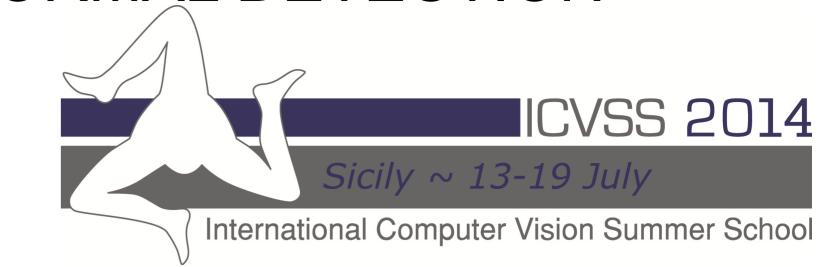


LOCAL SPARSE REPRESENTATION IN ABNORMAL DETECTION

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1. Abstract

We propose to detect abnormal events via a sparse subset clustering algorithm. Specifically, we provide a reasonable normal bases through repeated K spectral clustering. Then for each testing feature we first select spatio-temporal neighbors and use them to form a local space. An abnormal event is found if any abnormal feature is found that satisfies: the distance between its local space and the normal space is large. Our evaluations on two datasets validate our method's effectiveness.

2. Background

Sparse representation is applied to model data as a linear combination of a few elements from an over-complete basis set, early work in this field deals with sparse representation of signals/vectors lying in a single low-dimensional linear subspace or a union of low-dimensional linear subspaces. Sparse Subset Clustering (SSC) [1] extends sparse representation from one to multiple subsets. Sparse representation can be applied in abnormal event detection, where abnormal events are detected based on the dissimilarity between an abnormal event and the normal bases. However, over-complete bases found by different approaches can be different, which means that the least square error or the construction error also varies according to which bases are used to represent the subspaces. This in turn affects the robustness of the abnormality measurement.

3. Methods

3.1 Framework Overview

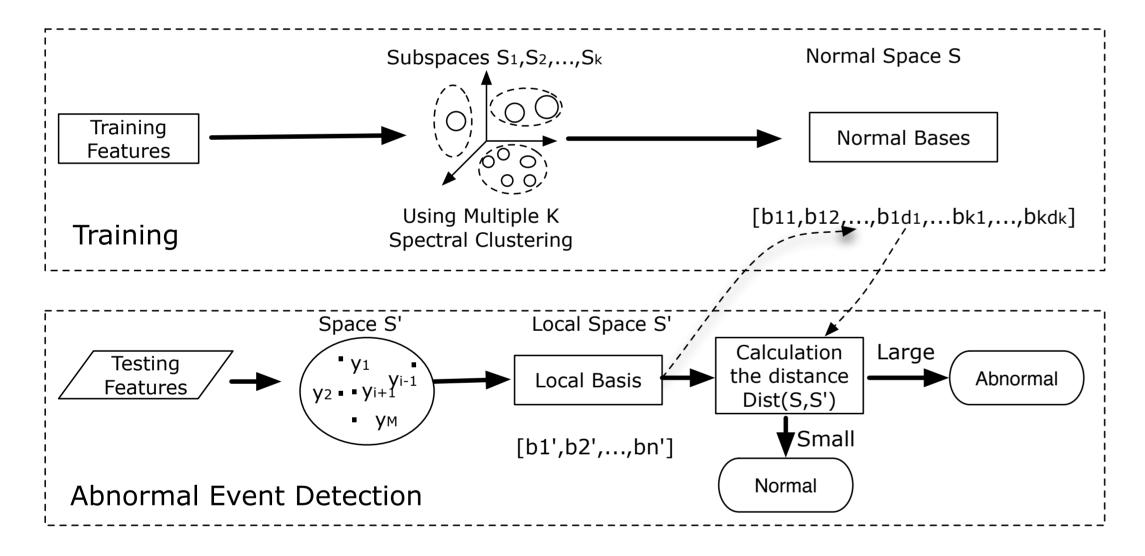


Figure 1: Our framework of normal bases learning and abnormal detection.

3.2 Feature

- Each frame is resized to 120×160 and uniformly partitioned into patches;
- Consecutive 5 frames of the same form a cuboid;
- Prototypical motion patterns are extracted in the cuboid.

3.3 Normal bases construction from the training set

$$\min_{\beta} \frac{1}{2} \|\chi - S\beta\|_2^2 + \lambda \|\beta\|_1$$
 S: bases β : sparse coefficients χ : features λ : penalty

- The unknown priori knowledge about the number of subspaces, a high testing cost;
- Meanwhile, the eigenvectors of the Laplacian in spectral clustering are suitable for representing its subspaces;

Solution: using the K spectral clustering algorithm multiple times to form normal bases

3.4 Local space from the testing set

 $S' = [B'_1, B'_2, ..., B'_n]$ S' is spanned by local neighbors of the testing feature

3.5 Abnormality measurement

Abnormality is measured on the distance of two spaces: the normal space and the local space.

4. Experiments

Datasets:

- The USCD dataset: frame-level and pixel level evaluation
- Subway Entrance dataset:









a) A training frame in USCD.

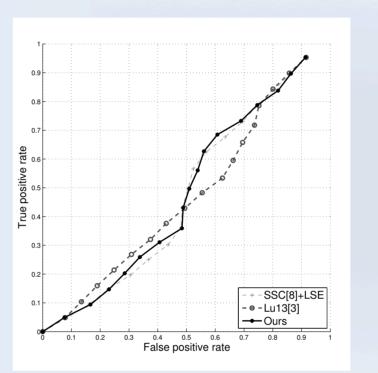
b) A detected abnormality: bike.

c) A training frame in Subway.

b) A detected abnormality: no payment.

Figure 2: Representative frames from two datasets.

Comparative results with SSE [1]+LSE, Lu13 [2] on the USCD dataset:



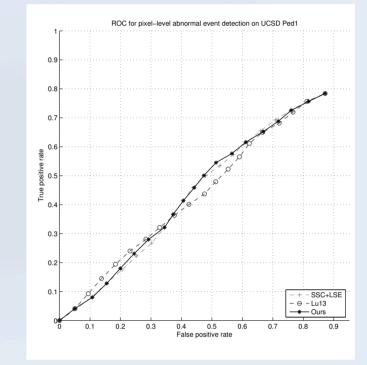
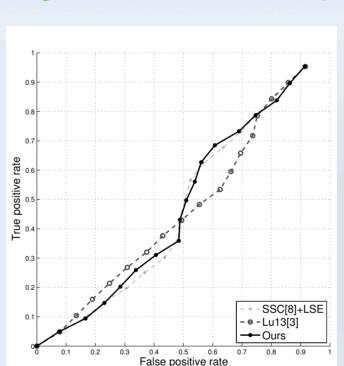


Figure 3: Frame and pixel level comparison on USCD Ped1.



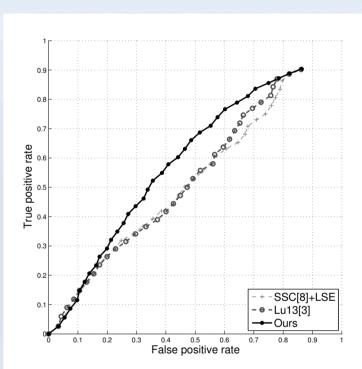


Figure 4: Frame and pixel level comparison on USCD Ped2.

	WD	NP	Total
GT	26	13	100%
[3]	25	9	87.18%
[4]	21	6	69.23%
[2]	25	7	82.05%
Ours	23	12	89.74%

Table 1: Comparison using the Subway Entrance data.

5. Conclusion

We propose an abnormal event detection measurement via sparse subset clustering. Our algorithm provides reasonable normal bases that does not require expensive calculation and, more importantly, the abnormality detection is more robust to noise data in the testing features.

6. References

- [1] E. Elhamifar and R. Vidal. Sparse subspace clustering. In CVPR, pages 2790–2797, 2009.
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