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A Background Modeling and Foreground Detection System using Scaling Coefficients for Video-based Surveillance Model

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Abstract:
In image processing, all the hassle of videotape is active research in the current era when background modeling and foregrounding are the phases of video processing used to identify objects that move under difficult conditions. It requires efficient methods to manage dynamic background and illumination changes, as well as algorithms that must meet real-time and low-memory needs. This article describes a foreground detection method using background modeling and scale factors determined by a new color model called red-light blue. They are used to compare two-key frames to find pixels with reduced brightness. In this regard, our system offers three consecutive operations, that is, in step 1: it overlaps the background with pixels. Step 2: Check the background pixels. Step 3: After validating Phases 1 and 2, it validates the background. After background calculation, foreground objects can be found using scaling factors and additional criteria.

Keywords : Background modeling, foreground detection, Scaling Coefficients.

1. Introduction:

Background Subtraction is an essential pre-processing step in many vision-based applications to capture a moving foreground from a fixed background. Background Subtraction between the current frame and the background model that contains a fixed portion of the space called the foreground mask. Video sequence analysis and understanding is an active area of research. Most applications in this area of research (video surveillance [1-2], optical motion detection [3], multimedia application [4]) are needed in the first step to capture moving objects. So the most important thing to do is to separate moving objects known as "foreground" from static information called "background". The most commonly used process is background subtraction and can be found in recent surveys [5–6].

Two problems closely related to background subtraction are detection of changes [7] and significant detection of motion [8]. Change Identification refers to the detection of changes between two images. Therefore, background subtraction is a special case where one model is a background image and the other is a current image, and changes occur due to moving objects. On the other hand, the main purpose of motion detection is to find semantic areas and filter out unimportant areas by installing a foreground mask.

2. Related Work

Various background subtraction studies appear in the literature, but none of them cover the entire overview in this area.

Illumination Invariant ChangeDetection

The method for detecting light changes is to calculate the mapping function between the pixel values and the background of the current image. Kim et al. [12] propose a Global Lighting Change (GIC) model. The non-linear function g is used to describe

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the mapping point between the pixel values and the current background image.

This work proposes a monotonous illumination method for detecting changes. It shows that the specified pixel value is a slightly customized version of another pixel value, and if it does not, changes occur. Sin criticized the problem of recognizing change.

Background Modeling and ForegroundDetection

BackgroundSubtractorMOG

In this algorithm, this refers to a background or foreground partitioning algorithm based on a Gaussian blend. It was introduced in 2001 by P. S. Gaussian Distributions (K = 3 to 5). The scales of the mixture represent the ratio of time that the colors could be. The possible background colors are long and stable.

BackgroundSubtractionMOG2

In this section, Z. Zivkovic et al. (2004) and (2006) proposed a background or foreground partitioning algorithm based on a Gaussian mixture, the main feature of which is that it selects an appropriate number of Gaussian distributions for each pixel. Due to the brightness changes, it offers better flexibility for different scenes. [13].

In 2000, McIvor [9] first investigated algorithms that allow model comparisons, but research is mainly limited by algorithms

Picard [10] in 2004 provided an overview of seven methods and an initial classification based on speed, memory requirements and accuracy. This report allows readers to compare the complexity of different methods and help them choose the most appropriate method for a particular application.

In 2010, Bowmans et al. [11] provided a comprehensive study of statistical background modeling techniques to identify the classification requirements for each approach according to the mathematical models used.

Some background patterns include:

The mixture of Gaussians models:

When modeling a Gaussian blend, the Gaussian method produces each pixel and uses an online approximation to update the model. In this method, we assume that the intensity values for each video pixel can be generated using a Gaussian composite model. General heuristics determine which intensity is most likely to occur. Incompatible pixels are called foreground pixels. It combines foreground pixels using 2D connected component analysis. The most common approach is a background model based on a Gaussian blend by Stauffer and Grimson.

Subspace learning models:

Subspace learning techniques were used to create the idea of displaying data content online, significantly reducing its size. The first principal component analysis method (PCA) was proposed by Olivers et al. [14].

Fuzzy models:

Critical conditions combined with video surveillance cause confusion and uncertainty throughout the background subtraction process. As a result, some authors have recently introduced fuzzy concepts at various stages of thematic deprivation. Bowman [11] provided a comprehensive overview of the fuzzy concepts used in thematic subtraction activities.

Robust PCA models:

Recently, robust principal component analysis models (RSPCAs) have been developed in the literature. Recently, Bowman and Jahja [11] launched a comprehensive review of RSPCA-PCP-based methods for testing and classifying existing knowledge recognition algorithms. From the literature we understand the overview of all background models.

3. System Model

Despite the many work involved in background subtraction and foregrounding, and the fact that this problem can be resolved or rethought, it does not seem to solve all the major problems we face using any traditional algorithm today. There are three main reasons for this:

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1. What is missing is a common framework, that is, each method has been developed in many different contexts (video surveillance, optical motion perception, etc.), taking into account different tasks.
2. There is a lack of scientific enhancements, the effects of sophisticated methods, such as the Gaussian mixture, and we take into account other recent models of representation.
3. Exclusion of a specific and realistic large-scale dataset with a detailed underlying truth that provides a balanced analysis of the real world requirements spectrum.
In this situation, we consider ourselves to be at the forefront of background deprivation, and the purpose of this article is to analyze, step by step, background modeling and the identification of new knowledge.

The flow of Background Subtraction Methods

Background Subtraction (BS) is a standard method for developing a foreground mask (i.e., a binary image containing pixels of moving objects) using camera static.
As the name implies, BS measures the foreground mask by subtracting the current image and background model, including the static portion of the scene, or, whatever may be considered the background, the characteristics of the study area.

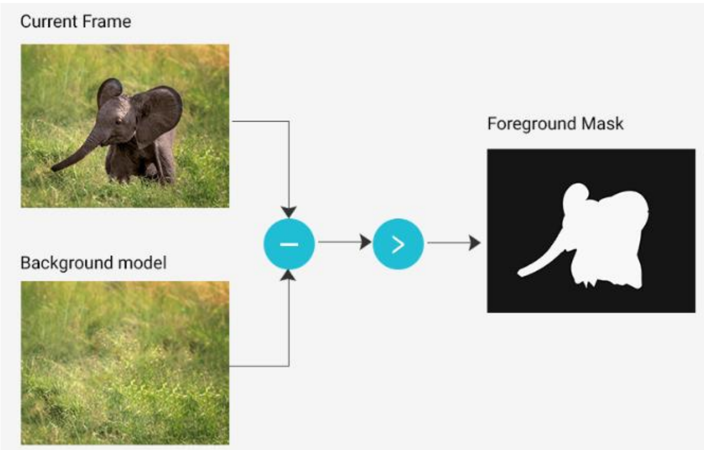

Figure 1.background subtraction model:

Background modeling comprises two major steps:
1. Background Initialization;
2. Background Update.
In the early step, we compute the first model of the background, while in the second step, that model is updated to comply with potential reforms in the scene.

The Lightness-Red-Green-Blue ColorModel

In this article, we present the Light-Red-Green-Blue (LRGB) color model as an alternative to image representation. The light component L is calculated using the Luma definition from the YUV color model [15]. The color difference components of red, green, and blue are calculated by subtracting the light from the corresponding RGB color components. It should be noted that the YUV color model uses the red and blue channel color differences as an intermediate; However, they can be generalized to the definitions of U and V. The LRGB color model uses all components of color contrast and lightness.

4. Background Modeling and Foreground Detection Algorithm

The background modelling and foreground algorithm described in this article differs from other algorithms in that it has three backgrounds (test background, proven background, final background) and scale factors for image comparison and illumination artefacts..

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The tasks of this algorithm are presented in the following subsections.

Proposed System Architecture

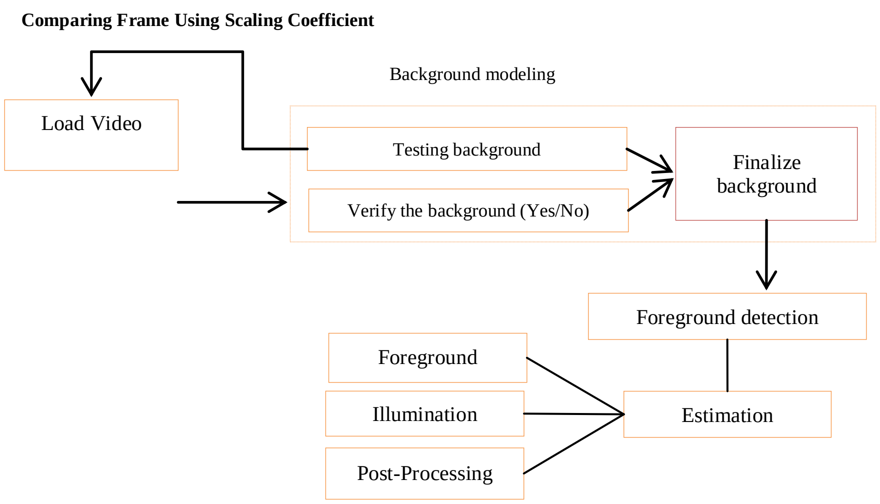

Figure 2.Proposed System Architecture.

Pre-processing:

There are two steps before processing each frame. To prevent noise, the input image is fuzzy with a 3x3 Gaussian kernel with standard deviation. When colored components are close to zero, the calculation of ki is less accurate; Therefore, for each pixel component, if the value of the pixel component is less than eight, it is set to eight to improve the scaling factor calculation.

Background Modelling

This work is done with three background images: the test background, the tested background, and the final background. The test background was compared with each preprocessed frame using scaling factors. Check background pixels that repeatedly match pre-processed pixels. Frames are placed in a tested background. Because the final background is a combination of a test background and a tested background, in some areas a verified background is not set.

An overview of the background modeling task is as follows:

Step 1: $t \leftarrow 0$

Step 2: Get Image $I_t\ (x,\ y)$.

Step 3: A value for $C_t\ (x,\ y)$ is chosen. When $t = 0$, it is $I_0(x,\ y)$.

Step 4: The final background is set to $I_0(x,\ y)$.

Step 5 : $t \leftarrow t+1$

Step 6: Get Image $I_t\ (x,\ y)$.

Step 7: Goto step 6 until there are no more frames to process.

Step 8: Step 7 is executed after foreground detection.

To exclude discrete pixels Et (x, y), the image is averaged only when t is the same. This situation takes into account the half-discrete points randomly appearing in the image.

Foreground Detection

There are three steps to foreground identification: initial foreground evaluation, lighting artifact evaluation, and post-processing.The steps for identifying the first detailed design are described in Algorithm 2.

Initial Foreground Estimation:

For each pixel, it calculates scale factors between the background Bt and the current image. If all scaling factors are close to each other, the pixel il

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(x, y) is classified as the background. Otherwise, it is in the foreground.

5. Results:

We used a video consisting of 35 images for the experimental result. Each frame took at least 0.80 seconds, but not more than 1.9 seconds. Global implementation of Matlab 2016 with Windows operating system.

Figure 3. Background Model design for the video

Figure 4. Current Frame in Video with background and foreground moving object

Figure 5. Background modeling and foreground detection algorithm using scale factors using color models.

From the above results, our proposed algorithms perform background modeling and foreground detection using scaling factors using color models.

6. Conclusion

This article demonstrates background modeling and foreground detection algorithm, in contrast to other approaches in which the current background model approach is perceived with a foreground mask that differs from the proposed model because it uses three motifs (test background, proven background, final background). and Leica image backgrounds, and scaling modules detect brightness artifacts that provide optimized results for video images.

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