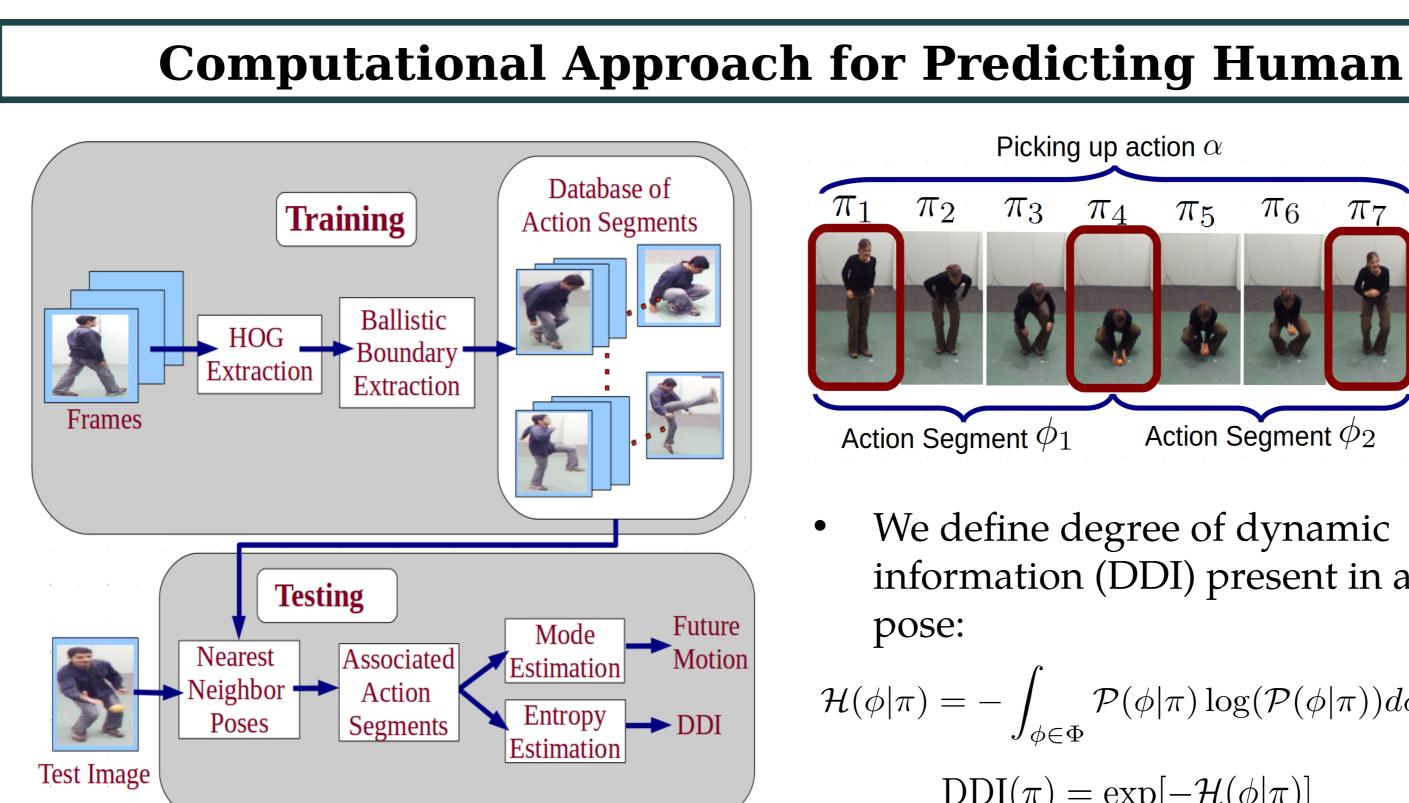
## **Predicting Dynamical Evolution of Human Activities from a Single Image**

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## **Motion Inference from** Human Pose

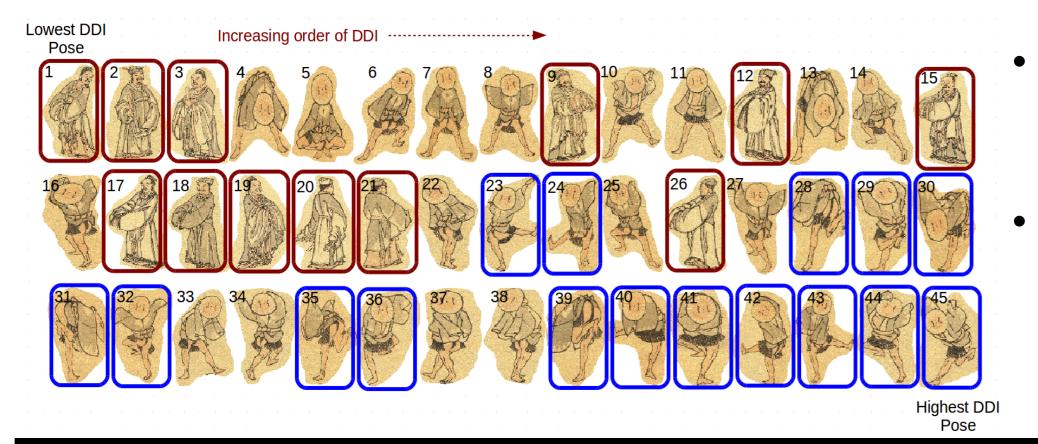
- Posture of a human body is an important indicator of ensuing motion e.g. the experiments of Hirai and Hiraki [1]
- Given a single pose, we use statistical inference on the Grassmannian to predict the future motion of a human computationally
- We quantify the extent to which future motion is constrained by a given pose
- We apply this approach to a variety of vision problems like human motion prediction and activity recognition

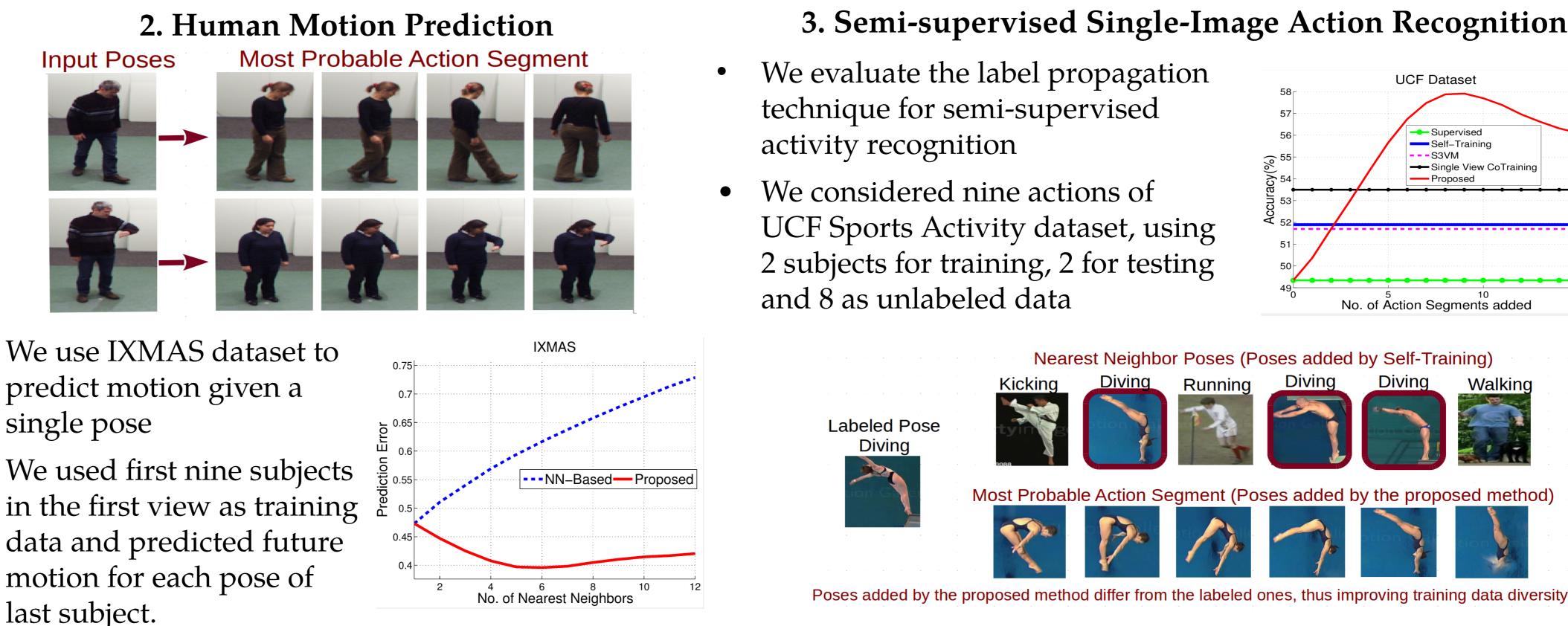




## **1.** Perceptual Evaluation on Manga Images

- We estimate the amount of motion information in the Hokusai Manga image database
- Osaka et al. [4] showed that the dancer images lacksquareactivated the motion sensitive regions of the visual cortex, while the priest images did not
- Our DDI metric shows very similar trends





[1] M. Hirai and K. Hiraki. The relative importance of spatial versus temporal structure in the perception of biological motion: An event-related potential study. Cognition, 99(1), 2006 [2] S. N. P. Vitaladevuni, V. Kellokumpu, and L. S. Davis. Action recognition using ballistic dynamics. In International Conference on Computer Vision and Pattern Recognition, 2008 [3] Y. Chikuse. Statistics on Special Manifolds. Springer-Verlag, 2003.

[4] N. Osaka, D. Matsuyoshi, T. Ikeda, and O. M. Implied motion because of instability in Hokusai Manga activates the human motion-sensitive extrastriate visual cortex: an FMRI study of the impact of visual art. Neuroreport, 21(4), 2010.

## **Computational Approach for Predicting Human Activity from a Single Image**

information (DDI) present in a

$$\mathcal{H}(\phi|\pi) = -\int_{\phi\in\Phi} \mathcal{P}(\phi|\pi)\log(\mathcal{P}(\phi|\pi))d\phi$$
$$\mathrm{DDI}(\pi) = \exp[-\mathcal{H}(\phi|\pi)]$$

## **Applications and Experimental Results**



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## **Estimating the conditional distribution**

- Modeling action segments using LDS  $z_{\phi}(t+1) = A_{\phi} z_{\phi}(t) + v_{\phi}(t), v_{\phi}(t) \sim N(0, \Xi)$  $y_{\phi}(t) = C_{\phi} z_{\phi}(t) + w_{\phi}(t), w_{\phi}(t) \sim N(0, \Theta)$  $\Omega_{\phi}^{\top} = \left[ C_{\phi}^{\top}, (C_{\phi}A_{\phi})^{\top}, \dots, (C_{\phi}A_{\phi}^{m-1})^{\top}, \dots \right]$  $\zeta^2(\Omega_i, \Omega_j) = p - tr(\Omega_j^T \Omega_i \Omega_i^T \Omega_j)$
- Density estimation on the Grassmannian [3]

$$\hat{\mathcal{P}}(\phi|\pi_s) = c_1 \sum_{\phi_i \in \mathcal{N}_{\phi(\pi_s)}} \Psi(M^{-\frac{1}{2}}(I_d - \Omega_i^\top \Omega \Omega^\top \Omega_i)M^{-\frac{1}{2}})$$

Statistical inference on the estimated density

 $\hat{\phi}(\pi_s) = \arg \max \hat{\mathcal{P}}(\phi_i | \pi_s)$  $\phi_i \in \mathcal{N}_{\phi(\pi_s)}$ 

### 3. Semi-supervised Single-Image Action Recognition

We evaluate the label propagation UCF Dataset Supervised Self-Training -S3VM ---- Single View CoTraining Proposed UCF Sports Activity dataset, using 2 subjects for training, 2 for testing No. of Action Segments added Nearest Neighbor Poses (Poses added by Self-Training) Diving Diving Diving Running Most Probable Action Segment (Poses added by the proposed method)