MODELLING A FOREGROUND FOR BACKGROUND SUBTRACTION FROM IMAGES

Probability Distribution of Pixel Positions based on Weighted Intensity Differences

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Abstract: To overcome a false detection problem caused by dynamic textures in background subtraction problems, a new modelling approach is suggested. While traditional background subtraction approaches model the background, an indirect method, to detect foreground objects, the approach described here models the foreground directly. The foreground model is given by the probability distribution of pixel positions in terms of sums of weighted intensity differences for each pixel position between all previous images and a new image. The combination of the weighting and the summing of the intensity differences produces a number of desirable effects. For instance, each position in the new image which has consistently large differences will have a high foreground probability value; each position having consistently small differences will have a low probability value; and positions having small differences for most of the previous images but large differences for a few of the previous images due to dynamic textures or noises will have medium probability values. The final distribution of the foreground position is computed by Kernel density estimation incorporating the neighboring pixel differences, and foreground objects are then identified by the probability value of this distribution. The performance of the suggested approach is then illustrated with two classes of problems and compared to other conventional approaches.

1 INTRODUCTION

The background subtraction problem is to detect abnormal objects from a new image given the sequence of its previous images. In most conventional background subtraction methods, a statistical model of the background image, called the background model, is formulated using the previous images and then compared to the new image to detect the abnormal objects, called the foreground. Since the background subtraction method has a wide area of application such as tracking, identification, surveillance, and defect detection, many approaches to formulating the background model have been introduced.

Wren *et al.*(1997) firstly proposed a background model based on a single Gaussian over the intensity value of each pixel. The single Gaussian model, however, could not correctly represent most outdoor scenes since small motion of objects or dynamic textures such as swaying trees or flows of water caused the associated pixels with different intensities to be considered as the foreground. To handle this problem, Stauffer and Grimson(1999) suggested a model using a mixture of Gaussians. Their approach could describe the background more accurately, but their results sometimes deteriorated when the number of Gaussians was selected improperly. Elgammal and Davis(2000) proposed a non-parametric approach to modelling the background. They adapted the kernel density estimation (Bishop, 2006) to build the background statistics without any assumption about the shape of the statistical model. However, when the dynamic textures heavily appear, their approach cause the distribution to be a widely spread shape where the associated pixels are detected as the foreground regardless of their intensity values. Dalley and Grimson(2008) proposed a model modified from the Stauffer and Grimson's one. In this model, a set of mixture components lying at the local spatial neighbourhood of a pixel was suggested rather than a mixture lying at the same pixel position. This model reduced the false detections, but the neighbours distribution introduced by a window caused loss of true foreground pixels.

To relax the false detection caused by dynamic

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textures, the approaches using additional features or formulations were proposed. Mittal and Paragios(2004) introduced the optical flow as the supplemental feature for the background model. With the spatial image gradient and temporal derivatives, the approach suppressed the false detection from the video frames of the ocean and the park with trees. Sheikh and Shah(2005) suggested both models of a background and a foreground. They collected foreground features from the image immediately preceding the current new image and used the features to compute the probability modelling the foreground. Since the two models by Mittal *et al.*(2004) and by Sheikh *et al.*(2005) use features from the image right before the current new image, it works well in those problems like video frames where the continuity of the sequence of images is preserved. However, its performance gets worse as the interval between two images in the sequence becomes larger.

In this paper, to overcome the false detection problems caused by the dynamic textures and noises, a new approach directly modelling a foreground is suggested. The proposed model is established with the probability distribution of pixel positions in terms of sum of weighted intensity differences between previous images and the new image. Based on this foreground position model, each pixel position on the new image having its probability value greater than the threshold is claimed to be the one forming the foreground.

2 MODELLING A FOREGROUND

2.1 Foreground Position Distribution

A foreground is defined to be a set of objects with motion. If an object has motion, its position changes from image to image. This means that the object's motion causes intensity differences of the associated positions. Thus, for a given position if its intensity difference between two compared images becomes relatively large, it is more probable for that position to be the one forming a foreground. Based on this consideration, the probability that each position in the new image becomes a foreground can be defined in terms of sum of its weighted intensity differences between the new image and all the previous images.

More formally, let the number of previous images in a sequence be N and let S be a set of pixel positions on an image, $S = \{(x,y) | 1 \leq x \leq W, 1 \leq y \leq H$, W is a *width* and H is a *height* of an image$\}$. Let $I_{j,k}$ for $j \in S, k = 1, \ldots, N, N+1$, be the intensity value of the position j on the kth image, where the $(N+1)$th image is the new image. If L is a random variable over all positions of pixels on the image, the probability $P_f(L = l)$ that a pixel at the position $l \in S$ on the new image becomes a foreground is given by

$$P_f(L=l) = \frac{1}{Z} \sum_{t=1}^{N} \sum_{m \in S} w(|I_{l,N+1} - I_{m,t}|) \cdot \delta(l,m) \quad (1)$$

where $w : R \to R$ is a weight function such that for every x in R, $w(x) = log(1+x)$. The weight function is defined to prevent the intensity difference from being too large once it becomes large enough to be identified as a foreground. It preserves the property of sum of original differences in identifying each position and also gives the reasonable range of the probability used for determining the threshold of the probability to distinguish the foreground from the dynamic textures and the background, which is explained in section 3.

Z is a normalizing constant given by

$$Z = \sum_{t=1}^{N} \sum_{l \in S} \sum_{m \in S} w(|I_{l,N+1} - I_{m,t}|) \cdot \delta(l,m) \quad (2)$$

where the position matching function δ returning 1 only when two matching positions are identical is such that

$$\delta(l,m) = \begin{cases} 1 & \text{, if } l = m \\ 0 & \text{, otherwise.} \end{cases} \quad (3)$$

2.2 Approximating Foreground Position Distribution

In computing the probability of equation (1), it is not easy to align two compared images exactly enough to compute the position matching function $\delta(l,m)$. To allow the slight misalignment, it is approximated with the Gaussian kernel function $K(l-m)$ (Bishop, 2006). The approximated probability $\hat{P}_f(L = l)$ is then

$$\hat{P}_f(L=l) = \frac{1}{\hat{Z}} \sum_{t=1}^{N} \sum_{m \in S} w(|I_{l,N+1} - I_{m,t}|) \cdot K(l-m) \quad (4)$$

where $\hat{Z}$ is a normalizing constant and K is a Gaussian kernel function. The normalizing constant $\hat{Z}$ is given by

$$\hat{Z} = \sum_{t=1}^{N} \sum_{l \in S} \sum_{m \in S} w(|I_{l,N+1} - I_{m,t}|) \cdot K(l-m) \quad (5)$$

and the Gaussian kernel function $K : R \times R \to R$ is such that

$$K(l-m) = \frac{1}{2\pi} \frac{1}{|\mathbf{H}|^{1/2}} \exp\left\{-\frac{1}{2}(l-m)^T \mathbf{H}^{-1} (l-m)\right\} \quad (6)$$

where $l-m$ is a 2-dimensional vector and $\mathbf{H}$ is a 2×2 bandwidth matrix of the kernel.

(a) (b) (c) (d) (e) (f) (g)

Figure 1: Background subtraction for natural scene 1. Approximated threshold by *K-means* algorithm: $T_A = 0.00005$ (a) One of previous images. (b) A new image. (c) $T = T_A \times 0.8$ (d) $T = T_A \times 0.9$ (e) $T = T_A \times 1.0$ (f) $T = T_A \times 1.1$ (g) $T = T_A \times 1.2$.

(a) (b) (c) (d) (e) (f) (g)

Figure 2: Background subtraction for natural scene 2. Approximated threshold by *K-means* algorithm: $T_A = 0.00005$ (a) One of previous images. (b) A new image. (c) $T = T_A \times 0.8$ (d) $T = T_A \times 0.9$ (e) $T = T_A \times 1.0$ (f) $T = T_A \times 1.1$ (g) $T = T_A \times 1.2$.

3 DETECTING A FOREGROUND

The probability of each position given by equation (4) shows how probable the position becomes the foreground as compared to other positions in the image. The larger value it has, the more probable it becomes the foreground. As mentioned in section 2.1, those positions of some object with motion have the large sum of intensity differences resulting in the high probability, which are thus to be considered as the foreground. Those positions of objects without motion however have the small sum of intensity differences resulting in the low probability, considered to be as the background. Finally those positions associated with dynamic textures or noises have the medium sum of intensity differences resulting in the intermediate probability, which should be not considered as the foreground. To identify those positions associated with foreground, thus it is necessary to find the boundary of probability values between foreground and dynamic textures. Although it is not easy to find the exact boundary in general, it may be approximated by grouping all probability values into three groups, high, intermediate, and low. Assuming three clusters, the *K-means* algorithm (Bishop, 2006) is applied to all probability values. The minimum value from the cluster consisting of high values is suggested as the approximated value of the boundary between the foreground and the dynamic textures, called the threshold. This value is then adjusted via training examples to get the best value of threshold.

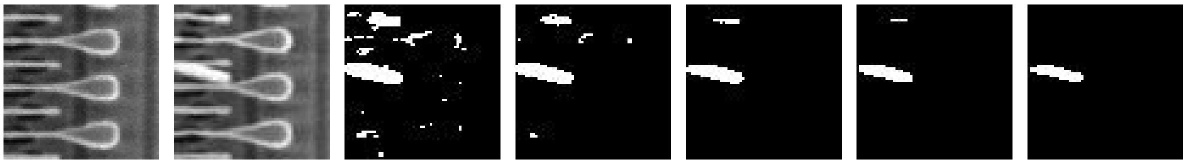
4 EXPERIMENTAL RESULTS

Our approach is applied to two classes of problems, background subtraction from natural scenes and defect detection from SEM(Scanning Electron Microscope) images, with four examples. The results are then compared to those from two conventional background subtraction approaches, one based on the kernel density estimation(BS-KDE)(Ahmed Elgammal and Davis, 2000) and the other based on the Gaussian mixture model(BS-GMM)(Gerald Dalley and Grimson, 2008) with 3×3 windows.

4.1 Background Subtraction Problems from Natural Scenes

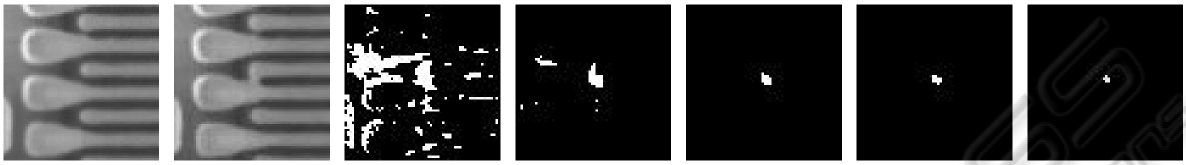
The goal of the background subtraction from natural scenes is to successfully detect the foreground objects from the new image avoiding the false detection due to dynamic textures. Images used for the following two examples are assumed to contain dynamic textures.

Example 1: Given a sequence of 30 previous images including Figure 1(a), the problem is to detect a person as the foreground from the new image of Figure 1(b): The probability values of all the pixels in the image are first computed from equation (4) using 30 previous images and the new image. The *K-means* algorithm applied to those computed values then gives the approximated threshold, $T_A = 0.00005$. Finally based on the detection results from using various values around T_A , which are shown from Figure 1(c),(d),(e),(f), and (g), the threshold T is given to be as same as T_A. The result using this threshold is compared to those from two other approaches in section



(a) (b) (c) (d) (e) (f) (g)

Figure 3: Defect detection for SEM image 1. Approximated threshold by *K-means* algorithm: $T_A = 0.00037$ (a) One of previous images. (b) A new image. (c) $T = T_A \times 0.9$ (d) $T = T_A \times 1.0$ (e) $T = T_A \times 1.1$ (f) $T = T_A \times 1.2$ (g) $T = T_A \times 1.3$.



(a) (b) (c) (d) (e) (f) (g)

Figure 4: Defect detection for SEM image 2. Approximated threshold by *K-means* algorithm: $T_A = 0.00005$ (a) One of previous images. (b) A new image. (c) $T = T_A \times 1.0$ (d) $T = T_A \times 1.3$ (e) $T = T_A \times 1.6$ (f) $T = T_A \times 1.7$ (g) $T = T_A \times 1.8$

4.3.

Example 2: Given a sequence of 30 previous images including Figure 2(a), the problem is to detect a car as the foreground from the new image of Figure 2(b): With similar procedure as in example 1, the approximated threshold T_A is computed to be 0.00005. Based on the detection results from using various values around T_A, which are shown from Figure 2(c),(d),(e),(f), and (g), the threshold T is given to be as same as T_A. The result using this threshold is compared to those from two other approaches in section 4.3.

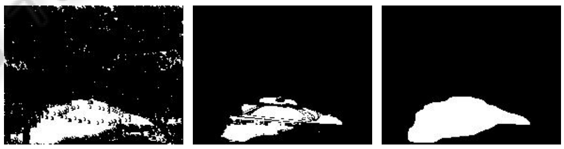
4.2 Defect Detection Problems from SEM Images

The goal of the defect detection from SEM images is to detect defects from the new image avoiding the false detection due to noises and shape variations of semiconductor's pattern where the sequence of previous images is considered as a set of reference images. Images used for the following two examples are assumed to contain noises associated with intensity values and shape variations of semiconductor's patterns.

Example 3: Given a sequence of 10 previous images including Figure 3(a), the problem is to detect defects as the foreground from the new image of Figure 3(b): With similar procedure as in previous examples, the approximated threshold T_A is given to be 0.00037. Based on the detection results from using various values around T_A, which are shown from Figure 3(c),(d),(e),(f), and (g), the threshold T is given to be $T = T_A \times 1.3 = 0.00048$. The result using this threshold is compared to those from two other approaches in section 4.3.

(a) (b) (c)

Figure 5: Comparison of background subtraction results for natural scene 1. (a) Result from BS-KDE. (b) Result from BS-GMM. (c) Result from our foreground model.



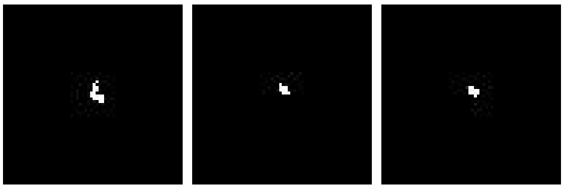
(a) (b) (c)

Figure 6: Comparison of background subtraction results for natural scene 2. (a) Result from BS-KDE. (b) Result from BS-GMM. (c) Result from our foreground model.

Example 4: Given a sequence of 5 previous images including Figure 4(a), the problem is to detect defects as the foreground from the new image of Figure 4(b): With similar procedure as in previous examples, the approximated threshold T_A is given to be 0.00030. Based on the detection results from using various values around T_A, which are shown from Figure 4(c),(d),(e),(f), and (g), the threshold T is given to be $T = T_A \times 1.6 = 0.00048$. The result using this threshold is compared to those from two other approaches in section 4.3.

(a) (b) (c)

Figure 7: Comparison of defect detection results for SEM image 1. (a) Result from BS-KDE. (b) Result from BS-GMM. (c) Result from our foreground model.



(a) (b) (c)

Figure 8: Comparison of defect detection results for SEM image 2. (a) Result from BS-KDE. (b) Result from BS-GMM. (c) Result from our foreground model.

4.3 Comparison to Other Approaches

For each of four examples in section 4.1 and 4.2, our approach is compared to two other approaches, the kernel density estimation (BS-KDE) (Ahmed Elgammal and Davis, 2000) and the Gaussian mixture model with 3×3 windows (BS-GMM) (Gerald Dalley and Grimson, 2008). Figure 5, 6, 7, and 8 shows results from using three approaches.

For the first two examples of the background subtraction problem, as shown in Figure 5 and 6, our approach results in clearly described objects of a person and a car. The results from two other approaches however describe not clear and noisy objects due to dynamic textures.

For the next two examples of the defect detection problem, as shown in Figure 7 and 8, our approach detects defects only but two other approaches of the BS-KDE and the BS-GMM detects defects and also other defect-free areas as defects.

5 CONCLUSIONS

A new approach using a foreground model was suggested for solving the background subtraction problem and the related defect detection problem. The foreground model has been formulated using the weighted intensity differences between a new image and all previous images. The suggested approach has relaxed the difficulty of detecting the foreground from the images containing dynamic textures and noises, as compared to the traditional approaches using a background model.

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