Method for Car in Dangerous Action Detection by Means of Wavelet Multi Resolution Analysis Based on Appropriate Support Length of Base Function

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***Abstract*—Multi-Resolution Analysis: MRA based on the mother wavelet function with which support length differs from the image of the automobile rear under run is performed, and the run characteristic of a car is searched for. Speed, deflection, etc. are analyzed and the method of detecting vehicles with high accident danger is proposed. The experimental results show that vehicles in a dangerous action can be detected by the proposed method.**

Keywords-Change detection; MRA; support length of mother wavelet

I. INTRODUCTION

There are strong demands on detection of the cars in dangerous actions in particular on freeways, highways at which high speed cars are passing through. Most of the freeways, highways equip cameras at some intervals to monitor traffic flow and detect such dangerous cars. Traffic flow monitoring with camera acquired car images is relatively easy to measure. It, however, is not so easy to detect dangerous cars. If dangerous cars are detected, then some cautions may be made with loud speaker to the dangerous cars and the surrounding cars to prevent car accidents.

Temporal change detections can be done with moving pictures by using differential operators such as Sobel, Prewitz, Laplacian, etc. [1]. It, however, is affected by the noises included in the moving pictures. Differential operators enhance noises usually. On the other hands, discrete wavelet transformation based Multi Resolution Analysis: MRA [2]-[8] allows spatio-temporal change detection with a variety of parameters, order and support length of base function of wavelet, shift and magnification of wavelet function, and levels of wavelet transformations. By tuning the parameters, appropriate MRA can be formed for detection of dangerous cars. There is another approach for car tracking method based on Kalman filter [9]. Also wavelet parameter estimation method is proposed [10]. Therefore, these object tracking and object trajectory analysis for drivers' behavior estimation can be done after the detection of dangerous cars.

The following section describes the proposed method for detection of dangerous cars followed by some experiments. Then conclusion is described with some discussions.

II. PROPOSED METHOD

A. Discrete Wavelet Transformation

Discrete wavelet transformation for the given time series of scalar variables, η_i are defined in equation (1) with square matrix, C_n (wavelet transformation matrix) which consists of low wavelet frequency component coefficients, p_i and high wavelet frequency component coefficients, q_i.

$$C_n \begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_n \end{bmatrix} \tag{1}$$

Then the given time series of scalar variables can be divided into two parts, low frequency and high frequency components. There is a variety of wavelet transformation matrix with the different parameters of the order and the support length of the base function. For instance, the wavelet transformation matrix for the 8^{th} order and two of the support length is shown in equation (2). In the case of the wavelet transformation matrix for the 8^{th} order with two support length is expressed in equation (3).

In the case of Daubechies base function, the wavelet transformation matrix with two of the support length can be calculated with equation (4) while that with four of the support length can be calculated with equation (5). Meanwhile, the wavelet transformation matrix with the arbitrary support length, (sup) can be calculated with equation (6).

$$C_8^{[2]}\begin{bmatrix}\eta_1\\ \eta_2\\ \eta_3\\ \eta_4\\ \eta_5\\ \eta_6\\ \eta_7\\ \eta_8\end{bmatrix}=\begin{bmatrix}p_0 & p_1 & & & & & & \\ q_0 & q_1 & & & & & & \\ & & p_0 & p_1 & & & & \\ & & q_0 & q_1 & & & & \\ & & & & p_0 & p_1 & & \\ & & & & q_0 & q_1 & & \\ & & & & & & p_0 & p_1\\ & & & & & & q_0 & q_1\end{bmatrix}\begin{bmatrix}\eta_1\\ \eta_2\\ \eta_3\\ \eta_4\\ \eta_5\\ \eta_6\\ \eta_7\\ \eta_8\end{bmatrix}=\begin{bmatrix}p_0x_1+p_1x_2\\ q_0\eta_1+q_1\eta_2\\ p_0\eta_3+p_1\eta_4\\ q_0\eta_3+q_1\eta_4\\ p_0\eta_5+p_1\eta_6\\ q_0\eta_5+q_1\eta_6\\ p_0\eta_7+p_1\eta_8\\ q_0\eta_7+q_1\eta_8\end{bmatrix} \tag{2}$$

$$C_8^{[4]}\begin{bmatrix}\eta_1\\ \eta_2\\ \eta_3\\ \eta_4\\ \eta_5\\ \eta_6\\ \eta_7\\ \eta_8\end{bmatrix}=\begin{bmatrix}p_0 & p_1 & p_2 & p_3 & & & & \\ q_0 & q_1 & q_2 & q_3 & & & & \\ & & p_0 & p_1 & p_2 & p_3 & & \\ & & q_0 & q_1 & q_2 & q_3 & & \\ & & & & p_0 & p_1 & p_2 & p_3\\ & & & & q_0 & q_1 & q_2 & q_3\\ p_2 & p_3 & & & & & p_0 & p_1\\ q_2 & q_3 & & & & & q_0 & q_1\end{bmatrix}\begin{bmatrix}\eta_1\\ \eta_2\\ \eta_3\\ \eta_4\\ \eta_5\\ \eta_6\\ \eta_7\\ \eta_8\end{bmatrix}=\begin{bmatrix}p_0\eta_1+p_1\eta_2+p_2\eta_3+p_3\eta_4\\ q_0\eta_1+q_1\eta_2+q_2\eta_3+q_3\eta_4\\ p_0\eta_3+p_1\eta_4+p_2\eta_5+p_3\eta_6\\ q_0\eta_3+q_1\eta_4+q_2\eta_5+q_3\eta_6\\ p_0\eta_5+p_1\eta_6+p_2\eta_7+p_3\eta_8\\ q_0\eta_5+q_1\eta_6+q_2\eta_7+q_3\eta_8\\ p_0\eta_7+p_1\eta_8+p_2\eta_1+p_3\eta_2\\ q_0\eta_7+q_1\eta_8+q_2\eta_1+q_3\eta_2\end{bmatrix} \tag{3}$$

$$\begin{aligned}&\left(C_n^{[2]}\right)^T C_n^{[2]}=I_n\\ &\quad p_0+p_1=\sqrt{2}\\ &\qquad q_0=p_1\\ &\qquad q_1=-p_0\\ &0^0q_0+1^0q_1=0\end{aligned} \tag{4}$$

$$\begin{aligned}\left(C_n^{[4]}\right)^T C_n^{[4]}&=I_n\\ p_0+p_1+p_2+p_3&=\sqrt{2}\\ q_0&=p_3\\ q_1&=-p_2\\ q_2&=p_1\\ q_3&=-p_0\\ 0^0q_0+1^0q_1+2^0q_2+3^0q_3&=0\\ 0^1q_0+1^1q_1+2^1q_2+3^1q_3&=0\end{aligned} \tag{5}$$

$$\begin{aligned}&\left(C_n^{[\sup]}\right)^T C_n^{[\sup]}=I_n\\ &\qquad\sum_{j=0}^{\sup-1}p_j=\sqrt{2}\\ &\qquad\qquad q_j=(-1)^j p_{((\sup-1)-j)}\quad \left(j=0,1,2,\ldots,(\sup-1)\right)\\ &\qquad\qquad \sum_{j=0}^{\sup-1}j^r q_j=0\quad \left(r=0,1,2,\ldots,(\frac{\sup}{2}-1)\right)\end{aligned} \tag{6}$$

B. Multi Resolution Analysis: MRA

The input data of scalar variables can be transformed to high (H) and low (L) wavelet frequency components with the wavelet transformation matrix. This Discrete Wavelet Transformation: DWT is called as the first level of DWT. L component can be divided into H and L components. This DWT is called as the second level of DWT. Furthermore, these transformations can be repeatedly applied to the L components again. These DWT is called as decomposition. The level is corresponding to the frequency components. In other words, arbitrary frequency component can be extracted with the different level of wavelet frequency component.

Because of the $C^TC=C^{-1}C$, it is possible to reconstruct original input data of scalar variables with the all levels of H components and the highest level of L component. This process is called with reconstruction, or Inverse Discrete Wavelet Transformation: IDWT.

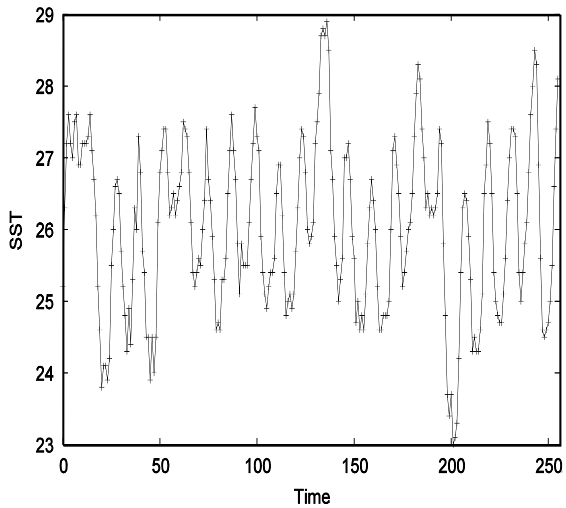
DWT and IDWRT can also be defined to the two dimensional image data as well as three dimensional moving pictures. Furthermore, these can be applied to arbitrary dimensional data *f* as follows,

$$(fC)^T)C^T)\ldots)C^T) \tag{7}$$

For instance, DWT divides two dimensional input data into LL, HL, LH, and HH. The first and the second characters denote horizontal and vertical directions, respectively.

C. Effect of the Support Length

In order to clarify the effect of the support length, relatively calmly changed Southern Oscillation Index: SOI is compared to relatively rapidly changed SOI which are shown in Figure 1 (a) and (b), respectively. DWT is applied at once (first level) to the data with the different support length. After that IDWT is applied to the transformed wavelet frequency component with L component only. Root Mean Square Error: RMSE between the reconstructed data and the original data is evaluated. The results are shown in Figure 2.



(a)Relatively calm

(b) Relatively rapid

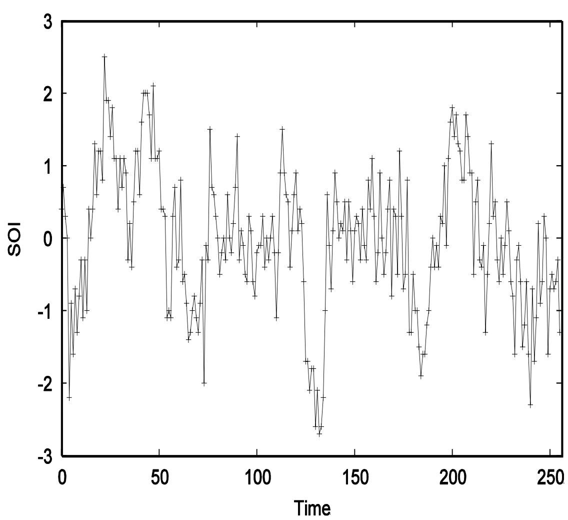
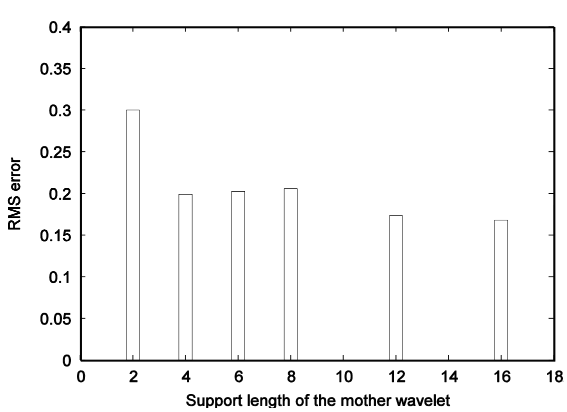
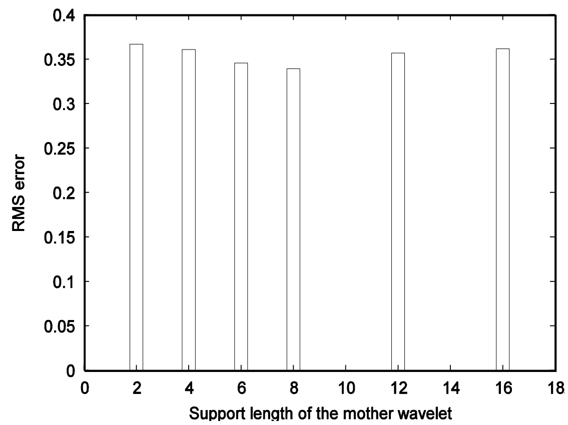


Fig. 1. Two different types of time series of data



(a)Relatively calm



(b) Relatively rapid

Fig. 2. Root Mean Square error between original and reconstructed time series data through DWT with different support length (2-16) of mother wavelet.

RMSE is represented reproducibility without high frequency component. Therefore, it is said that long support length (16) is appropriate for relatively calmly changed time series of data in terms of reproducibility while around 8 of support length is suitable for relatively rapidly changed data. Consequently, there is an appropriate support length depending on how rapidly changed the input time series data.

D. Methoid for Dangerous Car Detection

Using moving pictures acquired with traffic flow monitoring cameras, dangerous car can be detected. In order to detect car, edge detection method is applied to the moving pictures. Edges can be detected by the process of which 3D DWT (decomposition) is applied to the original moving pictures, then IDWT (reconstruction) is applied to the decomposed wavelet frequency components without LLL component which results in enhancement of high frequency component (edge enhancement). Therefore, spatial-temporal changes can be detected.

It is well known that the tail of car in dangerous actions used to be vibrated (slipping and sliding motion) with around a couple of Hz in horizontal direction. It is possible to detect such actions (direction and vibration frequency component) by using the aforementioned DWT and IDWT processes. Therefore, dangerous car detection is capable.

III. EXPERIMENTS

A. Data Used

Example of the moving picture for the car in dangerous action is shown in Figure 3. Image size is 128 by 128 pixels while the quatization bit is 8. Meanwhile, the frame rate is 8 frames per second. This moving picture is acquired with traffic flow monitor camera for four second.

This moving picture is downloaded from the site of

http://www.youtube.com/watch?v=COdlLcgGUQ.

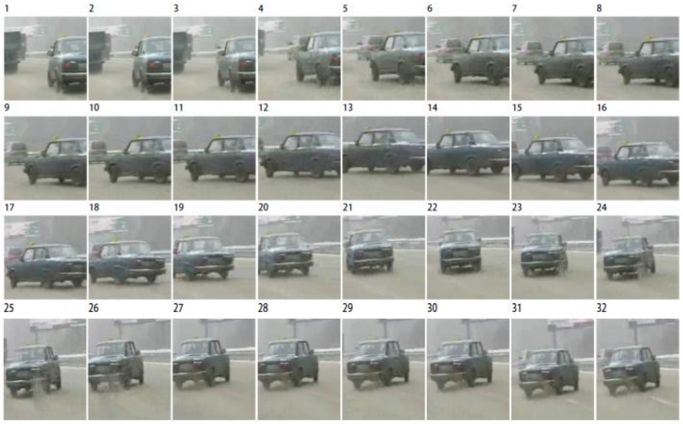
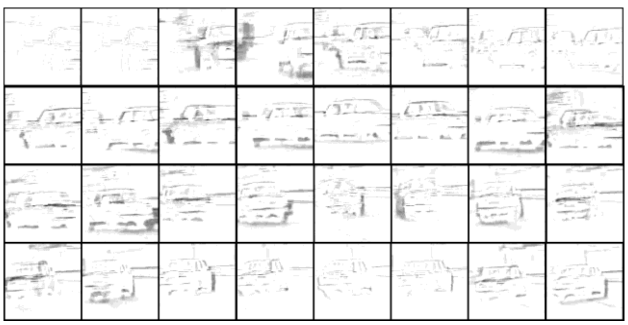


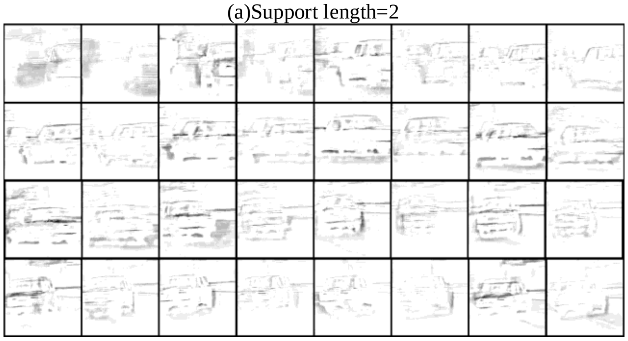
Fig. 3. Original moving picture of the car in a dangerous action from the site of http://www.youtube.com/watch?v=COdlLcgGUQ.

B. *Effect of Suport Length*

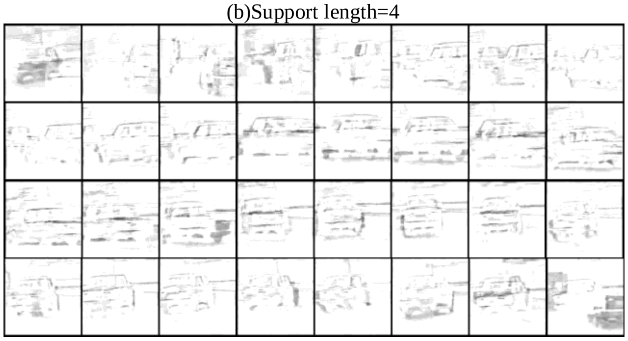
Spatial-temporal change detection is performed for the example of moving picture by using the proposed method with the different support length of base function of Daubechies mother wavelet ranges from 2 to 16. Figure 4 shows the resultant images.



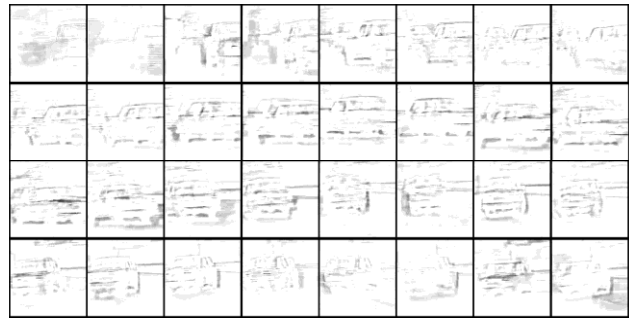
(a)Support length=2



(b)Support length=4



(c)Support length=8



(d)Support length=16

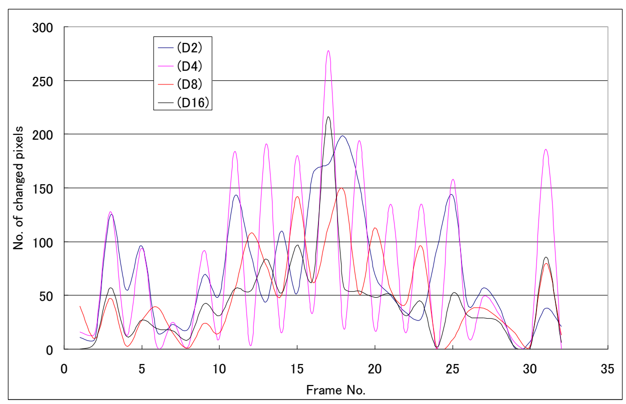
Fig. 4. Moving parameter estimation through 3D wavelet transformation with the different support length of 2, 4, 8, and 16 of Daubechies mother wavelet.

From Figure 4, it is found that dangerous actions can be detected at 23 frame number and after. Due to the fact that the frequency component derived from the proposed method is a couple of Hz, it is found that this car is in dangerous actions after 23 frames.

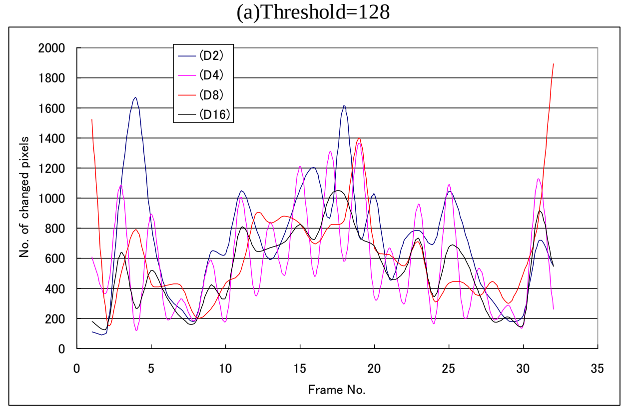
In comparison of these detected edges and spatial-temporal changes, it is found that 8 of support length would be best followed by 16 and 4 and 2.

C. *Detected Spatio-Temporal Changed Pixels*

Through binarization of the Figure 4 with the appropriate threshold, spatial-temporal changed pixels can be detected. Figure 5 shows the number of the detected spatial-temporal changed pixels with the threshold of 128 and 64, respectively.



(a)Threshold=128



(b)Threshold=64

Fig. 5. The number of detected change pixels through the proposed method with the different support length of mother wavelet (Daubechies).

Figure 5 (a) shows that there are two peaks situated at around 12 to 23 frame and at around 25 to 28 frame. It also shows the hunching of the number changed pixels for small support length. This is caused by the influence due to shorter support length. In accordance with increasing of support length, this hunching effect is getting small. Therefore, longer support length is better than shorter support length in terms of spatial-temporal change detection. It is obvious that the number of detected changed pixels for the threshold is 64 is greater than that of the threshold is 128 by approximately 5.6 times.

IV. CONCLUSION

Multi-Resolution Analysis: MRA based on the mother wavelet function with which support length differs from the image of the automobile rear under run is performed, and the run characteristic of a car is searched for. Speed, deflection, etc. are analyzed and the method of detecting vehicles with high accident danger is proposed. The experimental results show that vehicles in a dangerous action can be detected by the proposed method with the different support length of wavelet base function.

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