MODELING MUTUAL CONTEXT OF OBJECT AND HUMAN POSE



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HUMAN POSE ESTIMATION



HUMAN POSE ESTIMATION

Human-Object Interaction

Holistic image based classification



Detailed understanding and reasoning

Human pose estimation





OBJECT DETECTION



OBJECT DETECTION

Human-Object Interaction

Holistic image based classification



Detailed understanding and reasoning

- Human pose estimation
- · Object detection

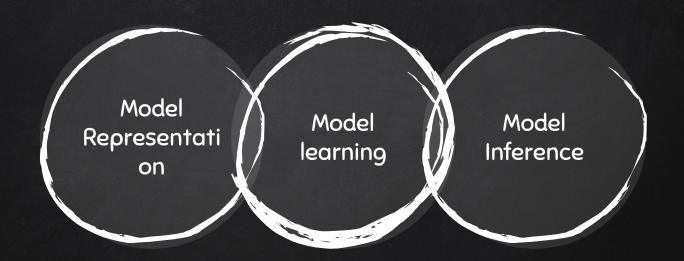




Mutual context of Object and human pose in HOI.

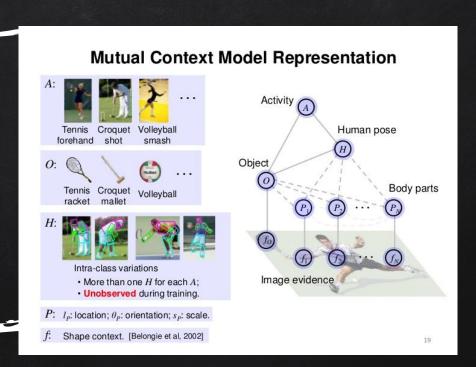


MUTUAL CONTEXT OF OBJECT AND HUMAN POSE





MUTUAL CONTEXT MODEL REPRESENTATION

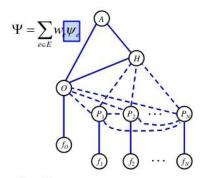






MODEL LEARNING

Model Learning



Approach:

Maximum likelihood

$$\psi_e(A,O) \quad \psi_e(A,H) \quad \psi_e(O,H)$$

$$\psi_e(H,P_n) \quad \psi_e(O,P_n) \quad \psi_e(P_m,P_n)$$

Standard AdaBoost

$$\psi_e(O, f_O) \ \psi_e(P_n, f_{P_n})$$

Goals:

Hidden human poses

Structural connectivity

Potential parameters

Potential weights



FEATURE
EXTRACTION
: EVIDENCE
RETRIEVAL

MODEL SENERATION

STRUCTURED LEARNING

TESTING
INTERFACE:
FIND
CLOSEST
MATCHING
MODEL



FEATURE EXTRACTION / EVIDENCE RETRIEVAL



FEATURE EXTRACTION / EVIDENCE RETRIEVAL

1).

TRAIN A DETECTOR USING SHAPE CONTEXT AS FEATURE DESCRIPTOR: AS SPECIFIED BY AUTHOR, USES CONCEPT OF ADAPTIVE BOOSTING.

FOR BOTH OBJECTS AND HUMAN BODY PARTS

2).

USING HOG AND SVM CLASSIFIER.

3).

Fast R-CNN: Fast Regionbased Convolutional Networks for object detection

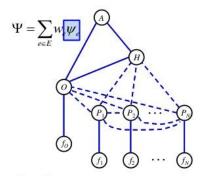


MODEL GENERATION: STRUCTURED LEARNING



MODEL GENERATION: STRUCTURED LEARNING MODEL USING MARKOV RANDOM FIELD

Model Learning



Goals:

Hidden human poses

Structural connectivity

Potential parameters

Potential weights

Approach:

Maximum likelihood

$$\psi_{\epsilon}(A,O) \quad \psi_{\epsilon}(A,H) \quad \psi_{\epsilon}(O,H)$$
 $\psi_{\epsilon}(H,P_n) \quad \psi_{\epsilon}(O,P_n) \quad \psi_{\epsilon}(P_m,P_n)$

Standard AdaBoost

$$\psi_e(O, f_O) \ \psi_e(P_n, f_{P_n})$$



MODEL GENERATION: STRUCTURED LEARNING

- 1). Co-occurrence context for the activity class, object, and human pose.
- 2). $\psi e(O,Pn)$ models the spatial relationship between the object O and the body part Pn, which is computed by $bin(IO IPn) \cdot bin(\theta O \theta Pn) \cdot \mathcal{N}(sO/sPn)$
- 3). $\psi e(Pm, Pn)$ models the spatial relationship between different body parts.
- 4). $\psi e(H, Pn)$ models the compatibility between the pose class H and a body part Pn.
- 5). $\psi e(O, fO)$ and $\psi e(Pn, fPn)$ model the dependence of the object and a body part with their corresponding image evidence. (as discussed in previous section).



MODEL GENERATION: STRUCTURED LEARNING

1). Hill-climbing structure learning:

Hill climbing with tabu list acts as structure space.

2). Max-margin parameter estimation:

Parameter estimation using maxmargin so as to ensure generalized learning. Analysis of our learning algorithm



TESTING INTERFACE: FIND CLOSEST MATCHING MODEL



Research Paper:

http://vision.stanford. edu/documents/YaoFei-Fei_CVPR2010b.pdf

DataSet:

Sports images. HOI referred are sports related poses.

DataSet details:

Cricket Cricket Croquet defensive shot bowling shot Tennis Tennis Volleyball forehand serve smash



Any questions?

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