



DISCRIMINATIVE SALIENCY-POSE-ATTENTION COVARIANCE FOR ACTION RECOGNITION



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MOTIVATION

Most covariance-based representations of actions are focused on statistical features of poses by empirical averaging weighting. Note that the poses have a variety of saliency levels for different actions. Neglecting pose saliency could make the covariance-based feature representations inaccurate and further degrade the performance of recognition tasks.

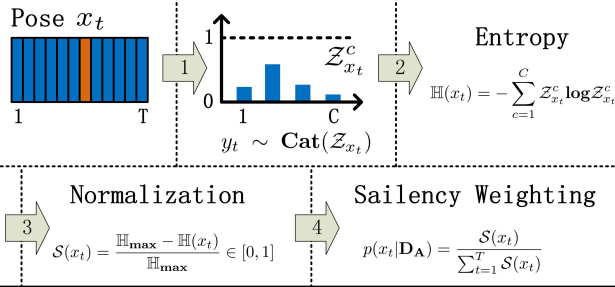
PROPOSED METHOD

In this paper, we propose a novel saliency weighting covariance feature representation, Saliency-Pose-Attention Covariance (SPA-Cov), which reduces the negative effects from the ambiguous pose samples. Specifically, we utilize a discriminative approach to derive probability distribution of action categories for each pose, which is modeled by the uncertainty of information entropy to obtain the salient weighting.

Empirical Covariance (Empirical-Cov)

$$\Sigma_{D_A} = \frac{1}{T} \sum_{t=1}^T \mathcal{F}(x_t - \mu)$$

Calculating Saliency Weighting



Saliency-Pose-Attention Covariance (SPA-Cov)

$$\Sigma_{D_A}^S = \int_{x_t} p(x_t | D_A) \mathcal{F}(x_t - \mu_S) dx_t$$

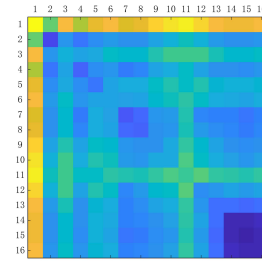
SINGULARITY ISSUE

Posterior Distribution $p(\Sigma_{D_A} | D_A, \mu_A) \propto \text{Prior} \times \text{Likelihood} = \mathcal{IW}(\Sigma_{D_A} | S_T^{-1}, \gamma_T)$

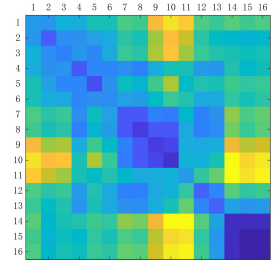
✓ Prior Regularization $\hat{\Sigma}_{D_A} = \pi \Sigma_0 + (1 - \pi) \Sigma_{D_A}$ ✗ Scaled Regularization $\hat{\Sigma}_{D_A} = \Sigma_{D_A} + \sigma \mathbf{I}$

VISUALIZATION COMPARISON

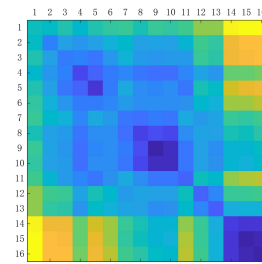
The average distances between 16 action categories in MSR-DailyActivity3D(S2) database.



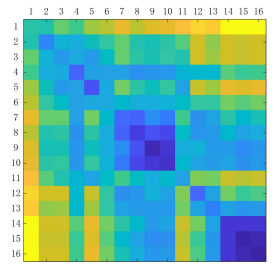
(A) Empirical-Cov



(B) Kernel Matrix (RBF)



(C) Kernelized-Cov



(D) SPA-Cov

RESULTS

Recognition accuracy (%) on MSR-Action3D (S1), MSR-DailyActivity3D (S2), MSRC-Kinect12 (S3). The sign of '-/-' means that no results are reported in the paper.

Methods/Databases	S1	S2	S3
Pose Set	90.0	-/-	-/-
Moving Pose	91.7	73.8	-/-
Empirical-Cov	74.0	85.0	89.2
Infinite-Cov	80.4	75.0	89.2
Temporal-Cov	90.5	93.5	91.7
Kernel-RBF	96.2	96.3	92.3
Kernel-POL	96.9	96.9	90.5
Kernelized-Cov	96.2	96.3	95.0
Proposed Posterior-Cov	96.2	96.3	89.5
Proposed SPA-Cov	96.2	97.5	90.5
Proposed Posterior-SPA-Cov	96.9	97.5	91.5

FUTURE WORK

We will explore more efficient methods to mine the saliency poses and extend it to much more cases, e.g. non-linear kernels, spatio-temporal representations, etc.