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Object Detection based Weighted-Center Surround Difference

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Abstract**—**Intelligent traffic surveillance technology is an issue in the field of traffic data analysis. Therefore, we need the technology to detect moving objects in real-time while there are variations in background and natural light.

In this paper, we proposed a Weighted-Center Surround Difference method for object detection in outdoor environments. The proposed system detects objects using the saliency map that is obtained by analyzing the weight of each layers of Gaussian pyramid. In order to validate the effectiveness of our system, we implemented the proposed method using a digital signal processor, TMS320DM6437. Experimental results show that blurred noisy around objects was effectively eliminated and the object detection accuracy is improved.

Keywords**—**Saliency Map, Center Surround Difference, Object Detection, Surveillance System

I. INTRODUCTION

INTELLIGENT video surveillance technology continues to grow and borders, airports, power plants and major infrastructure such as security and surveillance are being used in various fields. Among them, intelligent traffic monitoring system based on the visual information is used to determine to measure traffic or road conditions, including traffic accidents, and many of the detected information. In outdoor environments, vehicles, people or other moving objects accurately detecting is based technologies for intelligent traffic monitoring system.

There are several difficulties to detect objects such as cars and people based fixed camera video information located in an outdoor environment. Multiple moving objects in an outdoor environment constantly changing natural light must be detected without the loss. Also, an object moving in different directions even if it may seem distorted size or shape is required to detect accurately. In addition, the technology for the industrialization of the practical, real-time embedded environment that can be used for object detection system is required.

Methods to detect objects from real-time video information were background subtraction, eigen-background, and visual attention model. Background subtraction method has the advantage, relatively low volume of operations, but because it uses a fixed background data are vulnerable to changes in the background has disadvantages [1-2]. As a way to solve this problem by analyzing the background to detect objects eigen-background method has been studied [3-4]. However, this method samples the amount of data, learning and renewal cycle is determined based on the detection performance has a problem. Another method for object detection Mixture-of Gaussian(MoG) is used, but high miss-detection rates according to changes in the background has disadvantages[5-6]. Image based bottom-up Saliency Map(SM) among the visual attention model methods is suitable for real-time embedded multi-object detection method because it do not need of training data and is robust to changes in ambient background[7]. However, the blurred noisy around the object caused by an image-resize operations in the process of creating of Gaussian pyramid degrades the object detection performance.

In this paper, Weighted-Center Surround Difference (WCSD) using the object detection system is proposed. The proposed system is improved performance of object detection by interpreting the weights of the relationship of each layer of the Gaussian pyramid and removing the blurred noisy.

II. WEIGHTED-CENTER SURROUND DIFFERENCE

SM technique consists of two steps, Static Saliency Map(SSM) step, Dynamic Saliency Map(DSM) step. We propose that WCSD method is respectively applied for intensity image I and Sobel-edge image E from an RGB image in the SSM step to obtain the SSM S. And then, the DSM D is obtained by calculating entropy ε from S_t to S_{t-n}. Thresholding the intensity of D and morphology applied to detect the objects.

A. Static Saliency Map

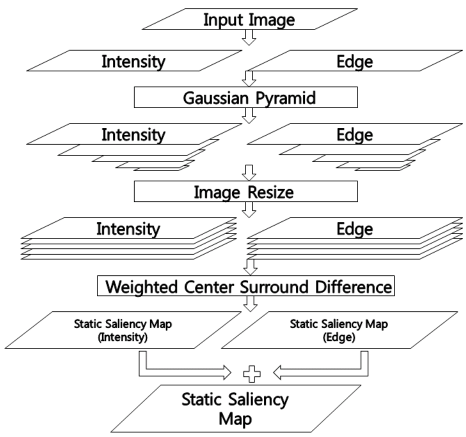

Fig. 1 Processing structure of SSM using WCSD

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1) Generate the intensity image I using (1) and create Sobel-edge image E on the input RGB color images.

$$I_{u,v} = 0.299R + 0.587G + 0.114B \qquad (1)$$

2) The horizontal and vertical images of the each layer of I and E down-sampling in half to obtain Gaussian pyramid G^I, G^E.
3) Create the difference map Θ^I, Θ^E as each layer n of G^I, G^E up-sampling back to the same size of intensity image I, Sobel-edge image E.
4) The bilinear interpolation and Gaussian blurring is used for up/down sampling, respectively.

For each layer to obtain WCSD are shown in Algorithm I.

ALGORITHM I
WEIGHTED-CENTER SURROUND DIFFERENCE

begin initilize $p \leftarrow 0, k \leftarrow 0$
  do $p \leftarrow p+1$
    do $k \leftarrow k+1$
      if $p \neq k$ then $\psi_{u,v} \leftarrow \psi_{u,v} + \left|\Theta_{p,x,y} - \Theta_{k,x,y}\right|$
    until $k = n$
    $\Psi_{u,v} \leftarrow (\Psi_{u,v} + \psi_{u,v}) * \xi_i$
  until $p = n$
  $S_{u,v} = (\Psi_{u,v} - \Psi_{\min}) / (\Psi_{\max} - \Psi_{\min})$
end

Where, ψ is the accumulated value of the difference of the difference map Θ, and Ψ is the cumulative weight of each phase of the applied value ξ. SSM of S^I, S^E, are obtained by calculating n-dimensional Θ^I, Θ^E with WCDS. Generating SSM S is shown in (2).

$$S_{u,v} = \frac{S^I_{u,v} + S^E_{u,v}}{2} \qquad (2)$$

B. Dynamic Saliency Map

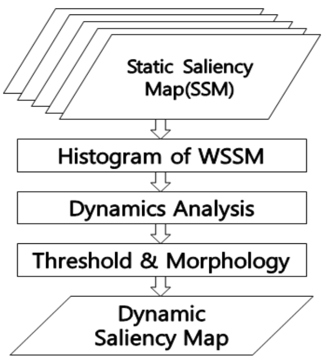

Fig. 2 Processing structure of DSM

DSM, as shown in Figure 2 generates the histogram H of the luminance i for each pixel from S_t to S_{t-n} and entropy ε as shown (3).

$$\varepsilon = \sum_{i=1}^{M} \varepsilon_{i-1} - \frac{\mathrm{H}_i \log(\mathrm{H}_i)}{\log 2},\ \mathrm{H}_{\min} - \mathrm{H}_{\max} > d_{th},\ \mathrm{H}_i \neq 0 \qquad (3)$$

$$\theta_{u,v} = \sqrt{\varepsilon^2} \qquad (4)$$

d_{th} is the dynamic saliency map threshold in (3). The dynamic variable θ is generated from entropy ε as shown in (4). And then DSM D is obtained through the thresholding and the morphology.

III. EXPERIMENTAL RESULTS

TMS320DM6437 600MHz development board as shown in Fig.3, 4 was tested to evaluate the performance of the proposed object detection based WCSD. The input images with 200 frames are recorded from the installed CCTV images at the intersection in KAIST(Korea Advanced Institute of Science and Technology) campus when constantly changing natural light and moving vehicles and people. We produced template image with a resolution of 160x120 to evaluate the detection performance.

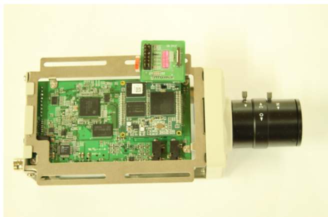

Fig. 3 Object Detection Embedded System

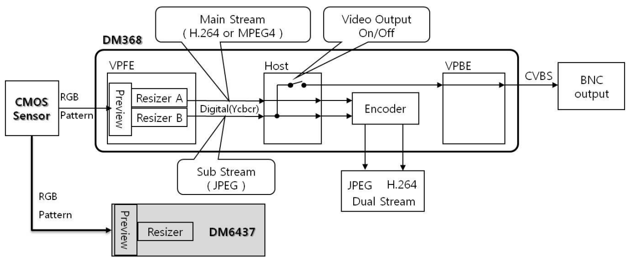

Fig. 4 Configuration of Object Detection Embedded System

We used Gaussian pyramid with five layers. The performance evaluation method is shown in Table I.

TABLE I
CRITERIA OF PERFORMANCE MEASURE

TP rate	TP/(TP+FN)
FP rate	FP/(FP+TN)
Precision	TP/(TP+FP)
Recall	TP/(TP+FN)=TP rate
Accuracy	(TP+FN)/(P+N)
F-Measure	2/(1/Precision+1/Recall)

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A. Detection Performance of Changing Weighed-Center Surround Difference Weight W_k

The detection performance is decreased because the repeated image-resize process on the steps of creating the saliency map occurs the blurred noisy around the object. To solve this problem was to apply WCSD weigh W_k . $W_k = [\xi_1, \xi_2, \xi_3, \xi_4, \xi_5]^T$ is the weight able to experiment to obtain the optimal value. There were 3,731 kinds of cases from $W_1 = [0,0,1,1,13]^T$ to $W_{3,731} = [13,1,1,0,0]^T$ and we tested them repeatedly. As shown in Fig. 5, WCSD weight W_k is proportional to the resize rate on the creating step of Gaussian pyramid. However, the resized layer with 10x7 resolution rather degraded the object detection performance.

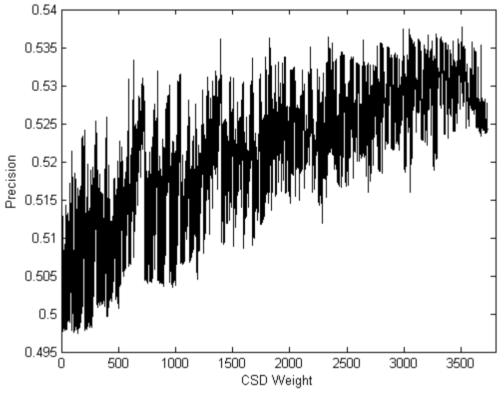

Fig. 5 Precision result of changing W_k

B. Detection Performance of Changing Dynamic Threshold d_{th}

Fig. 6 shows the accuracy when dynamic threshold d_{th} is repeatedly changed from 0 to 100. The accuracy is 0.8 when dynamic threshold is from 20 to 50.

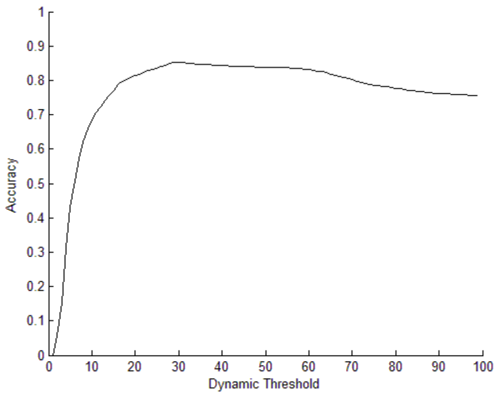

Fig. 6 Accuracy of changing d_{th}

C. Result of Static Saliency Map

Fig.7 shows the result images applied W_k and d_{th} from the result of experiments A and B. The blurred noisy around the object was removed and object detection performance is improved as shown in Table II.

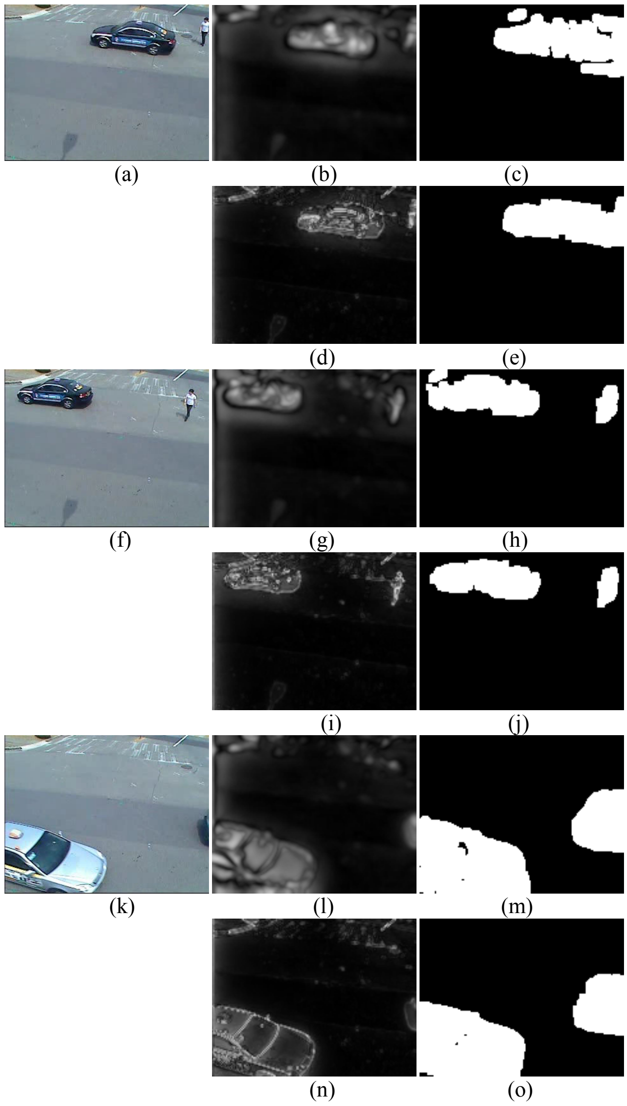

Fig. 7 Result image of saliency map((a)(f)(k): input image, (b)(g)(l): SM without WCSD, (d)(i)(n): SM with WCSD, (c)(h)(m): DM without WCSD , (e)(j)(o):DM with WCSD)

TABLE II
COMPARISON OF PERFORMANCE MEASURES OF WCSD

	Without W_k	With W_k
TP rate	0.018	0.013
FP rate	0.381	0.426
Precision	0.488	0.537
Recall	0.381	0.426
Accuracy	0.953	0.962
F-Measure	0.401	0.456

IV. Conclusion

In this paper, WCSD proposed to improve object detection performance. We verified the proposed system is able to remove the blurred noise of existing Saliency Map.proposed system Saliency Map of the proposed system that exists in the existing blurred noisy and was removed, the object detection performance improved.

As shown in Fig. 7, varying the speed of the object along the object's shape was not eliminated a long loose. In the future, if we consider not static time analysis but also dynamic time analysis, these problems are solved.

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