An Algorithm to Detect Moving Vehicles using Binary Redundant Discrete Wavelet Transforms

Xiantong Huang[1], Shumin Duan[2], Xinfeng Yang[*1]

[1.] *School of Computer and Information Engineering*, Nanyang Institute of Technology, Nanyang, Henan 473004, China
[2.] *College of Tourism*, Kaifeng University, Kaifeng, Henan 475004, China

Abstract **— The coefficients of binary redundant discrete wavelet transforms in each sub band are highly relevant as they: i) contain direction selectivity, ii) the sub-band signal is of the same size as the input signal, and iii) offer translation invariant properties. We present in this paper a motion region extraction method based on redundant discrete wavelet transforms. The moving objects are directly detected in the wavelet domain which overcomes the defects of traditional time-domain detection methods.**

Keywords - intelligent transportation system; moving vehicle detection; binary redundant discrete wavelet; frequency domain

I. INTRODUCTION

"Intelligent Traffic Monitoring System" is an electronic device which is able to fulfill part of police functions. It contains the traffic illegal scene automatic forensics equipment and the illegal punishment information management system, as well as legal and effective execution. It combines computer vision, artificial intelligence, pattern recognition, image processing, modern control, communication technology, large-scale database management and other advanced technology, involves to optical, radio, computers, electronic information, networks, and many other fields. It is an important part of traffic information collection subsystem of intelligent transport systems, along with the development of intelligent transportation and development. Intelligent traffic monitoring system as part of China's intelligent transportation construction is playing an increasingly important role. With the introduction of a variety of standards and norms, it will promote the industry toward standardized and orderly direction.

Moving vehicle detection means to real-time extraction of vehicle targets from video streams, Determine the target location, regional and color characteristics, and the static features are used to modeling describe the foreground objects. Target detection first needs video segmentation; the change region will be split out from the video sequence, and then through the classification and identification technology to get the target. Fast and accurate moving object segmentation has a very important significance for target classification, vehicle tracking and understanding behavior patterns in traffic scene. However, due to the images collected in the traffic scene is impacted by the weather and light conditions changes, background clutter, shadows, etc., the segmentation and detection of moving target is with a certain degree of difficulty.

II. TIME DOMAIN MOVING VEHICLE DETECTION

A. Optical flow field analysis

Using the relationship between the gray-scale value of the image pixel changes and the moving object in the video to do motion detection is called optical flow method. For two-dimensional image, the gray (or brightness) distribution difference in the image sequence contains information of moving objects in the scene, thereby transferring space motion information onto a two-dimensional image can be expressed as optical flow field, and it reflects the gray change trends of each pixel that is the instantaneous velocity field [1]. Let $I(x,y,t)$ for the gray value of pixel (x,y) at time t, u and v respectively are the components of the optical flow vector in the x and y directions: $u = dx/dt, v = dy/dt$, By $dI(x,y,t)/dt = 0$, the gradient constraint equation of optical flow[2] is:

$$I_x u + I_y v + I_t = 0 \tag{1}$$

Or in vector form:

$$\nabla I \cdot u + I_t = 0 \tag{2}$$

In formula (1) and (2), I_x 、 I_y 、 I_t is the partial derivative of pixel gray value in x 、 y 、 t three directions, $\nabla I = (I_x, I_y)^T$ is the spatial gradient, $V = (U,V)^T$ is optical flow vector [3].

Relationship between I_x 、 I_y 、 I_t and optical flow vector is defined by the gradient constraint equation, but the solution of u and v component is non-unique. Thus in practical applications, an additional constraint must be

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attached to constrain $V=(U,V)^T$, thereby finally obtain the optical flow field [4]. For traffic video surveillance, cameras on high poles roadside are generally fixed; the problem can be greatly simplified, because in terms of the road traffic background, the optical flow is ideally zero, optical flow is only in foreground (vehicle moving targets), it is only necessary to determine the rate $\sqrt{u^2+v^2}$ in the gradient direction, and the optical flow rate in the gradient direction was $V=|I_t/\sqrt{I_x^2+I_y^2}|$, so as to set a threshold value T, if $V(x,y)>T$, then the pixel (x,y) is the target, otherwise the road background.

Segmentation techniques based on optical flow, because only consider using optical flow data to make decisions, so is limited by the accuracy of optical flow, inevitably affected by noise, and the edge accuracy of moving object segmented is not enough, segmentation results usually are not complete. In addition, optical flow detection is based on the same brightness of the background; most traffic images do not satisfy this condition, the road shadow and the vehicle grayscale change with movement, in addition, the background image affected more easily by the weather, so in the practical field of traffic monitoring, using optical flow method to detect vehicle is less. Fig. 1 shows the adjacent two frames in monitoring sequence and the optical flow field vectors between them.

Figure 1. Motion optical flow

B. Inter-frame difference method

1) The difference between two adjacent frames

Difference time-domain is a method that two frames which interval time is Δt (general $\Delta t << 1s$) are differentiated to form difference graph, and then get the moving target area by using the threshold to obtain the binarization map[5]. Because the operation is very simple, and there are many efficient algorithms for the binarization of difference image, thus well suited for real-time detection of moving objects, set input frames at time t_1 is $f_1(x,y)$, input frames at time t_2 is $f_2(x,y)$, if there is a traffic during this period, there should be $f_2(x,y)=f_1(x-\Delta x,y-\Delta y)$, order:

$$\Delta f(x,y)=|f_2(x,y)-f_1(x,y)| \tag{3}$$

For the static part of the image, $\Delta x=\Delta y=0$, then $\Delta f(x,y)=0$, and for the moving parts, $\Delta f(x,y)\neq 0$, thereby obtain the motion area [6]. In actual use, after the two adjacent frame difference, moving targets within easily produce hollow phenomenon, because the region segmented by binarization is actually a merger of two locations of the object, it is larger than the actual area of the object. Secondly, it is very sensitive to noise and the detected location of the object is inaccurate. Motion detection area in the algorithm is at time t and time ($t-\Delta t$), it is related to the problem of video sampling rate. For vehicles with fast moving speed, if the time difference is not properly selected, it is easy to mistakenly detect two separate objects. For vehicles with slow moving speed, if the selection of time difference is inappropriate, only a small part of the target can be detected. Generally the multi-frame difference method or motion edge detection method can be used to improve it.

2) Multi-frame difference method

Multi-frame subtraction (continuous processing of multi-frame image) is proposed to overcome the problems of adjacent inter-frame difference method [7], usually in a series of images captured by the camera, three consecutive frames or more image frames are pairwise differentiated, with the binary image sequence $\{I_m\}$, image D_m is defined:

$$D_m(i,j)=\left|I_m(i,j)-I_{m-1}(i,j)\right| \tag{4}$$

The detection results are obtained by logical sums of plurality binary image after subtracted:

$$D_{n,T}(i,j)=\begin{cases}1 & D_{n-1,T}(i,j)=1\,\&\,D_{n,T}(i,j)=1\\ 0 & else\end{cases} \tag{5}$$

Wherein, T is the threshold. However, due to the actual traffic situation is very complex, too slow or fast motion situations have occurred, the stability of using differential intersection to test results are still poor, the reliability is low.

3) Moving edge detection method

The edge points of moving targets in time-varying images can also provide certain speed information, a time-varying edge point is defined as $E_t(x,y,t)$:

$$E_t(x,y,t)=\left|F_{xy}\right|\left|\frac{df(x,y,t)}{dt}\right| \tag{6}$$

In formula (6), $F_{xy}=(f_x,f_y)$ and $df(x,y,t)/dt$ respectively is the space and time derivative of image sequence $f(x,y,t)$ at time t and point , Canny edge detector can be generally used to obtain spatial gradient, the gray-scale difference $\left|f(x,y,t)-f(x,y,t+1)\right|$ of the two-frame image is used as the time derivative. Order $V(x,y)=(u,v)$, then:

$$F_{xy} * V(x,y) = -\frac{df(x,y,t)}{dt} \tag{7}$$

Substituted into the formula (6) and get: $E_t(x,y,t) = -(F_{xy}F_{xy})V(x,y)$, which indicates if the image contrast is poor, the motion edge point detection effect is poor. Define: $E_t(x,y,t) = E(x,y,t)\left[D(x,y)^k\right]$ and $E(x,y,t)$ is the edge map of $f(x,y,t)$, $D(x,y)$ is the gray dissimilar metrics between $f(x,y,t_1)$ and $f(x,y,t_2)$. k is a constant, assume edge map $E_{t,1,2}$ is obtained from the first and second frame, edge map $E_{t,2,3}$ is obtained from the second and third frame, then the motion edge can be obtained by the logical sums.

$$E_{t,1,2}(x,y) = E(x,y)D_{1,2}(x,y) \tag{8}$$

$$E_{t,2,3}(x,y) = E(x,y)D_{2,3}(x,y) \tag{9}$$

The motion edge E_{mp} is:

$$\begin{aligned} E_{mp}(x,y) &= E_{t,1,2}(x,y)E_{t,2,3}(x,y) \\ &= E^2(x,y)D_{1,2}(x,y)D_{2,3}(x,y) \end{aligned} \tag{10}$$

In practical application, the edge detection generally only get information for the faster vehicles, while the edges of vehicle running slower can easily be missed, the edge information retention of vehicle interior is not good, and the algorithm runs on the basis of inter-frame difference method, and various defects of inter-frame difference method also affect the performance of the algorithm, edge matching of real-time cannot be guaranteed, so the application of traffic monitoring is very limited.

III. FREQUENCY DOMAIN MOVING VEHICLE DETECTION

Currently motion detection focused on the time domain, the related research of frequency domain motion detection is relatively rare, and this paper proposes a moving vehicle detection algorithm based on binary redundant discrete wavelet.

A. *Binary redundant discrete wavelets transform theory*

At present, the general wavelet transform of image processing is realized by Mallat algorithm [8]. Set image multi-resolution analysis (MRA) composed by a nested linear space $\cdots \subset V_{-1} \subset V_0 \subset V_1 \subset \cdots$ following conditions:

- The union of nested spaces is dense in the square product space;
- The intersection of nested spaces only contains zero vectors;
- If $f(t) \subset V_k$, then $f(2t) \subset V_{k-1}$, and vice versa;
- Present function (scale function) $\phi(t)$, such that $\{\phi(t-k):\mathrm{k}\}$ is the radical of V_0, and $\phi(t)$ are defined as a function of following conditions: $\int_{-\infty}^{+\infty}\phi(t)dt = 1$, $\left\|\phi(t)\right\|^2 = \int_{-\infty}^{+\infty}|\phi(t)|^2 dt = 1$, $<\phi(t),\phi(t-n)>=\delta(n)$.

Then there is $c(n), n = 0, \pm1, \pm2\cdots$, such that $\phi(2^{-k}t) = \sum_{n=-\infty}^{\infty} c(n)\phi(2^{-(k-1)}t-n)$, explain $V_k \subset V_{k-1}$, which constitutes an MRA. The image of that, union of all subspaces $(V_{-\infty})$ is dense in $L^2(R)$, explain that $V_{-\infty}$ can approach any signal $f(t)\big|\in L^2\big|(R)$. If order $f_k(t)$ as the orthogonal projection of $f(t)$ on the subspace V_k, there are $f_k(t) = \sum_{-\infty}^{\infty} a(k,n)\phi(2^{-(k-1)}t-n)$, $k = 0, \pm1, \pm2\cdots$ can get $a(k,n) = \sum_{-\infty}^{\infty} a(k-1,\mathrm{m})c(m-2n)\big/2$. Suppose $\phi(t)$ is a function of V_{-1}, and satisfy:

- $\int_{-\infty}^{\infty} \varphi(t)dt = 0$
- $\int_{-\infty}^{\infty} |\phi(t)|^2 dt = 1$
- $<\phi(t),\phi(t-n)>=\delta(n)$
- $<\phi(t),\phi(t-n)>=0$

Then $\phi(t)$ is the wavelet that the DWT corresponding to the above-mentioned MRA needs. Order W_0 as the linear vector space with the radical of $\{\phi(t-n): n \ \mathrm{int}\, eger\}$, then $V_{K-1} = \bigoplus_{j=k}^{\infty} W_j$, and then $V_{-\infty} = \bigoplus_{j=-\infty}^{\infty} W_j$, and then $f_{-\infty}(t) = \sum_{k=-\infty}^{\hbar}\sum_{t=-\infty}^{\infty} b(k,l)\phi(2^{-k}t-l)$. Similarly, $b(k,n) = \sum_{-\infty}^{\infty} a(k-1,m)d(m-2n)\big/2$ can be exported, order $h(n) \equiv c(n)/2$, $g(n) \equiv d(n)/2$, $h(n) \equiv h(-n)$, $g(n) \equiv g(-n)$, then $a(k,n) = \sum_{-\infty}^{\infty} a(k-1,m)h(2n-m)$, $b(k,n) = \sum_{-\infty}^{\infty} a(k-1,m)g(2n-m)$, this can be seen as $a(k,n)$ and $b(k,n)$ obtained by sampling after $a(k-1,m)$ filtered by filter h. If considered from the frequency domain, order $H(w)=\sum_n h(n)e^{-jwn}$, then $\left|H(w)\right|^2+\left|H(w+\pi)\right|^2=1$, That is, H is an orthogonal mirror filter (QMF). Through multi-resolution analysis, the solution of wavelet can be transformed into the design problem of digital filter.

If the two-dimensional signal $x(n,m),(n=1,2,\cdots,N;m=1,2,\cdots,N)$ is subjected to two-dimensional redundant discrete wavelet transform, the horizontal detail component, the vertical detail component and the diagonal detail component respectively are $A_j(x,y)$, $H_j(x,y)$, $V_j(x,y)$ and $D_j(x,y)$, the analysis filter and synthesis filter of the wavelet filter bank respectively are $\{h(k),g(k)\}$ and $\{\bar{h}(k),\bar{g}(k)\}$, the two-dimensional signal decomposition process is:

$$A_j(x,y)=A_{j-1}(x,y)*([h]_{\uparrow 2^{j-1}},[h]_{\uparrow 2^{j-1}})(-x,-y)$$
$$H_j(x,y)=H_{j-1}(x,y)*([h]_{\uparrow 2^{j-1}},[g]_{\uparrow 2^{j-1}})(-x,-y)$$
$$V_j(x,y)=V_{j-1}(x,y)*([g]_{\uparrow 2^{j-1}},[h]_{\uparrow 2^{j-1}})(-x,-y)$$
$$D_j(x,y)=D_{j-1}(x,y)*([g]_{\uparrow 2^{j-1}},[g]_{\uparrow 2^{j-1}})(-x,-y)$$

Reconstruction process is:

$$\begin{aligned}A_{j-1}(x,y)&=A_j(x,y)*([\bar{h}]_{\uparrow 2^{j-1}},[\bar{h}]_{\uparrow 2^{j-1}})(x,y)\\&+H_j(x,y)*([\bar{h}]_{\uparrow 2^{j-1}},[\bar{g}]_{\uparrow 2^{j-1}})(x,y)\\&+V_j(x,y)*([\bar{g}]_{\uparrow 2^{j-1}},[\bar{h}]_{\uparrow 2^{j-1}})(x,y)\\&+D_j(x,y)*([\bar{g}]_{\uparrow 2^{j-1}},[\bar{g}]_{\uparrow 2^{j-1}})(x,y)\end{aligned}$$

Compared with the traditional DWT transform, the two-dimensional redundant discrete wavelet transform reduces down-sampling and up-sampling in the reconstruction process, the output coefficients are twice as large as the input coefficients at each stage of decomposition, and the filter banks need to be up-sampled to accommodate the increased data. For practical monitoring applications, according to the wavelet filter theory, the two-dimensional image data $p(i,j)$ is redundant discrete wavelet transformed by the following way:

(1) Construct a low-pass filter F_1 and a high pass filter F_2:

$$F_1=\left[-0.125,0.25,0.75,0.25,-0.125\right]$$
$$F_2=[0.25,-0.5,0.25]$$

(2) The left and right border of $p(i,j)$ is extended two columns to form X, extended one column to form T;

(3) Set the size of the image $p(i,j)$ is $height\times width$, through formula (11) and (12) it will be divided into low frequency and high frequency components:

$$\begin{aligned}PL(i,j)&=F_1(1)\cdot X(i,j+4)\\&+F_1(2)\cdot X(i,j+3)\\&+F_1(3)\cdot X(i,j+2)\\&+F_1(4)\cdot X(i,j+1)+F_1(5)\cdot X(i,j)\end{aligned}\tag{11}$$

$$\begin{aligned}PH(i,j)&=F_1(1)\cdot T(i,j+2)\\&+F_2(2)\cdot T(i,j+1)+F_2(3)\cdot T(i,j)\end{aligned}\tag{12}$$

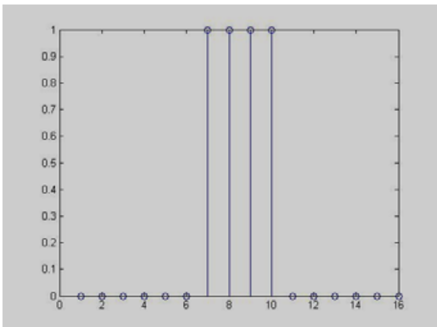
among them $0<i<height+1$, $0<j<width+1$;

(4) PL and PH transposed separately and operated as the above-mentioned can obtain PLL, PLH, PHL and PHH;

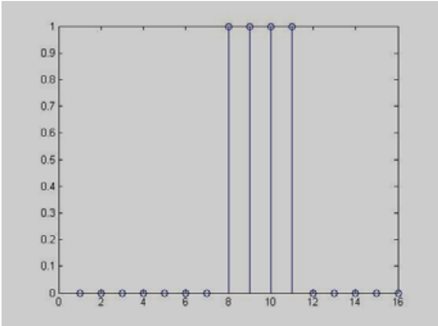
(5) Multi-level redundant wavelet transform can be obtained by repeating the above process.

Because the parity wavelet coefficients are preserved, each transformed subband of BRDWT is the same size as the original signal, the original signal position of the coefficient and the position of the redundant discrete wavelet coefficients in the subband are corresponding to each other. Since it is a discrete wavelet transform with no down-sampling and has translation invariant properties, the wavelet coefficients between the original image and the translated image also have a moving relationship [9]. And the ordinary discrete wavelet transform is down-sampled in the decomposition process, so that it does not have the translation invariance. Fig. 2 shows an original signal $v(n)$ and signal $v(n-1)$ that the original signal is shifted by one unit to the right; discrete wavelet transform and binary redundant discrete wavelet transform are applied to the two signals separately.

It can be seen from Fig. 3 and Fig. 4, the translation relation of the signal is completely preserved in the binary redundant discrete wavelet domain, and the translations in the time domain and the frequency domain are equal. Therefore, accurate motion detection can be carried out in the binary redundant discrete wavelet domain, which can be used for video moving object extraction, and the translational variability of ordinary discrete wavelet transform makes it not have the characteristics of motion detection.

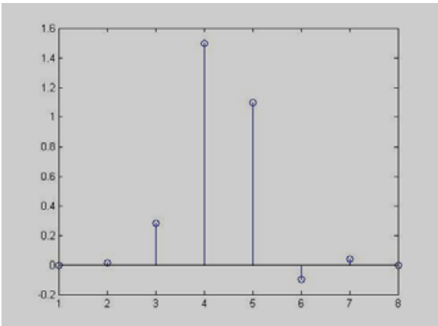


(a) $v(n)$

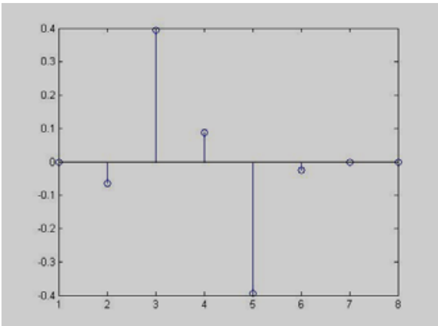


(b) $v(n-1)$

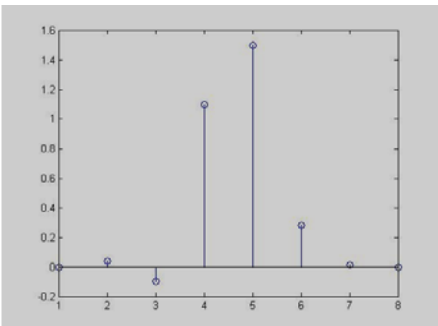
Figure 2. Signal $v(n)$ and its shifted version $v(n-1)$



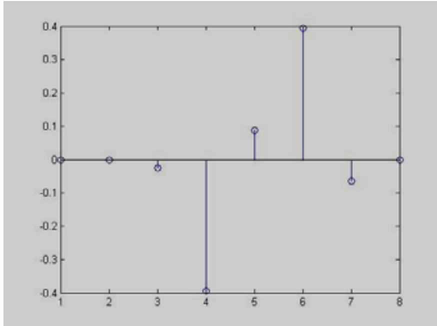
(a) DWT low band of $v(n)$



(b) DWT high band of $v(n)$

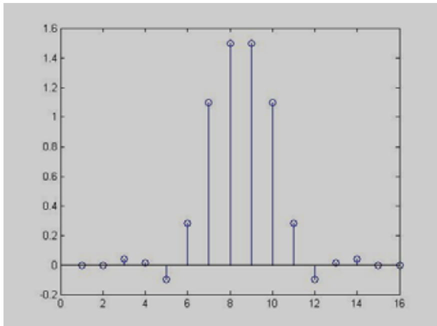


(c) DWT low band of $v(n-1)$

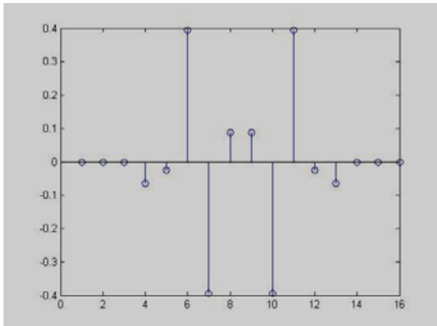


(d) DWT high band of $v(n-1)$

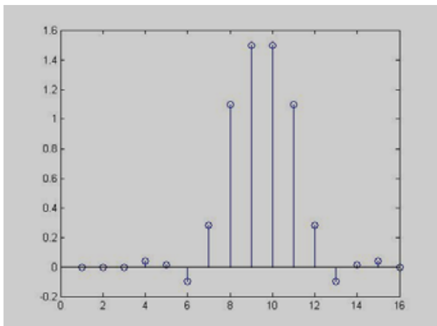
Figure 3. DWT of $v(n)$ and $v(n-1)$



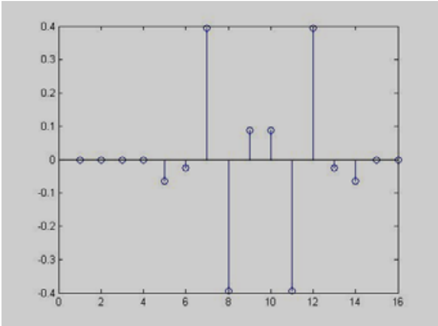
(a) RDWT low band of $v(n)$



(b) RDWT high band of $v(n)$



(c) RDWT low band of $v(n-1)$



(d) RDWT high band of $v(n-1)$

Figure 4. RDWT of $v(n)$ and $v(n-1)$

B. Binary redundant discrete wavelet domain motion detection

For a one-dimensional signal $f(t)$, binary discrete wavelet transform (BDWT) is:

$$S_{2^j} f(t) = f(t) * \phi_{2^j}(t) \tag{13}$$

$$W_{2^j} f(t) = f(t) * \phi_{2^j}(t) \tag{14}$$

Wherein $S_{2^j} f(t)$ is the projection of $f(t)$ in space V_j, $W_{2^j} f(t)$ is the projection of $f(t)$ in space W_j. In the frequency domain it can be expressed as:

$$S_{2^j} \overline{f}(w) = \overline{f}(w) \cdot \overline{\phi}(2^j w) = S_{2^{j-1}} \overline{f}(w) H(2^{j-1} w) \tag{15}$$

$$W_{2^j} \overline{f}(w) = \overline{f}(w) \cdot \overline{\phi}(2^j w) = S_{2^{j-1}} \overline{f}(w) G(2^{j-1} w) \tag{16}$$

So formula (13) and (14) can be rewritten as:

$$S_{2^j} f(t) = \sum_{l \in Z} S_{2^{j-1}} f(t-l) h_{j-1}(l) \tag{17}$$

$$W_{2^j} f(t) = \sum_{l \in Z} S_{2^{j-1}} f(t-l) g_{j-1}(l) \tag{18}$$

Set discrete sampling digital signal is $d(n) = S_1 f(t)|_{t=nT} = S_1 f(n)$, then:

$$S_{2^j} f(t) = \sum_{l \in Z} S_{2^{j-1}} f(n-l) h_{j-1}(l) \quad j = 1, 2, \ldots \tag{19}$$

$$W_{2^j} f(t) = \sum_{l \in Z} S_{2^{j-1}} f(n-1) g_{j-1}(l) \quad j = 1, 2, \ldots \tag{20}$$

For the two-dimensional digital image, a discrete wavelet transform (RDWT) can be used as a special example of binary discrete wavelet transform. Since there is no down-sampling, the time-sampling rate of different scales is fixed, and the inherent translational variation of discrete wavelet transform is eliminated here. The result of redundant discrete wavelet transform is the same as the input signal. The motion information $MAS(x, y)$ can be obtained according to the difference of each subband:

$$MAS(x,y) = \sum_{j=J_0}^{J_1} \begin{pmatrix} |LL_1^{(j)}(x,y) - LL_2^{(j)}(x,y)| \\ + |LH_1^{(j)}(x,y) - LH_2^{(j)}(x,y)| \\ + |HL_1^{(j)}(x,y) - HL_2^{(j)}(x,y)| \\ + |HH_1^{(j)}(x,y) - HH_2^{(j)}(x,y)| \end{pmatrix} \tag{21}$$

Wherein J_0 and J_1 represent the scale of beginning and ending. By the Otsu algorithm can get adaptive threshold T [10], then the binarization of MAS is performed to obtain the motion region: $motion(x,y) = \begin{cases} 1 & MAS(x,y) \geq T \\ 0 & MAS(x,y) < T \end{cases}$, Wherein a non-zero value represents the motion information points.

The binary motion region extracted by redundant discrete wavelet transform can be used as the original template of video object. However, because the interior of the object is usually flat, the feature is not obvious, so there is a certain gap in the template, so an assimilation algorithm is used to fill the template [11]. That is, scanning all the 0 value points of the image, for any 0 value points of P, consider any line L through the point, L if there are two points P_1 and P_2 on L, and satisfies:

- The values of P_1 and P_2 are both 1
- P_1 and P_2 are distributed on both sides of P
- $|P - P_1| < R$, $|P - P_2| < R$

Then the point P is set to 1, otherwise it remains 0. If the point P is set to 1, it is assumed that point P is assimilated in R according to line L, R is called assimilation radius. In the actual process of running the program, in order to reduce the amount of calculation, may not need to calculate all the direction, only consider the following four lines:

$L_1 : (x-1, y) - (x+1, y)$

$L_2 : (x-1, y+1) - (x+1, y-1)$

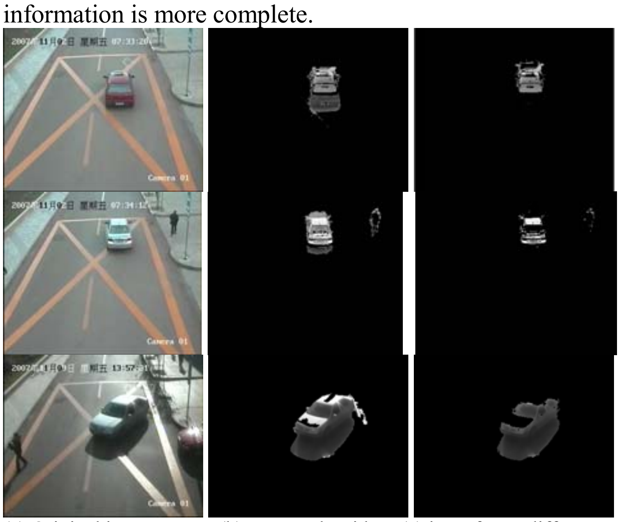
$L_3 : (x, y-1) - (x, y+1)$

$L_4 : (x-1, y-1) - (x+1, y+1)$

As the search process is only in a straight line in accordance with a certain step to increase or decrease the coordinates, without involving the multiplication and division operation, the program runs faster, save computing time.

IV. EXPERIMENT AND ANALYSIS

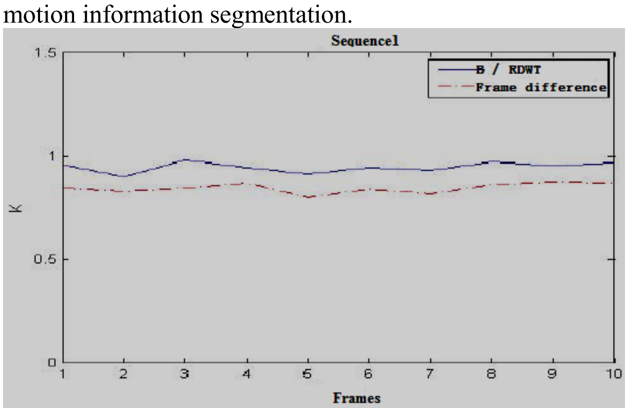
The BRDWT motion detection algorithm proposed in this paper and the inter-frame difference method commonly used in current video detection are respectively used to detect the moving vehicles in one of the three sets of traffic video sequences, and extract the information between adjacent frames, are filled with assimilation. The results shown in Fig. 5, it can be seen the target content details BRDWT motion detection algorithm extracted is richer, and information is more complete.

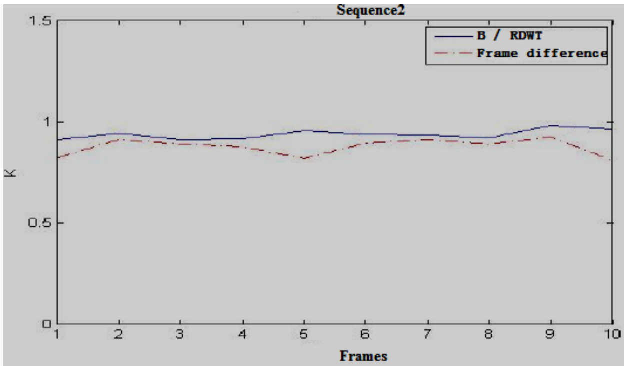


(a) Original image (b)RDWT algorithm (c) inter-frame difference

Figure 5. Comparison of motion detection

Meanwhile Defines segmentation accuracy $K = N / M$, where N is the number of pixels accurately detected and M is the total number of pixels of the foreground object. The comparison results are shown in Fig. 6. It can be seen from the comparison data that the BRDWT algorithm has higher accuracy and relative stability for the motion information segmentation.





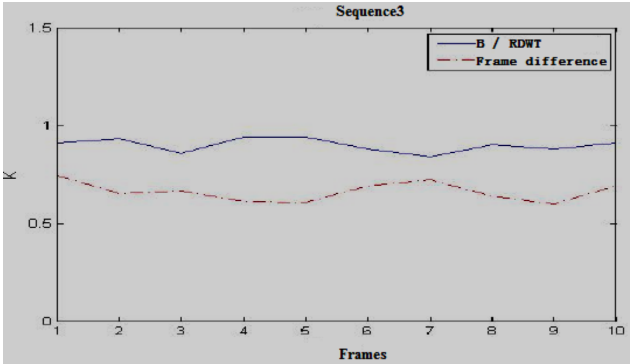


Figure 6. Comparison of segmentation accuracy

It can be seen from the above analysis that the difference between the motion video object detection algorithm based on binary redundant discrete wavelet transform and the previous algorithm is no longer based on the time domain as the video object segmentation operation, but converted to redundant discrete wavelet transform Domain extraction video object motion area. The experimental results show that the motion region extracted from this algorithm has good effect and outstanding detail, which is superior to the general inter-frame difference method, and the computation process is simple. In actual use, the more common way is for two images, one for a static background, the other one for the current frame, so background modeling has become an important content of motion detection.

V. CONCLUSIONS

In this paper, a new detection method for moving vehicle targets in intelligent traffic monitoring system is proposed by analyzing the defects of traditional optical flow method and inter-frame difference method in detecting moving objects. The motion region is extracted directly in the binary redundant discrete wavelet transform domain to detect the moving target. It can effectively overcome the shortcomings of traditional motion detection method by extracting the motion region in the binary redundant discrete wavelet domain, with good detection effect and outstanding detail. Even if the target motion is slow or similar to the background, the moving target can be accurately extracted, and has a lower computational complexity.

CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

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