



Research Article

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A Research of the Vehicle License Plate Based on Wavelet Packet Character Recognition

Bo-ping ZHANG and Guo-xi WU

College of Computer and Technology of Xuchang University, Xuchang, 461000, China

ABSTRACT

The. A kind of character recognition method of the vehicle license plate based on the wavelet packet is presented in this paper. A Wavelet Basin is reconstructed through analysis the character of the Wavelet Basin, and the orthogonality character which is used to reconstruct is given up, and the pressing branch character and symmetry character are preserving, the capability filter is improved on, the effect is all right.

Key words: vehicle plate recognition analysis, wavelet transform, wavelet packet, digital filtering

INTRODUCTION

Algorithms for License plate recognition mainly including three sections, namely License plate location, Character segmentation and Character recognition. At present, the further study of each algorithm is various. Huang wei's study, for example, focused on locating vehicle plates by using texture and The wavelet analysis [1] while Zhang Xining located vehicle plates by the frequency of image gradation change, Liu Yi came up with a method of a Feature Extraction and Classification of Lung Sounds Based on Wavelet Packet Multiscale Analysis and Gao Shilong proposed another new method and managed to apply it to character identification on vehicle plates. Rui Ting realized the quick correction of the plate angles through analyzing the features of projections and by utilizing the Fisher principle, Wu Ting chose the wavelet packet coefficient as effective feature, which is more likely to be isolated and made up a feature vector. One more plate identification method presented by Wang Runmin was based on wavelet packet and Zernike character recognition combined with the neural network and Yan Shiyu presented a character recognition method by using decomposition coefficient of wavelet packet. Wang Yutian overtook the shortage of character recognition and realized the quick isolation of signal with no aliasing.

Texture analysis and location in vehicle plate area are researched using wavelet analysis in this paper, wavelet packet is selected as a means of analysis.. A Wavelet Basin is reconstructed through analysis the character of the Wavelet Basin, and the orthogonality character which is used to reconstruct is gived up, and the pressing branch character and symmetry character are preserving, the capability filter is improved on, the effect is all right.

WAVELET PACKET TRANSFORM (WPT)

Orthogonal wavelet can merely resolve the low-frequency section and when it comes to high –frequency detail, it doesn't work. However, largely different from that, wavelet packet transform can resolve the high-frequency section more accurately as well. What's more, this type remains neither redundancy nor omission, so it can be better used in time-frequency localization analysis of middle and high-frequency signal. WPT overcome the shortages of WT, therefore, WPT have applications to be wider used [10,11] . To take a consideration in a Multi-resolution analysis way, $L^2(\mathbb{R}) = \bigoplus_{j \in \mathbb{Z}} W_j$ suggests that wavelet analysis is to factorize $L^2(\mathbb{R})$ into the orthogonal sum $W_j(j \in \mathbb{Z})$ according to different scale factor J. Every wavelet subspace $W_j(j \in \mathbb{Z})$ can be constructed by $\{\Psi_{j,k}\}_{k \in \mathbb{Z}}$. To achieve

higher frequency resolution, W_j can be further factorized. V_j and W_j is combined and defined as U_n^j . Make $U_j^0 = V_p, U_j^1 = W_j, j \in Z$, the orthogonal decomposition

$$V_{j+1} = V_j \oplus W_j, j \in Z \quad (1)$$

Can be transformed into

$$U_{j+1}^0 = U_j^0 \oplus U_j^1, j \in Z \quad (2)$$

The subspace U_j^n is defined as a closure space of $u_n(t)$, therefore U_j^{2n} is the closure space of $u_{2n}(t)$, and satisfy $u_n(t)$ to equations below:

$$\begin{cases} u_{2n}(t) = \sqrt{2} \sum_{k \in Z} g(k) u_n(2t - k) \\ u_{2n+1}(t) = \sqrt{2} \sum_{k \in Z} h(k) u_n(2t - k) \end{cases} \quad (3)$$

In the equation, $\{g(k)\}_{k \in Z}$ is the corresponding lowpass filter of the orthonormal scaling function $\phi(t)$ and $\{h(k)\}_{k \in Z}$ is the corresponding highpass filter of orthonormal wavelet function, and $h(k) = (-1)^k g(1-k)$. We can say recursive defined function $u_n, n=0,1,2,\dots$ is the WPT which is determined by the function $u_0 = \Phi$. When $n=0$, $u_0(t)$ and $u_1(t)$ become $\phi(t)$ and $\psi(t)$ respectively. According to this, wavelet decomposition is the special case of wavelet packet decomposition. Wavelet decomposition will be transformed into wavelet packet decomposition if every high frequency section is decomposed after general decomposition. In conclusion, WPT is considered to be the expansion and extension of WT.

When decomposing original images by WPT, not only is the high-frequency section decomposed, but the low-frequency section as well. So, compared to WT, WPT does better in accuracy and time-frequency. Admittedly, WPT can find out the plate figure and more effective in filter high-frequency signal in non-figure area and border messages, but their frequency-domain characteristics is not as good orthogonal wavelet, such a thing can be described by the different performance ($H(\omega)$ and $G(\omega)$) of frequency domain high pass filter $\{g_n\}_{n=0}^N$ and low pass filter $\{h_n\}_{n=0}^N$

$$\begin{aligned} |H(\omega)|^2 + |G(\omega)|^2 &= 1 \\ H(\omega - \pi) &= G(\omega) \end{aligned} \quad (4)$$

Compacted orthogonal wavelet basin has a lot of advantages, but as a nonlinearity function itself, or put it in another way, it is a asymmetric wavelet basin, the border location of plate area can be incorrect.

THE RECONSTRUCTION OF COMPACTED ORTHOGONAL WAVELET BASIN

To improve this situation, $H(\omega)$ and $G(\omega)$ are reconstructed:

$$H(\omega) = \begin{cases} 1, -\frac{\pi}{2} < \omega < \frac{\pi}{2} \\ 0, 0 < \omega < \frac{\pi}{2}, -\frac{\pi}{2} < \omega < 0 \end{cases} \quad (5)$$

$$G(\omega) = \begin{cases} 1, 0 < \omega < \frac{\pi}{2}, -\frac{\pi}{2} < \omega < 0 \\ 0, -\frac{\pi}{2} < \omega < \frac{\pi}{2} \end{cases} \quad (6)$$

This form of artificial filter can be designed through IIR digital filter. This filter should be suitable for MRA so that it can be analyzed by MRA. In this way, what is needed is to design a filter rather than a compacted biorthogonal symmetrical wavelet basin. A lot of studies have witnessed plenty of mathematical tools available. Compacted orthogonal wavelet performances well in properties and things could be vastly improved if we made it symmetric. To achieve this target, compacted biorthogonal symmetric wavelet is used for experiments and spline wavelet is used to transform the compacted orthogonal wavelet basin. We enhanced the properties and frequency-domain characteristics of $G(\omega)$ and $H(\omega)$ by sacrificing presented orthogonality to symmetry. It is not a compression or recovers.

A compacted orthogonal wavelet with a scale function $\phi(t)$ and a wavelet function $\Psi(t)$. Make a self-correlation between $\phi(t)$ and $\Psi(t)$.

$$\begin{cases} \theta(t) = \int_{\mathbb{R}} \phi(x)\phi(x+t)dx \\ \rho(t) = \int_{\mathbb{R}} \psi(x)\psi(x+t)dx \end{cases} \quad (7)$$

$\theta(t)$ can be proved to be one generator of MUA, $\rho(t)$ is the corresponding wavelet function of $\theta(t)$. Then $\theta(t)$ has several following properties:

P1. $\{\theta(t-k)\}$ is the Riesz base of VR i.e.

$$A_1 \sum_k |c_k^0|^2 \leq \left\| \sum_k c_k^0 \theta(t-k) \right\|^2 \leq B_1 \sum_k |c_k^0|^2, 0 < A_1 \leq B_1 < +\infty \quad (8)$$

Or put it in another way, $\hat{\theta}(\omega)$ is

$$0 < A_2 \leq \sum |\hat{\theta}(\omega + 2n\pi)|^2 \leq B_2 < +\infty \quad (9)$$

Actually, according to (7),

$$\theta(t) = \int_{\mathbb{R}} \phi(x)\phi(x+t)dx = \frac{1}{2\pi} \int \hat{\phi}(\omega) \overline{\hat{\phi}(\omega)} e^{i\omega t} d\omega \quad (10)$$

So we can get

$$\hat{\theta}(\omega) = |\hat{\phi}(\omega)|^2 \quad (11)$$

$$0 < \sum_{\mathbb{R}} |\hat{\theta}(\omega + 2n\pi)|^2 = \sum_{\mathbb{R}} |\hat{\phi}(\omega + 2n\pi)|^4 \leq \left(\sum_{\mathbb{R}} |\hat{\phi}(\omega + 2n\pi)|^2 \right)^2 = 1$$

It revealed that $\{\theta(t-k)\}$ is the Riesz base of VR.

P2 $\theta(t)$ is suitable for double scale equation

$$\theta(t) = \sum_{n=-N}^N a_n \theta(2t-n) \quad (12)$$

$$a_0 = 1$$

$$a_n = \frac{1}{2} \sum_{j=0}^{N-n} h_j h_{j+n}, n \neq 0 \quad (13)$$

$$a_{2n} = 0$$

N stands for the support length of $\phi(t)$, and $\{h_n\}_{n=0}^N$ is the double scale coefficient of $\phi(t)$. In addition,

$$\sum_{n=0}^N h_n = 2 \quad (14)$$

$$\sum_{j=0}^N h_j h_{j-2n} = 2\delta_0 \quad (15)$$

Actually, $a_n=1$ (according to orthonormality), as for different a_n :

$$\begin{aligned}
\theta(t) &= \int_{\mathbb{R}} \phi(x)\phi(x+t)dx \\
&= \int_{\mathbb{R}} \sum_{j=0}^N h_j \phi(2x-j) \sum_{k=0}^N h_k \phi(2x+2t-k)dx \\
&= \sum_{j=0}^N \sum_{k=0}^N h_j h_k \int_{\mathbb{R}} \phi(2x-j)\phi(2x+2t-k)dx \\
&= \frac{1}{2} \sum_{j=0}^N \sum_{k=0}^N h_j h_k \int_{\mathbb{R}} \phi(y)\phi(y+2t-k+j)dx \\
&= \frac{1}{2} \sum_{j=0}^N \sum_{k=0}^N h_j h_k \int_{\mathbb{R}} \theta(2t-k+j)dx \\
&= \sum_{n=-N}^N a_n \theta(2t-n)
\end{aligned}$$

a_n is the self-correlation of the discrete data $\{h_n\}_{n=0}^N$.

P3. $\theta(t)$ is even symmetric

$$\theta(t) = \theta(-t) \quad (16)$$

Taking 1,2,3 into consideration, the even symmetric function $\theta(t)$ is the exact generator of a certain function.

Properties of $\rho(t)$.

P1 $\{\rho(t-n)\}$ is the Riesz base, and $\rho(t)$ is even symmetric.

$$\rho(t) = \rho(-t) \quad (17)$$

p2 $\rho(t)$ is suitable for double scale equation

$$\rho(t) = \sum_{n=-N}^N b_n \theta(2t-n) \quad b_n = \frac{1}{2} \sum_{j=0}^{N-n} g_j g_{j+n}$$

$\{h_n\}_{n=0}^N$ is the double scale coefficient of $\Psi(t)$

$$\begin{aligned}
P3 \quad \theta(2\omega) &= A(\omega)\hat{\theta}(\omega) \\
\rho(2\omega) &= B(\omega)\hat{\theta}(\omega) \\
A(\omega) + B(\omega) &= 1
\end{aligned} \quad (18)$$

P4 $\rho(t)$ is an admissible wavelet

$$C_p = \int_{\mathbb{R}} \frac{|\hat{\rho}(\omega)|^2}{|\omega|} d\omega < +\infty$$

The time and frequency domain performances of the double scale equation concerning $\theta(t)$ and $\rho(t)$ are:

$$\begin{aligned}
\theta(t) &= \sum_{n=-N}^N a_n \theta(2t-n) \\
\hat{\theta}(2\omega) &= A(\omega)\hat{\theta}(\omega)
\end{aligned}$$

and

$$\begin{aligned}
\rho(t) &= \sum_{n=-N}^N b_n \theta(2t-n) \\
\hat{\rho}(2\omega) &= B(\omega)\hat{\theta}(\omega)
\end{aligned}$$

They revealed the frequency division property in MRA, i.e. $\theta(t)$ is the low-pass function and $\rho(t)$ is the band-pass function, $\{a_n\}_{n=0}^N$ and $\{b_n\}_{n=0}^N$ are low-pass filter and high-pass filter, respectively.

Because:

$$\begin{aligned}
\hat{\theta}(t) &= |\hat{\phi}(\omega)|^2, \hat{\rho}(t) = |\hat{\psi}(\omega)|^2 \\
A(\omega) &= |H(\omega)|^2, B(\omega) = |G(\omega)|^2 \\
A(\omega) + B(\omega) &= 1
\end{aligned}$$

The low-pass effect of $\theta(t)$ is better than $\Phi(t)$'s, when it comes to band-pass, $\rho(t)$ is better than $\Psi(t)$. As for digital filter, $\{a_n\}_{n=0}^N$ and $\{b_n\}_{n=0}^N$ performance more effective than $\{h_n\}_{n=0}^N$ and $\{g_n\}_{n=0}^N$ for a simple reason that the overlapping portion of $A(\omega)$ and $B(\omega)$ is smaller than that of $H(\omega)$ and $G(\omega)$.

To construct a digital low-pass filter, measures can be taken in two ways. On the one hand, discrete self-correlation

of Daubechies double scale coefficient $\{h_n\}_{n=0}^N$ is needed using (13), on the other hand, expansion of $|H(\omega)|^2$ can also be used.

Table1 $\{a_n\}_{n=0}^N$ Coefficient Table

Coefficient	0	$\{a_n\}_{n=0}^N$
N=1	0, +1, -1	0.5, 0.25, 0.25
N=3	0, 1, 2, 3, -1, -2, -3	0.5, 0.28125, 0.0, -0.03125, 0.28125, 0.0, -0.03125
N=5	0, 1, 2, 3, 4, 5, -1, -2, -3, -4, -5	0.5, 0.2106741573, 0.0, -0.048828125, 0.0, 0.005859375, 0.2106741573, 0.0, -0.048828125, 0.0, 0.005859375

ALGORITHM ACHIEVEMENT AND SIMULATION EXPERIMENT

There are no functions of Wavelet Basin suitable for this paper, a new specialized function is constructed, which the wavelet library in Matlab is added. According to the Algorithm in this paper, 380 different plate images are well identified with it. To begin with, compacted orthogonal wavelet is test to confirm the former assumption and analysis by experiments that it is difficult to find plate figure only use Wavelet Packet, and it is effective in filtering ordinary high-frequency signal and border messages. Compacted biorthogonal wavelet does have advantages, but as a nonlinear asymmetrical wavelet basin, it locates incorrectly sometimes when locating the border of plate. Here comes the next step that how to find a suitable wavelet basin. Compacted biorthogonal wavelet basin is experimented to deal with this problem and B-spline wavelet is chose which have several characters: (i) limited filter coefficients, (ii)rational coefficients, (iii) Symmetry, (iv)linearity. Biorthogonal2 is used and there are three layer wavelet tree, the experiment result is superior.

CONCLUSION

- i. While analyzing compacted orthogonal wavelet. It is possible to located wrong with some error in borders because of the asymmetry of the wavelet function.
- ii. While analyzing compacted biorthogonal wavelet, the effect in plate location will be largely proved, accounted for the symmetry of the wavelet function. However, as the generic effect on high-frequency interference, the general property is not much better than that of compacted orthogonal wavelet.
- iii. Constructing new Wavelet Basin through transforming the compacted orthogonal wavelet produced a marked effect, which traditional picture processing method couldn't achieve.

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REFERENCES

- [1] Huang Wei, Lu xiaobo. *Engineering Science*, **2004**,6(3):19-24
- [2] ZHANG Xining, ZHENG Nanning. *Information and Control*,**1988**,2(2):7-31
- [3] LIU Yi, ZHANG Cai-Ming etc. *Chinese Journal of Computers*, **2006**,29(5):769-778
- [4] GAO Shi-long, ZHOU Jie etc. *Journal of Sichuan University (Natural Science Edition)*, **2006**,43(6):1183-1186
- [5] HUANG Zhong-mei, ZHANG Xiao-hong etc. *Computer Applications*,**2007**,127(5): 1135-1138
- [6] WU T, YAN G ZH, YANG B H, et al. *Chinese Journal of Scientific Instrument*, **2007**,28(12):2230-2234
- [7] WANG Run- min, QIAN Sheng- you. *Computer Engineering and Applications*, **2007**, 43(14): 210- 212.
- [8] Yan Shiyu, Liu Chong etc. *Journal of Scientific Instrument*. **2012**, 33(8),1748-1753
- [9] WANG Yu-tian; YAN Bing etc. *Journal of Yanshan University*,**2013**,37(4):258-366.
- [10] Yaguo Lei, Ming J. Zuo, Zhengjia He, Yanyang Zi. *Expert Systems with Applications*, **2010**(37): 1419-1430.
- [11] Rui Zhou, Wen Bao, Ning Li, Xin Huang, Daren Yu. *Digital Signal Processing*, **2010**(20): 276-288.