POLITECNICO DI MILANO

Near-Duplicate Video Detection Exploiting Noise Residual Traces

S. Lameri, L. Bondi, P. Bestagini, S. Tubaro

Motivations

- Increasing amount of **user-generated** content online

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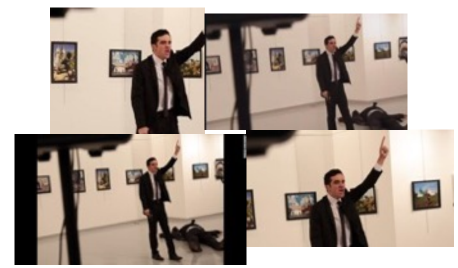
- The **same original content** can be edited and republished several times, thus generating different **near-duplicate** objects



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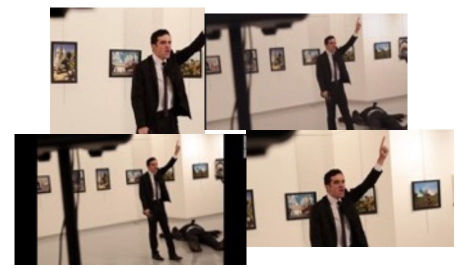
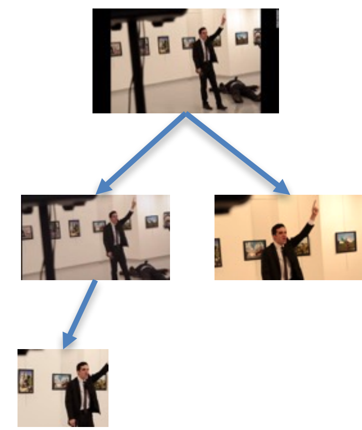


- **Video Phylogeny** jointly analyses multiple versions of the same object
  - To identify the original content that give birth to the NDs
  - To infer the generative structure behind NDs creation



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- Fundamental step in video phylogeny application is the **detection** of set of **near-duplicate** videos

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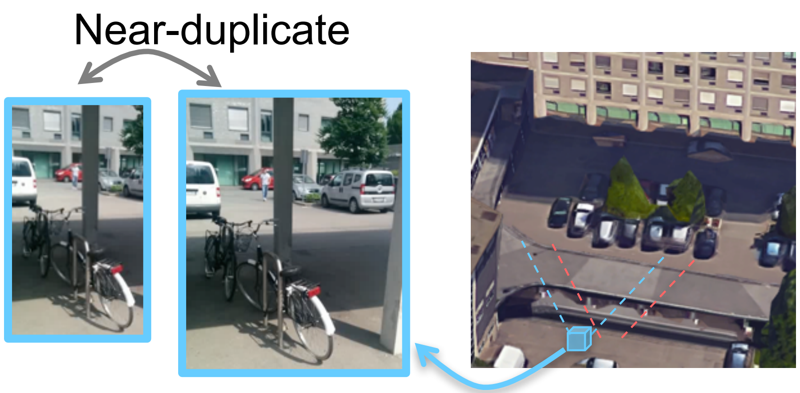

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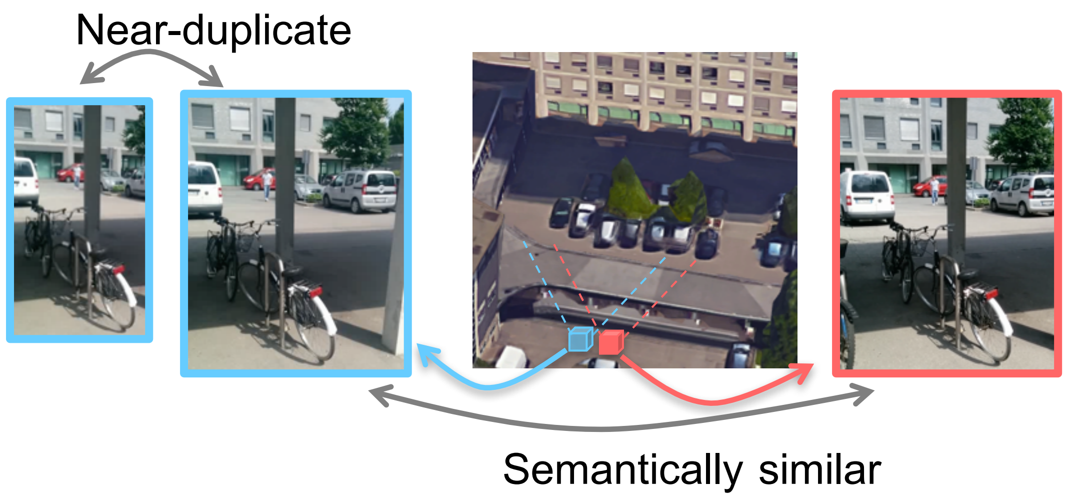

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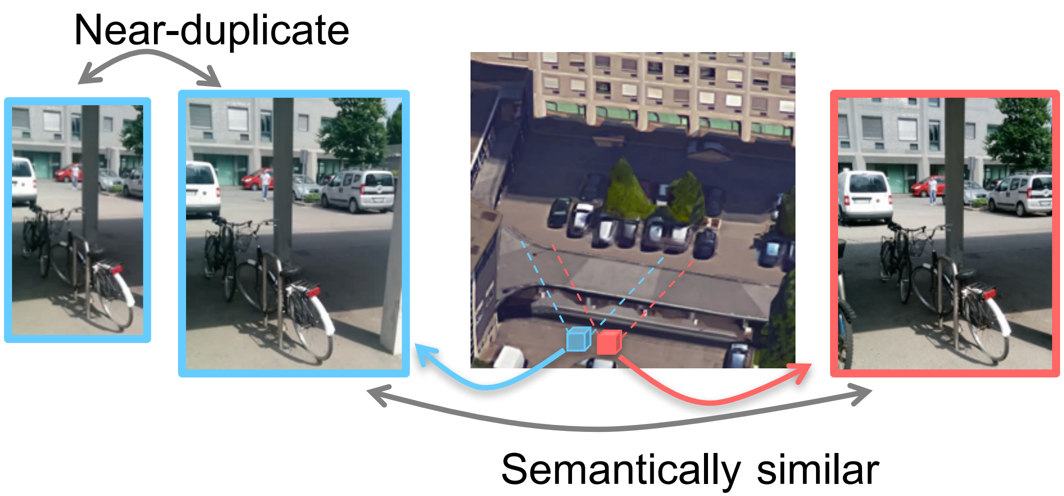

  - **Near-duplicates (ND)**, are edited copies of the **same video**
  - **Semantically similar (SSI)** videos capture the scene from different view points, with **different devices**
- *Problem*: SSI videos can be confused with ND

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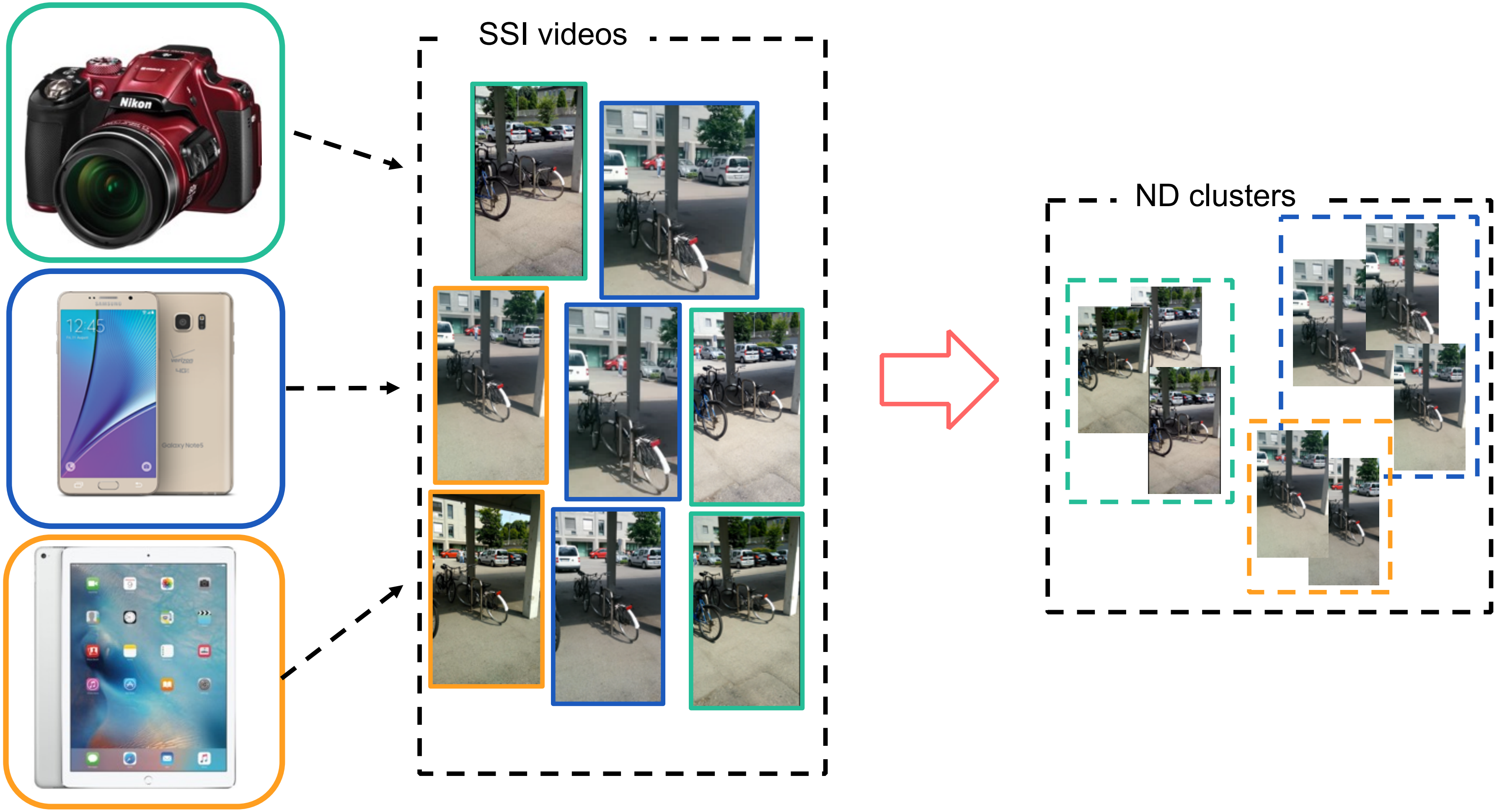

Basic Idea

- By definition **ND** videos
  - Depict the **same scene**
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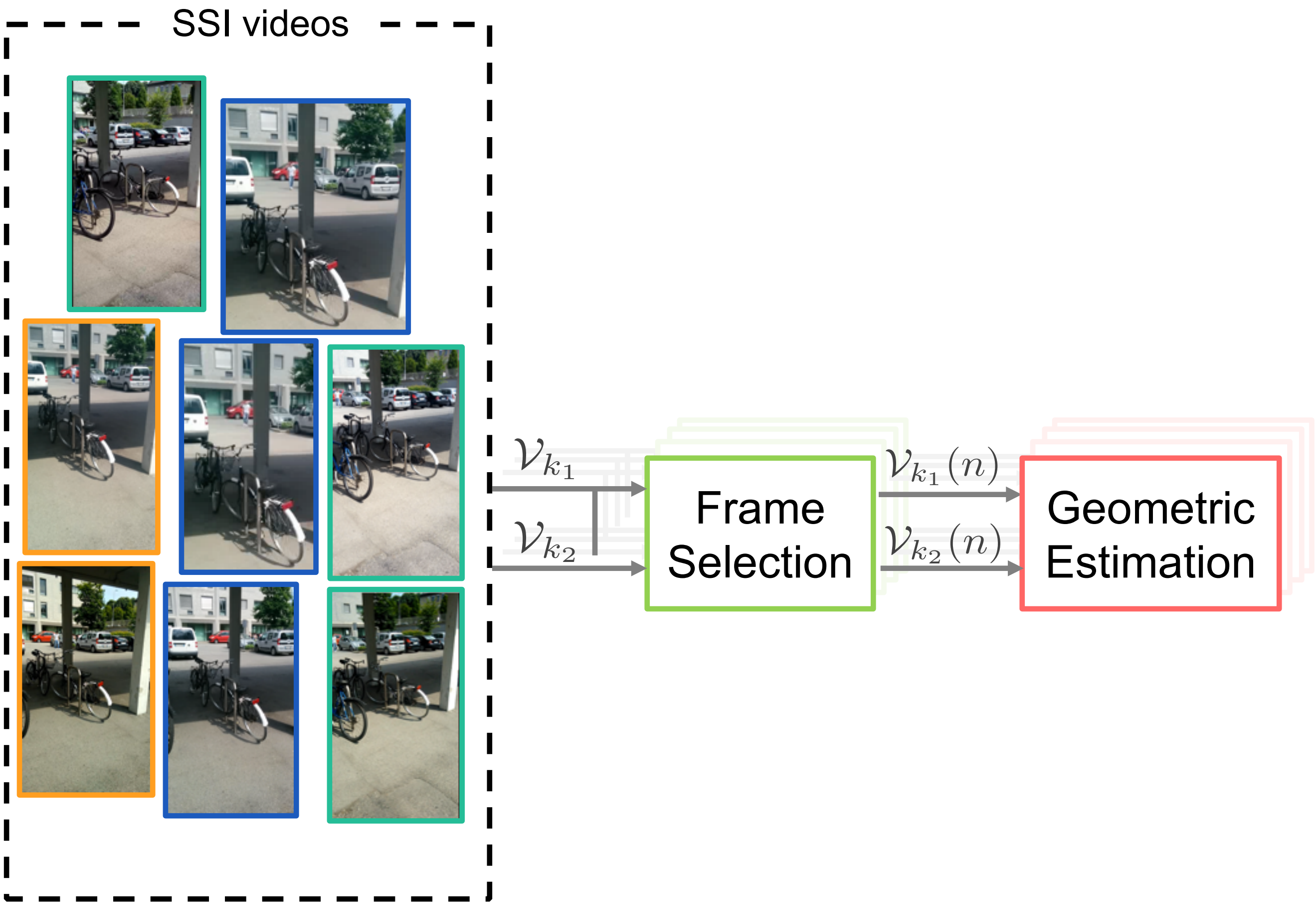
- ***ND clustering based on sensor noise analysis***

- *What is sensor noise?*
  - Due to its imperfections, every sensor cast a very weak noise-like pattern on every image it takes
  - This noise pattern plays the role of a **sensor fingerprint**

Proposed Algorithm

Proposed Algorithm



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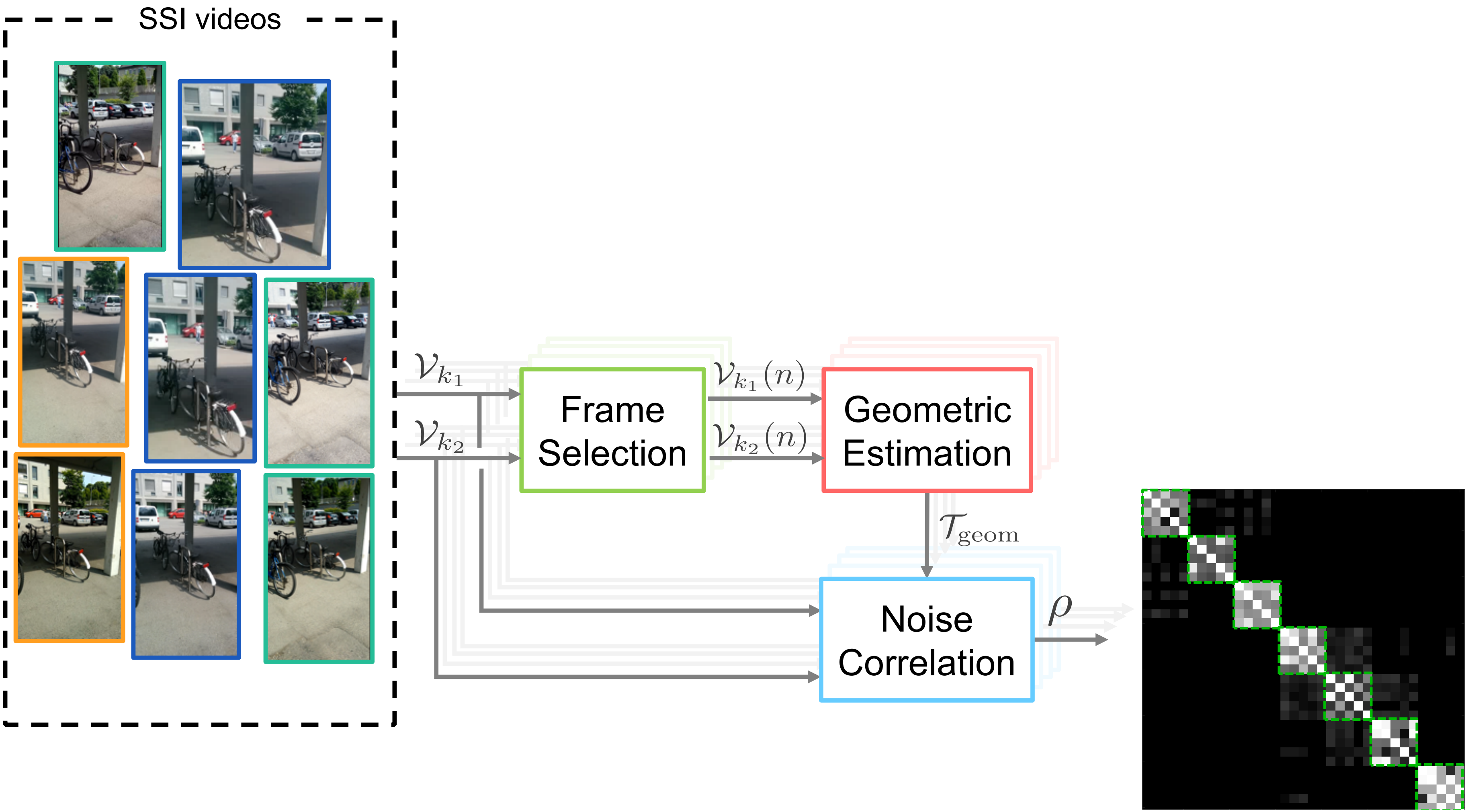

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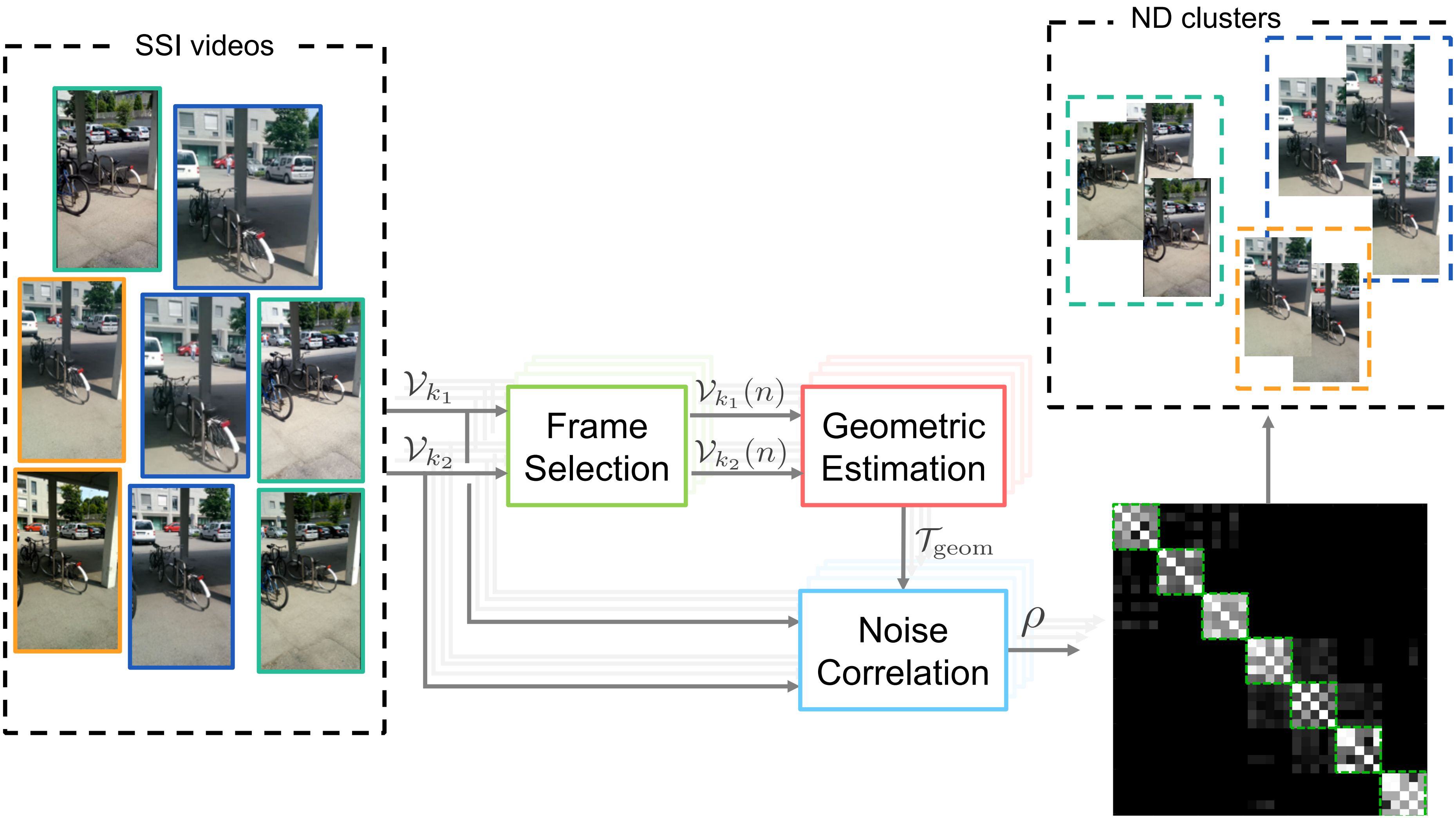

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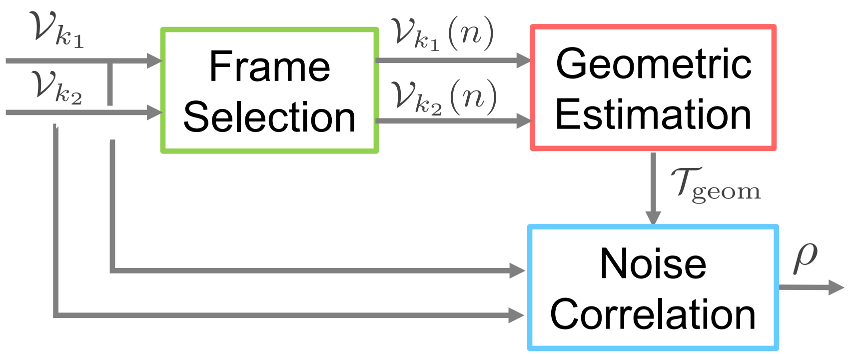

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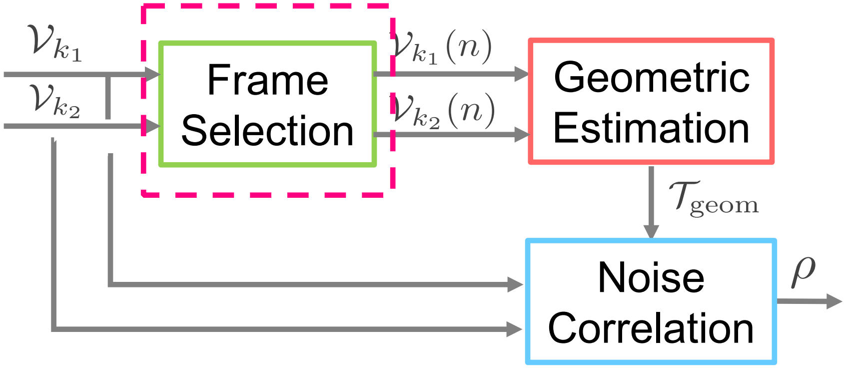
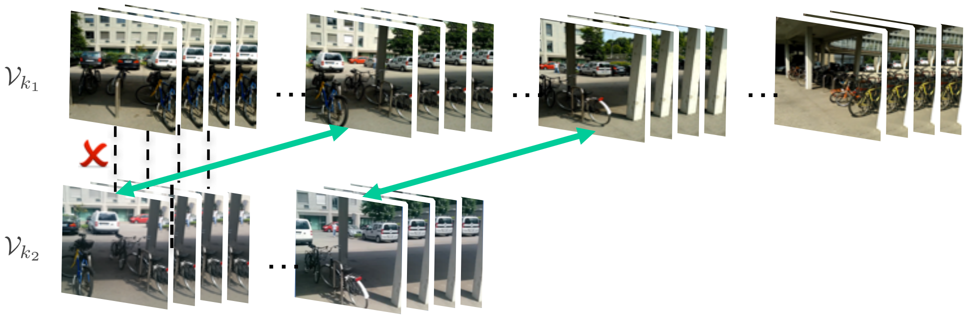
Proposed Algorithm
Frame Selection





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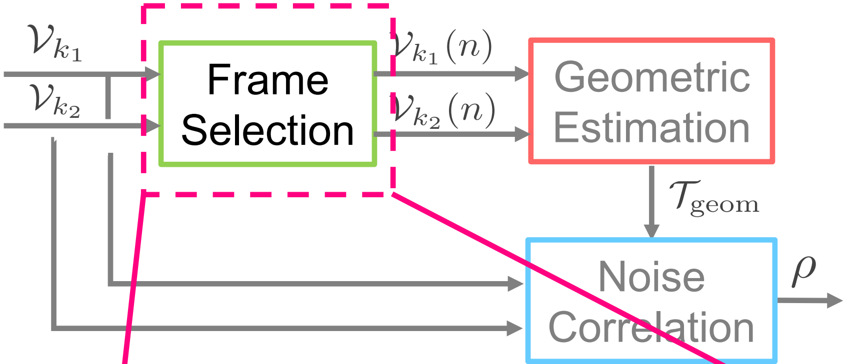

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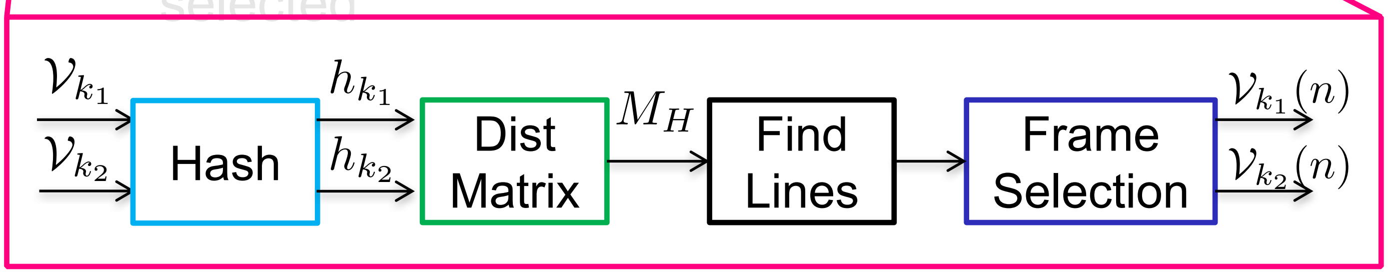

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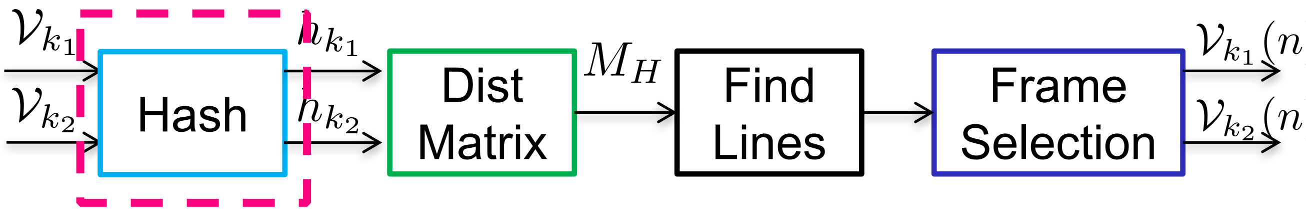

Video content over time is described by **binary hashes**

$\mathcal{V}_{k_1}$

$$h^1_{k_1} = 1001\ 0010\ \ldots\ 1011$$

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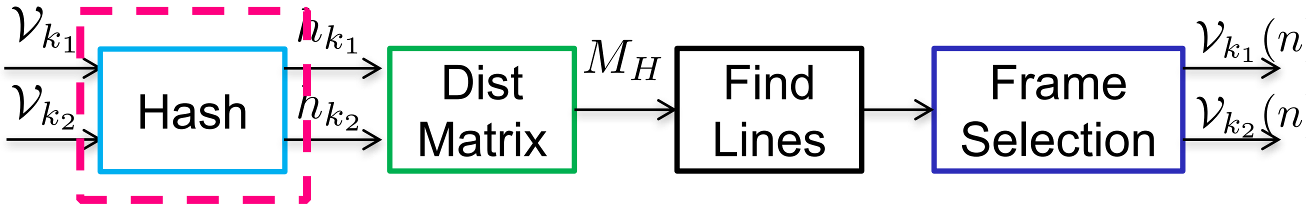

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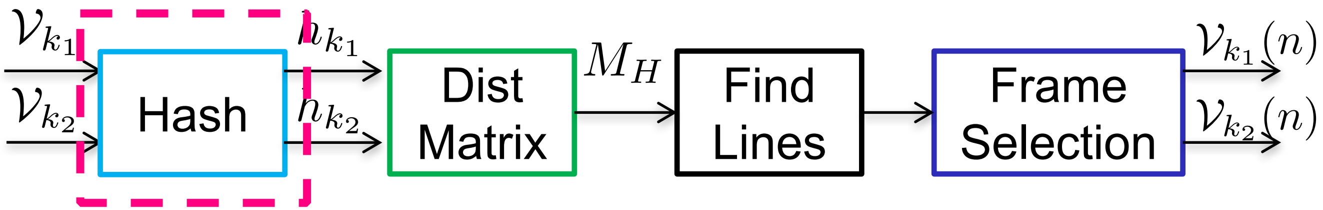

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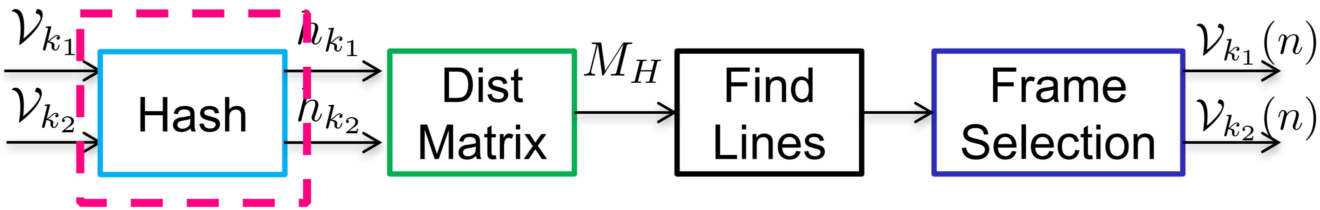

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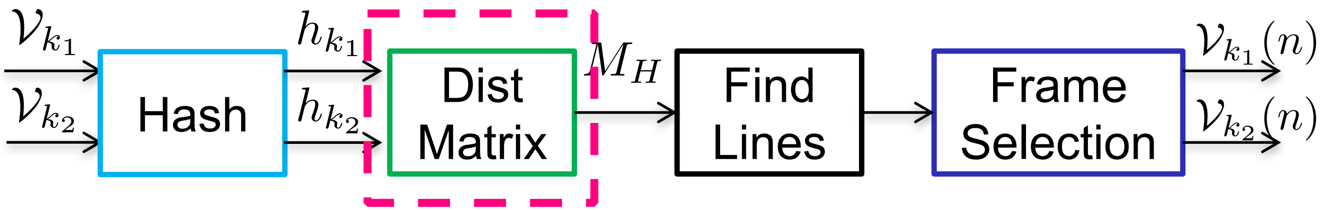

Pairs of hashes from different sequences are compared through **Hamming distance**

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$\mathcal{V}_{k_2}$

$$
\begin{array}{lcl}
1001\;0010\;\ldots\;1011 & \oplus & 0001\;0011\;\ldots\;1011 = 4 \\
1011\;0110\;\ldots\;0010 & \oplus & 1111\;0110\;\ldots\;0010 = 30 \\
\ldots & & \ldots \\
1110\;1110\;\ldots\;1010 & \oplus & 1110\;1110\;\ldots\;1010 = 0
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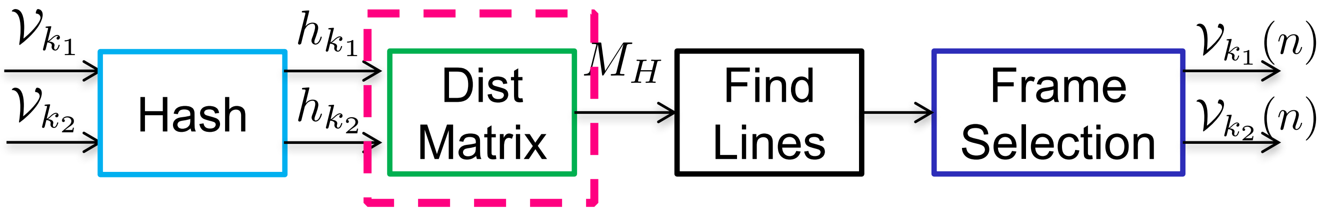

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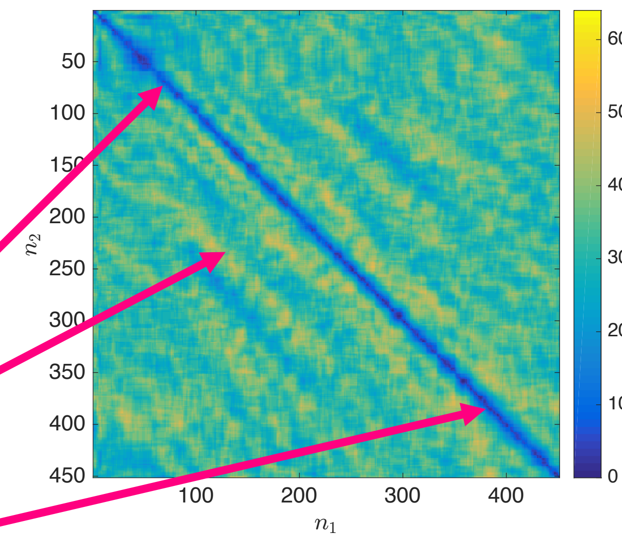

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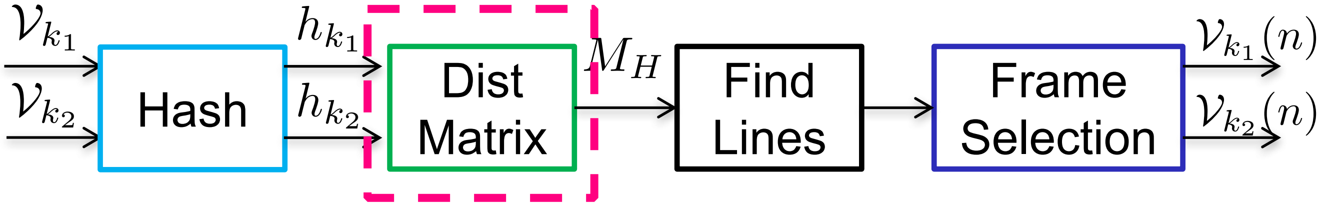
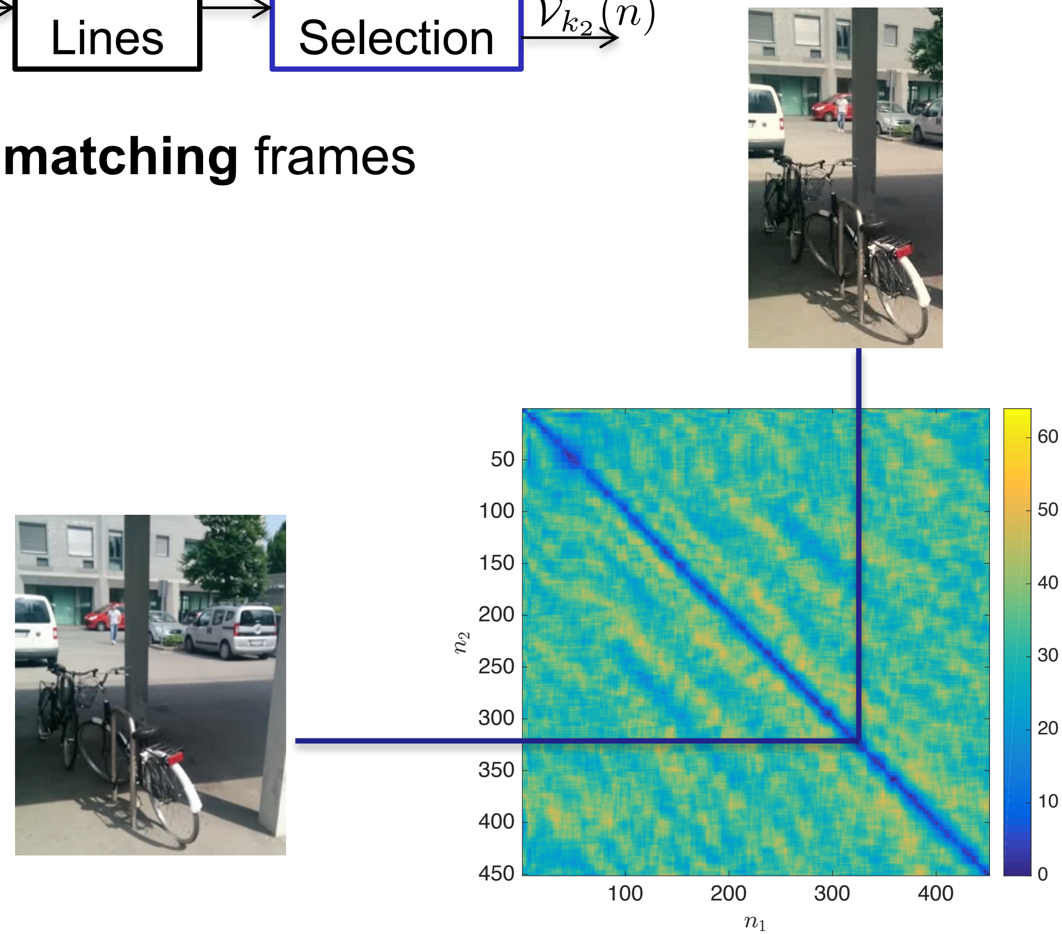


Low hash distance indicates **matching** frames



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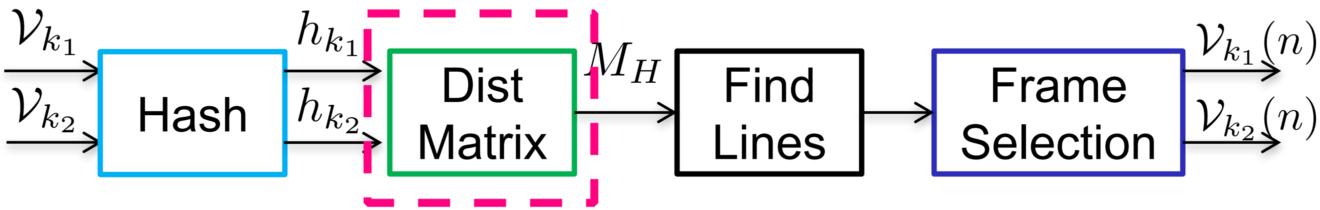
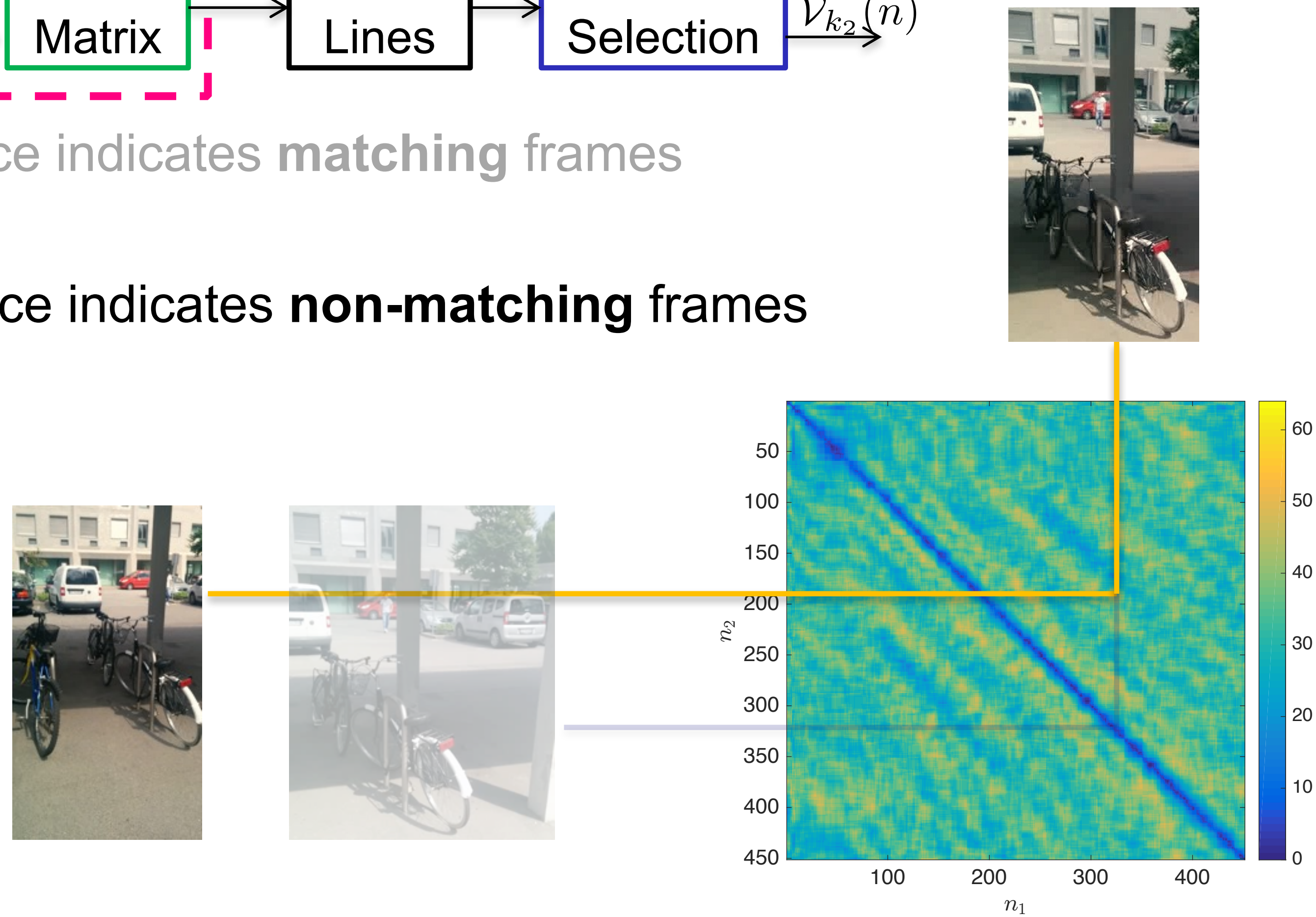


Low hash distance indicates **matching** frames

High hash distance indicates **non-matching** frames



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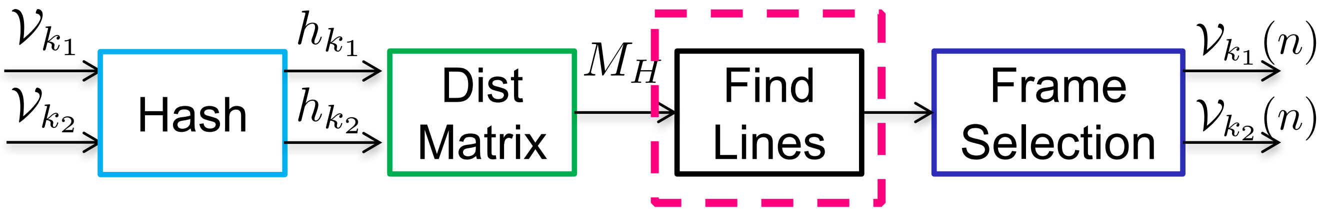
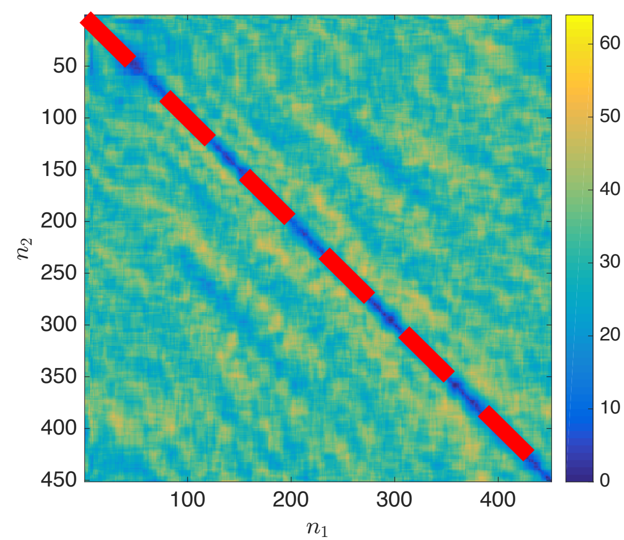


Frame selection procedure:

- Aligned low values are detected as they indicate **matching** frames



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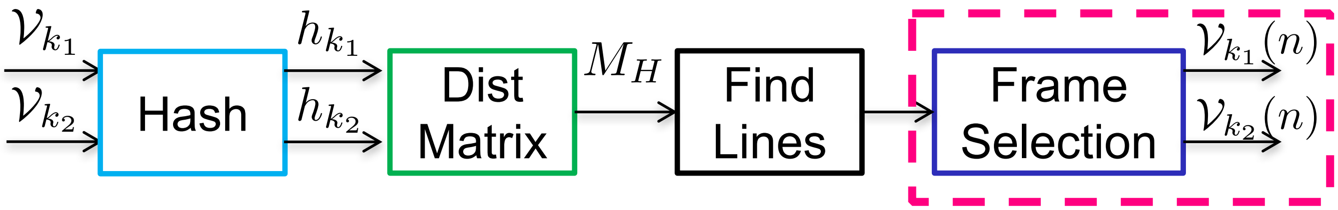
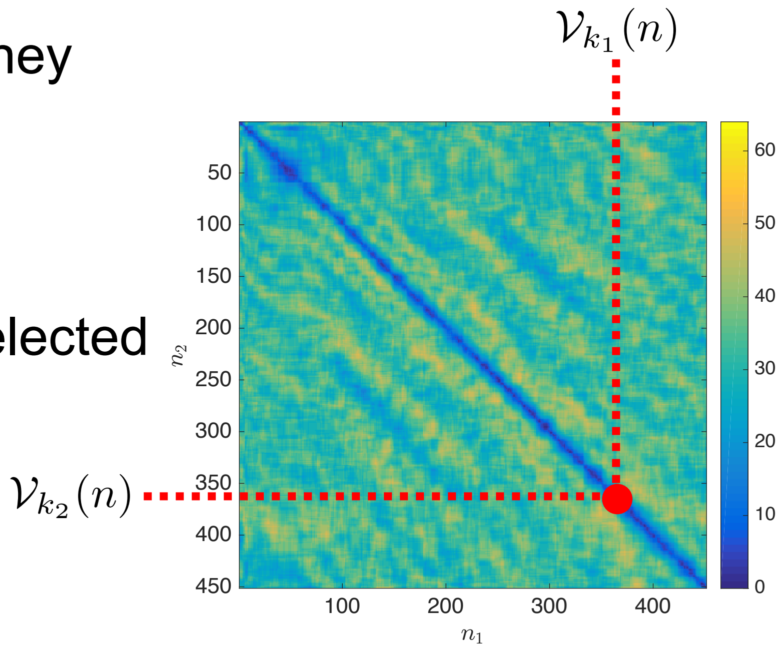
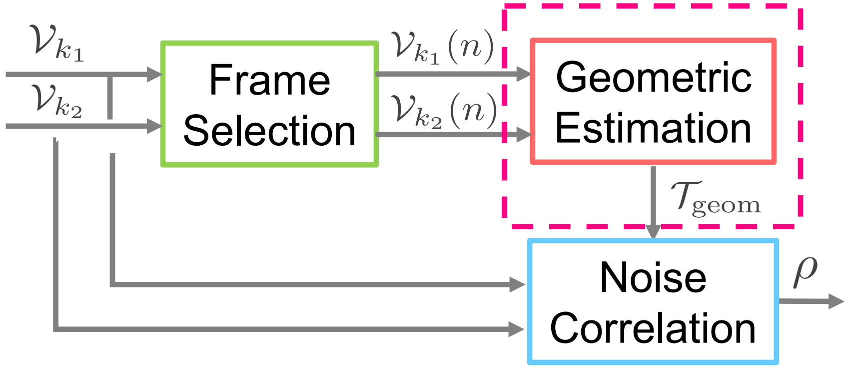


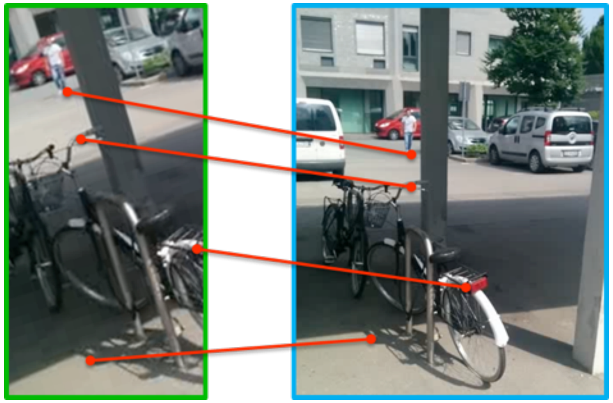
Frame selection procedure:

- Aligned low values are detected as they indicate **matching** frames
- The pair of matching frames with **minimum hash distance** value is selected



Proposed Algorithm
Geometric Estimation





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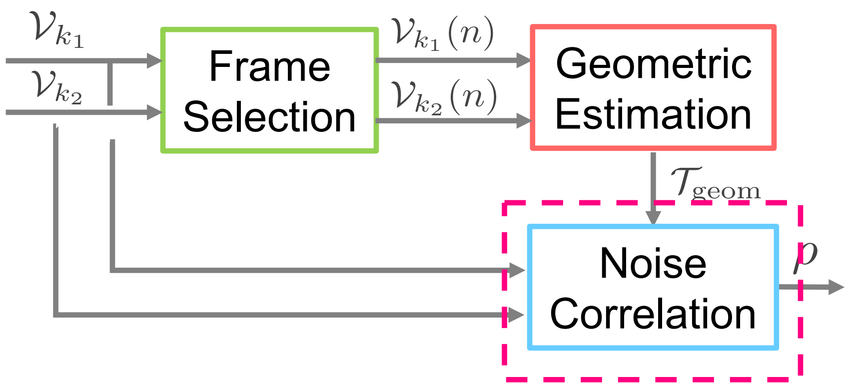
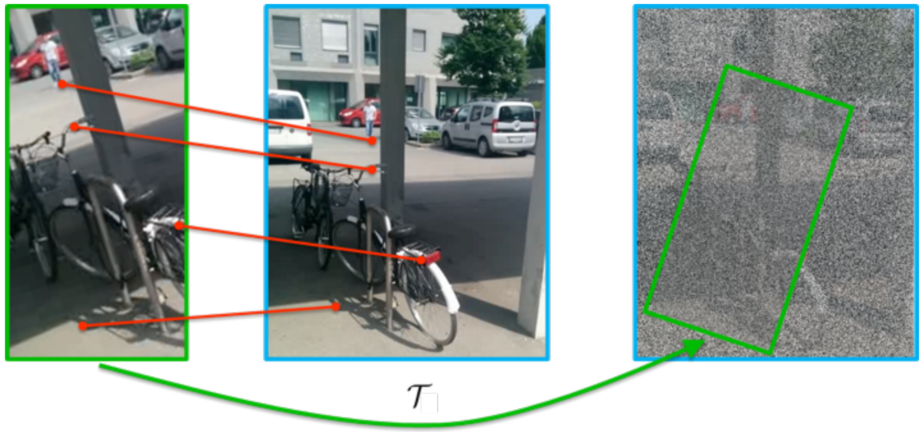
Noise Correlation





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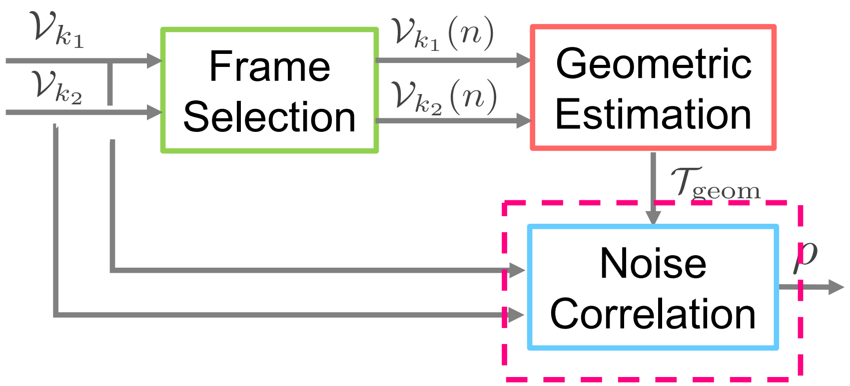

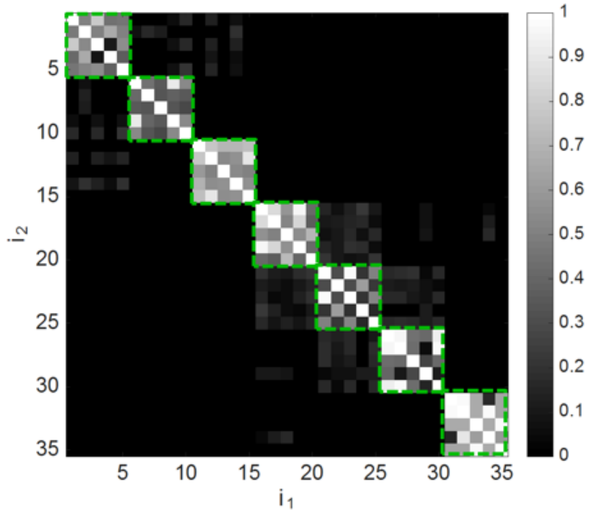

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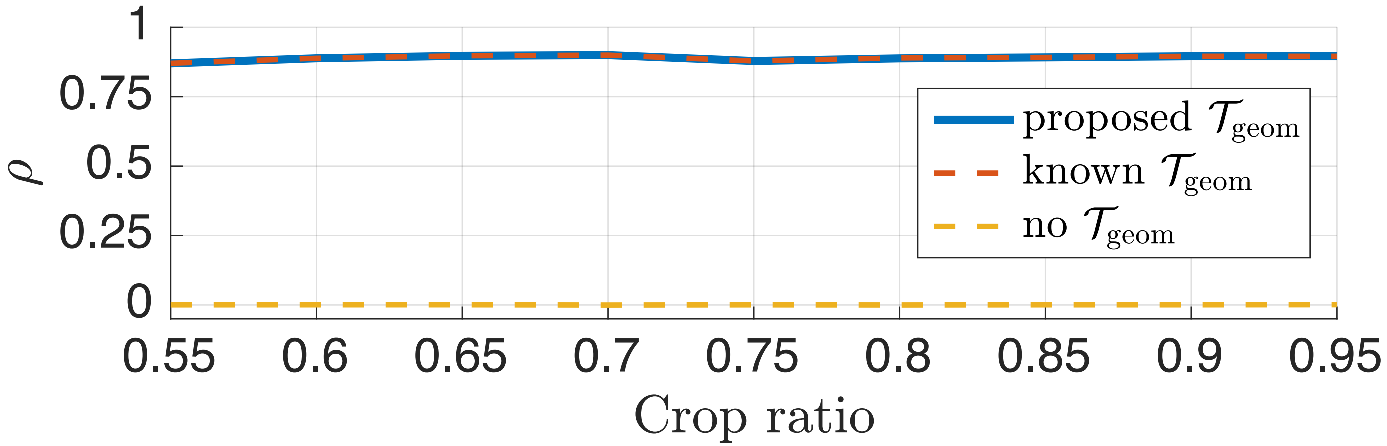
Experiments and results
Acquisitions

- 9 SSI videos acquired with 7 different smartphones
  - different view points and rotations, same filmed object
  - 15s to 40s sequence
  - some devices are the same model
  - no temporal synchronization
  - all videos resized to 640x360

Experiments and results
Geometric Estimation effectiveness

- *Crop dataset*: 693 ND with cropping ranging from 55% to 100%



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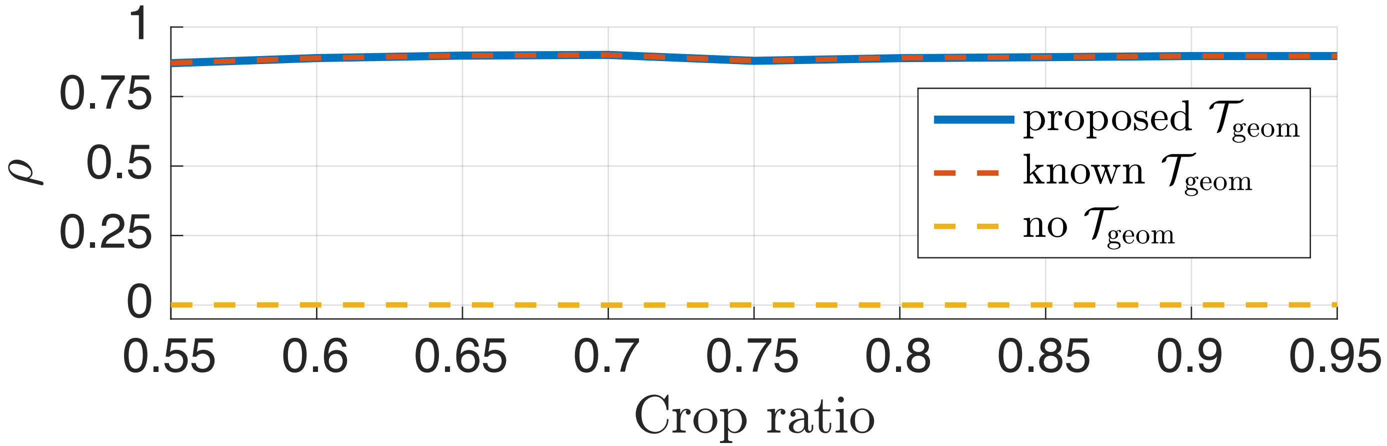
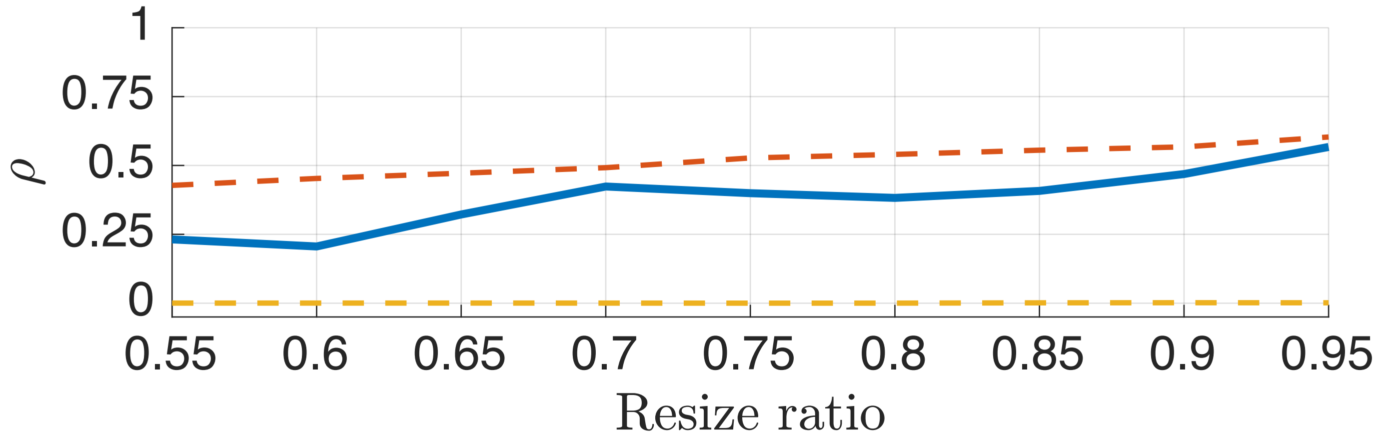
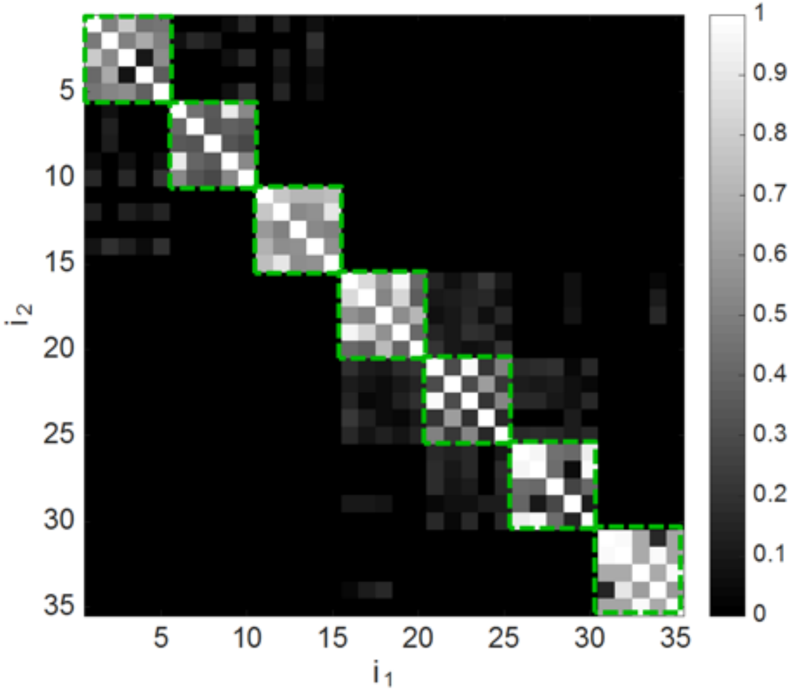


- *Resize dataset*: 693 ND with resizing ranging from 55% to 100%



Experiments and results
Clustering capabilities

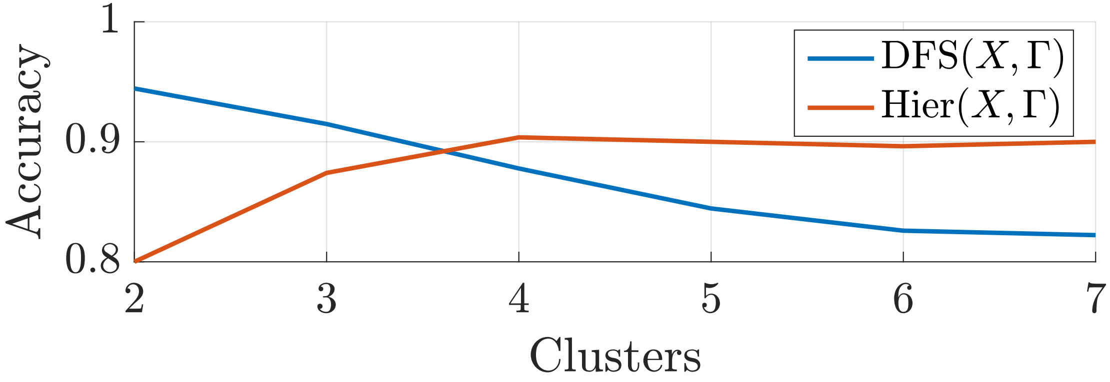
- *Clustering datasets*
  - 6 datasets with 2-7 ND clusters
  - Transformations obtained combining contrast enhancement, brightness adjustment, spatial cropping, resizing
  - More than 12k videos in total



- *Clustering approaches*
  - Depth First Search (DFS)
  - Hierarchical (Hier)

Experiments and results
Clustering capabilities

- Accuracy in detecting the **number of clusters**



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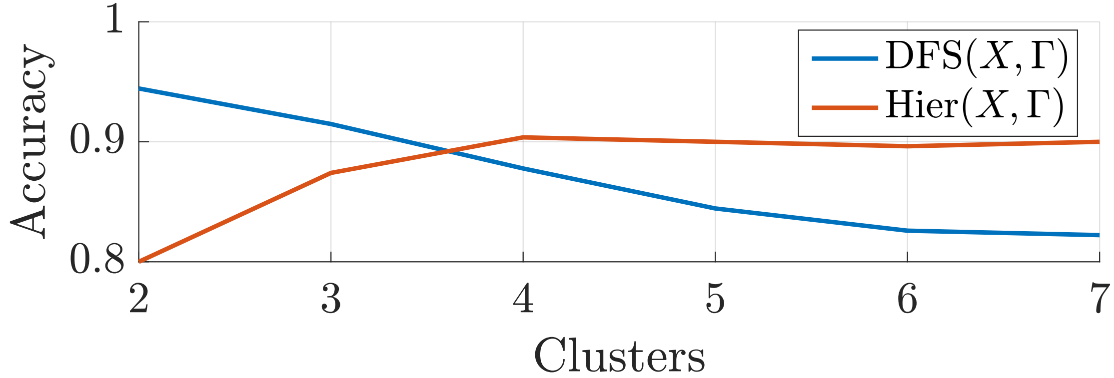
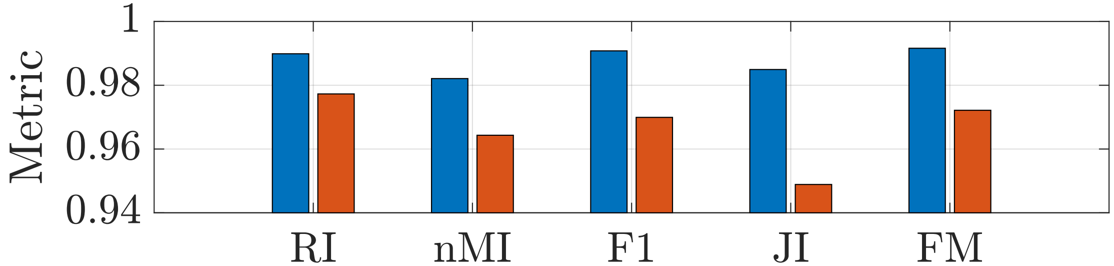
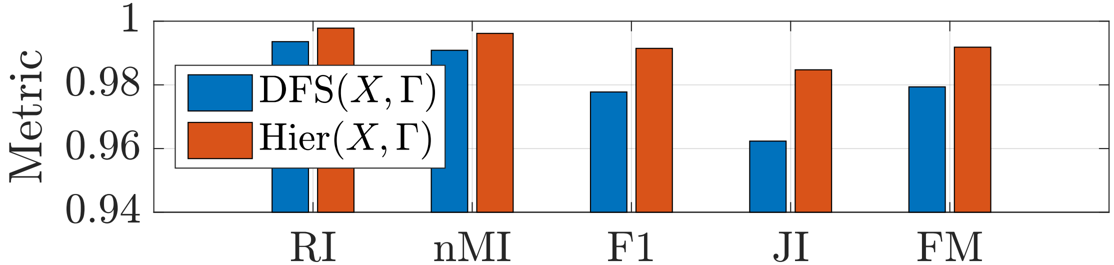


- How well pairs of ND are assigned to the same cluster



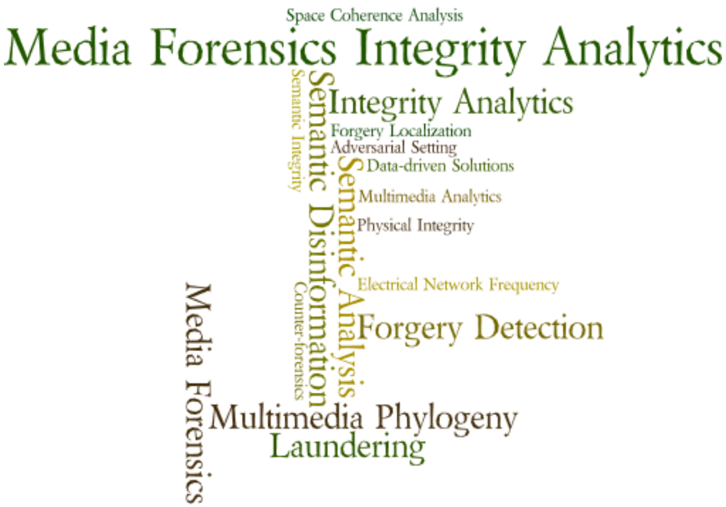
2 clusters



7 clusters

Conclusions

- We faced the problem of detecting **pool of near-duplicate** videos
- We proposed a pipeline based on the analysis of **noise residual** traces that
  - Disambiguates semantically similar videos form ND ones
  - Clusters together near-duplicate videos
- We verified the possibility of **geometrically registering** NDs noise residuals based on **keypoint matching**
- We showed the performances of **clustering** on different data realizations in terms of
  - Correctly detect the number of clusters
  - Separate SSI videos that are not NDs



Sponsored by DARPA and Air Force Research Laboratory (AFRL) under agreement number FA8750-16-2-0173

More information:
https://engineering.purdue.edu/MEDIFOR/

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