Automated Visual Surveillance using Kernel Tricks

Tarem Ahmed[1,2], Xianglin Wei[3], Supriyo Ahmed[2] and Al-Sakib Khan Pathan[1]

[1]International Islamic University Malaysia, Kuala Lumpur, Malaysia

[2]BRAC University, Dhaka, Bangladesh

[3]PLA University of Science and Technology, Nanjing, China

tarem@bracu.ac.bd, wei_xianglin@ieee.org, supriyo@bracu.ac.bd , sakib@iium.edu.my

1. Introduction

- Extensive network of multimodal surveillance and security sensors prevalent in many places.
- Task of simultaneously monitoring multiple images tedious and monotonous for a human.
- Existing algorithms involve high complexities, need significant memory and storage resources, and typically involve custom equipment.
- **We present three algorithms built using kernel machines to perform automated, real-time intruder detection in surveillance systems.**
- Proposed algorithms are adaptive and portable, with computational, storage and memory complexities independent of time, making them naturally suited to online use

2. Proposed Algorithms

2.1 Kernel–based Online Anomaly Detection (KOAD)

- Feature vector $\varphi(\mathbf{x}_t)$ is said to be *approximately linearly dependent* on $\{\varphi(\tilde{\mathbf{x}}_j)\}_{j=1}^{M}$ if :

$$\delta_t = \min_a \left\| \underbrace{\sum_{j=1}^{m} a_j \phi(\tilde{\mathbf{x}}_j)}_{\text{Dictionary approximation}} - \phi(\mathbf{x}_t) \right\|^2 < \underbrace{\nu}_{\text{Threshold}} \qquad (1)$$

- Using (1), recursively construct $D = \{\tilde{\mathbf{x}}_1, \tilde{\mathbf{x}}_2, \ldots, \tilde{\mathbf{x}}_m\}$ such that $\phi(D)$ *approximately* spans feature space.
- Should be possible to *approximately* describe region of normality in feature space using sparse *dictionary*, $D = \{\tilde{\mathbf{x}}_j\}_{j=1}^{M}$
- **At timestep t, evaluate δ_t , compare with thresholds ν_1 , ν_2 where $\nu_1 < \nu_2$:**
- **If $\delta_t > \nu_2$, infer $\mathbf{x}_t$ far from normality: Red Alarm;**
- **If $\delta_t < \nu_1$, infer $\mathbf{x}_t$ close to normality: Green;**
- **If $\nu_1 < \delta_t < \nu_2$, raise Orange, resolve later.**

2.2 Kernel Estimation –based Anomaly Detection (KEAD)

- Assuming that the underlying distribution covering normal points is stationary in interval $\{t\text{-}L{:}t\text{+}L\}$ leads to following expression for KDE at $\mathbf{x}_t$:

$$\tau_t = \frac{1}{2L+1} \sum_{i=t-L}^{t+L} k(\mathbf{x}_i, \mathbf{x}_t) \qquad (2)$$

where $k(\ ,\ )$ denotes the kernel function.

- One may then use dictionary $D_{t\text{-}1}$ and matrix $\mathbf{A}_t$ of optimal sparsification coefficient vectors a_t for past L timesteps to obtain **online detection statistic** $\hat{\tau}_t$:

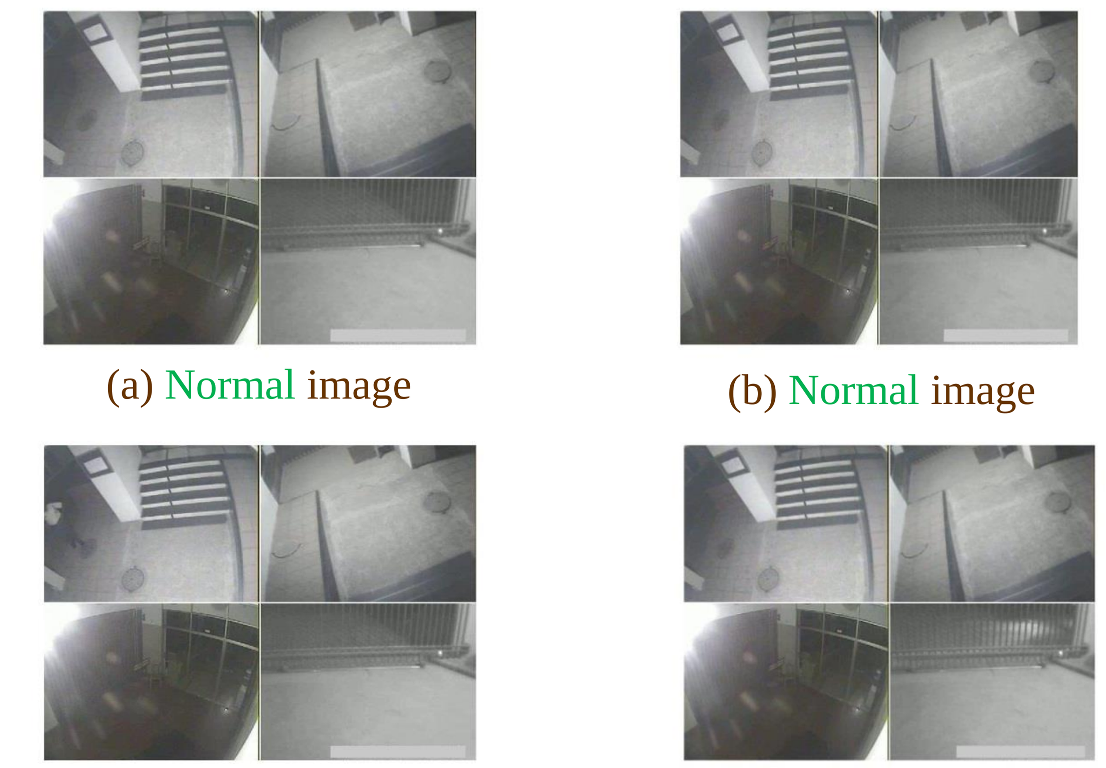
$$\hat{\tau}_t = \frac{1}{L} \sum_{i=1}^{L} \sum_{j=1}^{m_{t-1}} a_{lj}\, k(\tilde{\mathbf{x}}_j, \mathbf{x}_t) \qquad (3)$$

- At timestep t, evaluate $\hat{\tau}_t$, compare with threshold η_t :
- **If $\hat{\tau}_t > \eta_t$, infer $\mathbf{x}_t$ close to normality: Green;**
- **If $\hat{\tau}_t < \eta_t$, raise Orange, resolve later.**

2.3 Kernel Principal Component Analysis (KPCA)

- Maintain a sliding window X_t of C input vectors: $\{\mathbf{x}_i\}_{i=t-C+1}^{t}$
- Find the principal components by solving the eigenvalue problem for the input vector kernel matrix (the Gram matrix) for this block.
- Hence obtain a vector of the magnitude of the projection onto the residual, anomalous subspace pertaining to timesteps $\{t\text{-}C\text{+}1{:}t\}$.
- Value of residual magnitude pertaining to the current timestep compared with threshold to make anomaly decision.
- **If magnitude of residual pertaining to timestep t > threshold, raise red; else, green.**

3. Data



(a) Normal image (b) Normal image

(c) Anomalous image (d) Anomalous image

Fig. 1: Set of images collected from run-of-the-mill CCTV system in place at BRAC University, Dhaka, Bangladesh. Normal images seen in (a) and (b), potential intruder arrives in (c), more subtle anomaly of car lights being turned observed in (d).

4. Results

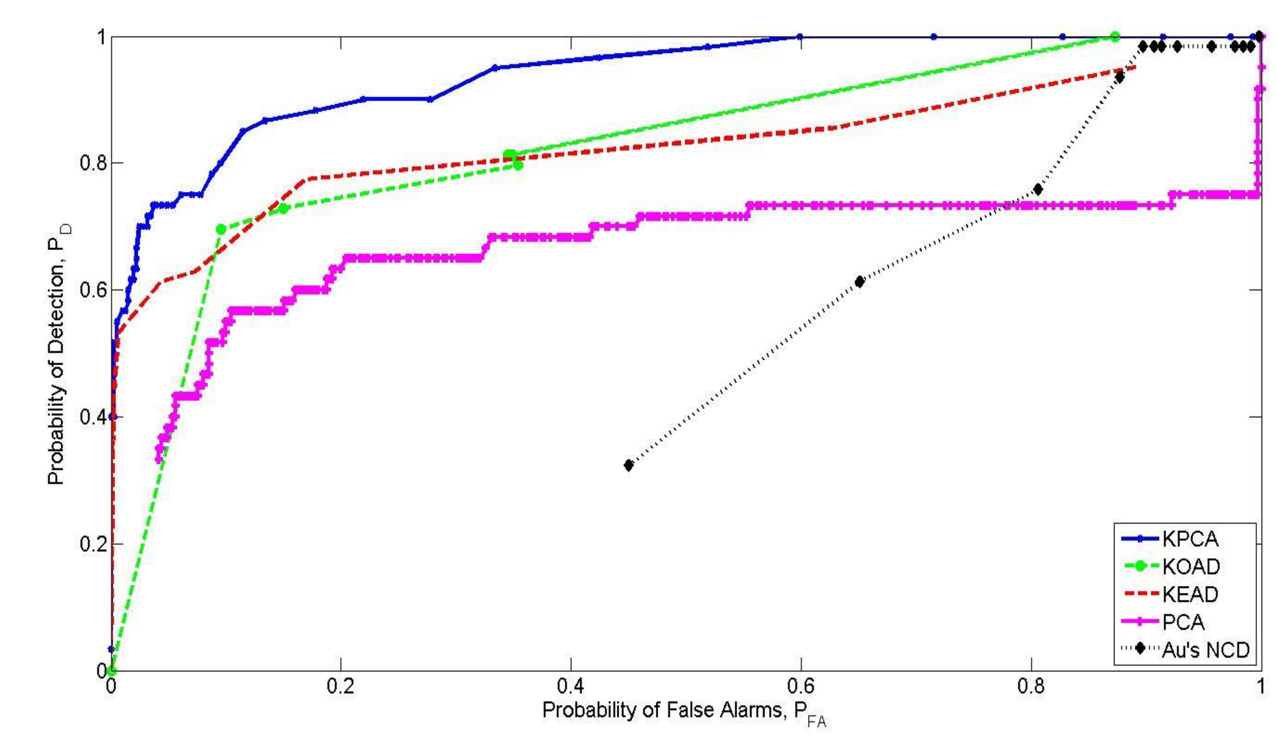


Fig. 2: ROC curves showing performances of proposed KPCA, KOAD and KEAD versus existing PCA and Au's NCD-based algorithms.

- Proposed KOAD, KEAD and KPCA compared to existing Principal Component Analysis (PCA) [1] and Normalized Compression Distance (NCD) [2] –based algorithms
- **All three proposed algorithms demonstrate superior performance.**

5. References

[1] A. Lakhina, K. Papagiannaki, M. Crovella, C. Diot, E. Kolaczyk and N. Taft, "Structural analysis of network traffic flows," in *Proc. ACM SIGMETRICS*, New York, NY, USA, June 2004.

[2] C. Au, S. Skaff and J. Clark, "Anomaly detection for video surveillance Applications," in *Proc. IEEE Int. Conf. on Pattern Recognition (ICPR)*, Hong Kong, China, May 2006..