UNSUPERVISED SPATIO-TEMPORAL FEATURE LEARNING FOR TACTILE DATA

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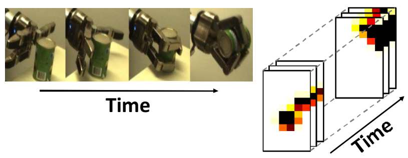
KEYWORDS: TACTILE, UNSUPERVISED FEATURE LEARNING, DEEP LEARNING, TEMPORAL SIGNAL, GRASP STABILITY, OBJECT RECOGNITION

Series of Tactile Data

- create a sequence of matrices over time
- reflects object and grasp properties
- is useful for a number of applications



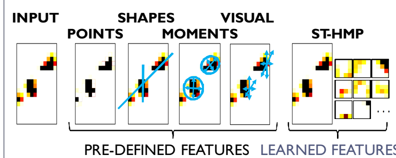
Flexible Representation

How to design a general and flexiable representation that is useful for various applications and data types?

Contribution

A new descriptor ST-HMP for unsupervised feature learning for time series of tactile measurements

ST-HMP vs. Previous Work



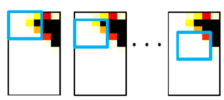
- Pre-defined: can be irrelevant, inflexible
- ST-HMP: learns from raw input, no need to specify characteristics a priori

Spatio-Temporal Hierarchical Matching Pursuit (ST-HMP)

STEP 1: SIGNAL REPRESENTATION

- Sampling patches using a sliding window

OBSERVED SIGNAL Y



- ST-HMP represents a signal as sparse linear combination of codewords

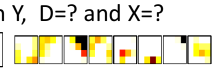
$$Y = D\,X$$

OBSERVED SIGNAL = OVERCOMPLETE DICTIONARY · SPARSE CODES

STEP 2: CODEBOOK LEARNING

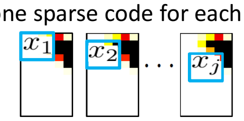
- Problem: given Y, D=? and X=?

DICTIONARY D



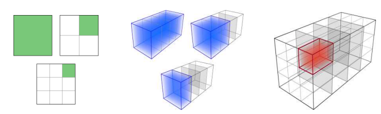
SPARSE CODES X $[x_1, \cdots, x_n, \cdots, x_N]$

- Underdetermined system of equations is solved by minimizing the error using K-SVD $\min_{D,X} \|Y - DX\|_F^2$
- Result: one sparse code for each patch



STEP 3: CODE AGGREGATION

- Sparse codes are max-pooled in space & time in cells of an increasing size

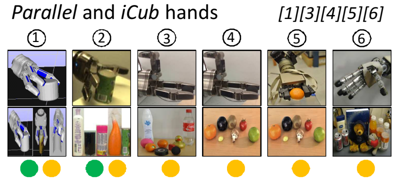


- Feature vector = concatenated aggregation results for each cell

Experimental Evaluation

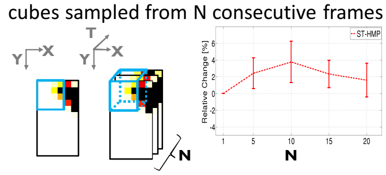
Databases

- Applications: grasp stability assessment, object recognition
- Six databases: *Schunk Dexterous*, *Schunk Parallel* and *iCub* hands [1][3][4][5][6]



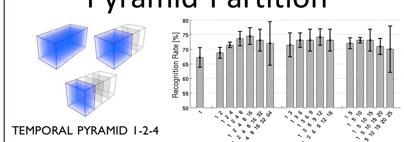
ST-Dictionary

- Dictionary learned for 3D spatio-temporal cubes sampled from N consecutive frames



- Improves until information captured by the ST-dic and ST-pyramid is redundant

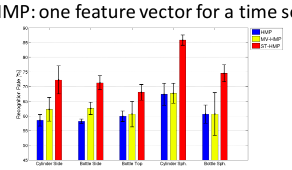
Pyramid Partition



- Using multiple levels significantly improves recognition rate
- Allows to adapt to processes of different temporal resolution

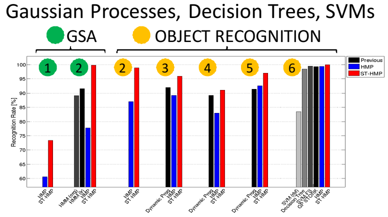
Encoding ST Information

- HMP: computed for every frame (only spatial)
- MV-HMP: majority voting over HMP results (temporal information weakly captured)
- ST-HMP: one feature vector for a time series



ST-HMP vs. Previous Work

- Comparison with HMMs, Dynamic Prog. Gaussian Processes, Decision Trees, SVMs



Conclusions

Extensive evaluation showed that ST-HMP:

- **outperforms by a large margin**
  - methods ignoring temporal component
  - state of the art: HMMs, DP, GP, DT, SVMs
- **is a universal descriptor** that can be successfully applied to:
  - different applications
  - data collected using different robot hands and objects

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