Charles Sturt University

MULTI-MODAL SPATIO-TEMPORAL PYRAMID MATCHING FOR 3D HUMAN ACTION RECOGNITION

Bin Liang (bliang@csu.edu.au)



Registration Australian Workshop on Video/Image Coding, Processing, and Understanding VICPU-2015

School of Computing and Mathematics, Charles Sturt University, Australia

Motivations

- Complex human actions may have several temporal stages. In each stage, the temporal structural information is crucial to model complex actions.
- 3D locations of action motion encode strong discriminative information. Representing the 3D spatial information is quite challenging.
- A single modality is usually insufficient to solve the problem of recognizing human actions.



- Each depth frame is projected onto three orthogonal Cartesian planes.
- The projected sequence is partitioned into multi-scale sub-volumes.
- A depth sequence is represented by PMHT in multiple temporal scales. **Depth Feature Extraction and Sparse Coding**
- Only appearance-based features (HOG and SIFT) are used.

Sparse Coding:

$$\{\mathbf{A}_{v}, \mathbf{D}_{v}\} = \underset{\mathbf{A}_{v}, \mathbf{D}_{v}}{\operatorname{argmin}} \left\{ \sum_{i=1}^{n_{v}} \|\mathbf{x}_{i}^{v} - \mathbf{D}_{v} \alpha_{i}^{v}\|_{2}^{2} + \lambda \|\alpha_{i}^{v}\|_{1} \right\}$$
s.t.
$$\|\mathbf{d}_{j}^{v}\|_{2} \leq 1, \quad \text{for } \forall j = 1, \dots, p_{v}$$

Spatio-Temporal Pyramid Cuboid Representation



Cuboid fusion combines the spatial-dependent sparse codes from the corresponding grids on three planes to construct the cuboid representation (| Jenotes vector concatenation).



 ς

The temporal information is well kept by temporal segments.

Skeleton Features

TPM is not sensitive to the temporal shift or misalignment since lower level of the pyramid keeps less temporal information.

Multi-Modal Fusion

- **Representation-level Fusion**: the representations generated from two modalities are concatenated together to form a final representation as the input to the classifier.
- **Classifier-level Fusion**: the classifiers for two modalities are trained separately and classifier combination is performed subsequently to generate the final result.
 - Arithmetic Mean (AM), Geometric Mean (GM)
 - Logistic Regression (LR): learn weights for the combination.

Experimental Results

2014 Chalearn Multi-Modal Dataset

MSR Action 3D Dataset

Method	Modality	Accuracy
Bag of 3D points [23]	depth	74.70
HOJ3D [46]	skeleton	78.97
Eigenjoints [48]	skeleton	82.33
STOP [39]	depth	84.80
ROP [40]	depth	86.20
Actionlet Ensemble [42]	depth + skeleton	88.20
HON4D [34]	depth	88.89
DSTIP [44]	depth	89.30
3DMTM-PHOG [25]	depth	90.70
DMM-HOG [50]	depth	91.70
SNV + joint trajectories [49]	depth + skeleton	93.09
STPCM (normal fusion)	depth	92.45
STPCM (cuboid fusion)	depth	94.26
TPM	skeleton	87.61
STPCM + TPM	depth + skeleton	96.68

Method	Modality	Accuracy
2DMTM [24]	depth	76.99
Multi-modality Recognition [10]	RGB+depth+skeleton	90.30
Skeleton + 2DMTM [24]	skeleton + depth	92.80
STPCM (normal fusion)	depth	81.85
STPCM (cuboid fusion)	depth	86.56
TPM	skeleton	89.14
STPCM + TPM	depth + skeleton	93.67

MSR Action Pairs Dataset

Method	Modality	Accuracy
Actionlet Ensemble [42]	depth + skeleton	63.33
DMM-HOG [50]	depth	66.11
Actionlet Ensemble + Pyramid [42]	depth + skeleton	82.22
HON4D [34]	depth	96.67
SNV [49]	depth + skeleton	98.89
STPCM (normal fusion)	depth	88.57
STPCM (cuboid fusion)	depth	91.43
TPM	skeleton	85.71
STPCM + TPM	depth + skeleton	98.29



Evaluation of various multi-modal fusion schemes