MONOCULAR DEPTH-BASED BACKGROUND ESTIMATION

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Abstract: In this paper, we address the problem of reconstructing the background of a scene from a video sequence with occluding objects. The images are taken by hand-held cameras. Our method composes the background by selecting the appropriate pixels from previously aligned input images. To do that, we minimize a cost function that penalizes the deviations from the following assumptions: background represents objects whose distance to the camera is maximal, and background objects are stationary. Distance information is roughly obtained by a supervised learning approach that allows us to distinguish between close and distant image regions. Moving foreground objects are filtered out by using stationariness and motion boundary constancy measurements. The cost function is minimized by a graph cuts method. We demonstrate the applicability of our approach to recover an occlusion-free background in a set of sequences.

1 INTRODUCTION

During the last decade, the number of cameras has increased dramatically. This growth has been experienced in all areas, including traditionally ones such as video surveillance, video and photography for professionals and enthusiasts, and systems for driving assistance, but also in newest ones like in smartphones, and video gaming. This growing interest was mainly motivated by reductions in cost and improvement in the quality of digital cameras. Furthermore, the widespread use of computers has provided user-friendly ways to process images. Even applications for domestic use allow to any user manipulating an image to enhance it in many forms. For instance, image editing software includes basic tools like adjusting colors and cropping images, but also more complex ones like removing disturbing elements and merging images to compose collages or panoramas.

In this paper, we focus on how to automatically removal transient and moving objects from a set of images or a sequence where the background is partially occluded and located at far distance from the camera. Besides the obvious uses of this for image enhancement (e.g., removing objects that spoil a beautiful landscape photograph, or creating images without cluttered foreground objects), it has found many other applications in computer vision and graphics fields. For example, background estimation is usually the first step in background subtraction algorithms (Radke et al., 2005), where moving objects are detected by subtracting the observed image from an estimated reference background image. Segmentation of moving objects provides useful information from video processing applications such as image stitching, background substitution, compression, and tracking.

We assume that the background is composed by pixels representing objects whose distance to the camera is maximal, as in (Granados et al., 2008). This definition implies the knowledge of depth information, which is commonly unavailable. However, human beings easily identify which objects are in the foreground as well as those belonging to the background. This is because people can infer depth information even from a single image by combining monocular cues (e.g., perspective, textures, occlusions, etc.) that the visual system uses to understand their surroundings (Goldstein, 2010). In computer vision, estimating depths has been traditionally addressed by techniques that require multiple images (e.g., depth from stereo). Recently, proposals on accurate depth map estimations from a single image have been done (Saxena et al., 2009). However, for the purposes of background estimation, just a rough distinction between close and distant image regions can be enough. We propose a method to perform such distinction based on a supervised learning approach. This information is integrated in the background estimation process.

Our background model is then based on two assumptions: First, background represents objects placed at far distances from the camera; and second,

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background objects are stationary. According to that, we define a method to select from a set of images the appropriate pixels to compose the background. It is based on minimizing a cost function that penalizes deviations from our model. This method requires a set of aligned images, and to do this accurately, we propose an image registration process that takes advantage of our distant region segmentation method.

The rest of the paper is organized as follows. In Sec. 2, we introduce several related works. Our method is proposed in Sec. 3. Sec. 4 shows the experimental results. Finally, we conclude in Sec. 5.

2 RELATED WORK

Background estimation from a set of images has been widely studied in many areas of computer vision. In general, most of techniques to background estimation are based on strategies to avoid the use of depth because it is commonly unavailable (e.g., Kalman filtering, mixtures of Gaussians, among others). In (Harville et al., 2001), the authors exploit depth information recovered from stereo cameras to remove the background. However, the use of stereo cameras is often an unusual configuration in most systems.

Our approach is related to those algorithms based on energy minimization. Here, we review some of them, and state the novelty of our proposal. Following this strategy, in (Agarwala et al., 2004), background is estimated from a set of images by minimizing a cost function that penalizes the least common pixels.

In (Cohen, 2005), background estimation is formulated as a labeling problem, where a cost function penalizing stationariness and motion boundary inconsistencies is minimized by graph cuts.

In (Granados et al., 2008), the authors propose a method for a set of images taken from the same viewpoint with no restrictions on the time interval between them (i.e., non-time sequences). To do that, they adapt the motion boundary penalty from (Cohen, 2005) to a term that does not require temporal coherence.

Recently, in (Chen et al., 2010), the background is initialized from stable areas and an image inpainting technique is applied to predict the value of unstable pixels. Then, higher costs are assigned to labels that are more different from the predicted result.

Motivated by the previous works, we also consider the background estimation as a labeling problem. We use a similar cost function as in (Cohen, 2005), applying graph cuts to minimize it. However, to the best of our knowledge, any previous work has taken into account that depth information can be extracted from single images. Then, we propose a simple method to identify close/distant image regions and use this information to penalize deviations from our background model. Additionally, if there is camera motion, all previously reviewed methods require an initial image alignment before applying the proposed solution. We solve this problem by aligning the backgrounds of the input images basing on our distant region segmentation.

3 PROPOSED METHOD

3.1 Problem Statement

The input of our method is a sequence of aligned images of a scene. Our objective is to estimate the background by finding, for each pixel, an input image in which the background is visible. Then, the scene background is reconstructed by copying pixels from the appropriate input image. Each pixel has assigned a labeling corresponding to a frame number, and each possible labeling has an associated cost. The goal is obtaining a labeling that minimizes that cost.

Formally, let $I = \{I_1, \ldots I_N\}$ be a set of N input images. $\mathcal{P}$ denotes the set of pixels in an image. $I_n(p)$ denotes the color value at pixel position $p \in \mathcal{P}$ for n-th image I_n. Let $\mathcal{L} = \{1, \ldots, N\}$ be a set of labels, each one corresponding to an image in I. A labeling is a mapping $f : \mathcal{P} \to \mathcal{L}$, that means that a pixel $p \in \mathcal{P}$ has assigned the label $f_p \in \mathcal{L}$. Each labeling f generates an image $I_f : p \to I_{f_p}(p)$. Then, the background estimation problem is posed as finding a labeling f^* to construct the background $I_B = I_{f^*}$ such that f^* is a minimum cost labeling. In the next sections, we formalize the cost function to be minimized.

3.2 Energy Function

The energy function $E(f)$ of a labeling f is defined as (Boykov et al., 2001)

$$E(f) = \sum_{p \in \mathcal{P}} D_p(f_p) + \sum_{p,q \in \mathcal{N}} V_{p,q}(f_p, f_q) \quad , \qquad (1)$$

where D is the data term, and V is the smoothness term. The data term defines the cost of assigning the label f_p to pixel p. The smoothness term is the cost of assigning labels f_p and f_q to neighboring pixels p and q, such that $p, q \in \mathcal{N}$, being $\mathcal{N}$ the set of adjacent pixels in $\mathcal{P}$.

A labeling that minimize the energy E is found by using the α-expansion algorithm implemented by (Delong et al., 2011). For details about the optimization algorithm, please refer to (Boykov et al., 2001).

Smoothness term penalizes the intensity differences between neighboring regions (Kwatra et al., 2003), giving a higher cost when f_p and f_q do not match well

$$V_{p,q}(f_p,f_q)=\frac{(\|I_{f_p}(p)-I_{f_q}(p)\|+\|I_{f_p}(q)-I_{f_q}(q)\|)}{2} \quad (2)$$

The data term penalizes the labelings that do not hold the background model. Then, our data term accounts the color stationariness D^S, motion boundary consistency D^M, and proximity/distantness information D^P

$$D_p(f_p) = \alpha D^S_p(f_p) + \beta D^M_p(f_p) + \gamma D^P_p \ . \quad (3)$$

Since, the three components have different units, we first normalize each one between 0 and 1, and then we introduce different weights for each component to balance the contribution of each one. The first two terms in D were introduced by (Cohen, 2005), and the last term corresponds to our approach. In the next sections, we detail each term.

3.3 Stationariness

This term penalizes image regions whose color varies significantly along time. The stationariness cost $D^S_p(f_p)$ assigns a high cost to pixels with large color variance in a small time interval (Cohen, 2005). Formally,

$$D^S_p(f_p)=min\{Var_{f_p-1,f_p}(p),Var_{f_p,f_p+1}(p)\} \ , \quad (4)$$

where $Var_{i,j}(p)$ is the mean of the variance of each color channel from image I_i to I_j at pixel p, and $f_p \pm r \in \mathcal{L}$ denotes the r-th image posterior or previous to the current one, respectively.

3.4 Motion Boundary Consistency

We use motion boundaries to penalize pixels corresponding to moving objects. Motion boundaries occur in adjacent image regions having different image velocities due to motion parallax or independent moving objects (Black and Fleet, 2000). Based on that, the motion boundaries can be approximated as the gradient of the difference between an image and the background, which is justified since the boundary of a moving objects occur at locations where the images start to differ. Assuming that I_{f_p} is the background image and I_i is an input image containing moving objects, the difference image $F_{f_p,i} = \| I_{f_p} - I_i \|$ has a large gradient magnitude $\| \bigtriangledown F_{f_p,i} \|$ where I_{f_p} and I_i are poorly matched. Likewise, $\| \bigtriangledown I_i \|$ has large values at intensity edges. Motion boundary consistency penalizes motion boundaries that do not occur at background's intensity edges (Cohen, 2005)

$$D^M_p(f_p) = \frac{1}{N}\sum_{i\in\mathcal{L}} \frac{\| \bigtriangledown F_{f_p,i}(p) \|^2}{\| \bigtriangledown I_i(p) \|^2 + \varepsilon} \ , \quad (5)$$

where ε is a small value to avoid zero-division.

3.5 Proximity/Distantness Information

This term penalizes those image regions which are close in the scene, since we assume that the background is composed by distant regions. This implies that we require at least rough information about scene depths.

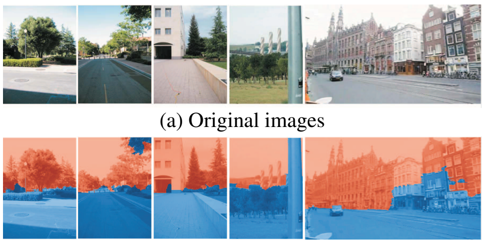
Even though depth estimation has been focused from techniques requiring multiple images (e.g., depth from stereo, structure from motion, etc.), recently, some proposals on depth estimation from a single image have been done (Saxena et al., 2009). They try to derivate exact distances to elements in the scene. However, according to our background definition, just having information about the proximity/distantness can be enough for background estimation. Instead of estimating a continuous depth map, we segment the distance space into close/distant regions.

For computing such segmentation, we train an AdaBoost classifier based on a set of discriminative features to distinguish between both kinds of regions according to a distance threshold. We use the following features: RGB and HSV color mean and histograms for each channel to distinguish between different objects; texture gradients characterized by Weibull parameters (Nedovic et al., 2010) and Gabor filters to capture surface orientations; and, pixel location to distinguish different regions in the image (sky, ground, etc.). Our visual features are computed at region rather than pixel level. Each image is oversegmented into superpixels, trying approximately to fit each image region to scene objects, and each superpixel is described using our visual features.

To train our classifier, we use images from the dataset provided by (Saxena et al., 2009). This dataset has a depth map associated to each image, which is used to label a set of positive/negative examples.

We have established the threshold to distinguish what is a distant region at 30 m since, for the camera used, beyond that distance the moving objects in the scene just show a scarce motion in the image, and most of them can be considered as part of the background.

Given a new image, the close/distant segmentation is obtained from the classifier predictions for each region. Results of this process are shown in Fig. 1.



(a) Original images

(b) Distant regions segmentation

Figure 1: Results of our approach to identify close and distant image regions: (a) Original images, (b) Computed mask where distant regions are in red and close regions are in blue. The first three images are from Saxena et al. testing set, and the last two are from video sequences.

We assign a cost to each pixel belonging to a close region R_c, which is the Euclidean distance between that pixel and the nearest pixel belonging to a distant region R_d

$$D_p^P = \begin{cases} 0 & \text{if } p \in R_d \\ min\{d(p,q) \mid q \in R_d\} & \text{if } p \in R_c \end{cases} , \qquad (6)$$

where R_c is the set of pixels belonging to close regions, R_d is the set of pixels in distant regions, and $d(p,q)$ is the Euclidean distance between two pixels coordinates.

Basically, we are stating that a close region has a higher associated cost when it is further away from any distant region. We also penalize those regions that being distant in the previous frame become closer in the current frame, because they probably belong to moving objects approaching to the camera.

3.6 Image Registration

The described cost minimization process can be applied as long as the set of images have been acquired from an static camera. If the camera is not static, first images have to be registered. To do that, we align each two consecutive images by using Lucas-Kanade algorithm. To perform such alignment between the current image I_{f_p} and next image I_{f_p+1}, we use as template T the distant regions of I_{f_p+1}. Distant regions are used to align images since they behave as an infinity plane providing accurate information about the camera motion, leading the images aligned with respect to the background. This plays a significant role during penalties computation because a precise alignment reduces the probability of selecting wrong pixels values to compose the background. Lucas-Kanade algorithm iteratively minimizes the difference between T and I_{f_p} under the following goal objective

$$\sum_q \left(I_{f_p}(W(q,\mathbf{a})) - T(q)\right)^2 , \qquad (7)$$

with respect to $\mathbf{a} = \{a_i\}_{i=1...6}$, where $W(q,\mathbf{a})$ is an affine warp

$$W(q,\mathbf{a}) = \begin{bmatrix} (1+a_1)q_x & a_3 q_y & a_5 \\ a_2 q_x & (1+a_4)q_y & a_6 \end{bmatrix} .$$

4 EXPERIMENTAL RESULTS

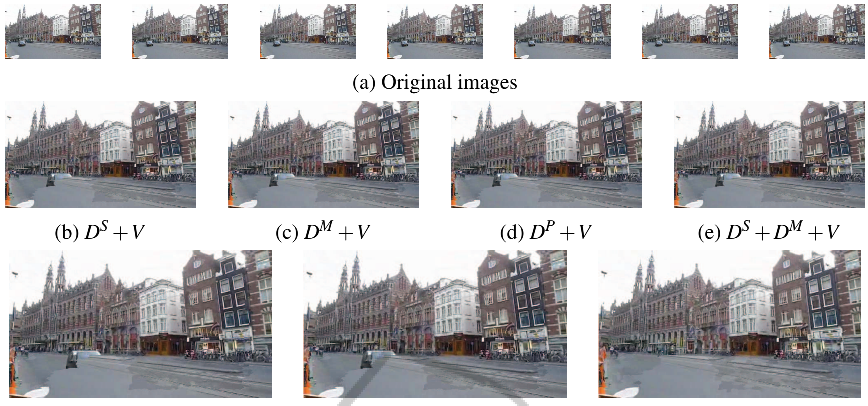
For evaluating our method we use the sequences shown in Figs. 3-5. Figures 3 and 4 were taken using hand held consumer cameras, requiring alignment between frames. Both sequences were extracted from Youtube, having low-quality due to the compression applied. However, our method shows good results in obtaining background even under this quality. Sequence in Fig. 5 was taken fixing the camera with a tripod, without temporal coherence between frames (Granados et al., 2008).

The parameters values to control the effect of each term in the data term were experimentally defined as $\alpha = .3$, $\beta = .4$, and $\gamma = .3$, which gave us good results.

The effect of each term in the energy function is depicted in Fig. 2. First, terms are considered in isolation (see Fig. 2(b)-(d)). All of them contribute to reduce the transient objects. As Fig. 2(d) shows, the proximity/distantness term in isolation keeps the car which is located further away from the camera. This occurs since we are not considering color or motion changes. Thus, the far-away car has a low-cost due to it has a high probability of belonging to the background. Then, a progressive improvement of the background estimation is obtained by combinations between the data term components (see Fig. 2(e)-(g)). Finally, using all terms a significantly improvement is reached (see Fig. 2(h)), which implies that they are complementary. Note also that the result of our method overcomes the Cohen's method result shown in Fig. 2(e), which fails to remove some artifacts.

We compare our proposal against the popular median filtering algorithm and the approach of (Agarwala et al., 2004), which is in the state-of-the-art of background estimation. Figures 3-5 show the results of applying our approach to different sequences.

In Fig. 3, we show the result of our method in a scene with an independent moving object (i.e., the car approaching to the camera). Fig. 3(b) depicts how the car is penalized since it is moving, and how the penalization increases as the car become closer. Note that distant regions have a low-cost due to our depth-based term. Our method effectively removes the car while median filter method keeps some ghost of it, as Fig. 3(c) shows. Fig. 3(d) shows the result of Agarwala et al. In many cases, as in Fig. 3(f), this method requires a user interaction to remove some artifacts

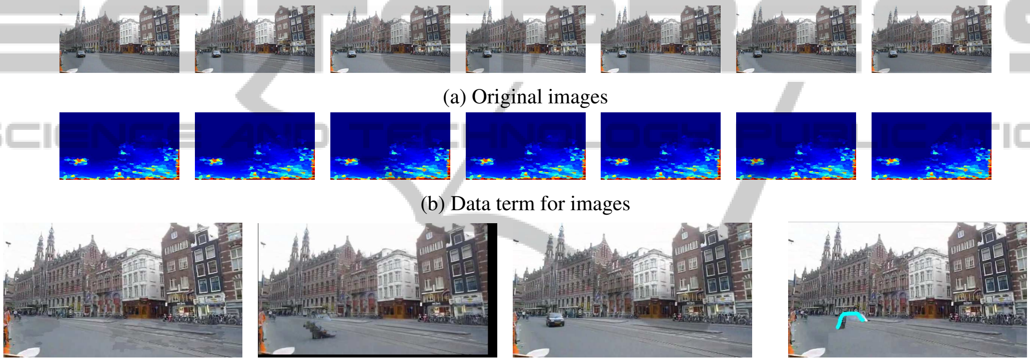


(a) Original images

(b) $D^S + V$ (c) $D^M + V$ (d) $D^P + V$ (e) $D^S + D^M + V$

(f) $D^S + D^P + V$ (g) $D^M + D^P + V$ (h) $D^S + D^M + D^P + V$

Figure 2: (a) *City* sequence, (b)-(h) Interaction between terms. Including our term on the cost function allow us to reach a better background estimation results. This implies that all terms are complementary.

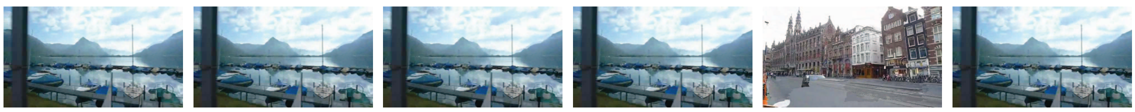


(a) Original images

(b) Data term for images

(c) Our method (d) Median filter (e) Agarwala et al. (f) Interactive step applied to (e).

Figure 3: (a) Seven images of the *City* sequence, (b) Data term for each image (red corresponds to high-cost values, blue to low-cost values). Estimations using: (c) Our method, (d) Median filter, and (e) Agarwala et al., 2004, (f) Interactive step required to remove some artifacts in Agarwala et al. method.



(a) Original images (b) Our method (c) Median filter (d) Agarwala et al.

Figure 4: (a) The *Train* sequence. Estimations using: (b) Our method, (c) Median filter, and (d) Agarwala et al., 2004.

that are still present in the obtained result. After that step, Agarwala et al. method reaches a comparable performance with respect to our method. In the rest of experiments, such manual processing is performed when it is necessary to ensure a comparable result.

Figure 4 shows an experiment done to evaluate our method under low-quality images. This kind of videos are not intentionally captured for extracting the background, however it can be obtained without transient objects. Even under low-quality videos our proposal correctly estimates the background.

Figure 5 shows the performance our method in a scene without temporal coherence between frames. However, our approach behaves reasonably well under this setting. Although some ghosts are present in shadows, our results are comparable with respect to Agarwala et al. The remaining artifacts can be removed by using a gradient-domain fusion as in (Agarwala et al., 2004; Granados et al., 2008).

From a quantitative viewpoint, we compute the mean absolute difference between our results against the manually refined results of Agarwala et al. The mean of such difference is equal to 0.06, implying that both methods are close one to another.

Despite that both methods seem to behave similarly, our approach is fully automatic while the

(a) Original images

(b) Our method

(c) Agarwala et al.

Figure 5: (a) Images of the *Market* scene. Estimations using: (b) Our method, (c) Agarwala et al., 2004.

method of Agarwala et al. requires user interactions for refinement. For instance, when the estimated background is still containing foreground objects, the user must selects these regions which will be replaced by new ones offered by the system. In some cases, this interactive step must be repeatedly performed to achieve an acceptable result. Moreover, Agarwala et al. apply additional steps as, for instance, gradient-domain fusion to remove image artifacts. By contrast, our method is simpler and straightforward.

5 CONCLUSIONS

In this paper, we presented a method to background estimation containing moving/transient objects, which uses depth information for such purpose. Usually, this information is unavailable for monocular cameras. However, we recovered information about proximity/distantness of a region in an image, which is enough for our purpose. This segmentation is used to found the background by penalizing close regions in a cost function, which integrates color, motion, and depth terms. We minimized the cost function by using a graph cuts approach.

We tested our approach with sequences taken under different conditions (e.g., moving/static camera, temporal/non-temporal coherence, low/high-quality). Experimental results shown that our method significantly outperforms the median filter approach. Also, our approach is comparable to state-of-the-art methods. Unlike Agarwala et al., we perform this task automatically, without any user intervention.

As further work, we plan to complement our approach with a gradient-domain fusion to remove artifacts that are still present in dissimilar images. Finally, we plan to focus on selecting appropriate frames to compose the background since many frames in a sequence do not contribute to the final estimation.

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