Change detection in the sequences of images in complex scenes

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Problem

Problem:

increasing the robustness of simple background modelling algorithms to changing illumination conditions

Drawbacks of simple algorithms:

- don’t take into account changing light conditions;
- most of them are based on the physical properties of light – the particular law of the color transformation is expected when an illumination change takes place.

Proposed solution

We propose:

mutual comparative morphological filtering. It is resistant to changes in illumination conditions, does not apply predefined color transformation laws and is individual for each video.

Without filtration

With filtration

Dataset - *Wang, Y. et al. Cdnet 2014*

Comparative filters – definitions

Comparative filter takes as input two images for comparison: model or template f and test image g.

- *Definition 1.* Comparative filter is a function $\psi(f,g)\colon \Omega \times \Omega \to \Omega$, that for any fixed model image $f \in \Omega$, is a morphological filter $\psi_f(g) : \psi_f(g) = \psi(f,g)$.

The word morphological means that image g is filtered by the shape of image f.

- *Definition 2.* Comparative filter $\psi(f,g)$ is mutual if it is created from images f and g to filter image g. I.e. it is necessary to process a pair of corresponding images f and g (or pair of their fragments) in every image point to filter image g.

$$\psi^w(f,g)(x,y) = g_0^w(x,y) + |K(f^w, g^w)|(g(x,y) - g_0^w(x,y))$$

Comparative filters – definitions

Mutual comparative filtering within a window w:

$$g^w = g^{w(x,y)}(u,v) = \begin{cases} g(x,y), (u,v) \in w(x,y); \\ 0, \qquad\qquad (u,v) \notin w(x,y); \end{cases}$$

$$K(f^w, g^w) = \frac{(f^w - f_0^w, g^w - g_0^w)}{\|f^w - f_0^w\| \|g^w - g_0^w\|}.$$

$g_0^w(x,y)$ – mean value $g(x,y)$ within the window w $\equiv$ $w(x,y)$, $K(f^w, g^w)$ – local normalized correlation coefficient within the window $w(x,y)$.

Detection of relative changes in the scene is based on the background normalization, depends on the size of the window and can be carried out as follows:

$$\Delta g_f = |g - \psi^w(f,g)|$$

Comparative filters / morphological filters

The main advantage of comparative filters over the classical morphological filters*, that are used for image shape comparison, is that comparative filters do not require segmentation of images into semantic areas, and accordingly the result of image shape comparison is no longer dependent on the quality of the segmentation.

* *Vizilter, Yu. et al. 2014. Shape-Based Image Matching Using Heat Kernels and Diffusion Maps.*

Canny, J., 1986. A Computational Approach To Edge Detection.

Comparative filters – examples

Here you can see mutual comparative filtering of image g by the shape of image f with different window size w

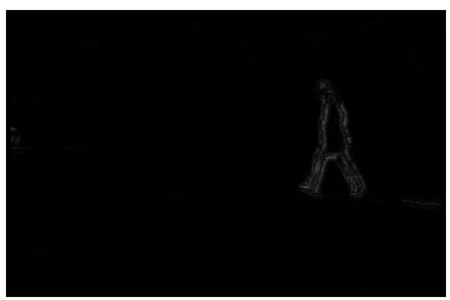
f

g

$\Psi_f(g)$

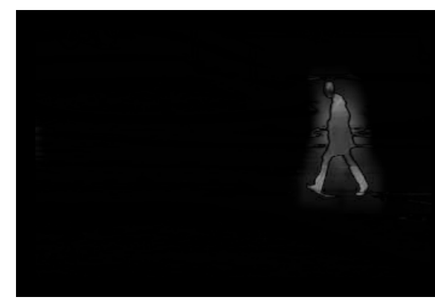
Δg_f

$\Psi_f(g)$



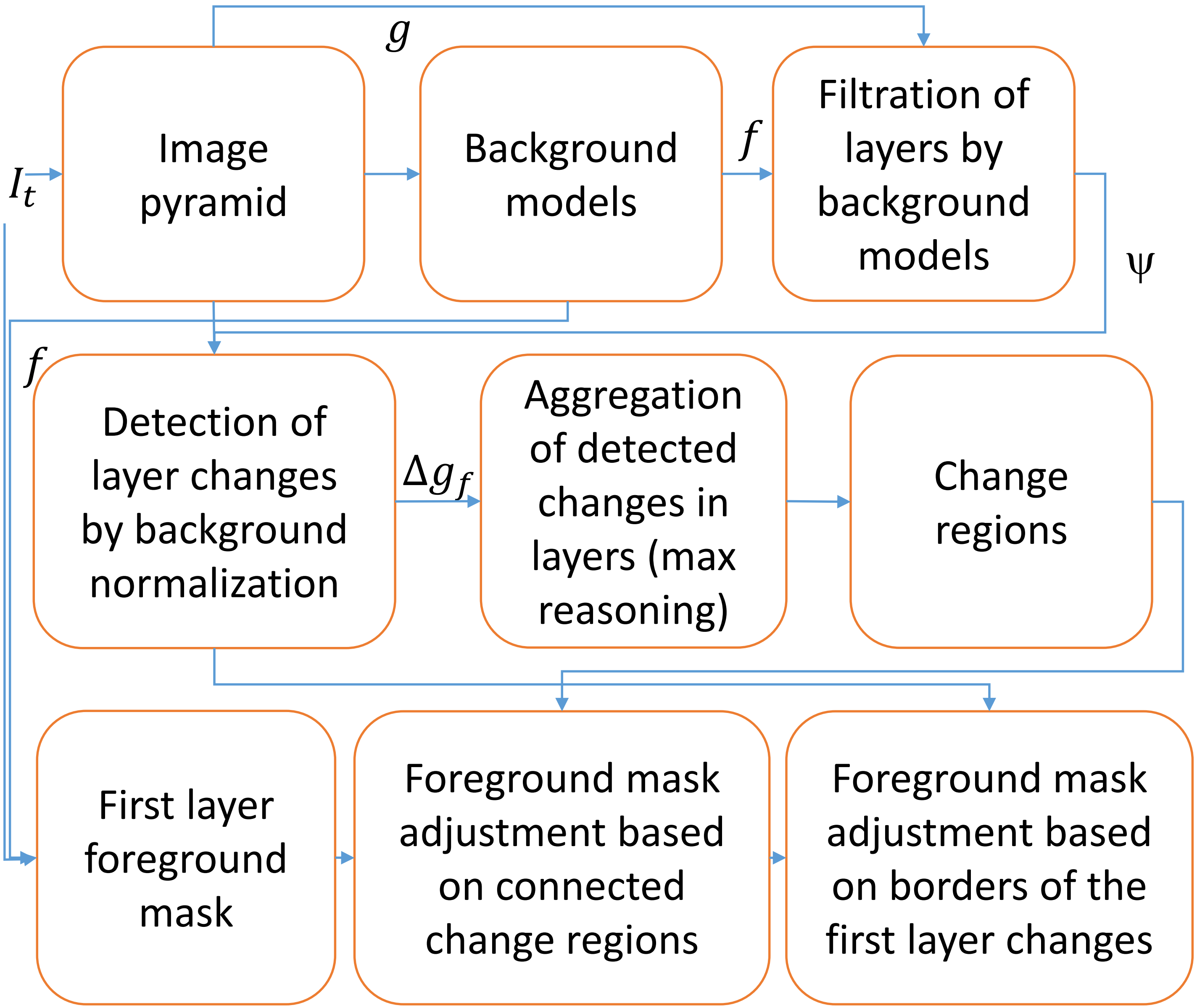
Δg_f

$\Psi_f(g)$



Δg_f

Image processing workflow



Algorithm steps 1-3

It – input image at the moment *t*

Ct – final change mask at the moment *t*

1. For each new image I_t, that is obtained at the moment t, construct the image pyramid $\{I_{s,t}\}$. The image pyramid allows us to detect regions with changes of various sizes s by using the window of constant small size.
2. Background models $m_{s,t}$ are built for every layer in the pyramid based on previous *n*-observations $(I_{t-1}, \dots, I_{t-n})$.
3. Mutual comparative filters $\psi^w(m_{s,t}, I_{s,t})$ are computed for every layer based on background models and image pyramid images:

$$\psi^w(m_{s,t}, I_{s,t}) = I_{s,t}^{w,0} + \left| K(m_{s,t}^w, I_{s,t}^w) \right| \cdot (I_{s,t} - I_{s,t}^{w,0})$$

Algorithm steps 4-6

4. The change detection $\Delta I_{s,t,m}(x,y)$ in every pyramid layer follows next:

$$\Delta I_{s,t,m}(x,y) = \left| I_{s,t}(x,y) - \psi^{w}(m_{s,t}(x,y), I_{s,t}(x,y)) \right|$$

5. All layers are resampled to the original image size and information is aggregated by «max» reasoning:

$$\Delta I_{t}(x,y) = \max\{\Delta I_{s,t,m}(x,y)\}$$

6. Potential changes are detected by $M(x,y)$ thresholding and connected regions are obtained from potential changes:

$$M(x,y) = \begin{cases} foreground : \Delta I_{t}(x,y) \geq threshold \\ background : \Delta I_{t}(x,y) < threshold \end{cases}$$

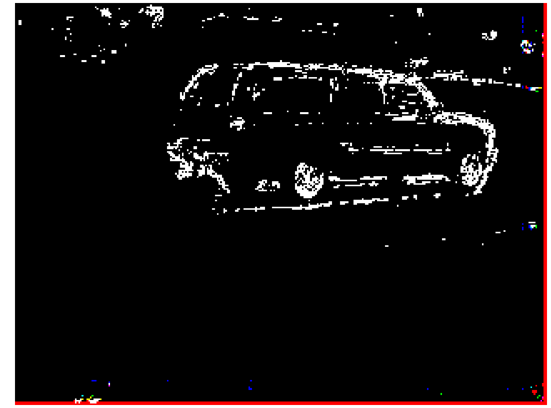
Algorithm steps 7-9

7. The foreground mask for the image I_t (1st layer from the pyramid) based on the 1st layer background model should be obtained by the usual way for chosen background model.
8. The foreground mask adjustment based on connected regions $M(x, y)$ (big adjustment) follows next: we take only those foreground pixels, which belong to the connected regions with changes;
9. The foreground mask adjustment based on borders of real changes (small adjustment). The borders of true foreground objects usually are in the 1-st layer of changes $\Delta I_{1,t,m}(x, y)$ due to small window size. So, we shrink the foreground mask to the $\Delta I_{1,t,m}(x, y)$ borders which are highlighted for us by non-maximum suppression algorithm. After that, opening and closing morphology operations are used.

Example of the image processing

f

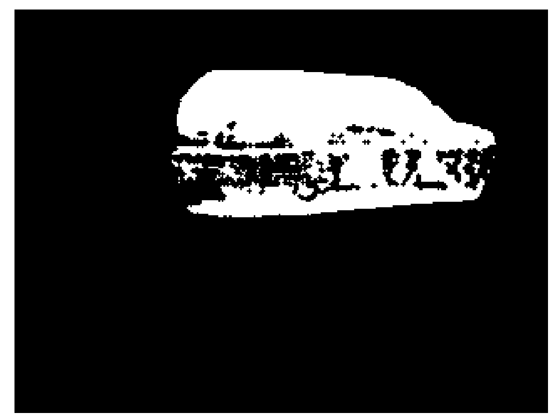
I_t



$\Delta I_{1,t,m}(x, y)$

$M(x, y)$

background model
(1-st layer
foreground mask)



C_t

Results

Original

GT

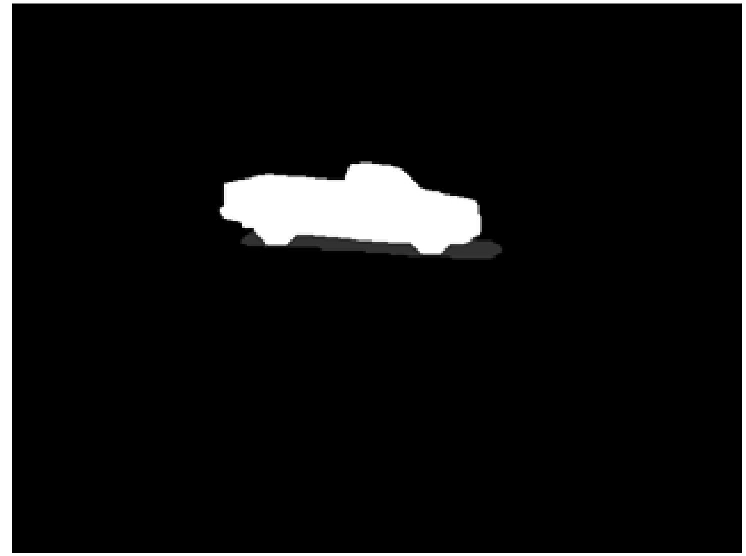
BG model

Result

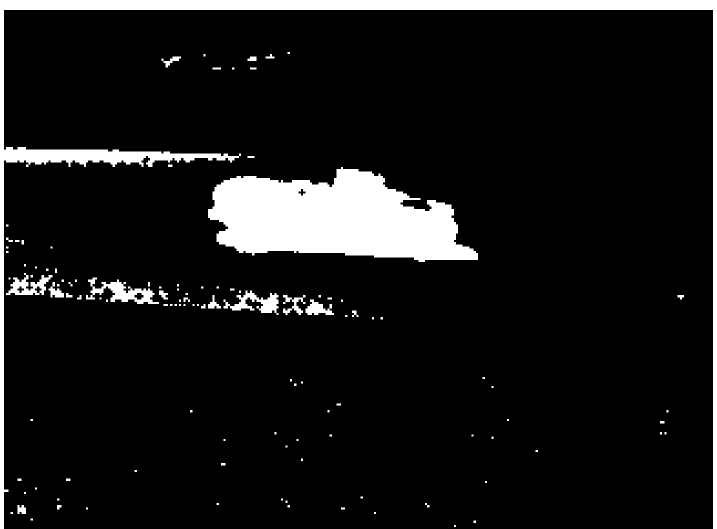
Results

Original

GT



BG model



Result

Conclusions

- Almost each background modeling algorithm benefits from our modification in challenging illumination conditions

- It can be widely used for the change detection on the pair of images (photos or aerial images, roughly aligned)

- False positives of the background model (*Vishnyakov, Vizilter, Knyaz, ISPRS 2012*) on the test dataset (*Wang, Y. et al. Cdnet 2014*) in complex lightning conditions reduces approximately by 10 times, when true positives reduces by 0.5-1%.