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MACHINE LEARNING FOR TARGET DETECTION

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Abstract

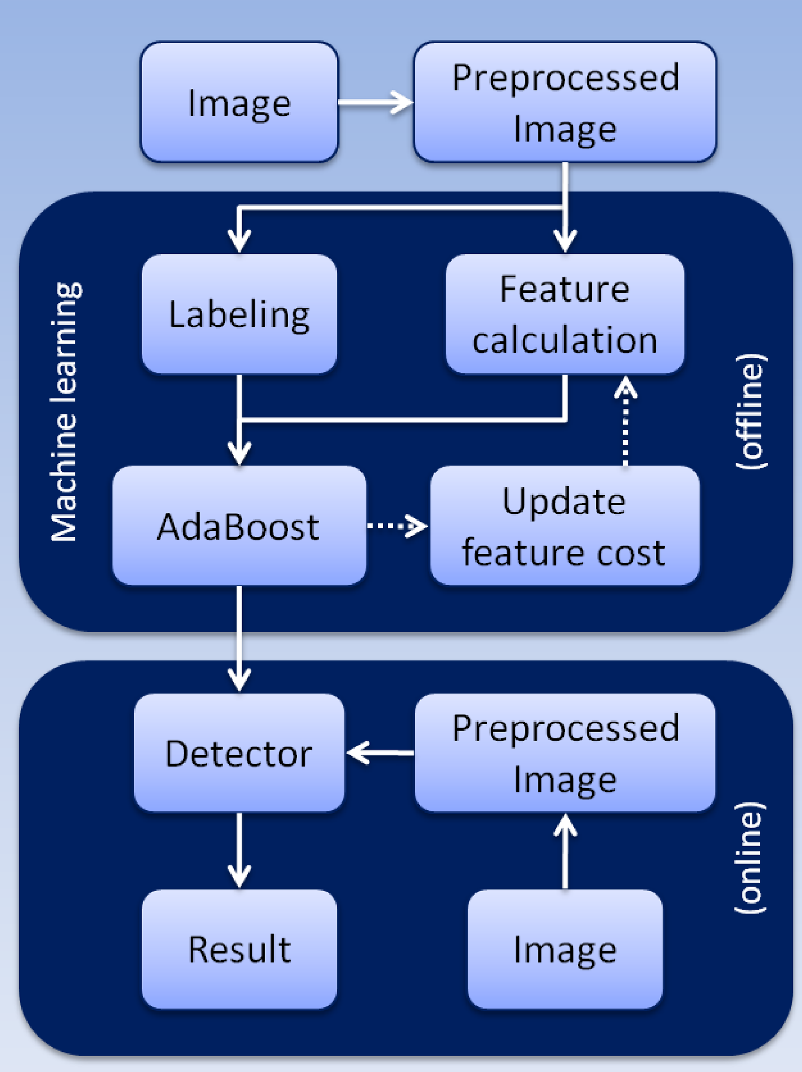
Deterministic approaches to detect targets (e.g. compression artifacts, skin or nuclei) generally fail to cope with the highly varying appearance of targets.

Machine learning strategies like AdaBoost offer more flexibility and have the ability to generalize.

We developed a framework to train a detector with high performance and low computational cost.

To this end, we modified AdaBoost to include awareness of computational feature cost by introducing a bias towards previously selected features.

General framework



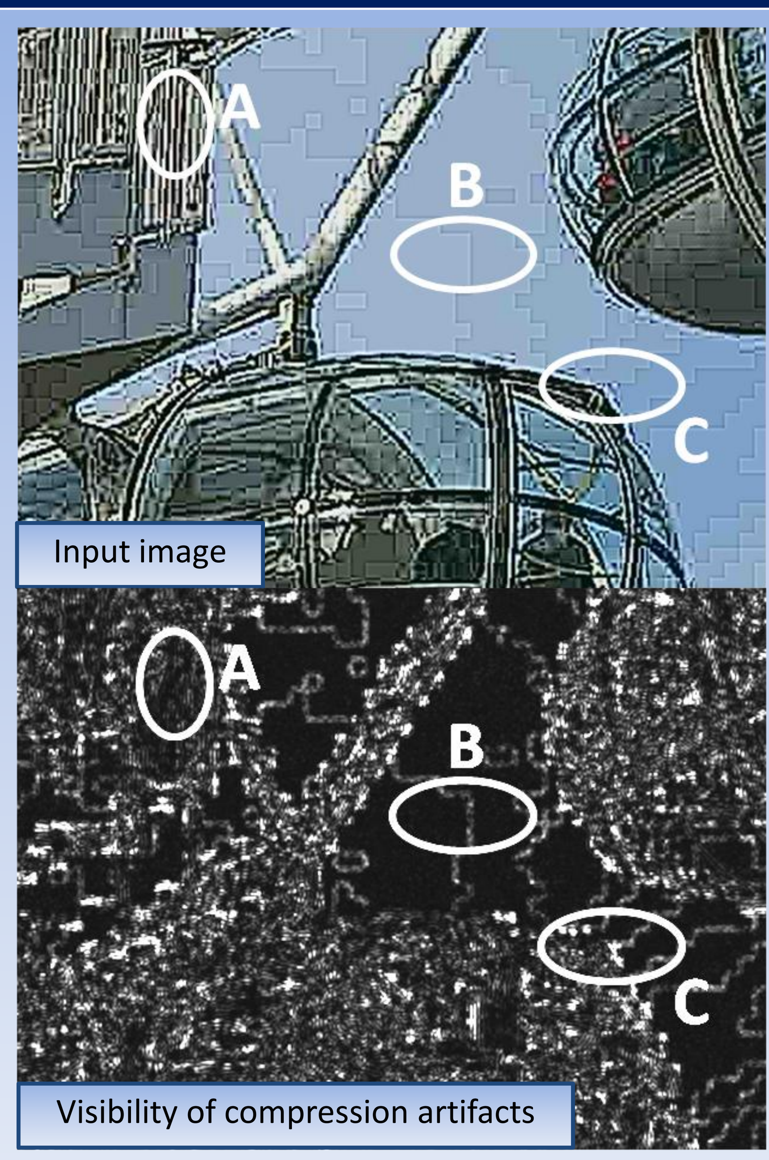
AdaBoost

- Supervised machine learning technique introduced by Freund & Shapire in 1995
- Fast, simple and easy to implement
- Became well-known through face detection, using cascade of classifiers (Viola & Jones in 2001)

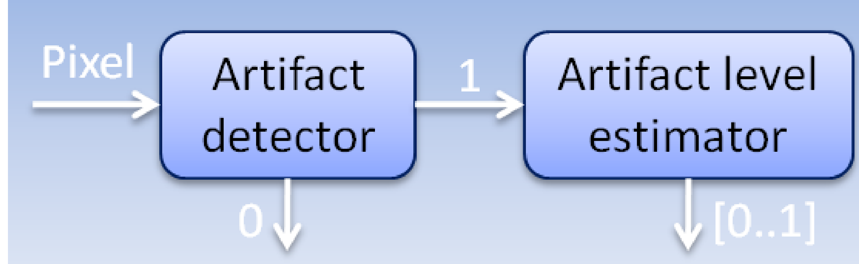
Compression artifacts

- In decoded digital video, the visibility of compression artifacts depends on the global compression ratio and the local video content.

Labeling



Level estimation



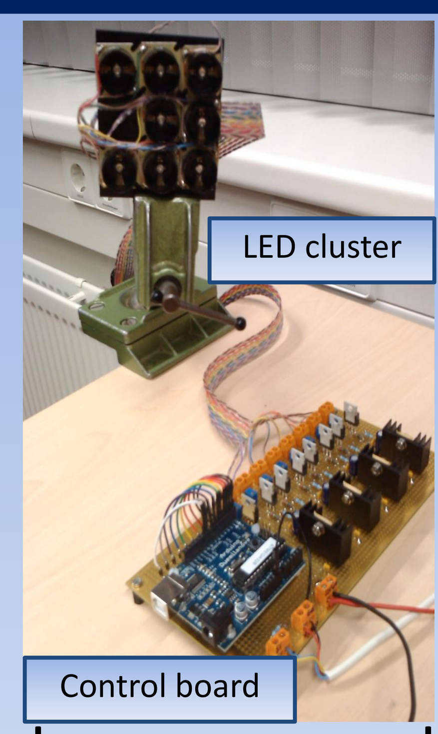
Results

- We developed a no-reference metric for local estimation of the visibility of the artifacts, which is robust to scaling and sensitive to all types of compression artifacts.
- Two separate metrics (for flat and for detailed areas, respectively) are necessary to cover all types of artifacts.
- Combined with artifact reduction, our new metrics enable a far superior performance compared to relevant alternatives.

Multi-spectral imaging

- Multi-spectral imaging can be beneficial for many computer vision applications (e.g. skin detection).
- Robust skin detection is useful for applications like face detection and gesture analysis.

Setup



- We have assembled a system comprising multiple LEDs with different spectra to illuminate a scene using a conventional RGB camera to acquire the images.

Features

- Ambient-light robust
- Robust to skin variation

$$I^P_{mn} = t\int \overbrace{s^P(\lambda)}^{\text{Reflectance}}\overbrace{c_m(\lambda)}^{\text{Camera}}\overbrace{[p^P_n(\lambda)}^{\text{LED}} + \overbrace{A^P(\lambda)]}^{\text{Ambient light}} d(\lambda)$$

$$I^P_{mj} - I^P_{mk} = t\int s^P(\lambda)c_m(\lambda)[p^P_j(\lambda) - p^P_k(\lambda)]d\lambda$$

$$(I^P_{mj} - I^P_{mk})_N = \frac{I^P_{mj} - I^P_{mk}}{\max(|I^P_{mj'} - I^P_{mk'}|)}$$

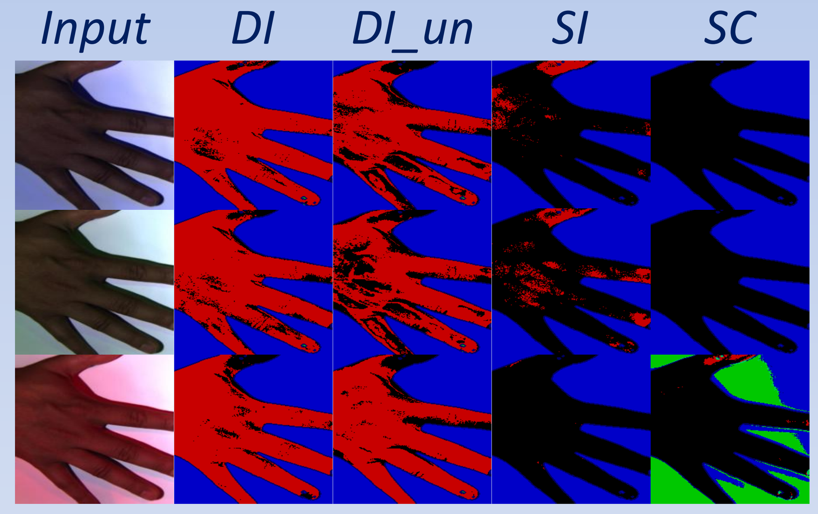
Results

- Proposed method (*DI*)
- Reference methods
  - *DI_un:* unnormalized
  - *SI:* single image
  - *SC:* model-based [Kovac]

Legend
Correctly detected skin
Missed detections
Correctly detected non-skin
Falsely detected as skin

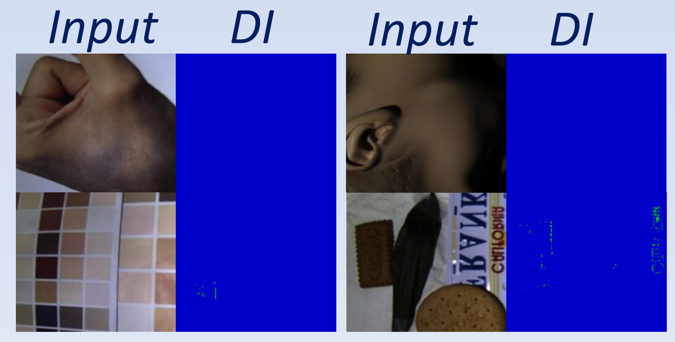
- Positive testing images

Input *DI* *DI_un* *SI* *SC*



- Negative testing images

Input *DI* *Input* *DI*



Histopathology images

- Recently, an ultra-fast scanner was introduced, with which pathological imagery becomes available in digital format.
- This enables automated assessments that enhance quality and reduce throughput time of the diagnosis.
- Nucleus detection represents a key component for many pathological applications.

Features

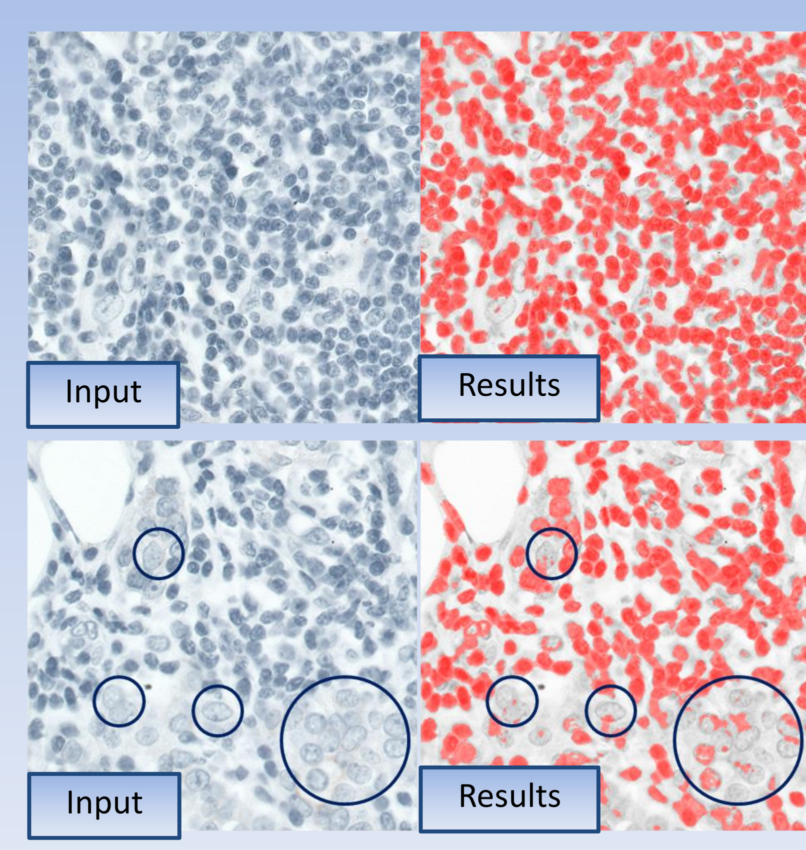
- Local features, such as standard deviation, dynamic range and local average.
- 1D & 2D Haar-like features using integral image.

Labeling

- Semi-automatically labeled IHC-images using thresholding and manual adjustments.

Results

- Detection rate of 99% and false alarm rate of 5% based on 35 IHC-images



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