Feature Fusion in Machine Learning Problems

Huan Song[†], Jayaraman J. Thiagarajan[‡], Karthikeyan N. Ramamurthy[*], Andreas Spanias[†], Pavan Turaga[†]

[†] SenSIP Center, School of Electrical, Computer and Energy Engineering, ASU

[‡] Lawrence Livermore National Labs, [*] IBM T.J. Watson Research Center

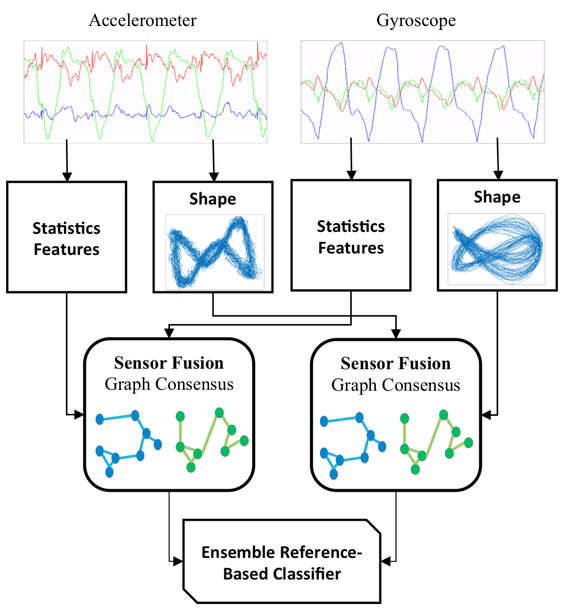
Abstract

- In machine learning problems, different types of feature could characterize different aspects of data.
- Effective fusion of different features could handle data noise, combine complementary information and improve recognition performance.

Feature fusion on mobile phone sensors for activity recognition

Problem statement:

- Data from mobile phone sensors is noisy and not very reliable. Building systematic fusion could make predictor robust to measurement inaccuracies and boost its classification.
- Since the goal is to perform recognition on mobile devices, it is prohibitive to employ complex feature engineering and learning techniques.



Data acquisition:

- 32 subjects with diversities in gender, age, weight and height.
- Activities include walking, running and biking with different speeds.

Consensus graph for sensor fusion:

$$\min_{\mathbf{U}} \underbrace{\sum_{t=1}^{T} \mathrm{Tr}(\mathbf{U}^T\mathbf{X}_t\mathbf{L}_t\mathbf{X}_t^T\mathbf{U})}_{\text{Local discriminative embedding}} - \alpha \underbrace{\sum_{t=1}^{T} \mathrm{Tr}(\mathbf{U}\mathbf{U}^T\mathbf{U}_t\mathbf{U}_t^T)}_{\text{Geometric mean of individual projections}}$$

$$\text{s.t.} \quad \sum_{t=1}^{T} \mathrm{Tr}(\mathbf{U}^T\mathbf{X}_t\mathbf{L}_t'\mathbf{X}_t^T\mathbf{U}) = c, \mathbf{U}^T\mathbf{U} = \mathbf{I}$$

Ensemble classification for feature fusion:

1) Build reference set based on K closest samples (30) from each class. Form the similarity $\{\boldsymbol{s}_f'\}_{f=1}^{F}$.
2) Similarity to class c as $(\boldsymbol{s}_f')^c$. Assign the label of the class having largest S^c value

$$S^c = \sum_f \sum_n (\mathbf{s}_f')^c.$$

Feature extraction:

- Statistical feature:

Mean, STD, auto-regresstive coefficients, etc.

- Shape feature from Time Delay Embedding (TDE):

TDE represents the periodic structure of the signal. Use simple histogram of pair-wise distance.

Experimental results and comparison to using different sensor/feature combinations

Sensor	Feature	Recognition Rate
Accelerometer	Shape (LDE)	57.8
Gyroscope	Shape (LDE)	51.66
Shape (Consensus)		68.73
Accelerometer	Stats (LDE)	70.05
Gyroscope	Stats (LDE)	69.95
Stats (Consensus)		73.2
Two Stage Approach		**80.14**

Feature fusion using kernel-based auto-context modelling

Problem statement:

- In visual recognition systems, low-level features such as shape and color are often employed. However high-level features, referred to as **context**, is crucial in image understanding.
- Adaptive fusion of low-level feature and context feature could improve the recognition performance.

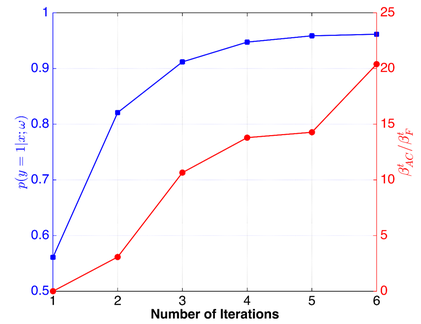


Illustration of the convergence behavior of proposed algorithm. As algorithm iterates, better approximation of the conditional probabilities is obtained and auto-context kernel becomes increasingly important.

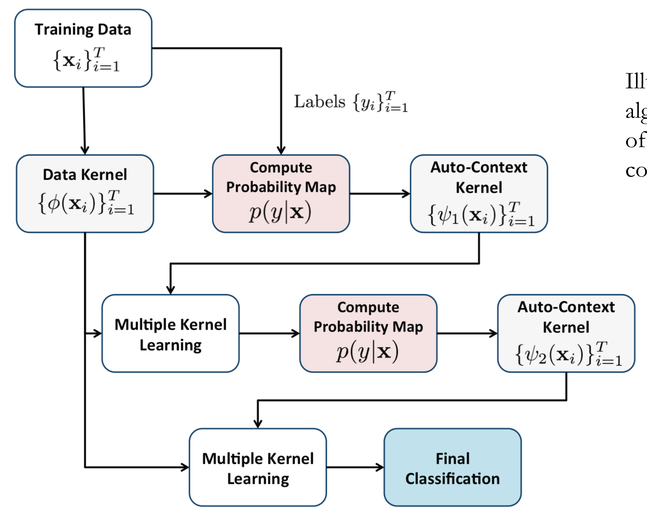


Image feature kernel: RBF kernel for the bag-of-words descriptors extracted on SIFT and Hue-histogram

Auto-context kernel: RBF kernel for the conditional probabilities $p(y|\boldsymbol{x})$ estimated from kernel SVM

Multiple Kernel Learning:

Denote RKHS corresponding to image features and auto-context by $k_F(.,.)$ and $k_{AC}(.,.)$

$$k(\mathbf{x}_i, \mathbf{x}_j) = \beta_F k_F(\mathbf{x}_i, \mathbf{x}_j) + \beta_{AC} k_{AC}(\mathbf{x}_i, \mathbf{x}_j), \quad \text{where } \beta_F, \beta_{AC} \geq 0 \text{ and } \beta_F + \beta_{AC} = 1.$$

Experimental results on Soccer and UCI image segmentation datasets

Dataset	k_F+SVM	k_{AC}+SVM	Ours
Soccer	76.2	76.2	**81.9**
UCI Segmentation	86.9	85	**87.9**

Acknowledgement

This Research is supported in part by the SenSIP center, NSF award 15400540 and Intel Corporation

Publications

[1] Consensus Inference on Mobile Phone Sensors for Activity Recognition, H. Song, J. J. Thiagarajan, K. N. Ramamurthy, A. Spanias, P. Turaga. IEEE International Conference on Acoustic, Speech and Signal Processing 2016, Shanghai, China

[2] Auto-context Modeling Using Multiple Kernel Learning, H. Song, J. J. Thiagarajan, K. N. Ramamurthy, A. Spanias, Submitted to IEEE International Conference on Image Processing 2016, Phoenix, AZ