Detecting Drops On Lens in Wireless Multimedia Sensor Network Nodes

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ROSE 2009, Lecco
Outline

- The issue
- Our approach
- The observation model
- The blur measure
- The change detection test
- Experiments
- Concluding remarks
The issue

- We consider Wireless Multimedia Sensor Networks (WMSN) used for monitoring outdoor environment.

- The nodes (or the network) should then be able to determine when there is some structural information loss in the image acquisition system.

- In particular we consider the degradation induced by drops on the camera lens, as this may result because of rain, humidity, waves…
What’s up when a rain drop falls on camera lens
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The issue

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**WSN** Constraints:

- Images have to be **processed locally**
  - In order to avoid **sending huge amount of data** on the network
  - Thus processing must have **low computational complexity**

- **Do not assume stationarity** in the observed scene,
  - frames could have been acquired at very different instants as the image acquisition is not continuous
  - we have **no a priori information** about the scene
Our Approach

- Drops on camera lens are modeled as a **blur operator**.

- We combine
  - a **low-complexity blur measure**
  - a **sophisticated change detection test** on these measures

- The **blur measure** can be computed **directly on each sensor node**

- The blur measures are **scalar** that can be sent on the network

- The **test** can be reasonably **executed on cluster head**
Our Approach

- Each node periodically compute blur measures
Our Approach

- Each node periodically computes blur measures and sends them to the remote station.
Our Approach

- The remote station run the test and determine if one node is acquiring corrupted data
Our Approach

- and then the network adopts some strategy to compensate the node
The Observation Model

- For the sake of simplicity the observed image $z$ is modeled as the result of a **degradation process** $D$ that acts on the original (and unknown) image $y$:

$$z(x) = D(y)(x) = B(y)(x) + \eta(x), \ x \in \mathcal{X}$$

$$B(y)(x) = \int_{\mathcal{X}} y(x) h(x, s) ds$$ is the blur operator

$h(x, \cdot)$ is the Point Spread Function at pixel $x$

$\eta$ is the noise term

$\mathcal{X}$ is the image domain
The Observation Model

- Space invariant blur \( h(x, s) = g(x - s) \quad x \in \mathcal{X} \)
The Observation Model

- Space variant blur

$$h(x, s) = g(x, s) \quad x \in \mathcal{X}$$
The Observation Model

- Space invariant blur

\[ h(x, s) = \begin{cases} 
\delta(x - s), & x \in \mathcal{X}_0 \\
g(x, s), & x \in \mathcal{X}_1 
\end{cases}, \quad \mathcal{X}_0 \cup \mathcal{X}_1 = \mathcal{X} \]
The Observation Model

- We assume that we have a sequence of images

\[ z_i(x) = B_i(y_i)(x) + \eta(x), \quad i = 1, \ldots, N \]

and possibly the original images \( y_{i-1} \) and \( y_i \) are different, as they have been acquired at different time instants.

- Since estimating such a blur is a very ill-posed, we simply measure the “amount of blur” in the resulting image.

- The blur operator may also change within the image sequence.
The Blur Measure

- We use a **blur-measure** taken from auto-focus algorithms

\[ m_i = \int_{\mathcal{X}} ||\nabla z_i(x)||_1 dx \]

where \( || \cdot ||_1 \) is the \( \ell^1 \) norm.

The observations are assumed to have 0 mean.

- The underlying mechanism of this measure reflects the intuitive idea that the blur suppresses the high frequency components of an image.

- The blur measure is computed on each observed image **separately**: **no comparison** is performed among \( z_i \) and \( z_{i-1} \), as these may be acquired in very different time instants.
The Blur Measures
The Blur Measures

![Image of a graph showing the blur measure over frame number. The x-axis represents frame number ranging from 0 to 2000, and the y-axis represents blur measure ranging from 1.5 to 4.5 \times 10^4. There are fluctuations in the graph, with a green dot indicating a specific frame number.]
The Blur Measures

![Image of a camera capturing a scene with buildings and a car, alongside a graph showing a plot of blur measure versus frame number. The graph indicates a decrease in blur measure over time.]
The Blur Measures

![Graph showing changes in blur measure over frame number]

- Frame Number
- Blur Measure

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The Blur Measures

![Graph showing the blur measure over frame numbers.](image)

Frame Number

- Blur Measure

- Frame Number

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The Blur Measures

![Graph showing the blur measure over frame number.](attachment:image.png)
Change Detection Test

- A statistical technique to monitor the state of a process over time.

- We use CI-CUSUM test on blur measures $m_i$ to detect changes in the statistical behavior of the degradation process $\mathcal{D}$
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  - Stationarity means the acquisition system has **no structural loss** due to blur: i.e. **no drop**.
Change Detection Test

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  - The arrival of **a drop on camera lens** changes the statistical behavior of the blur measures, and thus it is detected as a **non-stationarity** in the test.
Change Detection Test

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  - The arrival of a **drop on camera lens** changes the statistical behavior of the blur measures, and thus it is detected as a **non-stationarity** in the test.

- CI-CUSUM is **general** and is automatically configured from a **training set of** $m_i$ computed from images in the stationary state.
The training set is composed by 500 drop-free images.
The CI-CUSUM test estimates some figures of merit $\phi$ for $m_i$ in absence of drops, and define the null hypothesis, $\Theta^0$ as “being in the no-drop state”.

The alternative hypotheses $\Theta^1$ are defined as “not being in $\Theta^0$ ”, and thus address any type of changes w.r.t. the initial stationary state.
The Training Set

- Definition of the stationary and the alternative hypothesis
The test computes the figures of merit $\phi$ by grouping observations in the validation set.

For each group, the test computes the log-likelihoods between the figures of merit of the current state with those of the initial stationary state, and compare it with an automatically defined thresholds.
The Training Set

- Change Detection

![Graph showing Change Detection with training and validation sets, and indices Θ₀, Θ₁, φᵢ, and φₜₛ.]}
The Training Set

- Change Detection

![Graph of training and validation sets with annotations]

- Training set
- Validation set
- \( \Theta^0 \)
- \( \Theta^1_s \)
- \( \phi_{TS} \)
- \( \phi_i \)
The Training Set

- Change Detection

![Graph showing training and validation sets with corresponding metrics and frame numbers.](image-url)
The Training Set

- Change Detected at frame 1160
Experiments

- We adopted the following figures of merit

  - **DL** Detection Latency: the number of images acquired before identifying a change in the blurring process.

  - **FP** False Positive, the number detected changes not supported by a real change in the blurring process.

  - **FN** False Negative, the number missed changes in the blurring process
Experiments

- Detection Latency
Experiments

- False Positive
Experiments

- False Negative
Experiments on Synthetically Blurred Images

- We generated sequences from 75 grayscale images in a random order
Experiments on Synthetically Blurred Images

- We generated sequences from 75 grayscale images in a random order.
Experiments on Sythetically Blurred Images

- We generated sequences from 75 grayscale images in a random order.
- For simplicity, the blur has been generated with a 2D convolution with a Gaussian kernel $h$ having standard deviation $\nu$.

\[ B(y) = (y \ast h) \]

- Noise has been generated from a Normal distribution.

\[ \eta \sim N(0, \sigma^2) \]

- We considered different amount of blur and noise.

$\nu = 1, \ldots, 8 \quad \sigma = 0.02, 0.04, 0.06, 0.08$

- Each sequence contains 1000 blur-free images (500 are used for training the CI-CUSUM) and 1000 blurred images.
- Results have been averaged among 100 sequences for each parameter pair.
Experiments on Sythetically Blurred Images

- Two blur operators:
  - the blur affects the whole image

\[ \sigma = 0.08 \]
\[ \nu = 1 \]
Experiments on Synthetically Blurred Images

- Two blur operators:
  - the blur affects the **whole** image

\[ \sigma = 0.08 \]
\[ \nu = 4 \]
Experiments on Synthetically Blurred Images

- Two blur operators:
  - the blur affects the **whole** image

$$\sigma = 0.08$$
$$\nu = 8$$
Experiments on Sythetically Blurred Images

- Two blur operators:
  - the blur affects the **whole** image
  - the blur affects **part** of the image

\[
\sigma = 0.02 \\
\nu = 1
\]
Experiments on Synthetically Blurred Images

- Two blur operators:
  - the blur affects the **whole** image
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\[ \sigma = 0.02 \]

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Experiments on Sythetically Blurred Images

- Two blur operators:
  - the blur affects the **whole** image
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\[ \sigma = 0.02 \]
\[ \nu = 8 \]
Experiments on Sythetically Blurred Images

- Detection Latency: Blur on the whole image
Experiments on Synthetically Blurred Images

- Detection Latency: Blur on part of images
Experiments on Synthetically Blurred Images

- False Positive and False Negative results

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Experiments on Sythetically Blurred Images

- False Positive are independend of the amount of blur

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Experiments on Synthetically Blurred Images

- False Negative decreases as the blur amount increases

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Experiments on Camera Images

- We acquired 25 sequences of QVGA uncompressed frames
  - 1000 frames drop free
  - 1000 frames with drops
  - the first 500 drop-free frames have been used as training set
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<table>
<thead>
<tr>
<th>FP(%)</th>
<th>FN(%)</th>
<th>DL (Number of images)</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td>4</td>
<td>161.0</td>
</tr>
</tbody>
</table>
Concluding Remarks

- When processing video sequences, the FP are typically determined by the presence of occluding objects, whenever these did not appear in the training set.

- We need a training set which is representative of the scenario.

- In case some user-supervised information is available, this could be integrated by the test.
Ongoing Works

- Development of a lighter test to be implemented directly on the node.
- The nodes are able to monitor by themselves the degradation process.
- Integration of light/time information in the test.
Questions?