# Traffic Incident Detection from Road Camera Networks


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Agile All-Photonic Networks

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## 1. Introduction

- Road networks are often affected by disruptive traffic incidents.
- Examples include traffic congestions or accidents.
- Quick detection desired to initiate timely emergency response.

*Fig. 1: An example road network anomaly: a jam.*

**Our Contribution**:

- **We present two algorithms that flag anomalies in image sequences from a camera network:**
  - Kernel-based Online Anomaly Detection (KOAD);
  - One-Class Neighbour Machine (OCNM).
- A traffic incident should lead to an anomalous image.
- We test on a sequence of images captured by Transport Quebec's camera network over the Montreal area.

## 2. Kernel-based Online Anomaly Detection (KOAD): Introduction

- Recursive algorithm for online anomaly detection [1], [2].
- Incrementally learns a *dictionary* of input vectors that spans the *region of normality* in a chosen feature space.
- An anomaly is flagged immediately upon encountering a deviation from the norm.
- The dictionary maintained is dynamic and incorporates changes in the normal behaviour of the given network.

**Initialization**:

- Sequence of multivariate measurements: $\{\mathbf{x}_t\}_{t=1:T}$.
- Choose feature space with associated kernel:

$$k(\mathbf{x}_i,\mathbf{x}_j)=\langle\varphi(\mathbf{x}_i),\varphi(\mathbf{x}_j)\rangle \quad \text{where} \quad \varphi:\mathbf{x}\in\mathbb{R}^n\rightarrow\varphi(\mathbf{x})\in H^\infty$$

- Then feature vectors corresponding to normal traffic measurements should *cluster*.

**The Dictionary**:

- Should be possible to describe region of normality in feature space using sparse *dictionary*, $D=\{\tilde{\mathbf{x}}_j\}_{j=1}^{M}$
- Feature vector $\varphi(\mathbf{x}_t)$ is said to be *approximately linearly independent* on $\{\varphi(\tilde{\mathbf{x}}_j)\}_{j=1}^{M}$ if [3]:

$$\delta_t=\min_a\left\|\sum_{j=1}^{m_{t-1}}a_j\phi(\tilde{\mathbf{x}}_j)-\phi(\mathbf{x}_t)\right\|^2>\nu \qquad (1)$$

## 3. KOAD: The Algorithm

- At timestep $t$, evaluate $\delta_t$, compare with $\nu_1$, $\nu_2$ where $\nu_1<\nu_2$.
- If $\delta_t>\nu_2$, infer $\mathbf{x}_t$ far from normality: **Red1 Alarm.**
- If $\delta_t<\nu_1$, infer $\mathbf{x}_t$ close to normality: **Green.**
- If $\delta_t>\nu_1$, raise Orange Alarm and track the contribution of $\mathbf{x}_t$ in explaining the $l$ subsequent arrivals.
- At timestep $t+l$ resolve any Orange Alarm from timestep $t$. Done by performing a secondary *Usefulness Test* [2], and determining how many of the $l$ subsequent arrivals lie close to $\mathbf{x}_t$. We distinguish between cases where:
  - $\mathbf{x}_t$ is an **isolated event** and a **potential anomaly**; or
  - $\mathbf{x}_t$ represents a **migration of region of normality**.

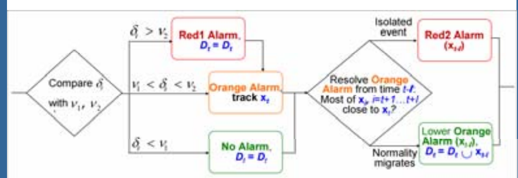


*Fig. 2: Flow chart of operations performed at any timestep t by KOAD algorithm. For details, see [1].*

## 4. One-Class Neighbor Machine (OCNM)

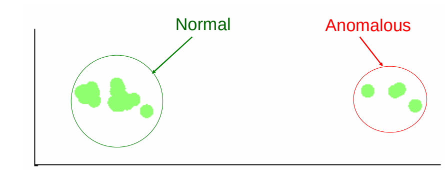


*Fig. 3: 2-D Isomap of CHIN-LOSA backbone flow, srcIP*

- Region of normality should correspond to a Minimum Volume Set (MVS).
- OCNM for estimating MVS proposed in [4].
- Requires choice of sparsity measure, $g$.
  - Examples: $k$-th nearest-neighbour distance, average of first $k$ nearest-neighbour distance.
- Sorts list of $g$, identifies points that lie inside MVS using pre-specified fraction $\mu$.

## 5. Data

**Data collection**:

- Network of webcams.
- Collect from 6 cameras.
- Get image sequences at each location, at five-min intervals.


*Fig. 4: Transports Quebec's camera network around Montreal.*

*Fig. 5: Normal image set.*

*Fig. 6: Anomalous image set.*

**Feature Extraction**:

- 2-D Discrete Wavelet Transform (DWT).
- Expected to extract spatially localized frequency information.
- Average energy in coeffs in subbands.

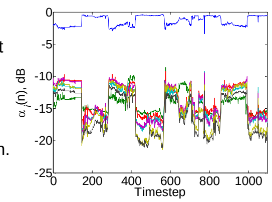


*Fig. 7: Energy in each subband after WT on example image.*

- At each timestep, at each camera, get *wavelet feature vector* of subband intensities

## 6. Results: Traffic Incident Detection

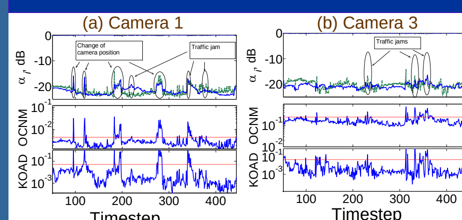


*Fig. 8: Top panels show progression in 2 of the 6 wavelet coefficients. Middle panels show OCNM k-th nearest neighbour distance metric. Bottom panels show KOAD $\delta_t$.*

- Detection algorithms flag anomalies at each location.
- Use $c$ = 3 out of $n$ = 6 voting scheme at central unit to differentiate true anomalies such as traffic jams from individual false alarms such as camera malfunctions.

## 7. Results: ROC Curve

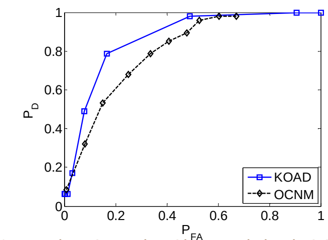


*Fig. 9: Receiver Operating Characteristics (ROC) curve showing tradeoff between Probability of Detection ($P_D$) and Probability of False Alarm ($P_{FA}$).*

- **KOAD** outperforms **OCNM**.
- Attributed to the adaptive nature that the dynamic dictionary provides **KOAD** with.

## 8. Conclusions and Future Work

- Preliminary results indicate the potential of Machine Learning approaches in quick traffic incident detection.
- Computations must be distributed to minimize communication costs.
- Complexity must be independent of time to enable online application.
  - **KOAD** complexity is.
  - **OCNM** complexity is not.

## 9. Acknowledgements


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## 10. References


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