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# TWO IMAGES COMPARISON WITH INVARIANCE TO ILLUMINATION PROPERTIES

Jean-Philippe Tarel

University Paris-EST, IFSTTAR, 14-20 Boulevard Newton, F-77420 Champs-sur-Marne, France

Jean-Philippe.Tarel@ifsttar.fr

## ABSTRACT

We propose a new way of performing pixel by pixel comparison between two images, taking advantage of interesting invariance properties with respect to illumination conditions and camera settings. Moreover, we show that the proposed operator is relatively robust to strong noise on one of the compared images. The new operator can be used for background subtraction which inherits its invariance properties. The useful properties of the proposed operators are illustrated in the experiments.

**Index Terms**— Image comparison, invariance to illumination, bilateral filtering.

## 1. INTRODUCTION

The usual difference operator between two images computes a map of pixel by pixel distances between gray-levels or colors. Such an operator can be normalized by the input signal and thus leads to the well-known Power Signal Noise Ratio (PSNR). Image difference operators are widely used for evaluation purposes in image processing such as compression, denoising and restoration. However, when comparing two images, people are more focused on where the objects lie than on their exact color values: it seems that people are able to compare images with a certain amount of robustness with respect to intensity or illumination changes. Several image difference operators were thus proposed based on our understanding of the human visual system, see for instance [1]. These operators are based on local features but not at the pixel level. Indeed, the only features which are invariant to illumination changes at the pixel level are edges. Image difference operators based on edges do not provide regions corresponding to objects.

We propose a new image difference operator which is invariant to a certain kind of illumination changes. By illumination changes, we mean an image intensity variation which is smooth on uniform areas and can only break at edges. As a consequence, an illumination change is not supposed to introduce any new edge in the image. A new shadow due to an illumination change is thus considered as a new object. The proposed operator is based on the image edges, to be invariant, but these edges are never explicitly computed. The

image difference computed by this operator does not contain only new edges but also regions of new objects. Thus it can be used for background subtraction.

In Sec. 2, the new image difference operator which owns interesting invariance properties is introduced and described. Its properties are highlighted. Then, in Sec. 3, experiments are reported to illustrate the advantages of the proposed image difference operators.

## 2. IMAGE DIFFERENCE OPERATORS

### 2.1. Possibility of invariance to illumination

The Usual Image Difference operator between two images  $I$  and  $J$  can be written as  $UID(I, J)(x)$ :

$$UID(I, J)(x) = d(I(x), J(x)) \quad (1)$$

where  $x$  is the pixel position and  $d(a, b)$  is a distance on intensity values  $a$  and  $b$ . By summing (1) over pixels  $x$ , a distance between images  $I$  and  $J$  is obtained.

This operator (1) is sensitive to noise on  $I$  and  $J$ . Thus, a spatial smoothing operator  $F$  can be applied, on both images  $I$  and  $J$ , to decrease the effect of noise. The Smooth Image Difference operator  $SID_F$  is thus the following:

$$SID_F(I, J)(x) = d(F(I)(x), F(J)(x)) \quad (2)$$

The filter  $F$  is not necessarily reversible, so the summing over pixels  $x$  of (2) is still symmetric but is not a distance, contrary to the sum of (1). It is only a dissimilarity measure.

$F$  can be a linear smoothing filter or better a smoothing filter which preserves object edges. Large classes of smoothing filters exist which preserve object edges, such as bilateral filters, and more generally, robust bilateral filters, as described in [2]. These filters are particular cases of a larger class of filters, the so-called guided bilateral filters. A guided bilateral filter serves to smooth an image with the help of a guide image. Joint/cross bilateral filters [3, 4] are particular cases within this class. Within the class of the guided bilateral filters, the operator (2) can be rewritten equivalently as:

$$SID_H(I, J)(x) = d(H_I(I)(x), H_J(J)(x)) \quad (3)$$

where  $H_B(A)$  is a guided bilateral filter on input image  $A$ , with the help of the guide image  $B$ .

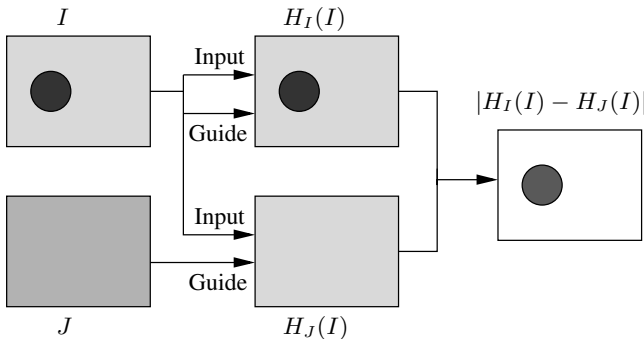
Thanks to FUI project TORNADO for funding.

If the introduction of spatial smoothing decreases the effect of noise, the operators (2) and (3) are not invariant to illumination changes between image  $I$  and  $J$ . This is due to the fact that there is a direct difference between  $I$  and  $J$  in operators (2) and (3). As a consequence, to introduce properties of invariance to illumination changes, we propose to substitute image  $J$  with image  $I$  in the input of the second filter  $H_J$  in (3). The new operator, we named Guide Image Difference operator  $GID_H(I, J)$  on images  $I$  and  $J$ , is thus given by:

$$GID_H(I, J)(x) = d(H_I(I)(x), H_J(I)(x)) \quad (4)$$

In this new operator,  $H_B(A)$  is assumed to be an iterative guided bilateral filter, as introduced in [2], but it can be any guided bilateral filter, i.e any smoothing filter on  $A$  where a guide image  $B$  is used to preserve in  $A$  the edges which are in  $B$ . The new operator (4) is not symmetric with respect to  $I$  and  $J$ , contrary to operators (1), (2) and (3). The sum over pixels  $x$  of (4) is not an image distance. It is only a dissimilarity measure.

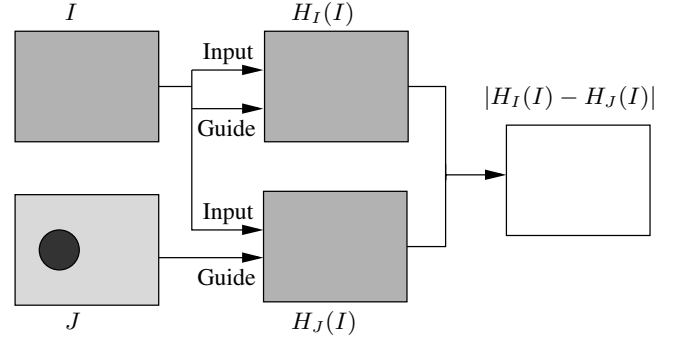
## 2.2. New and lost objects



**Fig. 1.** Guided Image Distance for a dark disk as the first input and with a constant image as the second input. The output is the dark disk on a zero background.

From now on, we assume that the distance  $d$  used to compare intensities is the absolute difference distance. In Fig. 1, the way operator (4) works is illustrated. In this example, the first input image  $I$  is a simple black disk over a gray background and the second input image  $J$  is a different gray background. The filtered image  $H_I(I)$  of  $I$  equals  $I$ . Indeed, edges are preserved by this operator since the guide image is the input image  $I$ . On the contrary, the filtered image  $H_J(I)$  does not necessarily equal the input image  $I$ . Indeed, the guide image  $J$  does not contain any edge. The output  $H_J(I)$  depends of the scale of the spatial smoothing. When this scale is lower than the size of the black disk and if the filter preserves edges,  $H_J(I)$  equals  $I$ . In such a situation, the output  $GID_H(I, J)$  is the zero image. On the contrary, when the smoothing scale is large enough compared to the

size of the black disk, the black disk is filtered out and can be completely removed in  $H_J(I)$ . Thus,  $H_J(I)$  is only the gray background of  $I$ . In such a situation, the output  $GID_H(I, J)$  is an image with zero into the background and the black disk contrast into the foreground. The black disk is thus detected in the image difference  $GID_H(I, J)$ . Notice that this detection is invariant to the value of the background intensity in  $J$ .



**Fig. 2.** Guided Image Distance for a constant image as the first input and with a dark disk as the second input. The output is a zero image.

Let us swap the role of the two input images. Now, the first input image  $I$  is a gray background and the second input image  $J$  is a black disk over a gray background, as illustrated in Fig. 2. The filtered image  $H_I(I)$  equals  $I$ . Indeed, nothing can be filtered out since  $I$  is constant. Whatever the smoothing scale of the filter, the output  $H_J(I)$  equals  $I$ . Again, nothing can be filtered since  $I$  is constant. Thus, the output  $GID_H(I, J)$  is the zero image. Notice that the output does not change when the value of the intensity of the black disk or of its background are modified in  $J$ .

The previous simple examples illustrate that the operator  $GID_H(I, J)$  in (4) is not symmetric and is able to detect regions in  $I$  which are not in  $J$ , when they are smaller than the smoothing size. In other words, the operator  $GID_H(I, J)$  detects new objects in  $I$  compared to  $J$ . Reversely, the operator  $GID_H(J, I)$  detects lost objects in  $I$  compared to  $J$ . One can notice that the loss of the symmetry property between first and second inputs in  $GID_H$  is useful, since it allows separating new and lost objects. Notice also, that if new or lost objects are detected thanks to their edges, edges are never explicitly estimated in the computation of operator (4).

## 2.3. Invariance to piecewise constant illumination changes following object edges

As noticed in the previous examples of Fig. 1 and Fig. 2, the operator  $GID_H$  in (4) owns interesting properties with respect to illumination changes on  $I$  and  $J$ . These properties are related to the properties of  $H$ . The guided bilateral filter  $H_B(A)$  used in the definition of the image difference operator



**Fig. 3.** Guided Image Difference operator applied on two image pairs. The output is shown in the third line after a morphological opening and a thresholding.

$GID_H$  consists in a local linear or non-linear filter weighted by a spatial weight which is usually a function of the intensity difference between two pixels in the guide image.

With respect to the first input, when a constant function is added to its intensities, the output  $GID_H(I, J)$  is not modified, if no saturation occurs. When a multiplicative factor is applied to the intensities of image  $I$ , the output  $GID_H(I, J)$  is multiplied by the same factor, if the differences in guide image intensities used in the guided bilateral filter are normalized by, for instance, the guide image standard deviation. In practice, with a linear factor close to one to prevent saturating the input image, even without standard deviation normalization, the output  $GID_H(I, J)$  is mainly and approximately multiplied by this factor. In summary, the output of  $GID_H(I, J)$  is invariant with respect to the addition of a constant intensity on the first input, and mainly covariant with respect to the product by a multiplicative factor.

With respect to the second input, when a constant function is added to its intensities, the output  $GID_H(I, J)$  is not modified, if no saturation occurs, like for the first input. To preserve edges in the guide image, the spatial weight on the difference of intensities over the guide image is a decreasing positive function which thus quickly achieves the zero value. For this kind of guided bilateral filter, the global invariance property can be extended to a more local invariance

property : adding piecewise constant intensities where the intensity breaks only at the guide image edges does not modify the output. This invariance is valid while the contrast along guide image edge is not so decreased as to leave the interval where the spatial weight function is zero.

To achieve invariance with respect to a multiplicative factor on the second input, the guided bilateral filter result should also be invariant to a multiplicative factor on the guide image. This can be obtained, as before, by normalizing the guide image with the standard deviation of its intensities, within the filter. As previously argued, the multiplicative factor is close to one not to saturate the guide image and thus only robustness with respect to this factor is needed in practice. This robustness to close to one multiplicative factors can be obtained as a consequence of the invariance with respect to the addition of an intensity constant. In summary, the output  $GID_H(I, J)$  is invariant with respect to the adding of a global constant intensity on the second input and to the adding of piecewise constant intensity following image guide edges. It is also robust with respect to the product by a multiplicative factor.

In Fig. 3, the previous properties are illustrated by showing the output of the Guided Image Difference operator applied on two image pairs, each pair with an image with a vehicle and the other without the vehicle but with somewhat different illumination conditions. Despite these illumination conditions differences, both vehicles are correctly detected without false alarm.

#### 2.4. Robustness to noise

In addition to the interesting properties of the Guided Image Difference operator (4) with respect to illumination changes, the  $GID_H$  operator owns interesting properties with respect to noise in the first input image. Indeed, the effect of the noise on the first input is greatly decreased on the result due to the fact that the first input image is smoothed with a large smoothing scale during its computation.

#### 2.5. Faster computation

The computational cost of the Usual Image Difference operator (1) is very low. Its complexity is linear with respect to the image size, i.e in  $O(n)$ , where  $n$  is the number of pixels in each input image.

The computational cost of the Guided Image Difference operator (4) is higher. Indeed, its complexity is related to the computational cost of the guided bilateral filter  $H$  which is used two times to compute  $GID_H$ . The complexity of the guided bilateral filter is  $O(nw^2)$ , when it is linear, where  $w$  is the size of the spatial smoothing window. When the filter is non-linear, the complexity is higher. Following [2], a possible implementation of the non-linear guided bilateral filter is iterative and thus, its complexity is  $O(nw^2i)$ , where  $i$  is the number of iterations. The size  $w$  must be larger than the max-

imum size of the objects which need to be detected, leading to an increased computational cost compared to *UID*.

Fast implementations of the bilateral filter were proposed by several authors, see for instance [5]. These usually extends to joint/cross bilateral filters [6]. However, fast implementation are not available for all filters within the guided bilateral class. For a faster computation, we thus focus on binary weights: a pixel value is considered only if the difference between the guide image intensity at this pixel and the guide image intensity at the center of the window is higher than a given threshold  $t$ . The so-called binary weighted median filter can thus be formally written as:

$$H_B(A)(x) = \text{median}_{y \in W_w, |B(x+y) - B(x)| \leq t} A(x+y) \quad (5)$$

where  $W_w$  is the set of pixel positions within the window of size  $w$  relative to the position of the pixel at the center of the window. The binary weighted median filter can be computed directly and not necessarily in an iterative way as proposed in [2]. The direct implementation of (5) leads to a complexity of  $O(nw^2 \log(w))$ . The median filter being able to handle a maximum of 50% of outliers, if we want to detect a new or a lost object of radius  $s$ , the window size should be set, at least, to  $\sqrt{2}s$ .

## 2.6. Background subtraction

Background subtraction is usually used to detect moving objects in an image sequence. The background image  $B_t$  can be computed by many of the different methods, for instance: mean exponential decay, mean or median sliding window. With the help of  $B_t$ , moving objects can be easily detected by computing  $GID(I_t, B_t)$  for each frame  $I_t$  of the image sequence ( $I_t$ ) with  $t \geq 0$ .

The output  $GID(I_t, B_t)$  being invariant to piecewise illumination changes in  $B_t$  following edges of  $B_t$ , as explained in Sec. 2.3, the resulting background subtraction method inherits the same property, whatever the time averaging method chosen for computing the background  $B_t$ . In particular, it is not affected by fast illumination changes, provide that these changes do not create closed edges smaller than the smoothing filter size  $w$ . From Sec. 2.4, the output of  $GID(I_t, B_t)$  is robust to noise in the frame  $I_t$ . Moreover,  $B_t$  being an average along time, noise in the frames has little effect on the output  $GID(I_t, B_t)$ .

## 3. EXPERIMENTS

To illustrate how new objects can be detected despite illumination variations, two pairs of results are shown in Fig. 4 using the directional guided median filter  $H$  in the Guided Image Difference operator  $GID_H$ . In the first line, a scene with vehicles is shown. In the second line, the same scene is shown but without vehicle and with rather different illumination conditions. These original images are courtesy of



**Fig. 4.** Guided Image Difference operator applied on two image pairs. The output is shown in the third line after a morphological opening and a thresholding.

Vaisala. The results of the GID operator with the first image as first input and second image as second input are shown in the third column. Zero values are shown as white in the output. Vehicles may be partially detected due to a gray color similar to the one of the road, but with a very reduce number of false alarm despite important illumination changes. On the last image, the shadow of the crash barrier is detected since its width is smaller than the smoothing size.

## 4. CONCLUSION

We propose a new image difference operator between two images which has several useful properties: it is not symmetric, which makes it possible to distinguish new and lost objects; it is invariant to piecewise constant illumination changes on the second input image when following its edges; it is robust to multiplicative effects; it is robust to noise in the first input image. This operator relies on a guided bilateral filter and is thus named Guide Image Difference operator. These interesting properties can be used for background subtraction. The proposed GID may be used with advantages not only for background subtraction but also for the evaluation of image processing algorithm, pattern recognition and stereo reconstruction.

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