Stable PCA for Detection Anomaly in Video Surveillance

Lam Tran, Carmeliza Navasca, Jiebo Luo
lam.tran@rochester.edu, cnavasca@uab.edu, jluo@cs.rochester.edu

Problem

Given a sequence of video frames, how does one identify whether anomalous activities stand out in the current frame when compared to the previous frames. There are several methods proposed for this problem, namely in subspace tracking methods, such as Dynamic Sparse Coding [2], and Robust Tensor Subspace Learning [3]. Our work is motivated by [4] and [1].

Our Approach

Our approach is to utilize the stable PCA technique [1] to decompose the data matrix into its background and foreground. The columns of the data matrix is the vectorized video frames. Then the foreground frames are then measured for anomaly.

Principal Component Pursuit

Principal component pursuit is a convex programming method for *separating* a data matrix into a sum of a low rank and sparse matrices. The following optimization,

$$\begin{aligned} &\text{minimize} \quad \|L\|_* + \lambda\|S\| \\ &\text{subject to} \quad L + S = M \end{aligned}$$

is solved for the optimal low rank L^* and sparse S^* matrices from a given data matrix M. Here we denote $\|L\|_* := \sum_i \sigma_i(M)$ as the trace class norm of L and $\|S\|_1 = \sum_{ij} |S_{ij}|$ as the ℓ_1 norm of S.

Future Work

- Develop principal component pursuit for tensors.
- Develop local with global anomaly detections.
- Implement subspace detection.

Acknowledgements

This research was partially supported by the NSF Graduate Research Fellowship.

Algorithm

The algorithm for is based on augmented lagrange multiplier (ALM) ([33,51] in Candes) with the augmented Lagrangian

$$l(L,S,Y) = \|L\|_* + \lambda\|S\|_1 + \langle Y, M - L - S\rangle + \frac{\mu}{2}\|M - L - S\|_F^2$$

with multiplier Y.

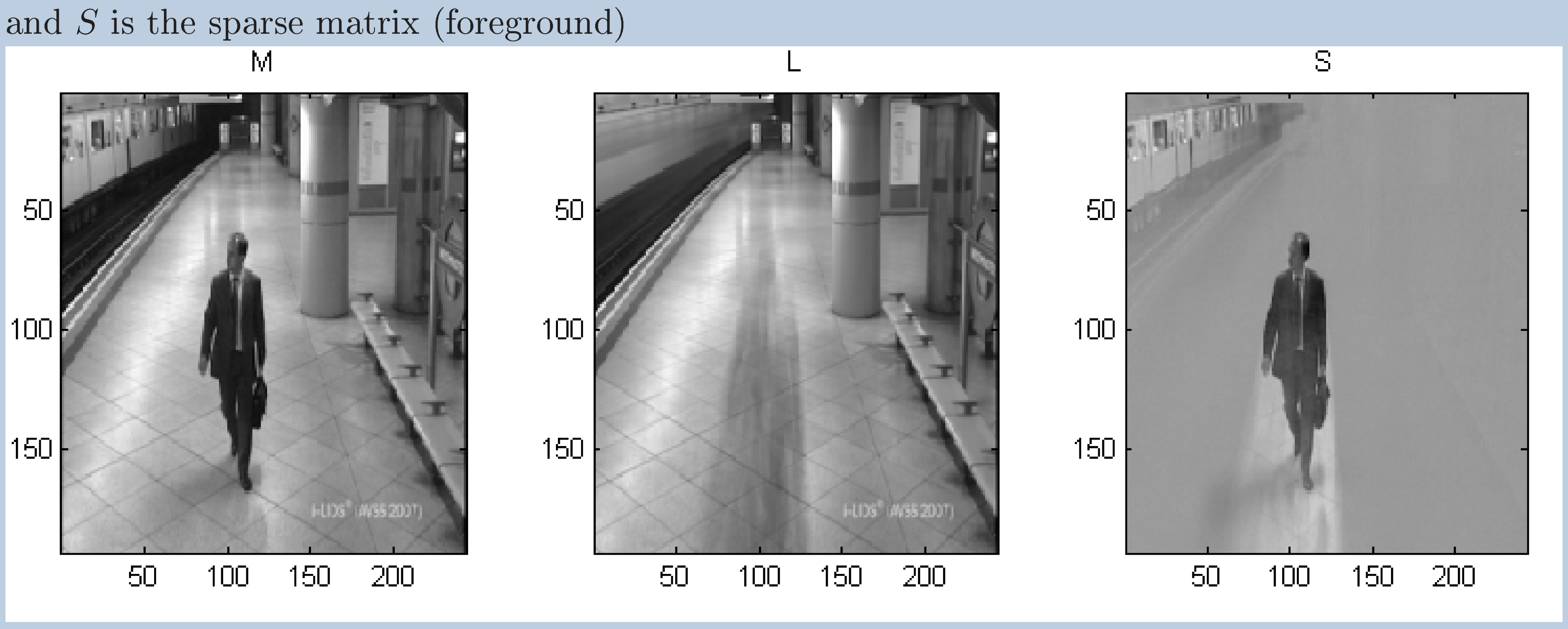
Algorithm 1 (Principal Component Pursuit by Alternating Directions

1: **initialize:** $S_0 = Y_0 = 0, \mu > 0$.
2: **while** not converged **do**
3: compute $L_{k+1} = \mathcal{D}_{\mu^{-1}}(M - S_k + \mu^{-1}Y_k)$;
4: compute $S_{k+1} = \mathcal{S}_{\lambda\mu^{-1}}(M - L_{k+1} + \mu^{-1}Y_k)$;
5: compute $Y_{k+1} = Y_k + \mu(M - L_{k+1} - S_{k+1})$;
6: **end while**
7: **output:** L, S.

Let $\mathcal{S}_{\frac{\lambda}{\mu}} : R \to R$ is the shrinkage operator defined as $\mathcal{S}_{\frac{\lambda}{\mu}} = sgn(x)\max(|x| - \frac{\lambda}{\mu}, 0)$ and $\mathcal{D}_{\lambda^{-1}}(X) = U\mathcal{S}_{\lambda^{-1}}(\Sigma)V^*$ with $X = U\Sigma V^*$ is the singular value thresholding operator.

Spare Matrix (Foreground) Modeling From Video

An Example of Data Separation: M is a frame in the video, L is the low rank matrix (background), and S is the sparse matrix (foreground)

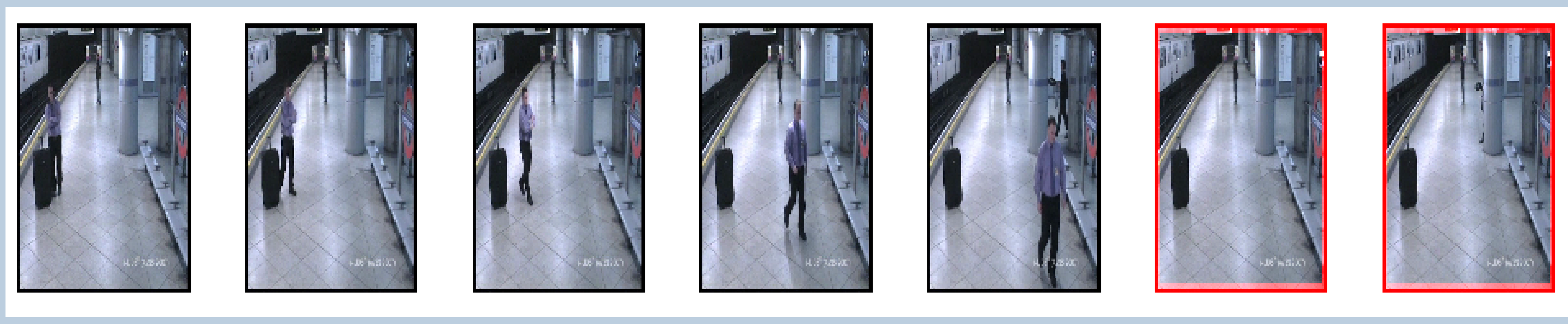


Anomaly Classification: Let the error for frame t be the Frobenius 2-norm

$$e_t = \|S_t\|_F^2.$$

Classify frame t as abnormal when

$$e_t \geq \text{mean}\left(e_i|_{i=1}^T\right) + 2 \cdot \text{std}\left(e_i|_{i=1}^T\right)$$



The figures with red boundary are classified as abnormal.

References

[1] E.J. Candès X. Li, Y. Ma and J. Wright, Robust Principal Component Analysis?, *Journal of ACM,* 58(1), 1-37, 2009.
[2] B. Zhao, Li Fei-Fei and E.P. Xing, Online Detection of Unusual Events in Videos via Dynamic Sparse Coding, *CVPR,* 3313-3320, 2012.
[3] Jie. Li, G. Han, J. Wen and X. Gao, Robust Tensor Subspace Learning for Anomaly Detection, *IJMLC,* 89-98, 2011.
[4] J. Sun, D. Tao, C. Faloutsos, Beyond Streams and Graphs: Dynamic Tensor Analysis, *KDD,* 374-383, 2006.