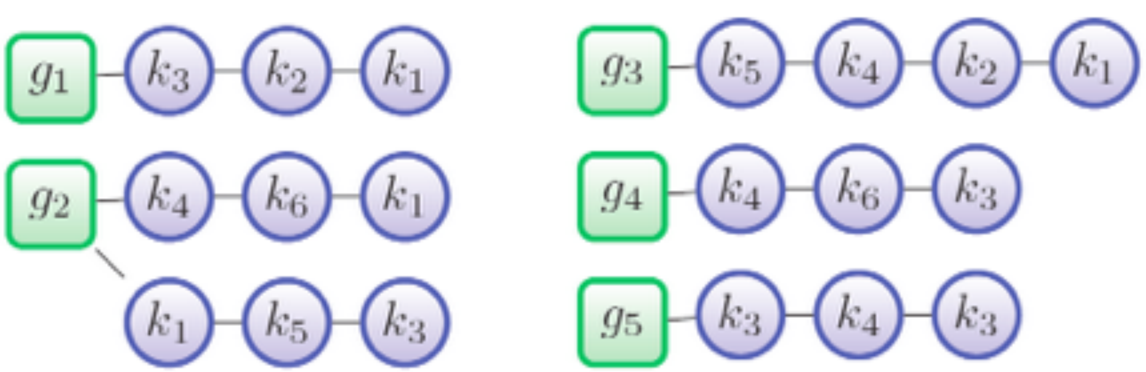
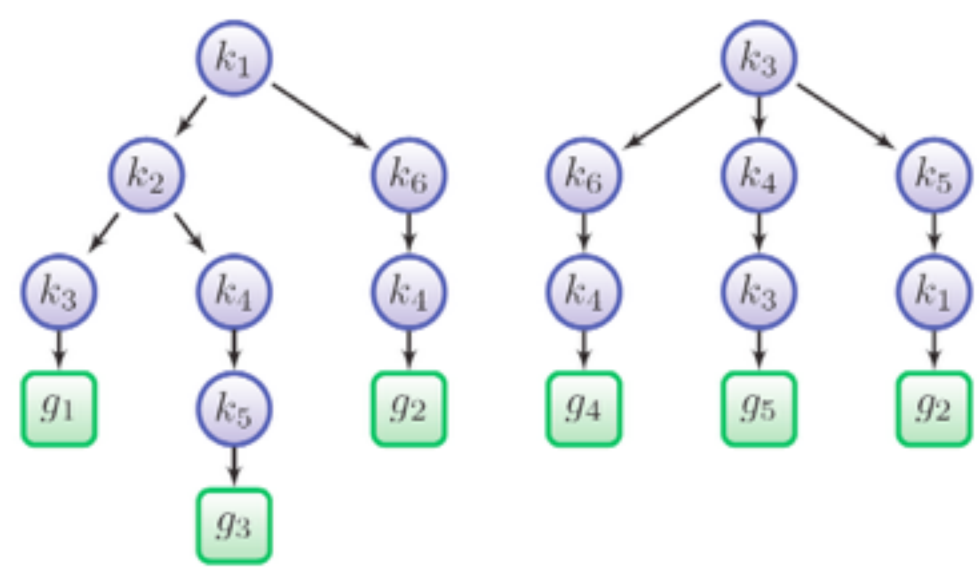
Many alternatives: action graph, decision forests, bag of features, SVM, nearest neighbor classifier,…

(Miranda *et al*, 2012): SVM + decision forest

nearest neighbor classifier

$$\tilde{f}(p) = \begin{cases} k_p = \underset{k \in \mathcal{K}}{\operatorname{argmin}} \, \Delta(k, p) & \text{if } \Delta(k_p, p) < \epsilon, \\ \text{-1} & \text{otherwise.} \end{cases}$$





Experiments

Experiment Setup

✓ Objective: comparison with Miranda *et al* (2012)

✓ Same set of 11 gestures

✓ Gestures briefly described to 10 inexperienced individuals

✓ Users should sequentially perform each gesture in a single record

✓ Unsuccessfully segmented gestures exceptionally retrained

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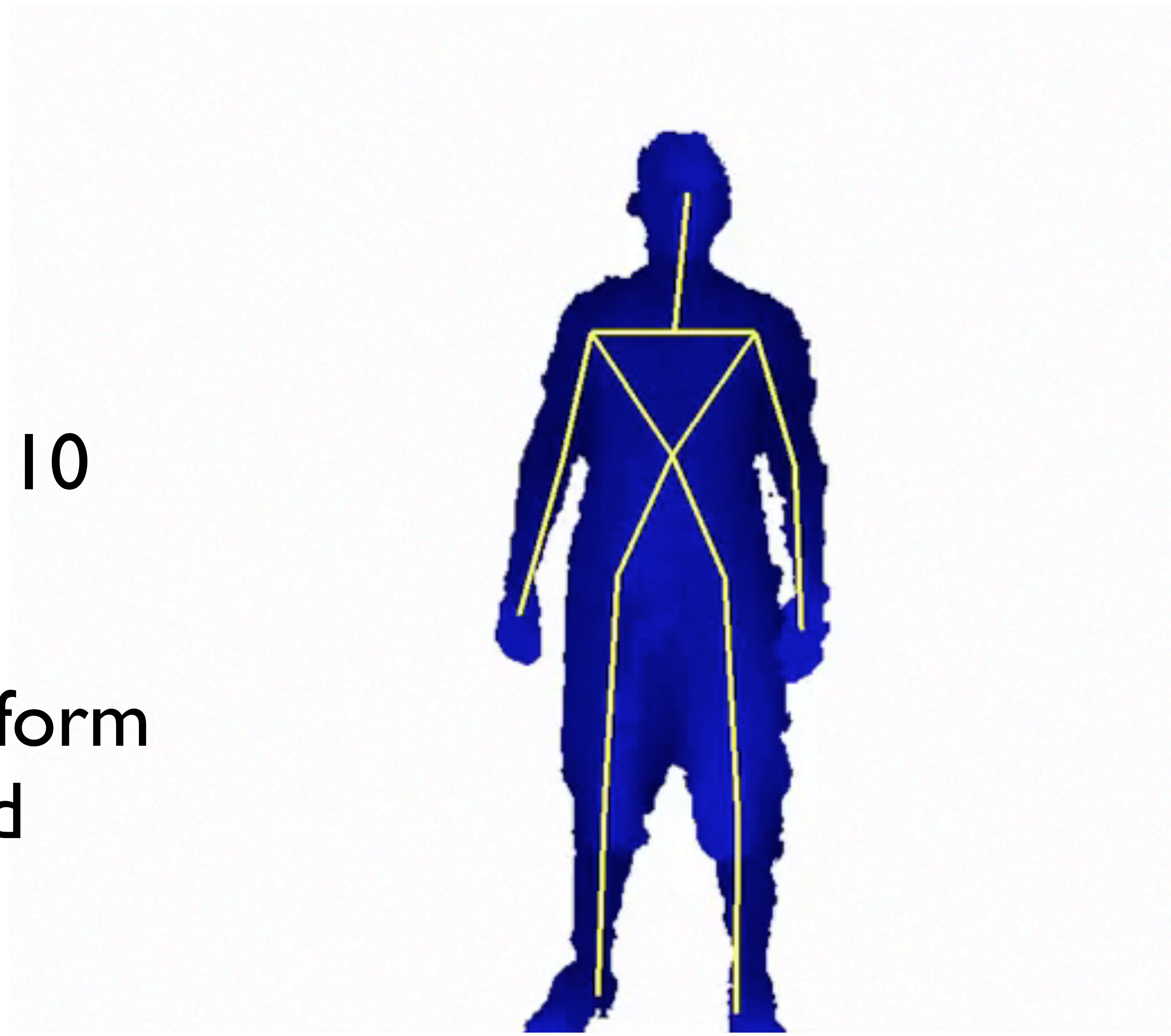
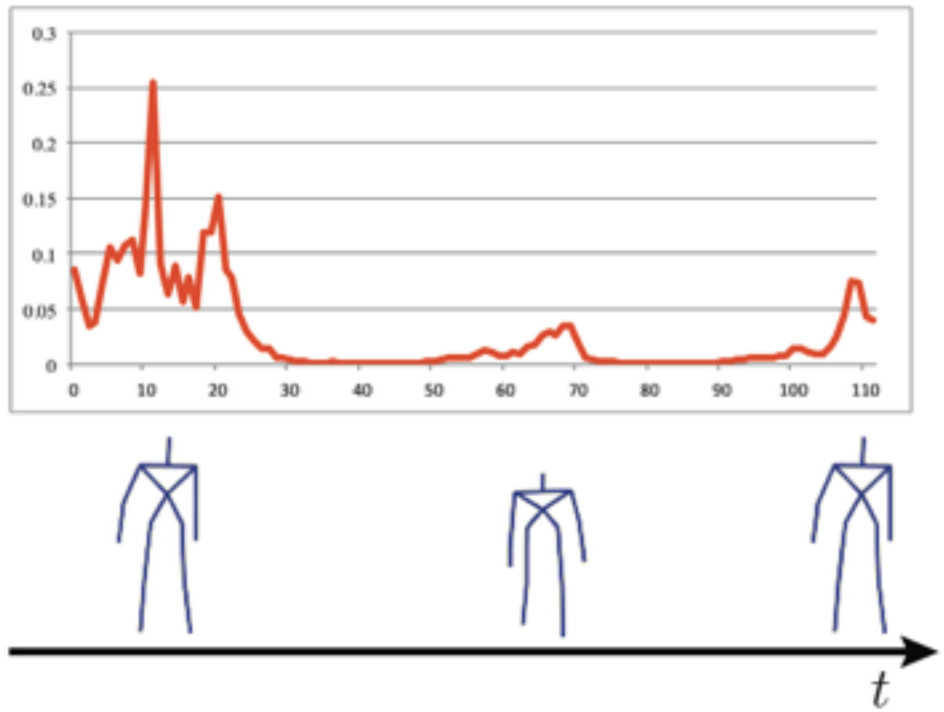


Segmentation robustness

From 10 users recordings:

gesture	id	segmentation accuracy
Turn Next Page	$\hat{g}_A$	10
Turn Previous Page	$\hat{g}_B$	10
Raise Right Arm	$\hat{g}_C$	10
Raise Left Arm	$\hat{g}_D$	10
Open Clap	$\hat{g}_E$	8
Open Arms	$\hat{g}_F$	9
Put Hands Up Lat.	$\hat{g}_G$	9
Put Hands Up Front	$\hat{g}_H$	10
Lower Right Arm	$\hat{g}_I$	8
Bow	$\hat{g}_J$	6
Goodbye	$\hat{g}_K$	7
average (%)		**88**

over-segmentation:



Segmentation robustness

Simplified training for gesture recognition

example: online segmentation and key pose selection

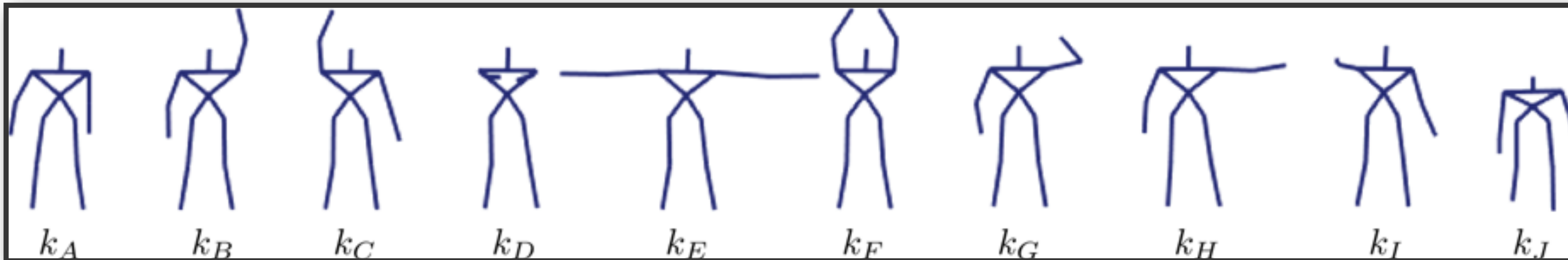
Segmentation robustness

Simplified training for gesture recognition

example: online segmentation and key pose selection

Discriminant key pose selection

10 to 12 key poses per set



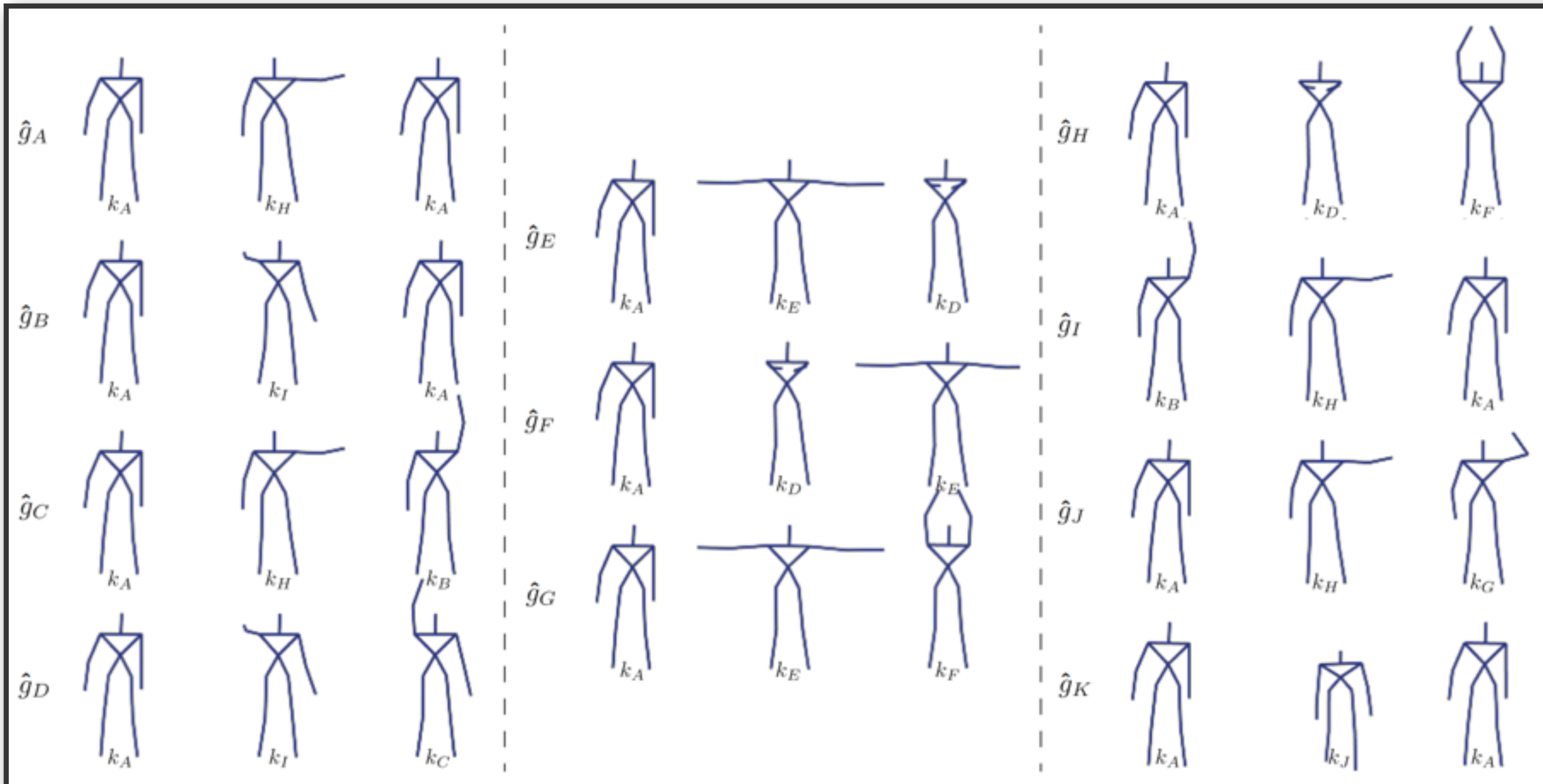
Key poses similar to manually designed key poses from Miranda *et al* (2012)

Miranda *et al* (2012) uses 11 key poses!

Bigger ϵ : less key poses, less accurate executions needed

Smaller ϵ : more key poses, more accurate executions needed

Discriminant key pose selection

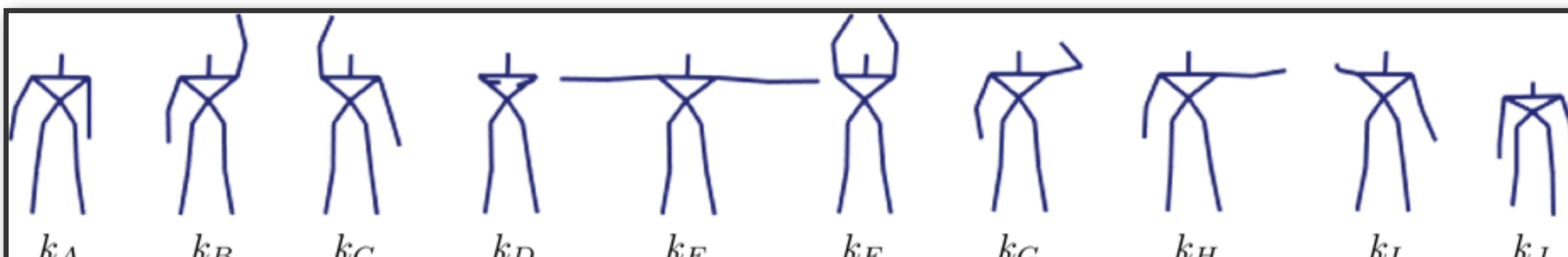


Faugeroux et al., 2014

Gesture recognition

Each user executed each gesture 10 times

gesture	**id**	**segmentation accuracy**	**recognized gestures per user**										**ours**	**[14]**
			u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8	u_9	u_{10}	(%)	(%)
Turn Next Page	$\hat{g}_A$	10	10	8	10	10	9	9	10	9	9	9	**93**	**95**
Turn Previous Page	$\hat{g}_B$	10	10	9	10	10	9	6	9	9	9	10	**91**	**95**
Raise Right Arm	$\hat{g}_C$	10	9	8	9	8	7	10	9	10	8	10	**88**	**94**
Raise Left Arm	$\hat{g}_D$	10	10	10	9	10	9	9	10	9	10	9	**95**	**94**
Open Clap	$\hat{g}_E$	8	10	10	10	9	9	8	10	9	8	10	**93**	**99**
Open Arms	$\hat{g}_F$	9	9	9	10	8	9	10	10	9	8	9	**91**	**97**
Put Hands Up Lat.	$\hat{g}_G$	9	10	10	10	10	10	9	10	10	10	10	**99**	**100**
Put Hands Up Front	$\hat{g}_H$	10	10	9	7	9	10	9	10	10	10	9	**93**	**96**
Lower Right Arm	$\hat{g}_I$	8	8	7	6	8	7	8	8	8	8	7	**75**	**82**
Bow	$\hat{g}_J$	6	10	10	10	9	10	10	10	9	10	10	**98**	**100**
Goodbye	$\hat{g}_K$	7	9	9	10	7	9	10	9	10	8	7	**88**	**92**
average (%)		**88**	**90**	**92**	**89**	**89**	**91**	**89**	**93**	**89**	**91**	**92**		



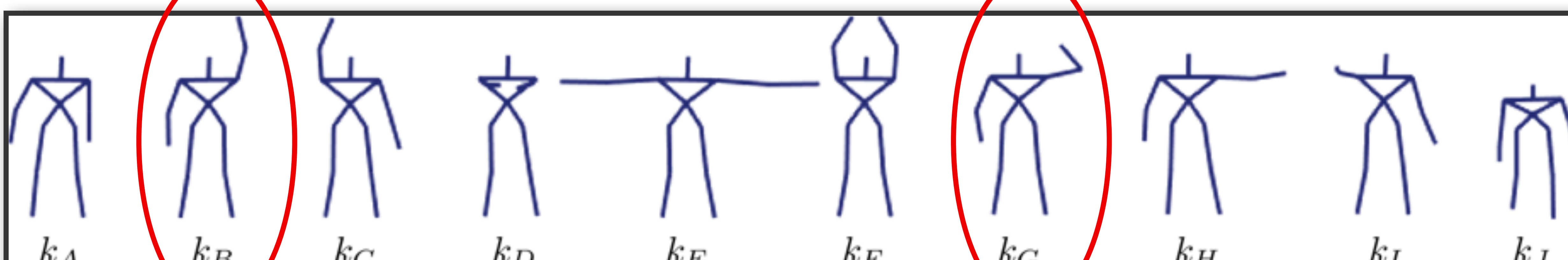
Faugeroux et al., 2014

Simplified training for gesture recognition

Gesture recognition

Each user executed each gesture 10 times

gesture	id	segmentation accuracy	recognized gestures per user u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8	u_9	u_{10}	ours (%)	[14] (%)
Turn Next Page	$\hat{g}_A$	10	10	8	10	10	9	9	10	9	9	9	**93**	**95**
Turn Previous Page	$\hat{g}_B$	10	10	9	10	10	9	6	9	9	9	10	**91**	**95**
Raise Right Arm	$\hat{g}_C$	10	9	8	9	8	7	10	9	10	8	10	**88**	**94**
Raise Left Arm	$\hat{g}_D$	10	10	10	9	10	9	9	10	9	10	9	**95**	**94**
Open Clap	$\hat{g}_E$	8	10	10	10	9	9	8	10	9	8	10	**93**	**99**
Open Arms	$\hat{g}_F$	9	9	9	10	8	9	10	10	9	8	9	**91**	**97**
Put Hands Up Lat.	$\hat{g}_G$	9	10	10	10	10	10	9	10	10	10	10	**99**	**100**
Put Hands Up Front	$\hat{g}_H$	10	10	9	7	9	10	9	10	10	10	9	**93**	**96**
Lower Right Arm	$\hat{g}_I$	8	8	7	6	8	7	8	8	8	8	7	**75**	**82**
Bow	$\hat{g}_J$	6	10	10	10	9	10	10	10	9	10	10	**98**	**100**
Goodbye	$\hat{g}_K$	7	9	9	10	7	9	10	9	10	8	7	**88**	**92**
average (%)		**88**	**90**	**92**	**89**	**89**	**91**	**89**	**93**	**89**	**91**	**92**		



Faugeroux et al., 2014

Simplified training for gesture recognition

Performance

Real time training:

Segmentation + computing key pose representations

Real time gesture recognition.

Offline experiment:

Segmentation + computing key pose representations:

1239 frames (44.3 secs)

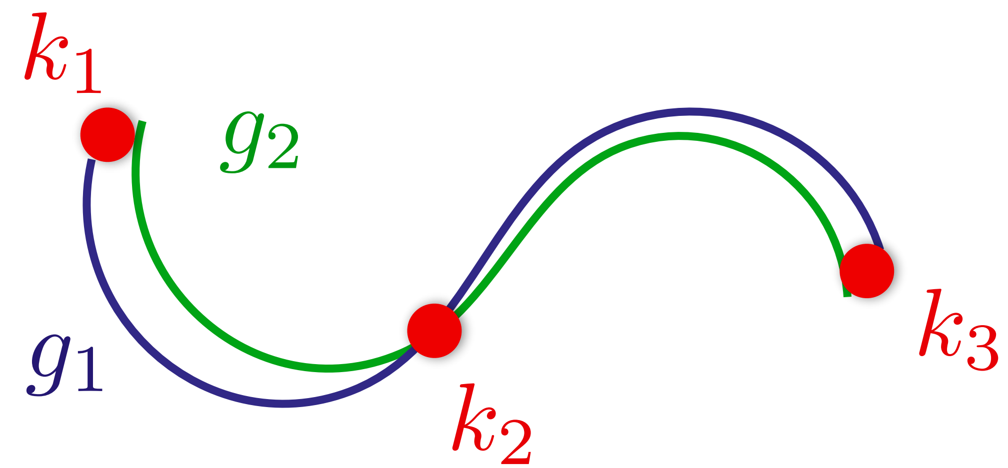
20 gestures

Total time: 0.33 secs

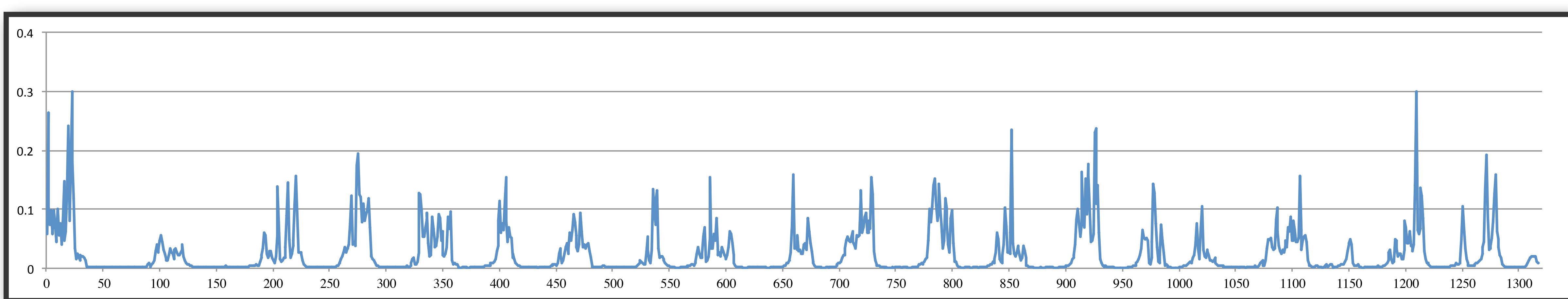
Limitations & Future work

✓ Execution speed not considered

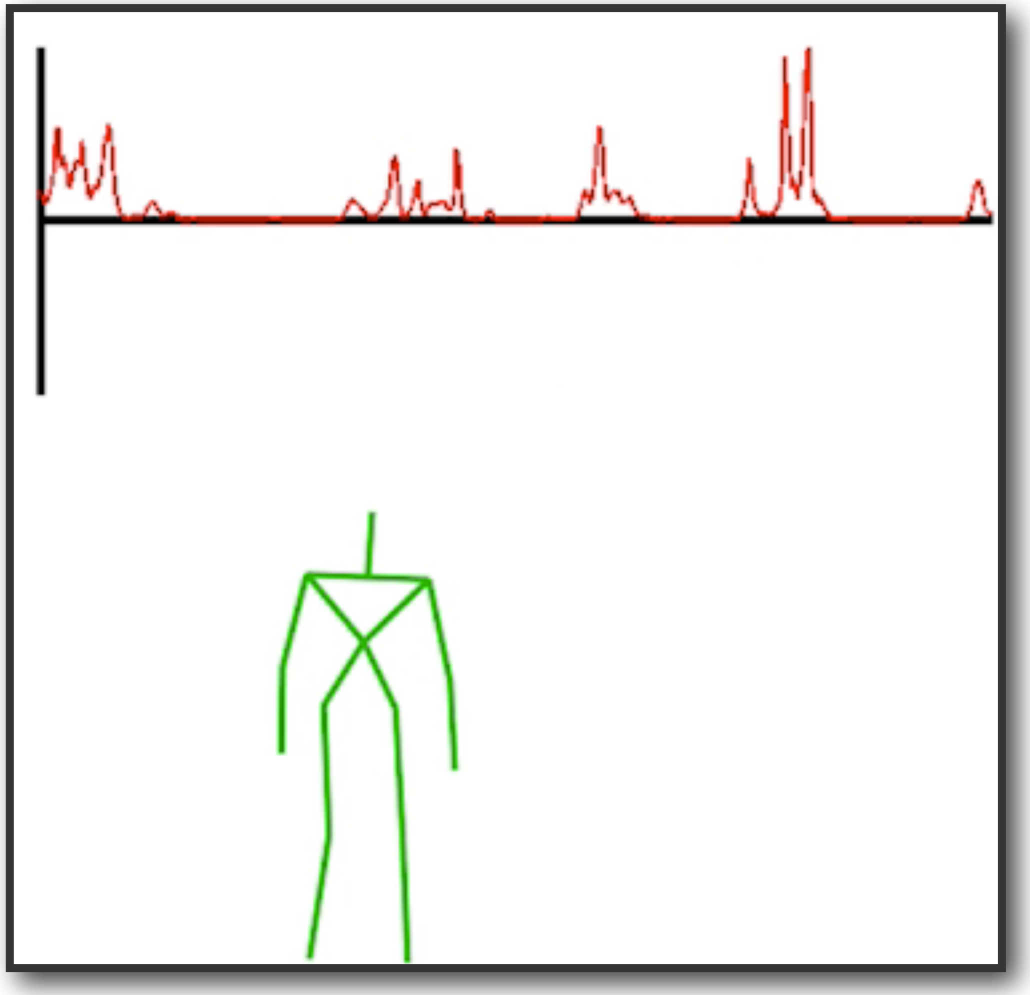
✓ Fixed threshold ϵ

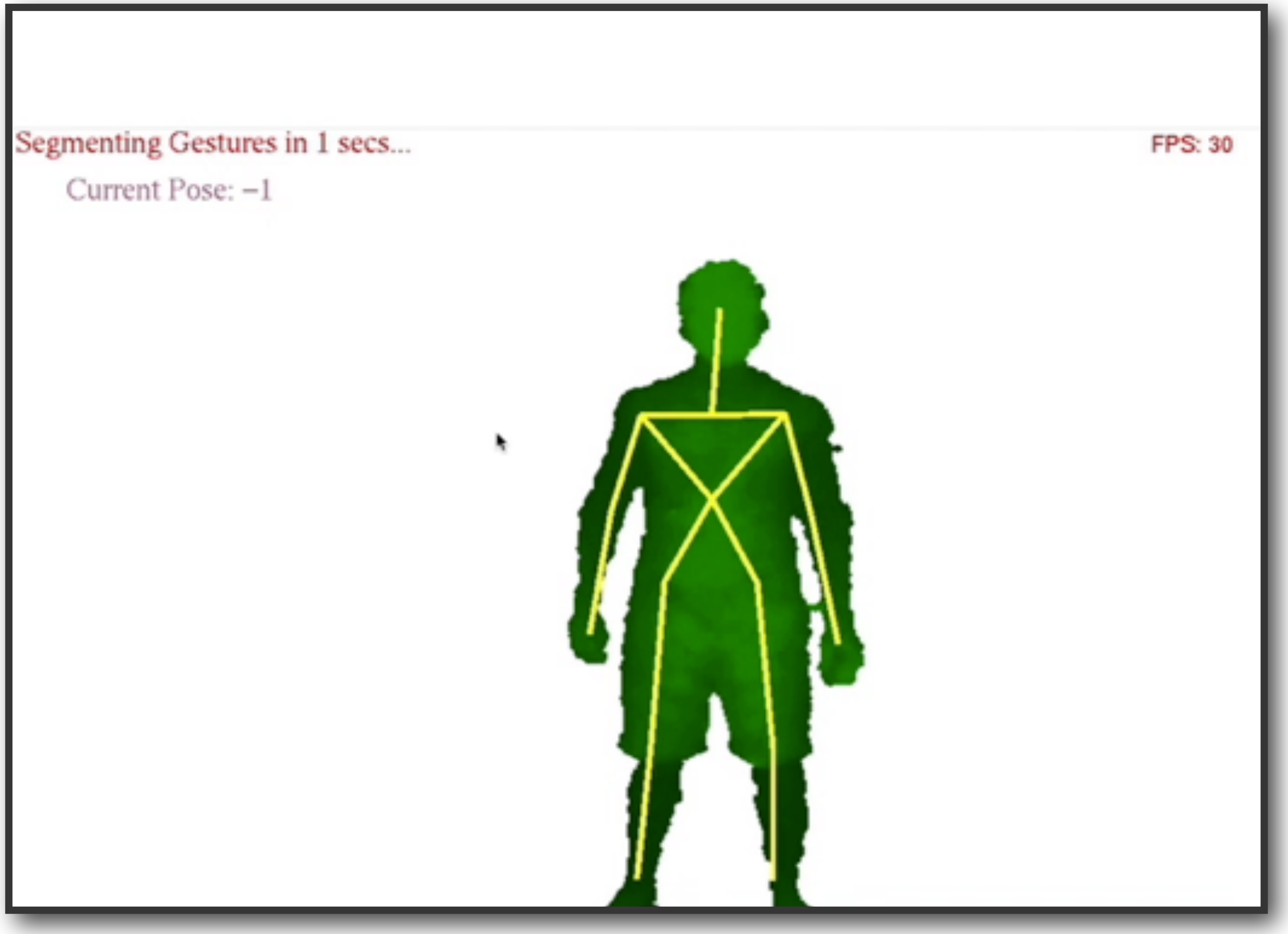


✓ Only the first curvature is used for segmentation



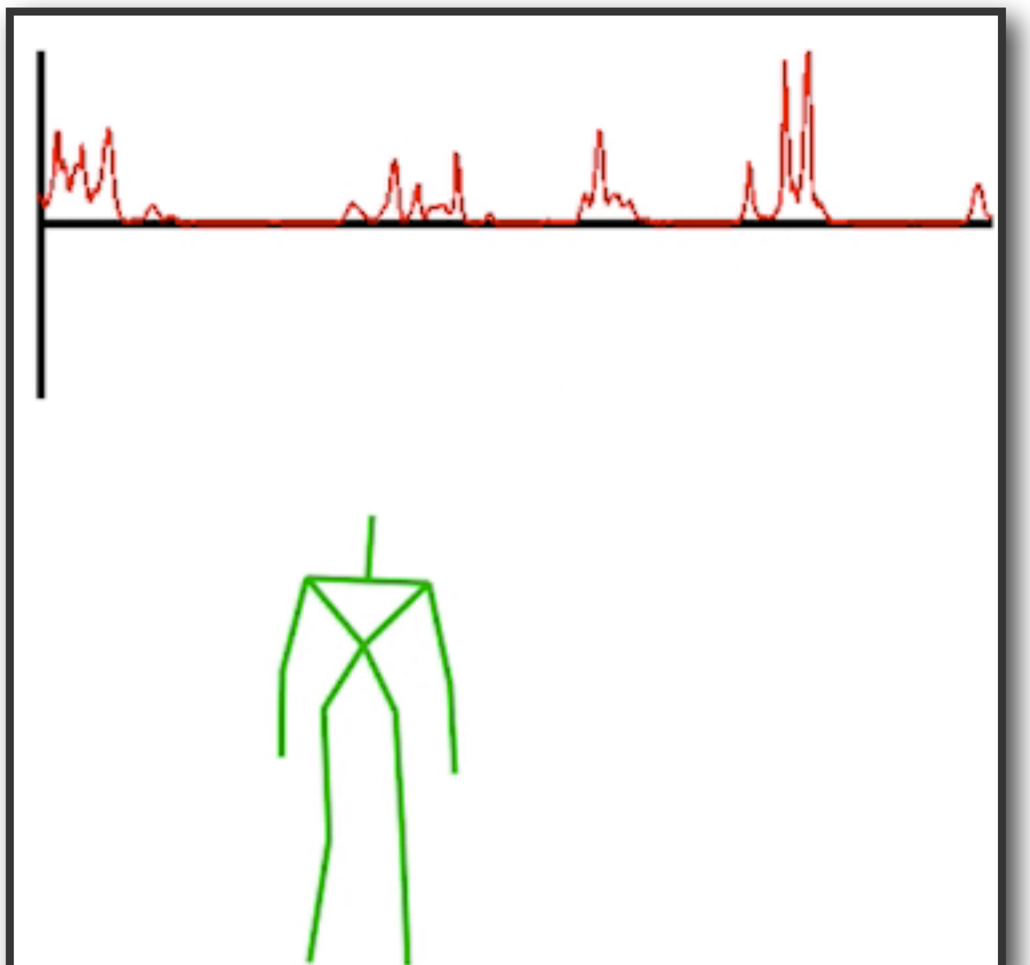
Thank you for your attention!

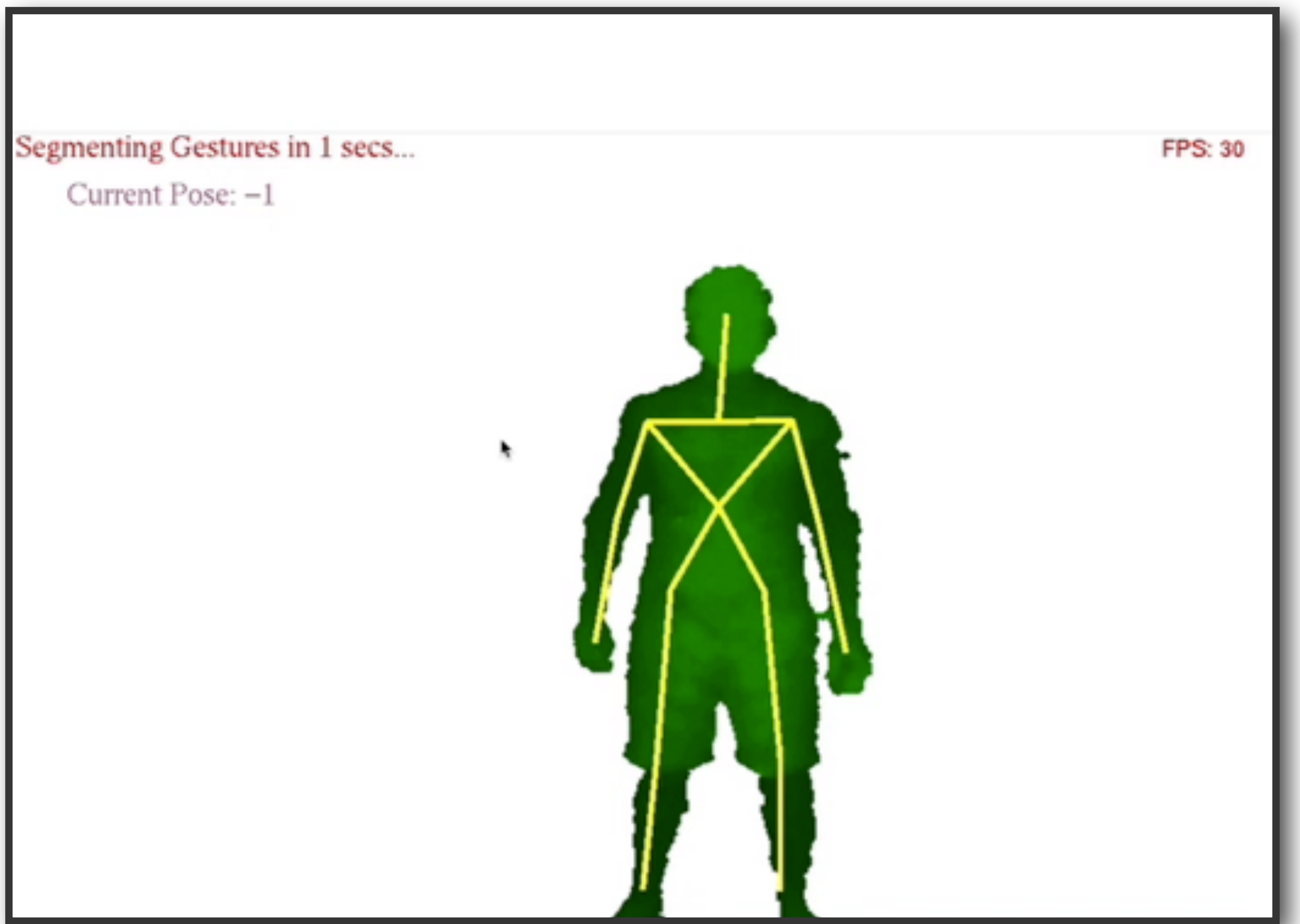




Questions?

Thank you for your attention!





Questions?