

## A Wavelet-based Algorithm for Vehicle Flow Information Extraction

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### Abstract

*This paper proposed an improved algorithm applied in video intelligent traffic control system for vehicle detection. The accuracy of original algorithm, which is based on the comparison of contrast and luminance distortion of present image with background, reduces greatly under bad weather because of false detection caused by noises in captured images. In this paper we chose Daubechies wavelet as mother wavelet to add a 2-dimension wavelet process before the algorithm, just after the image is captured, to de-noise each captured image. We used FPGA-based equipments to test the algorithm, and the experiment proved higher performance of improved algorithm, especially under bad weather.*

**Keywords:** vehicle flow, contrast distortion, luminance distortion, Daubechies wavelet, de-noising

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### 1. Introduction

To solve the problem of urban congestion and obstruction, video intelligent traffic control system is well-known as the best approach, in which the length of red and green lights time are variable through vehicle flow. There are 3 subsystems in video intelligent traffic control system, which are vehicle-detecting subsystem, vehicle-counting subsystem and time-controlling subsystem. Vehicle-detecting subsystem, which is mainly for detecting the vehicle in a given area, is the most important part in video intelligent traffic control system, and it determines the efficiency of whole system. The algorithm based on contrast and luminance distortion [1] is an accurate algorithm for vehicle detection. That is, comparing the contrast and luminance distortion of present image, which is captured with certain frequencies, with background image. If the 2 parameters pass through a threshold from large to small, there is a car passing into the designated area, and then if they pass through another threshold from small to large, there is a car passing away from the area. When the 2 processes happen successively, vehicle-counting subsystem would count up by one. The background image is updated every fixed interval of time. However, when weather gets too bad, such as snow, rainstorm and sand storm, the captured image would be full of noises. Therefore, sometimes the contrast distortion and luminance distortion may pass the 2 processes but there is no car passing, causing error to the result.

In this paper, we focus on the improvement of this algorithm. We add a wavelet processing [2] after capture of background image and present image for de-noising, before the process of the algorithm based on contrast and luminance distortion. Daubechies wavelet (dbN) has a good expansion ability [3] so we choose Daubechies(db8) as mother wavelet.

The paper was organized as follows. Section 2 described the algorithm based on contrast and luminance distortion, which was original algorithm. Section 3 analyzed Daubechies wavelet transformation, steps of getting filter coefficients and wavelet de-noising, and structure of improved algorithm. Results of simulation and comparison experiment were shown in Section 4. Finally we made conclusion in Section 5.

## 2. The Algorithm Based on Contrast and Luminance Distortion

To start the whole system, the camera should be adjusted so that it can capture the image of appropriate area. Generally the length of the area is as same as that of a car, and the width is as same as the road. That is shown in Figure 1.

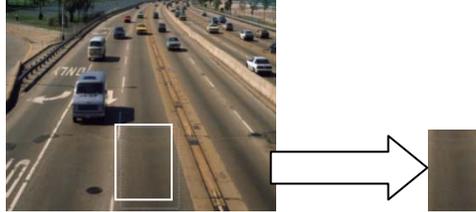


Figure 1. Choosing area

**Definition**  $X$  is background image and  $Y$  is present image, and each image is with  $N$  pixels. The gray value of each pixel is written as

$$x = \{x_i \mid i = 1, 2, \dots, N\} \quad (1)$$

$$y = \{y_i \mid i = 1, 2, \dots, N\} \quad (2)$$

The variance of  $x$  and  $y$  are

$$\sigma_x^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2 \quad (3)$$

$$\sigma_y^2 = \frac{1}{N-1} \sum_{i=1}^N (y_i - \bar{y})^2 \quad (4)$$

Therefore, the contrast distortion of an image is written as

$$c = \frac{2\sigma_x\sigma_y + C_1}{\sigma_x^2 + \sigma_y^2 + C_1} \quad (5)$$

And the luminance distortion is

$$lum = \frac{2\bar{x}\bar{y} + C_2}{(\bar{x})^2 + (\bar{y})^2 + C_2} \quad (6)$$

In equation (6),  $\bar{x}$  and  $\bar{y}$  are the average value of  $x$  and  $y$ . To avoid that the denominator of either  $c$  or  $lum$  is 0,  $C_1$  and  $C_2$  are added.  $C_1 = (K_1L)^2$  and  $C_2 = (K_2L)^2$ .  $L$  is dynamic range of pixel grayscale (e.g. if the image is 8-bit grayscale image,  $L$  is 255). Generally  $K_1 = 0.03$  and  $K_2 = 0.01$ .

In the whole system the background image is periodically updated, but it shouldn't include cars. Thus a threshold (background threshold) should be set before. That is, when it is time for background updating but  $c$  and  $lum$  are below the threshold, there must be cars in the area and background would not update. After obtaining background, the system starts

initialization process, working out the variance  $\sigma_x$  and average value  $\bar{x}$  of background image. After that the system starts real-time sampling process which samples the image of road and then works out the  $\sigma_y$  and  $\bar{y}$  of present image, then works out  $c$  and  $lum$  according to equations (5) and (6). When the differences of present and background image are quite modest,  $c$  and  $lum$  are near to 1. And when a car runs into the chosen area completely, they are to the minimum (near to 0). Therefore, we can set 2 thresholds  $a$  and  $b$  through experiment and if  $c$  and  $lum$  pass through  $a$  from large to small, there is a car passing into the area. And then if they pass through  $b$  from small to large, the car is passing away, and after the 2 processes the system count up by one.

The contrast distortion in the algorithm is relevant to the variances of pixel grayscale thus the shadow effect could be efficiently suppressed. And luminance distortion is relevant to the average of pixel grayscale, so the accuracy of algorithm won't be affected by light changes. And the algorithm is about contrast and luminance distortion, not point-to-point correspondence, thus the accuracy won't be affected by camera shaking. However, bad weather would cause noises in captured image, thus affecting the accuracy seriously.

### 3. Daubechies Wavelet and the Improved Algorithm

To improve the accuracy of algorithm under bad weather, a 2-dimension wavelet processing is added before original algorithm. In this paper, we choose Daubechies wavelet as mother wavelet.

#### 3.1. Daubechies Wavelet

In orthogonal condition the Fourier Transform of Daubechies(db8) [4] wavelet filter function satisfies the equation

$$|H(\omega)|^2 + |H(\omega + \pi)|^2 = 1 \quad (7)$$

If  $H(\omega) = \sum_n h_n e^{-in\omega}$  then

$$H(\omega) = \left[ \frac{1}{2}(1 + e^{i\omega}) \right]^8 Q(e^{-i\omega}) \quad (8)$$

Hence  $Q(e^{-i\omega})$  is a real coefficient polynomial, and  $|Q(e^{-i\omega})|^2 = Q(e^{i\omega})Q(e^{-i\omega})$ .

And since  $\left| \frac{1}{2}(1 + e^{i\omega}) \right|^2 = \left| \cos^2 \omega / 2 \right|$ , thus

$$|H(\omega)|^2 = [\cos^2(\omega / 2)]^8 |Q(e^{-i\omega})|^2 \quad (9)$$

$$|H(\omega + \pi)|^2 = [\sin^2(\omega / 2)]^8 |Q(e^{-i(\omega + \pi)})|^2 \quad (10)$$

From equation (9), (11), (12) and Reisz theorem,

$$|Q(e^{-i\omega})|^2 = \sum_{k=0}^7 C_{7+k}^k \left( \sin^2 \frac{\omega}{2} \right)^k + \left( \sin^2 \frac{\omega}{2} \right)^8 R \left( \frac{1}{2} - \sin^2 \frac{\omega}{2} \right) \quad (11)$$

Then we could obtain  $|Q(e^{i\omega})|^2$  from equation (7), (8) and (11). Now we can work out the coefficients of Daubechies wavelet filter  $H(\omega)$  as following steps:

Firstly, we should obtain  $|Q(e^{i\omega})|^2$  under  $R(x) = 0$ , and then we can transfer  $|Q(e^{i\omega})|^2$  to the function of  $\cos(\omega)$ , so we obtain a univariate equation with higher order, and we set it as  $V(\theta)$  and  $\theta = \cos(\omega)$ . After that, all the roots  $\theta_i$  of this equation could be obtained, and then we use  $\theta_i = z + \frac{1}{z}$  to obtain all the  $z$ . Thirdly, as for the complex roots, we pick one pair of each 2 pairs out and one of each pair as for real roots, we therefore obtain  $Q(z) = A \prod (z - z_i)$  from them. The  $A$  could be obtained from  $Q(i) = \sqrt{V(i)}$ , and we could therefore obtain  $h_n$  with  $Q(z)$  finally.

**3.2. Wavelet-based Image Processing**

Wavelet image processing is 2-dimension discrete wavelet transform [5], which consists of line wavelet transformation and column wavelet transformation. First we should get low-frequency filter coefficients  $h_n$  and high-frequency filter coefficients  $g_n$  through the method above. As for image de-noising based on Daubechies wavelet [6], firstly we should decompose the image  $y$  and obtain wavelet coefficients with Mallat algorithm, which is described in Figure 2.

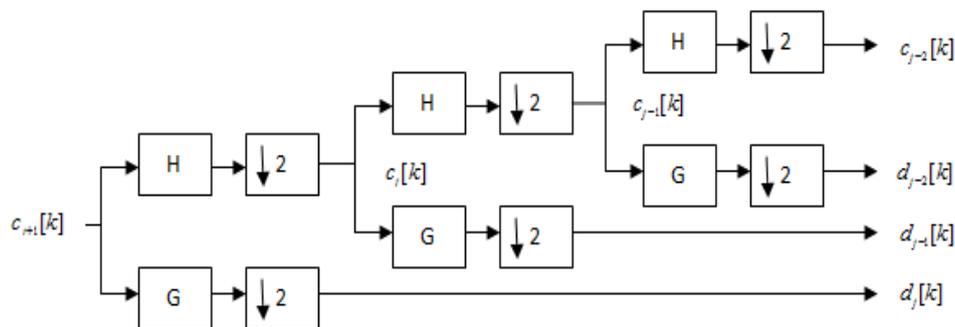


Figure 2. Mallat algorithm

Here,  $H$  is low-frequency filter and  $G$  is high-frequency filter.  $\downarrow 2$  is down-sampling by two in wavelet transform.  $c_{j+1}[k], c_j[k], c_{j-1}[k], c_{j-2}[k]$  are scale coefficients and  $d_{j+1}[k], d_j[k], d_{j-1}[k], d_{j-2}[k]$  are wavelet coefficients.

The image signal is a matrix of pixels, and each pixel is the gray value of a point. Generally, each line and column of the matrix could be regarded as 1-dimension signal [7]. We start with line processing, using Mallat algorithm for decomposing each line to get wavelet coefficients and scale coefficients. Then we use soft-threshold de-noising method [8] for threshold de-noising as following

$$\hat{X} = T_H(\gamma, t) = \begin{cases} \text{sgn}(\gamma)(|\gamma| - t), & |\gamma| \geq t \\ 0, & |\gamma| < t \end{cases} \quad (12)$$

In equation (12)  $t$  is threshold, and  $\gamma$  is wavelet coefficient, so  $\gamma = d_j[k]$ . After de-noising, we use inverse process of decomposition to reconstruct the matrix. Then we do the same process to each column of the reconstructed matrix.

Therefore the de-noised image  $\hat{y}$  could be obtained, and wavelet process is finished. Next it's process of the algorithm based on contrast and luminance distortion.

The block diagram of improved algorithm is shown in Figure 3.

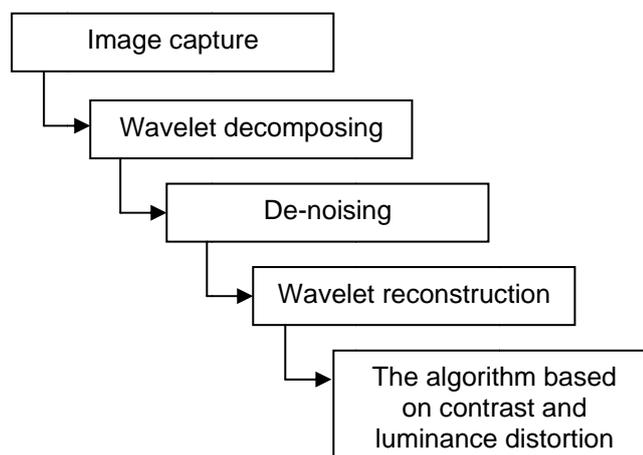


Figure 3. The improved algorithm

#### 4. Simulation and Experiment

Figure 2 and 3 show the simulation of wavelet image processing. Figure 2 shows the original image and Figure 3 shows the de-noised image.



Figure 4. Original image



Figure 5. De-noised image

The decomposition level [9] is an important factor in practical application. In this simulation the level of wavelet is 5, and all the components in level 1, level 2, level 3 and level 4 are removed. We use soft-threshold de-noising method and the threshold value of level 5 is 214.3. After this process most of the noises are removed, and the passing car is still so obvious to be identified by system.

In this experiment, we choose FPGA-based equipment [10], using CCD camera for image capture and LCD for display. We replace snow by paper scraps. As for wavelet process in FPGA, we choose lifting-based 2DDWT algorithm [11] with parallel architecture which can improve processing speed. We use a set of equipment with wavelet processing and another without it simultaneously to get the vehicle flow information in 1 hour. And the results are as following:

Table 1. Experiment results

No.	Weather	Vehicle flow	Results of original algorithm/ Error/Accuracy	Results of improved algorithm/ Error/ Accuracy
1	Sun	1587	1635/48/96.98%	1544/43/97.29%
2	Sun	1462	1517/55/96.24%	1412/50/96.58%
3	Snow	1256	1328/72/94.27%	1300/44/96.50%
4	Snow	1518	1621/103/93.21%	1568/50/96.81%
5	Sandstorm	1188	1260/72/93.94%	1232/44/96.30%
6	Sandstorm	1203	1274/71/94.10%	1246/43/96.42%

From the experiment results it is shown that the accuracy of improved algorithm is higher than original algorithm. This is especially obvious under bad weather such as snow and sandstorm. The average accuracy of original algorithm in bad weather (No.3-6) is 93.88%, but it is 96.51% of improved algorithm.

## 5. Conclusion

In this paper we proposed an improved algorithm for vehicle flow monitoring based on Daubechies wavelet. The experiment proved its higher accuracy than the algorithm without wavelet processing, especially under bad weather. The video intelligent traffic control system with the improvezzzd algorithm would surely have stronger performance of anti-interference and automatically adjust the length of time more rationally.

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