Cross-view Activity Recognition using Hankelets

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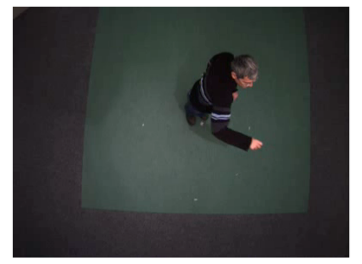
Abstract

*We introduce a new feature for cross-view activity recognition: the "**Hankelet**". This type of feature captures dynamic properties of short tracklets that are invariant to viewpoint changes and time shifts. Experiments using Hankelets on the IXMAS database show a **20% improvement** over the state of the art.*

GOAL

To recognize an activity from a different viewpoint than the one used for training.



Testing Data

EXISTING APPROACHES

- Geometric constraints [32]
- Track body joints [21,22]
- 3D Models [8,15,30,31]
- Quasi-invariant geometric features [10,11]
- **Transfer features across views [7,16]** (75.3% accuracy on IXMAS)

Best performance is far below the state of art performance for single view activity recognition.

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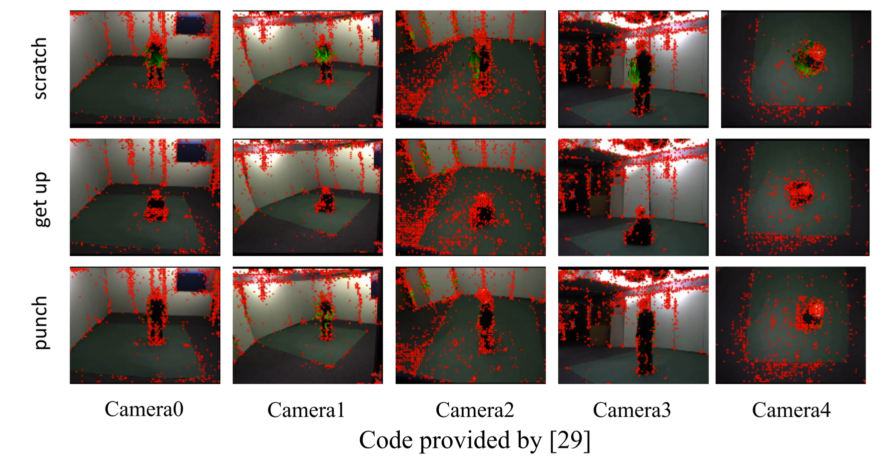
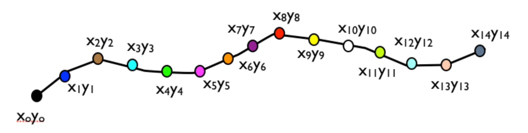
HANKELETS

A Dynamics-based Feature: Hankelet

Tracklets Detection (shown in green)



Detected Tracklet

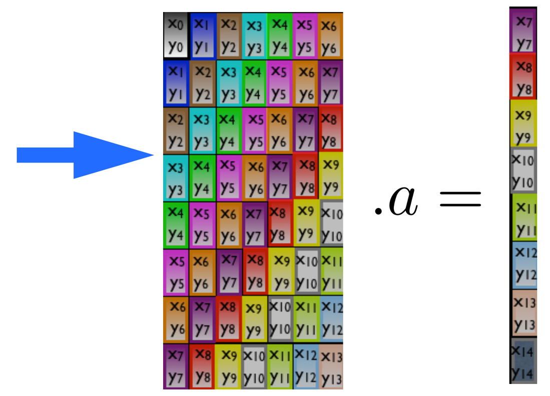


$$\mathbf{p}_k = \begin{bmatrix} x_k \\ y_k \end{bmatrix} = \mathbf{C}\mathbf{X}_k$$

$$\mathbf{X}_k = \mathbf{A}\mathbf{X}_{k-1} \quad \mathbf{X}_o \text{ given}$$

$$\sum_{i=1}^{rank(H)} a_i \begin{bmatrix} x_{k-i} \\ y_{k-i} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix}$$

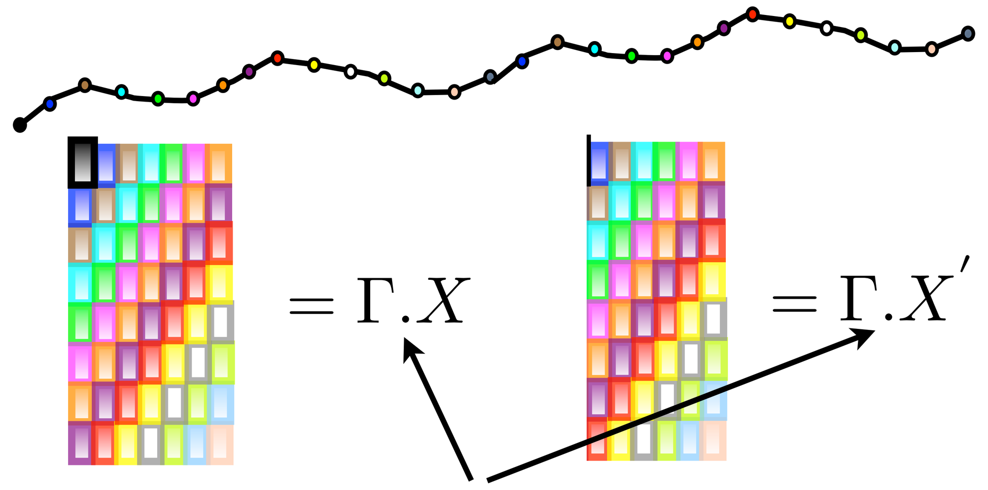
n^th order regressor



Hankelet

$$\hat{\mathbf{H}} = \frac{\mathbf{H}}{\|\mathbf{H}\mathbf{H}^T\|_F^{1/2}}$$

Hankelets: Initial Frame Invariance



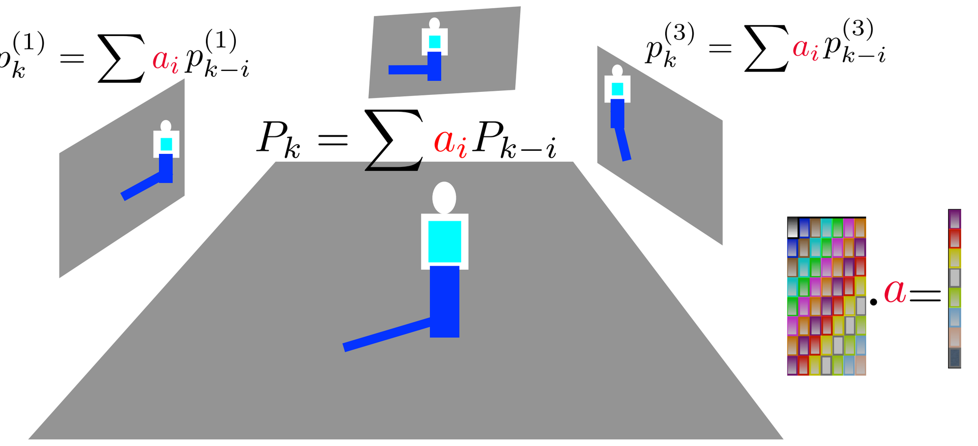
$$= \Gamma.X \qquad = \Gamma.X'$$

The columns of the Hankelets span the same space, regardless of the initial frame.

$$\mathbf{\Gamma} = \begin{bmatrix} \mathbf{C}^T & \ldots & (\mathbf{C}\mathbf{A}^m)^T \end{bmatrix}^T$$

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}_o & \ldots & \mathbf{X}_m \end{bmatrix}^T$$

Hankelets: Viewpoint invariance



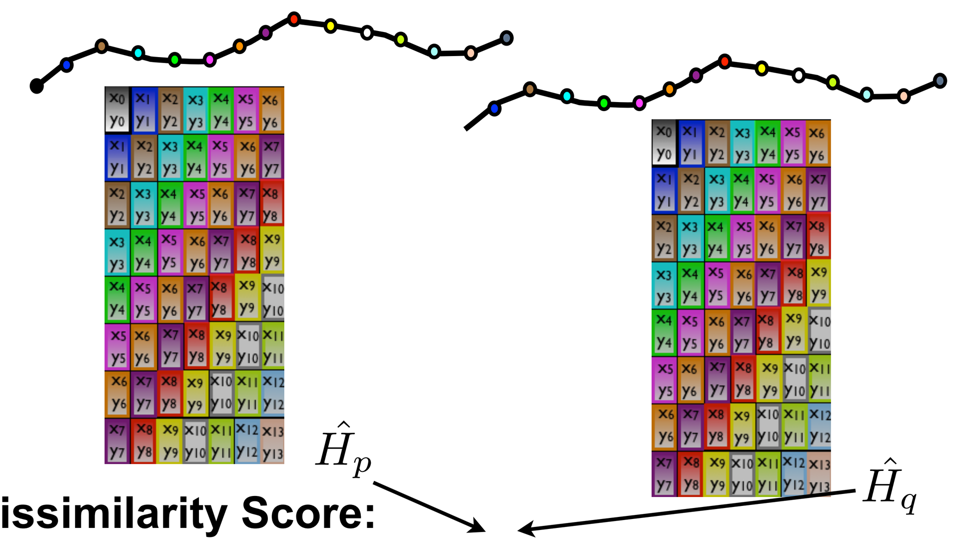
$$p_k^{(1)} = \sum a_i p_{k-i}^{(1)} \qquad p_k^{(2)} = \sum a_i p_{k-i}^{(2)} \qquad p_k^{(3)} = \sum a_i p_{k-i}^{(3)}$$

$$P_k = \sum a_i P_{k-i}$$

Regressor is invariant to affine transformations

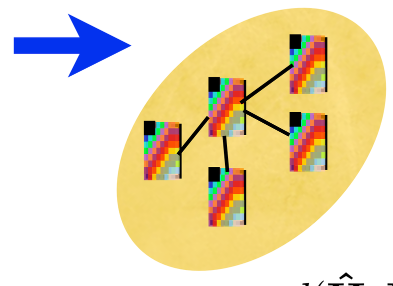
$$p_k^{(j)} = \Pi_j P_k = \Pi_j \sum a_i P_{k-i} = \sum a_i \Pi_j P_{k-i} = \sum a_i p_{k-i}^{(j)}$$

Hankelet Codebook: Clustering



Dissimilarity Score:

$$d(\hat{\mathbf{H}}_p \hat{\mathbf{H}}_q) = 2 - \|\hat{\mathbf{H}}_p \hat{\mathbf{H}}_p^T + \hat{\mathbf{H}}_q \hat{\mathbf{H}}_q^T\|_F$$



$$\hat{\mathbf{H}}_p = \mathbf{U}_p \mathbf{\Sigma}_p \mathbf{V}_p^T$$

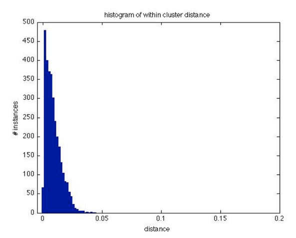
$$\hat{\mathbf{H}}_q = \mathbf{U}_q \mathbf{\Sigma}_q \mathbf{V}_q^T$$

$$\mathbf{\Theta}_{pq} = (\mathbf{U}_p \mathbf{\Sigma}_p)^T (\mathbf{U}_q \mathbf{\Sigma}_q)$$

$$d(\hat{\mathbf{H}}_p \hat{\mathbf{H}}_q) = 2 - \sqrt{2 + 2\|\mathbf{\Theta}_{pq}\|_F^2}$$

- Captures "alignment" between the column spaces.
- Robust to noisy measurements.
- Computationally efficient.
- Dissimilarity within cluster follows a Gamma pdf:

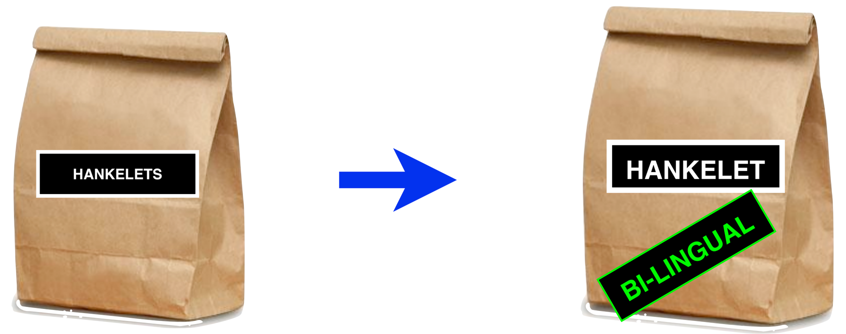
$$p(d|w) = \begin{cases} \frac{a^b d^{b-1}}{(b-1)!} e^{-ad} & \text{for } d > 0 \\ 0 & \text{otherwise} \end{cases}$$

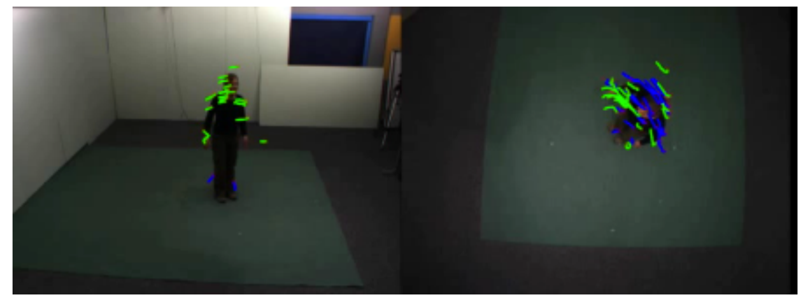


BAGS of HANKELETS

While Hankelets carry viewpoint invariance, they are not immune to self-occlusions and limited field of view.

Improving Cross-view Performance: Bag of BI-LINGUAL Hankelets





Bi-lingual tracklets marked in green

Bi-lingual Hankelets: subset visible from different viewpoints

Experimental Results

Single View: KTH Dataset

Algorithm	*Perf*
Ours	95.89
Cao et al. [3]	95.02
Wang et al.[29]	94.2
Le et al. [13]	93.9
Li et al [14]	93.6

Act Type	Acc
Boxing	95.71
HClapping	95.48
HWaving	99.09
Walking	99.52
Running	91.52
Jogging	94.05

Cross-View: IXMAS Dataset

Train classifier with data from one viewpoint, test with data from a different one

	Cam 0		Cam 1		Cam 2		Cam 3		Cam 4	
	BoHks	cuboids	BoHks	cuboids	BoHks	cuboids	BoHks	cuboids	BoHks	cuboids
Cam 0			83.70	14.40	59.20	10.69	57.37	10.61	33.62	19.09
Cam 1	84.27	16.12			61.58	11.11	62.75	7.41	26.93	9.22
Cam 2	62.52	10.27	65.17	65.17			71.96	12.90	60.14	8.08
Cam 3	57.05	11.15	61.45	61.45	71.04	9.98			31.24	9.30
Cam 4	39.60	8.80	32.84	32.84	68.12	9.22	37.36	10.06		

Algorithm	*Perf.*
Ours	56.4%
cuboids [16]	10.9%

More than 400% accuracy improvement

Cross-View: IXMAS Dataset

Comparing against state-of-the-art cross-view techniques

Algorithm	*Perf*
Ours	90.57%
Liu et al. [16]	75.3%
Farhadi et al. [7]	58.1%
Junejo et al. [10]	59.5%
Farhadi et al. [6]	74.4%

Over 20% improvement

*See Table 5 in paper for detailed comparisons