Sequential Adaptive Detection for In-situ transmission electron microscopy

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Objectives

- Develop statistically efficient and computationally simple sequential change-point detection algorithm for for detecting transient sparse signals in Transmission Electron Microscopy (TEM) video sequences.

Introduction

Transmission Electron Microscopy (TEM) has long been a powerful tool for imaging material structure and characterizing material chemistry. Recent advances in electron detector technology and computational capacity have facilitated the development of high-speed data collection with microsecond frame rate acquisition speeds. Because of this, in-situ processing of the real-time collected data to detect emerging features become a highly desired property for the new TEM system. Currently, the data are captured real-time but analyzed off-line. We present a sequential adaptive change detection method for in-situ TEM signal detection. The method is developed by adapting the recent one-sample update based sequential detector.

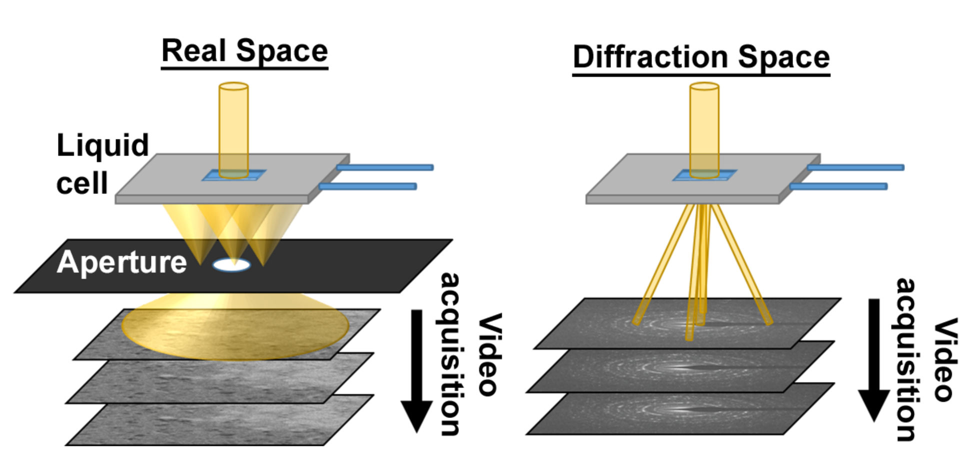

Figure 1: Diagrams demonstrating the basic principles of bright field imaging in TEM. TEM can operate in two modes, illustrated in Left Panel: in the real space; Right Panel: in the diffraction space. The real space images can be computed from the diffraction space images. The incident beam of electrons passes through the sample and a lens/aperture system is used to form the image.

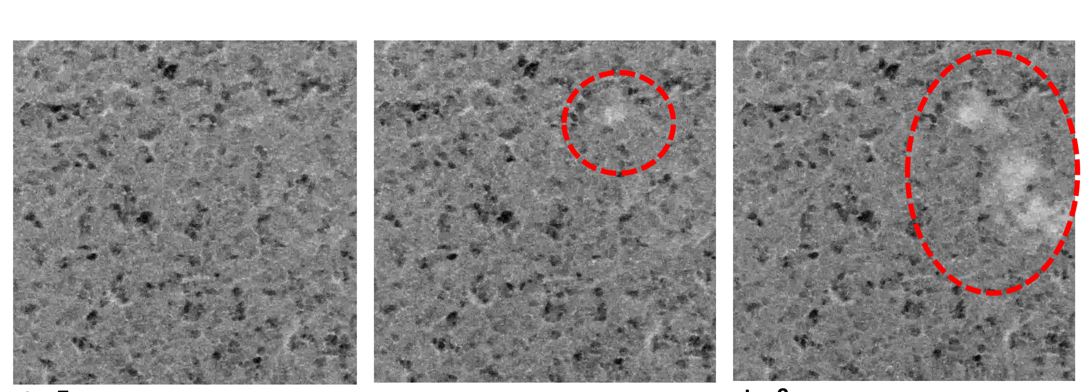

Figure 2: A sequence of metal corrosion images captured using bright-field TEM. The time (index for the image in the sequence) is labeled; the corrosion initiates at time t = 8 (marked by the red circle) and develops over time. The corroded area has a higher intensity signal than the rest of the film.

Problem formulation

Formally speaking, the sequential change-point detection problem can be cast into the following hypothesis test:

$$\begin{aligned}
\mathsf{H}_0: \quad & X_1, X_2, \ldots \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, I_d), \\
\mathsf{H}_1: \quad & X_1, \ldots, X_\nu \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, I_d), \\
& X_{\nu+1}, X_{\nu+2}, \ldots \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\theta, I_d), \quad \theta \in \mathcal{A}.
\end{aligned} \tag{1}$$

where the post-change mean θ is unknown and belong a set $\mathcal{A}$ defined as $\mathcal{A} = \{\theta : \|\theta\|_0 \leq s\}$, where $\|\cdot\|_0$ is the number of non-zero entries of θ and s is a prescribed value to characterize the sparsity.

Proposed method

The key idea is to incorporate an adaptive likelihood ratio test in the detection procedure (e.g., [Lorden and Pollak, 2005]). The likelihood ratio at time t for a hypothetical change-point location k is given by

$$\Lambda_{k,t} = \prod_{i=k}^{t} \frac{f_{\hat{\theta}_{k,i-1}}(X_i)}{f_{\theta_0}(X_i)}, \qquad \hat{\theta}_{k,k-1} = \theta_0,$$

where $\hat{\theta}_{k,i}$ is a function of the observations $\{X_k, \ldots, X_i\}$ that is computed by mirror descent in Algorithm 1 (assuming X_k is the first input). This is a one-sample update that can be computed very efficiently given one new observation. Then, our detection procedures are adaptive CUSUM (ACM) procedure:

$$T_{\text{ACM}}(b) = \inf\left\{t \geq 1 : \max_{1 \leq k \leq t} \log \Lambda_{k,t} > b\right\},$$

where b is a prescribed threshold.

Online mirror descent to estimate $\hat{\theta}_{k,i}$

Algorithm 1 Online mirror-descent (OMD) for $\{\hat{\theta}_{k,t}\}$

Require: A sequence of data $X_k, \ldots \in \mathbb{R}^d$; a closed and convex set $\Gamma \subset \mathbb{R}^d$ of the parameters; a decreasing sequence $\{\eta_t\}_{t \geq 1}$ of strictly positive step-sizes.

$\hat{\theta}_{k,k-1} = 0, \Lambda_{k,k-1} = 1$. {Initialization}
for all $t = k, k+1, \ldots,$ **do**
  Acquire a new observation X_t
  Compute loss $\ell_t(\hat{\theta}_{k,t-1}) := \|\hat{\theta}_{k,t-1}\|_2^2/2 - \hat{\theta}_{k,t-1}^\intercal X_t$
  Compute $\Lambda_{k,t} = \Lambda_{k,t-1} \times f_{\hat{\theta}_{k,t-1}}(X_t)/f_0(X_t)$
  $\tilde{\theta}_{k,t} = \hat{\theta}_{k,t-1} - \eta_t(\hat{\theta}_{k,t-1} - X_t)$ {Dual update}
  $\hat{\theta}_{k,t} = \arg\min_{u \in \Gamma} \|u - \tilde{\theta}_{k,t}\|_2$ {Projected primal update}
end for
return $\{\hat{\theta}_{k,t}\}_{t \geq 1}$ and $\{\Lambda_{k,t}\}_{t \geq 1}$.

Preprocessing

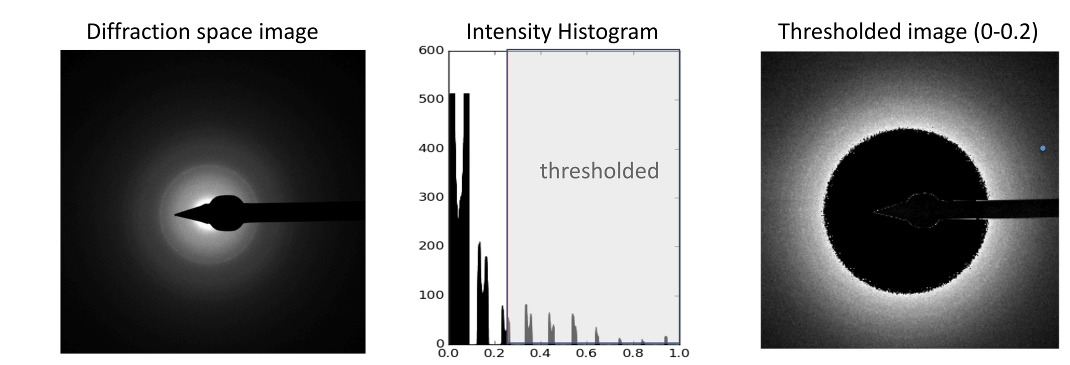

Figure 3: Left: a diffraction domain image; Middle: the histogram of the intensity; Right: The thresholded image if we only keep pixels of value in (0, 0.2).

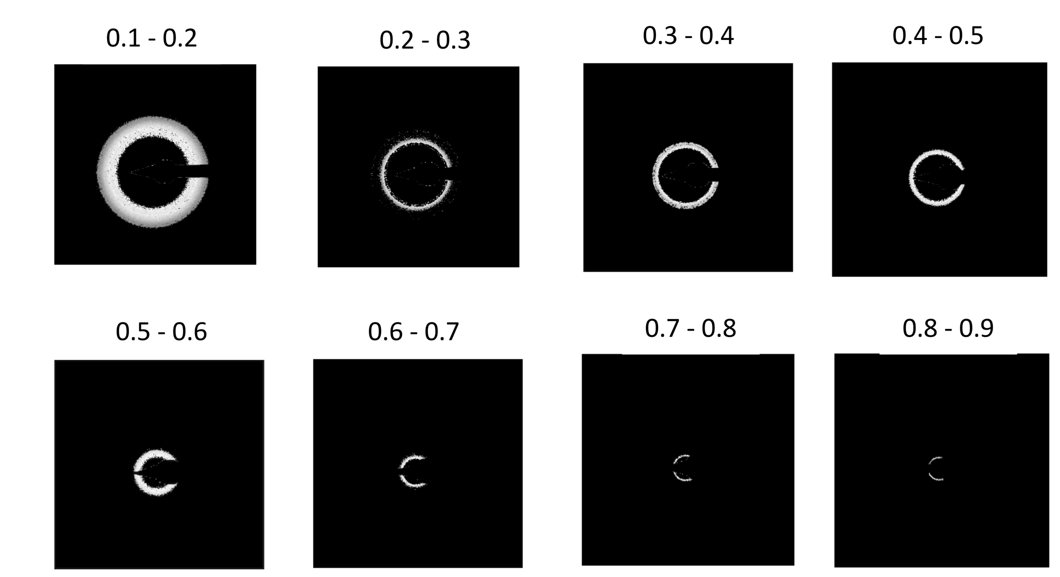

Figure 4: Background removal: we threshold a diffraction space image with different range of threshold values, and this yields rings at different radii. These concentric rings help to estimate their common center, and subsequently we subtract off the bright rights to remove these bright rings.

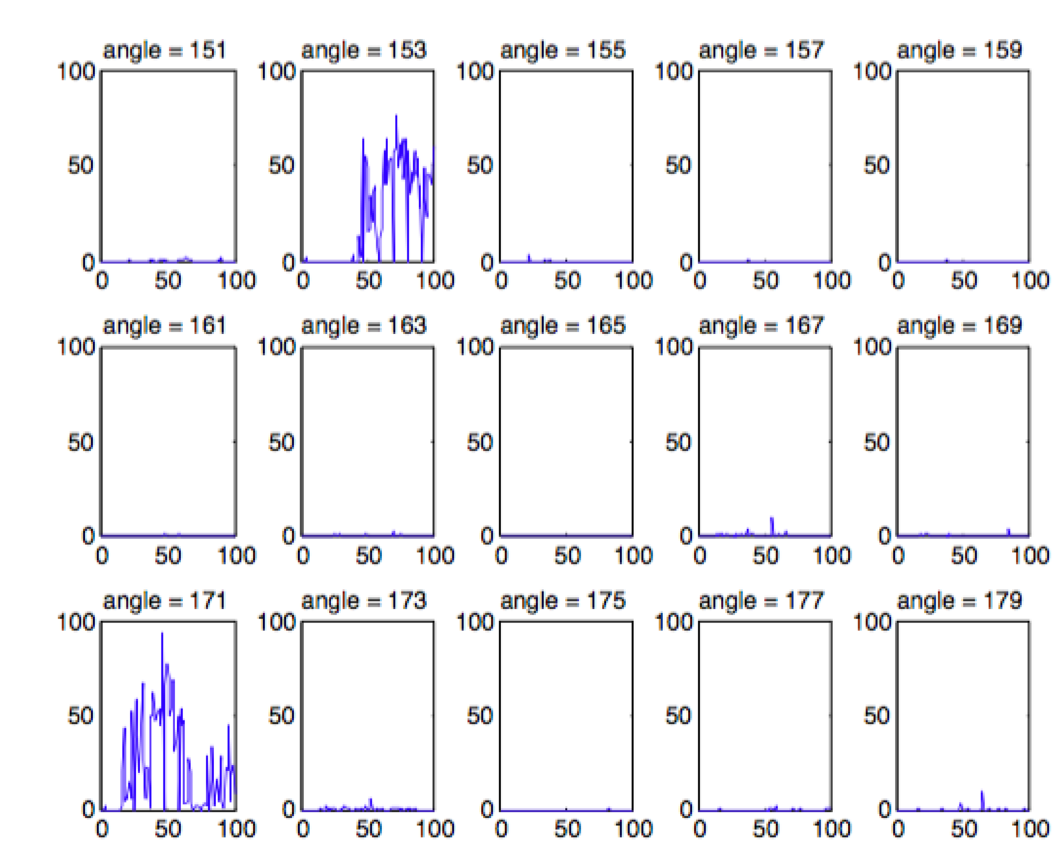

Figure 5: The extracted signals for the sequence of 100 images (selected angles).

Result

Domain knowledge tells us that the change happens at time $t = 17$. Our ACM procedure stop at $t = 18$. Classic CUSUM stop at $t = 24$ and classic GLR procedure raise an false alarm at $t = 10$.