

3D Human Pose Search using Oriented Cylinders

Selen Pehlivan Pınar Duygulu

Department of Computer Engineering
Bilkent University

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Problem



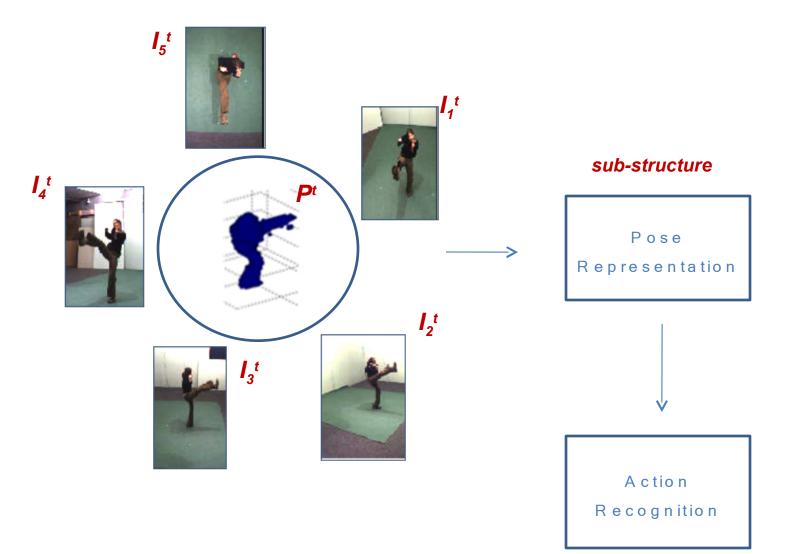
- Human action recognition
 - Applications
 - Surveillance, monitoring, HCI, games
- Multi-camera systems
 - Poses as volumes [Weinland et al. 06, Chen et al. 03, Cohen et al. 03, Huang et al. 05, Pierobon et al. 05, Lv et al. 07]

Human Poses



- Different than rigid body objects [Ankerst et al. 99, Kazhdan et al. 03, Johnson et al. 03]
- Articulated structure
- High number of potential configuration
- A compact representation





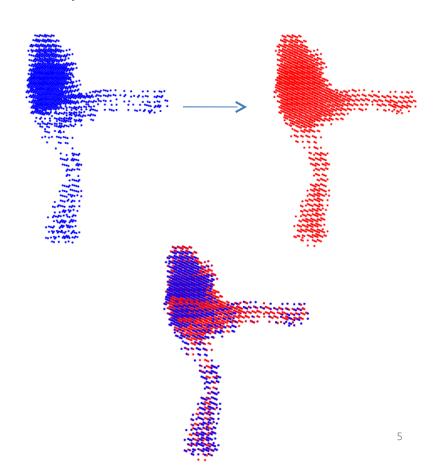
3D Poses Reconstruction

- Obtain a visual hull
- In the form of voxel grid
- Shape from silhouette technique
- EPVH [Franco and Boyer 03]



Enhancement

- Perform morphological closing
- Sphere







- body parts look like cylinders [Bilford 71 , Marr and Nishihara 78]
- varying
 - size
 - orientation

Approach



Step 1 Form Cylindrical Filters

Step 2 Search over 3D Pose

Step 3 Select High Response Regions

Step 4 Form Histograms

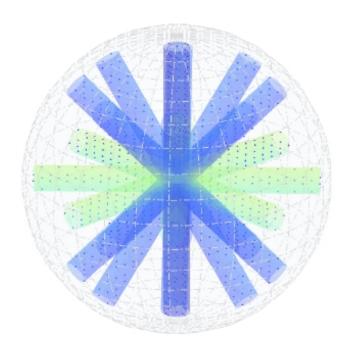
Pose Representation Step 1 Form Cylindrical Filters



- 3 D 0-1 Filters
- Filter set K per cylinder size
 - Cylinder [r x h]
 - Rotate α° apart around local axis
 - Let K be the filter set , the number of filters in K with α° apart:

$$|K| = 1 + (\frac{90}{\alpha} - 1)(\frac{360}{\alpha}) + (\frac{180}{\alpha})$$

3D filters are the grid located inside cylinders



Pose Representation Step 2 Search over 3D Pose

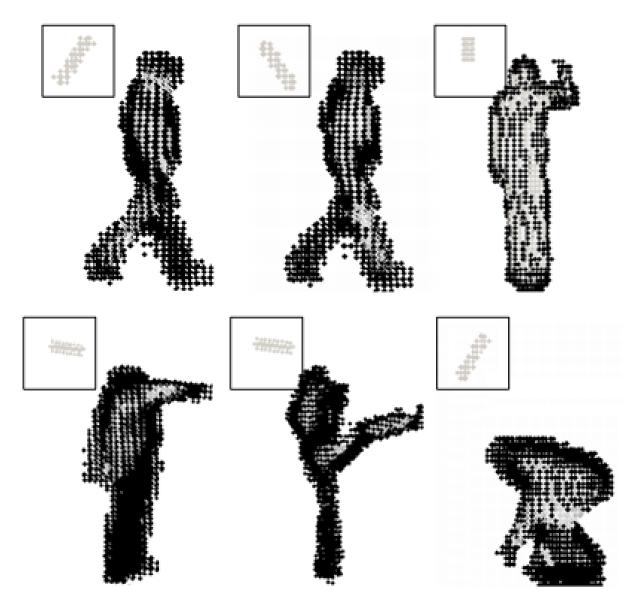


Convolve with 3D pose



Search Results





Pose Representation Step 3 Select High Response Regions

- High response regions
 - body parts with the same orientation

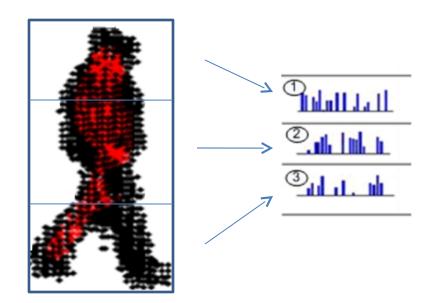
- Scale responses to the range of [0, 1]
- Select voxels with a score greater than a threshold



Pose Representation Step 4 Form Histograms



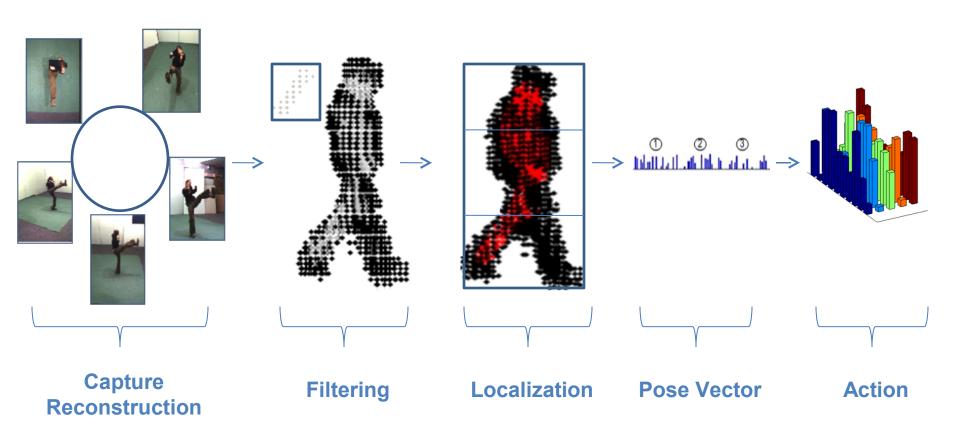
- Divide into N sub-volumes
- Form histograms of cylinders with a given size and orientation
- Then combine N histograms
- Normalize the feature vector



Pose Representation

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Distribution of Oriented Cylinders



Dataset



- IXMAS Dataset with 5 cameras [Weinland et al. 06]
- 5 actions
 - Walk
 - Wave
 - Kick
 - Punch
 - Pick up
- [64x64x64]











Pose Retrieval Method 1 NN-based Classification



[rxh]

[1x5]

[1x10]

[1x20]

α°
3 0

Т

0.8

N 3

Poses	Accuracy All	Accuracy [1 x5]	Accuracy [1x10]	Accuracy [1x20]
Walk	96.97	93.94	96.97	96.97
Wave	90.91	90.91	93.94	81.82
Punch	63.64	48.48	69.70	72.73
Kick	87.88	84.85	84.85	75.76
Pick	96.97	90.91	96.97	93.94

- Euclidean distance
- Leave one out

Pose Retrieval Method 2 SVM-based Classification



[1x5]

[1x10]

[1x20]

α°	
3 0	

T 0.8

N 3

Poses	Accuracy All	Accuracy [1 x5]	Accuracy [1x10]	Accuracy [1x20]
Walk	1 0 0	87.50	91.67	95.83
Wave	91.67	54.17	95.83	79.17
Punch	66.67	66.67	66.67	45.83
Kick	1 0 0	1 0 0	1 0 0	95.83
Pick	95.83	95.83	95.83	95.83

Multi-class SVM

RBF kernel

Training set: 3actors

Action Recognition

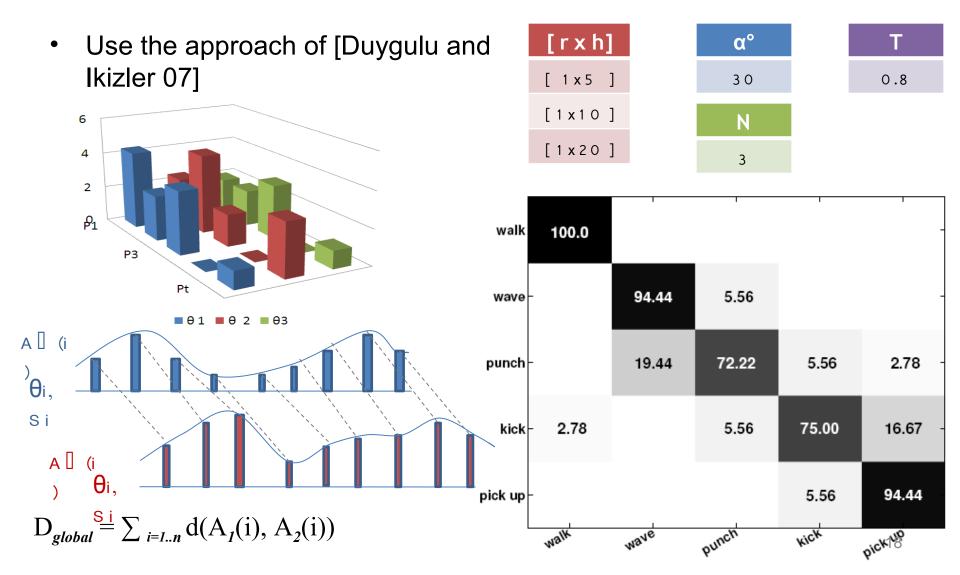


Method 1 Dynamic Time Warping[Rabiner et al. 93]

Method 2 Hidden Markov Model[Rabiner et al. 89]

Action Recognition Method 1 Dynamic Time Warping

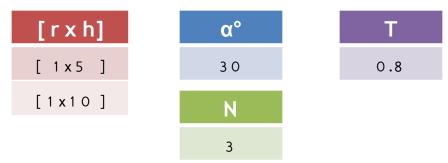


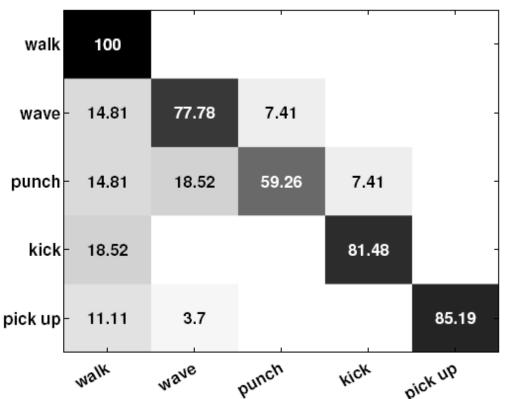


Action Recognition Method 2 Hidden Markov Model



- Cluster into 80 posewords
- 3 states





DTW vs. HMM



Poses	DTW All	DTW [1 x5][1x10]	HMM All	HMM [1x5][1x10]
Walk	97.22	1 0 0	1 0 0	1 0 0
Wave	94.44	94.44	77.78	62.96
Punch	69.44	72.22	59.26	70.37
Kick	66.67	7 5	81.48	62.96
Pick	91.67	94.44	85.19	74.07

Other Works

Weinland et al. 93.33%
Liu et al. 82.8%
Weinland et al. 81.27%
Lv et al. 80.6%
Yan et al. 78.0%

Conclusion & Discussion



- Samples are enough to handle viewpoint variations
- We can obtain better results with denser data
- We observe that cylinders with different lengths more robust than with different radiuses

Future work:

Experiments on

- more action categories
- different resolutions of volumes





