MOTION DETECTION IN VERY LOW ILLUMINATION ENVIRONMENT

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ABSTRACT

A motion detection algorithm which works in very low illumination environment is proposed. The algorithm overcomes the difficulty of manually setting a threshold value, and obtains an automatic segmentation of the motion region. The spurious regions due to the large CCD noise in low illumination environment are removed by a level set based post process, which takes the geometry of the image structures into account.

INTRODUCTION

Motion detection in low illuminance environment is one of the most difficult and important problems in surveillance camera applications. The difficulty of motion detection in low illumination lies in the fact that in low illuminance environment, the contrast between the color of the object to be detected and that of the background is low and that the CCD noise becomes more apparent. This situation raises two difficult problems. First, it is difficult to set an a priori known threshold value, since too low a value will introduce spurious regions, while too high a value will suppress meaningful regions. The difficulty increases in low illumination environment, since the range of the brightness value in the difference map is narrower than in day light environment. Second, the CCD noise, which results from the physical nature of CCD devices, becomes more dominant when the light intensity(or the SNR) is low. Therefore, the accuracy and precision of the segmentation result can be seriously affected, and the false alarm rate in intelligent surveillance camera systems can be raised. This type of CCD noise cannot be suppressed by mere thresholding, since in low illumination condition some noisy pixels that belong to the background in the difference map have brightness values larger than the brightness values of pixels that belong to the object to be detected.

Here, we propose an algorithm that deals with the above mentioned problems effectively. The algorithm performs a real-time motion detection in low illumination environment as well as in day light environment, without the need of setting a threshold value and with the capability of removing spurious regions caused by the noise. The proposed method works even in very low illumination environments.

LEVEL SET BASED BIMODAL SEGMENTATION

To exclude the need of setting a threshold value, we propose the use of the level set based bimodal segmentation on the difference map, such that the image becomes pre-segmented into motion/non-motion regions depending on the relative competition of the brightness values in an image.

Several models that perform level set based bimodal segmentation have been proposed in [2]-[4], where in [2], we proved that the bimodal segmentation has a global minimum, and thus proved that all the models give the same segmentation result. The level set function (denoted by ϕ) is an auxiliary two dimensional function, that indicates the motion/non-motion region after it is processed properly. Here, we use the model proposed in [3], which is the fastest, but for the purpose of motion segmentation, we use instead of a normal image, the background subtracted difference map, and solve the following ordinary differential equation:

$$\frac{d\phi}{dt} = -\lambda_1(\mathbb{D}I - c_1)^2 + \lambda_2(\mathbb{D}I - c_2)^2, \tag{1}$$

where ϕ is the level set function, $\mathbb{D}I$ is the difference map, λ_1 and λ_2 are positive constants, and c_1 and c_2 are the average values of $\mathbb{D}I$ in the region $\{\mathbf{r} \mid \phi(\mathbf{r}) \geq 0\}$ and $\{\mathbf{r} \mid \phi(\mathbf{r}) < 0\}$ respectively, where $\mathbf{r}$ denotes the position in the image. The equation (1) is implemented via an iteration scheme, and the values c_1 and c_2 are updated as ϕ is updated forward in time. After a few iterations, all the $\phi(\mathbf{r})$ values will cease to change their signs, and pixels that have relatively large intensity values become classified in the finally converged region $\{\mathbf{r} \mid \phi(\mathbf{r}) \geq 0\}$ while pixels with relatively small intensity values become classified in the region $\{\mathbf{r} \mid \phi(\mathbf{r}) < 0\}$. In this way, the region of the moving object, which normally corresponds to the region having rather large intensity values in the difference map, becomes segmented and represented by the region $\{\mathbf{r} \mid \phi(\mathbf{r}) \geq 0\}$, while the non-motion region becomes represented by the region $\{\mathbf{r} \mid \phi(\mathbf{r}) < 0\}$. The segmentation process is adaptive to the image and automatical, since there is no need to set an a priori known threshold value.

Figure 1(d) shows how a ill-determined threshold value can suppress meaningful regions. Figure 1(e) shows the result of applying the bimodal segmentation on the difference map (Fig. 1(c)) obtained in low illumination environment. Even though the moving object is automatically segmented, there are many spurious regions which have to be eliminated by the proposed elimination method in the next section.

LEVEL SET BASED ELIMINATION OF SPURIOUS REGIONS

The elimination of spurious regions due to the noise is performed in the following three steps: First, calculate a mean curvature map from the processed level set function obtained by (1). Second, calculate a new difference map by normalizing the original difference map with respect to the mean curvature map, and taking the segmentation result in section 2 into account. Third, perform a regularized bimodal segmentation on the new difference map.

To calculate the mean curvature map, the level set function obtained from (1) is first binarized, where the binarized pixel values corresponding to the region $\{\mathbf{r}|\phi(\mathbf{r}) \geq 0\}$ are 1, and those corresponding to the region $\{\mathbf{r}|\phi(\mathbf{r}) < 0\}$ are 0. Then, regarding the binarized image as a two dimensional surface in the three dimensional space, with the binarized pixel value (I_B) corresponding to the z axis, the mean curvature M is computed at each pixel as: $M = \nabla \cdot \left(\frac{\nabla I_B}{|\nabla I_B|}\right)$, where $\nabla\cdot$ is the divergence operator, and ∇ is the gradient operator. The mean curvature value can be regarded as a measure that measures the amount by which the image structures deviate from being flat. As a result, small image structures like spurious regions due to the noise tend to have large mean curvature values. Therefore, if the region in the difference map corresponding to the motion region obtained by (1) is divided by the mean curvature map, then most of the spurious regions will have relatively small values in the new difference map. The new difference map is obtained by dividing the original difference map ($\mathbb{D}I$) by the mean curvature map $\mathbb{M}$ and normalizing it as follows:

$$\mathbb{D}I_{new}(\mathbf{r}) = \begin{cases} \frac{\mathbb{D}I(\mathbf{r})}{\mathbb{M}(\mathbf{r})\,\mathbb{D}I_{max}}, & \text{if } \phi(\mathbf{r}) \geq 0 \\ \\ 0, & \text{if } \phi(\mathbf{r}) < 0 \text{ or } \mathbb{M}(\mathbf{r}) = 0, \end{cases} \tag{2}$$

where ϕ is the level set function obtained by (1), $\mathbb{M}(\mathbf{r})$ is the mean curvature value at the position $\mathbf{r}$, and $\mathbb{D}I_{max}$ is the maximum of all the $\mathbb{D}I_{new}(\mathbf{r})$ values.

Figure 1(f) shows the mean curvature map calculated from the binarized level set function, and Fig. 1(i) shows the corresponding normalized new difference map. The effect of dividing by the curvature map can be seen by comparing Fig. 1(c) and Fig. 1(i). The dense noise with relatively large intensity values in Fig. 1(c) appear to have become sparse in the new difference map, since small image structures have experienced a large decrease in their intensity values by the division through the mean curvature value. Therefore, if now a level set based bimodal segmentation with harmonic regularization is performed on the new difference map, the spurious regions due to the noise become entirely eliminated by the harmonic regularization.

The level set based bimodal segmentation with harmonic regularization term solves the following differential equation:

$$\frac{d\hat{\phi}}{dt} = -\frac{1}{c_1 + c_2}(\mathbb{D}I_{new} - c_1)^2 + \frac{1}{c_1 + c_2}(\mathbb{D}I_{new} - c_2)^2 + \nabla^2\hat{\phi} \tag{3}$$

The equation is the same as (1), except for the harmonic regularization term ($\nabla^2\hat{\phi}$). The first and the second term in the righthand side are normalized with respect to $c_1 + c_2$ such that the harmonic regularization term can compete with these terms. The harmonic regularization term smooths out the level set function fast such that the sparse spurious regions due to the sparse noise in the new difference map become entirely eliminated, while the valid motion regions survive due to the strong influence of the first two fidelity terms. The segmentation result that results from the competition can be seen in Fig. 1(h), which shows the motion region represented by the region $\{\mathbf{r} \mid \hat{\phi}(\mathbf{r}) \geq 0\}$. The spurious regions have been effectively eliminated while motion regions are well preserved. For comparison, Fig. 1(g) illustrates how a simple application of a morphological filter can fail in the complete elimination of spurious regions. Figure 2 shows the overall block diagram of the proposed motion detection method. The proposed method works in real time on a 320×240 frame with 2.1GHz PC due to the fast bimodal segmentation algorithm, which takes just 3–5 iterations for the classification.

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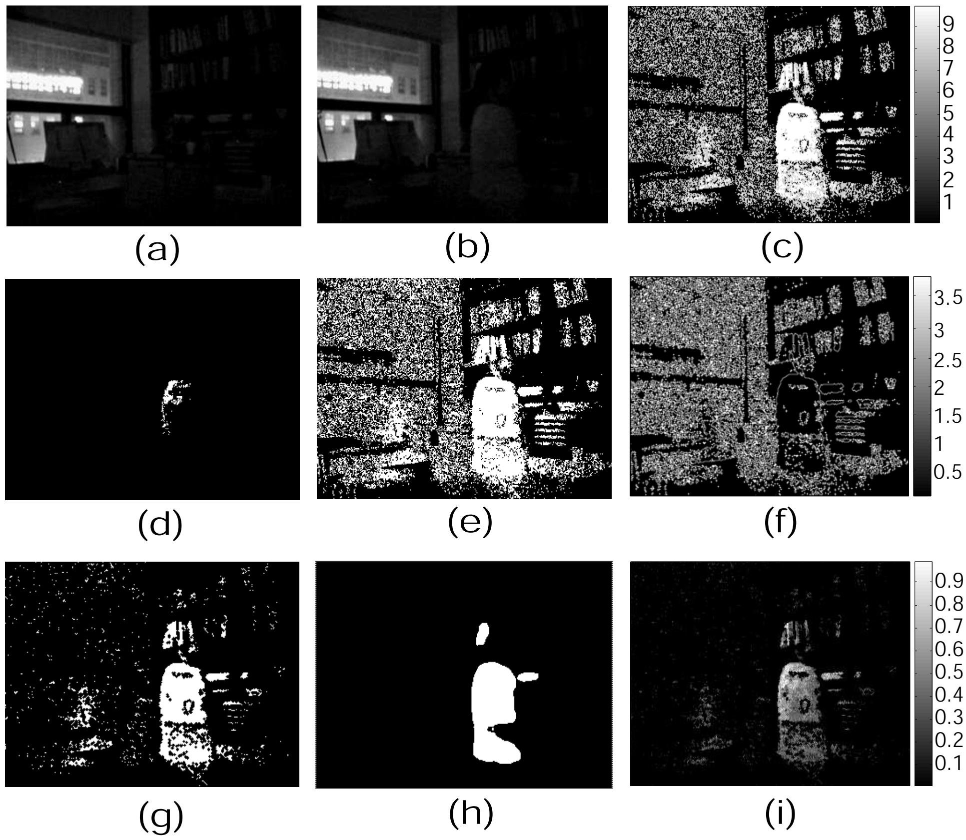

Figure 1. Segmentation result in low illumination environment: (a) reference background frame (b) incoming current frame (c) difference map (d) result of thresholding with threshold value=20 (e) segmentation result with (1) in section 2 (f) mean curvature map (g) result of eroding with morphological filter (h) final segmentation result with proposed method (i) new difference map.

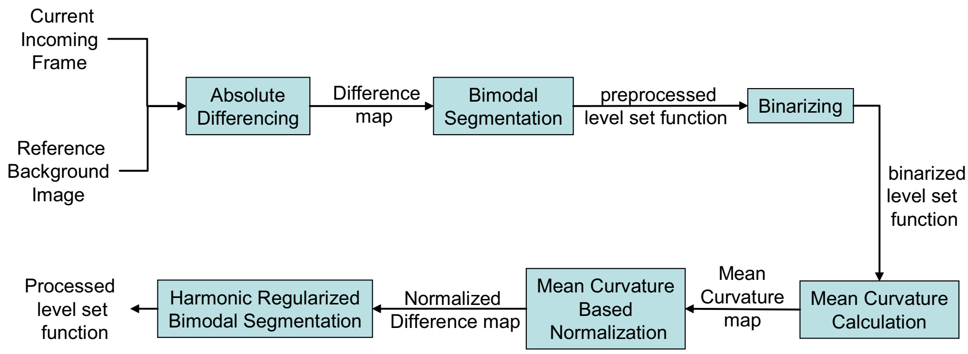

Figure 2. Overall block diagram of proposed method.

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