An Improved EZW Algorithm and Its Application in Intelligent Transportation Systems

Genshun Wan, Xuehua Song, Riccardo Bettati

Abstract—**A large number of digital images are produced during the acquisition of video signals at signalized intersection in an intelligent transportation system. Because of limited storage space and transmission bandwidth, the signals must be compressed effectively to satisfy application requirements in real time. We propose an improved Embedded Zerotree Wavelet algorithm to improve the wavelet compression performance by adopting image pretreatment, introducing dynamic threshold and adding new symbols. The experimental results show that the proposed algorithm improves both the effectiveness of data compression and its efficiency and so is well suited for real-time image acquisition, storage and transmission at signalized intersections.**

Index Terms—**intelligent transportation, image compression, Embedded Zerotree Wavelet (EZW)**

I. Introduction

MODERN Intelligent Transportation Systems (ITS), in particular urban areas, depend critically on the timely and accurate collection of traffic flow information to infer traffic conditions and to guide short-term traffic management. In recent years, digital video and image processing technologies have emerged as a cost-effective way to collect high-fidelity traffic flow information in real time [1]. As the popularity of imaging-based traffic data acquisition systems has grown, so has the demand for better transmission quality and reduced access latency to the generated traffic data [2]. Given the enormous amount of raw image and video data collected in the field and the inherent cost of storage space and transmission bandwidth, it is of great significance to architect and design this type of traffic monitoring systems so as to reduce the cost of communicating the local traffic information from the field (signalized intersections, high-volume lanes, tunnels, etc.) to the central traffic management centers [3].

In this paper we propose an image-compression based scheme to both reduce the bandwidth requirement of image data transmission and improve the overall data delivery latency. Fundamentally, image compression uses data encoding technology to represent the original raw images in a more space-efficient way while allowing for high-quality reconstruction of the images when needed. The resulting savings lighten the burden of the transmission and storage of high-quality images [4]. High compression ratios are achieved by reducing data redundancy and by taking advantage of the characteristics of the human visual system. Compared with other encoding schemes, Embedded Zerotree Wavelet (EZW) encoding is an effective method, which uses wavelet transforms and has high coding efficiency [5] [6]. This paper proposes a number of improvements to the basic EZW algorithm and to the image pro-processing that improve the performance of real-time image acquisition, storage and transmission of image data at signalized intersections in intelligent transportation systems.

II. Wavelet transform and Embedded Zerotree Wavelet

A. Wavelet transform

As one of the most outstanding achievements in applied mathematics field at the end of the 20th century, the wavelet transform, as an effective time-scale signal analysis method, can extract information from signals efficiently. The wavelet

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transform has the ability to characterize local features in both the time domain and frequency domain accurately, and it has been called a "mathematical microscope" [7]. In its basic form, the wavelet transform consists of high-pass and low-pass filters at different scales, which decompose the signal into different frequency bands for further processing. This filtering is repeated until a predetermined threshold value is reached. The basic idea of the wavelet transform is just to represent or approximate the signals with a set of functions.

The so-called discrete wavelet transform is commonly adopted in image compression [7]. Let $h(x)$ be a basic wavelet function used to sample the zooming scale factor a as a_0^m and sample the panning scale factor b as $nb_0a_0^m$, where a_0, b_0, m, and n represent the initial zooming scale factor, the initial panning scale factor, the frequency range index, and the time-step change index, respectively. If the condition $a_0 > 1$, $b_0 \in R$, $m,n \in Z^2$ holds, the family of functions $h_{m,n}$ is

$$h_{m,n}(x) = a_0^{-m/2} h(a_0^{-m}x - nb_0) \qquad (1)$$

Thus the discrete wavelet transform for an arbitrary function $f(x) \in L^2(R)$ can be defined as

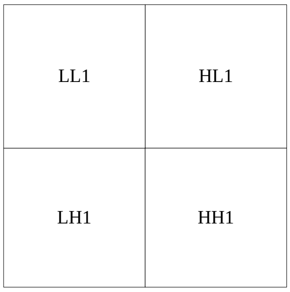
$$\mathrm{DW}_{m,n} = \int_{-\infty}^{+\infty} f(x) h_{m,n}(x) dx \qquad (2)$$

In order to reconstruct the function signal $f(x)$ from the equation (2), the operator $\mathrm{DW}_{m,n} : L^2(R) \to I^2(Z^2)$ must be bounded and invertible; that is to say, for $A > 0$ and $B < \infty$, Equation (3) must be valid for every function $f(x) \in L^2(R)$.

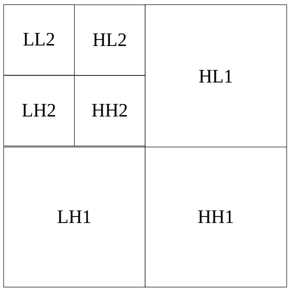
$$\mathrm{A}\| f \|^2 < \sum \left| \left\langle f(x), h_{m,n}(x) \right\rangle \right|^2 < \mathrm{B}\| f \|^2 \qquad (3)$$

In its basic form, discrete wavelet 2D image encoding performs wavelet coefficients coding for sub-image in different spatial scales and frequencies, based on a multi-resolution decomposition with right wavelet basis.

After the first wavelet transform of the image, the spatial distributions of the wavelet coefficients have a good correspondence with that of the original image. There are four sub-band images, which describe the original one from different angles as shown in Fig.1 (a) [8] [9]: LL (low frequency sub-band in both horizontal and vertical direction), LH (low frequency sub-band in horizontal direction and high frequency sub-band in vertical direction), HL (high frequency sub-band in horizontal direction and low frequency sub-band in vertical direction), HH (high frequency sub-band in both horizontal and vertical direction). Most of the image energy is stored in LL, while the details of the image can be found in HL, LH, and HH. In addition, LL can be further decomposed as displayed in Fig.1 (b).



(a)Frequency distributions after the first wavelet transform



(b)Frequency distributions after the second wavelet transform

Fig.1.Frequency distributions after the wavelet transform [10]

B. Embedded Zerotree Wavelet

Embedded Zerotree Wavelet encoding (EZW) [10] [11] further improves on basic discrete wavelet encoding by efficiently representing portions of the encoded symbol stream that can be safely eliminated because their aggregate energy falls below a predetermined threshold. Once a subband image falls below the threshold, it can be pruned from the overall image encoding, thus leading to a so-called zerotree of subband images that don't need to be further encoded and therefore can be encoded as zero. The flowchart of EZW encoding-decoding is displayed in Fig.2.

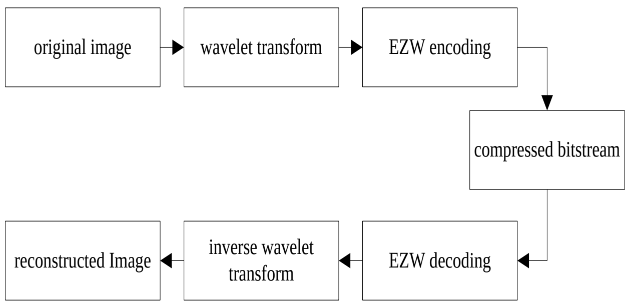


Fig.2.The flowchart of EZW encoding-decoding

The zerotree data structure is defined by using the self-similarity of wavelet transform sub-image at different

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scales. A wavelet coefficient x is said to be insignificant with respect to a given threshold T if $|x| < T$. In this case, once all wavelet coefficients of the same orientation in the same spatial location are insignificant, a zerotree can be formed, and it is called zerotree root (ZTR). In order to encode a zerotree, three additional symbols are defined: If the coefficient is insignificant but has some significant descendant, it is called Isolated Zero (IZ). In addition, the coefficients can be either positive or negative significant. As a result, the wavelet coefficients can be efficiently represented as a string of symbols from a 4-symbol alphabet: 1) zerotree root, 2) isolated zero, 3) positive significant and 4) negative significant.

EZW encoding is performed based on zerotrees, which are obtained after scanning the image several times, and one zerotree may be obtained by scanning the sub-image twice. Firstly, initial threshold T_0 should be chosen in the light of the maximum absolute value of wavelet coefficients to scan the image for the first time. And any wavelet coefficient less than threshold can be regarded as zero so as to form the first zerotree as the symbols defined above. Then, in the second scan, bit "1" or "0" may be used to describe the precision on the basis of the fact whether the absolute values are 1.5 times as big as the threshold. Finally, threshold should be halved to make preparation for the generation of the second zerotree. And this process should be repeated until the required precision is reached. In addition, the scanning mode is shown in Fig.3.

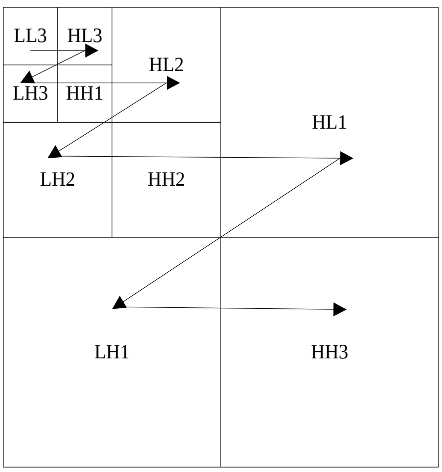

Fig.3.Scanning order of Embedded Zerotree Wavelet algorithm [10]

III. IMPROVED EMBEDDED ZEROTREE WAVELET ALGORITHM

During the scans, it is the fact that ZTR is more likely to appear with the process going on leads to the superfluous rescan and the waste of time. In addition, the efficiency of encoding may decline as a result of the redundant data and the underutilization of sub-band coefficients. And it can happen that significant wavelet coefficients may be lost during the quantization and the encoding steps. In this paper we therefore propose an improved EZW-based processing of traffic intersection images as follows to meet the information storage requirement and realize the function of making quick judgment to zerotree structure for the intelligent transportation images.

1) Image Pretreatment.

In modern intelligent transportation system, the methods to identify regions of interest are easily affected by the noise while they are characterized with advantages of simple structure, quick response. In order to get a better image reconstruction, appropriate image pretreatment, such as filtering and denoising, should be taken before the wavelet transform. And wavelet threshold denoising algorithm is effective for removing the noise from the image [12]. For white noise σ, denoising with a higher order soft threshold T_h is given by Equation (4) [13].

$$\eta(\omega) = \begin{cases} \omega + T_h - \dfrac{T_h}{2k+1}, & \omega < -T_h \\ \dfrac{1}{(2k+1)t^{2k}}\omega^{2k+1}, & |\omega| \le T_h \\ \omega - T_h + \dfrac{T_h}{2k+1}, & \omega > T_h \end{cases} \tag{4}$$

Where ω expresses the original wavelet coefficient, and $\eta(\omega)$ represents the wavelet coefficient after threshold processing. As shown in Fig.4, a smooth transition region sits in between the noise and useful signals, which accords with the continuation property of natural image.

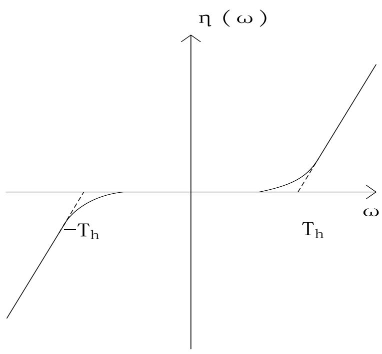

Fig.4. Soft threshold function [13]

2) Dynamic Threshold Recalculation.

Recalculate the threshold during every dominant and subordinate pass coding. Dynamic threshold is introduced during the process of successive quantification, which means that the threshold should be recalculated before each scanning. For example, the threshold T_0 should be initialized before the first dominant pass. A new coefficient matrix formed from the difference between effective coefficient and reconstituted value can be taken for the second dominant and subordinate pass. This is repeated until T=1. The regenerated dynamic threshold can fit the actual coefficient matrix well to better realize the quantization.

3) Addition of New Symbols.

We add two new symbols to better represent the structure of the zerotree: The symbol P_1 is used to designate a positive significant coefficient when there is no significant coefficient in its descendants, while N_1 is used to designate a negative significant coefficient when there is no significant coefficient in its descendants. These new symbols can be ignored in the subsequent scanning so as to reduce scanning time and improve coding efficiency. The resulting encoding flowchart of wavelet coefficient is shown in Fig.5.

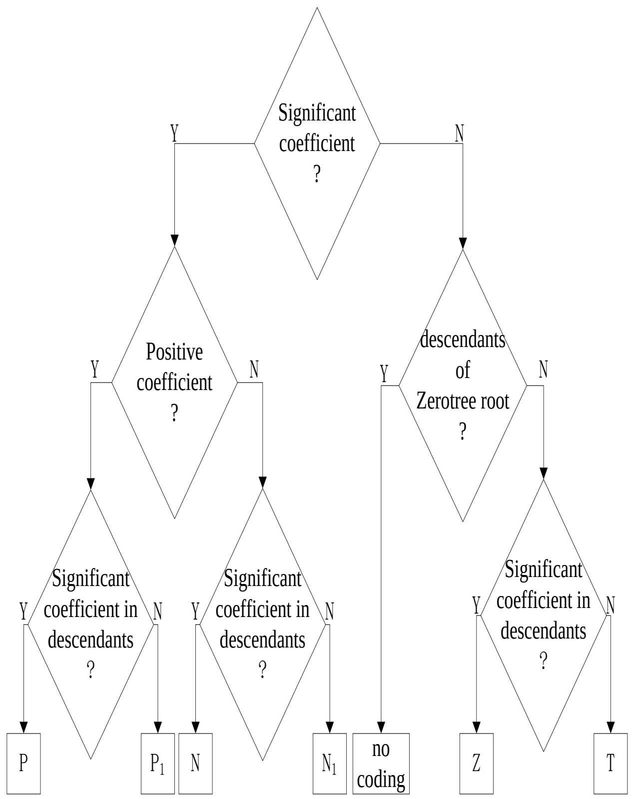

Fig.5.The encoding flowchart of wavelet coefficients (extension on [10])

The flowchart of improved Embedded Zerotree Wavelet algorithm is shown in Fig.6.

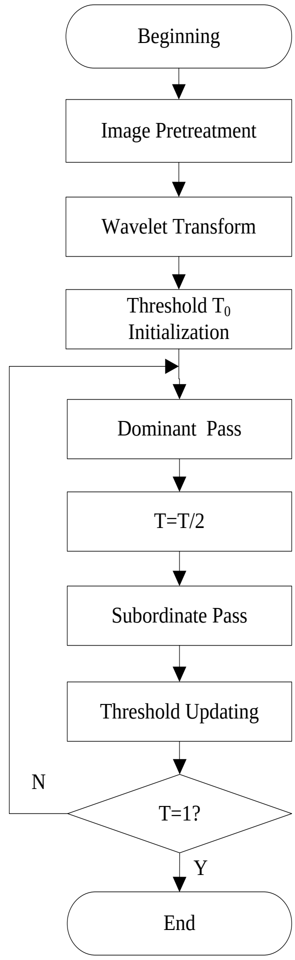

Fig.6.The flowchart of improved Embedded Zerotree Wavelet algorithm

IV. EXPERIMENT RESULTS AND ANALYSIS

To verify the proposed algorithm, more than 100 pictures [14] with a 256×256 resolution taken at different signalized intersections were analyzed. The pictures were collected by querying the Flickr image database with the term "traffic at intersection". The pictures were then appropriately downsampled to the 256×256 resolution. The wavelet basis bior3.7 was adopted to carry out wavelet transform in MATLAB 7.0 on a 2.93GHz desktop computer. The numbers of symbols during the scanning with EZW and improved EZW algorithm are shown in TABLE Ⅰ.

From the Comparison of the symbols during the scanning shown in TABEL Ⅰ, we can conclude that the improved EZW algorithm reduce the total number of symbols while the types of symbols are enriched. It avoided the superfluous rescan time and redundant bitstream ensuring that the coding efficiency can be improved.

TABLE Ⅰ

Comparison of the numbers of symbols with EZW and improved EZW algorithm (bit rate: 1.0 bpp)

No.	Algorithm	category	T	Z	P	N	P1	N1	Total
1	EZW	number	59201	9482	8030	9713	\	\	85426
		percent	69.3%	11.1%	9.4%	10. 2%	\	\	
	improved EZW	number	21907	9482	1163	1096	6867	7617	48132
		percent	45.5%	19.7%	2.4%	2.3%	14.3%	15.8%	
2	EZW	number	68458	12659	10330	9827	\	\	101274
		percent	67.6%	12.5%	10.2%	9.7%	\	\	
	improved EZW	number	32775	12659	1344	1521	8986	8306	65591
		percent	50.0%	19.3%	2.0%	2.3%	13.7%	12.7%	
3	EZW	number	65790	10982	9385	7695	\	\	93852
		percent	70.1%	11.7%	10.0%	8.2%	\	\	
	improved EZW	number	26575	10982	1251	998	8134	6697	54637
		percent	48.6%	20.1%	2.3%	1.8%	14.9%	12.3	

(a) Original Image 1 (b) Reconstructed Image 1 with EZW (c) Reconstructed Image 1 with improved EZW

(d) Original Image 2 (e) Reconstructed Image 2 with EZW (f) Reconstructed Image 2 with improved EZW

(g) Original Image 2 (h) Reconstructed Image 3 with EZW (i) Reconstructed Image 3 with improved EZW

Fig.7.Original image and reconstructed image with EZW or improved EZW algorithm

Three groups of original images and reconstructed images with the algorithm of EZW and the improved one are displayed in Fig.7.To measure the information loss of images, the mean square error (MSE) and the peak signal noise ratio (PSNR) are measured and compared. At the same bit rate, a bigger value for PSNR means a better image reconstruction. This indicates that the algorithm with the bigger PSNR has advantages over that with a smaller one. If the dimension of the images is defined as $M \times N$, then [15]:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[f(i,j) - f^{'}(i.j)\right]^2 \quad (5)$$

$$PSNR = 10\lg\frac{255^2}{MSE}(dB) \quad (6)$$

where $f(i,j)$ is gray level of the pixel in the original image, and $f^{'}(i,j)$ is gray level of the pixel in the reconstructed image $(i = 1,\ldots,\mathrm{M};\ j = 1,\ldots,\mathrm{N})$.

TABLE Ⅱ

Comparison of five random performance index with EZW and improved EZW algorithm (bit rate: 1.0 bpp)

No.	Algorithm	MSE	PSNR(dB)
1	EZW	11.89	37.38
	improved EZW	7.67	39.28
2	EZW	6.78	39.82
	improved EZW	4.18	41.92
3	EZW	8.26	38.96
	improved EZW	5.38	40.83
4	EZW	12.79	37.06
	improved EZW	8.26	38.94
5	EZW	10.79	37.80
	improved EZW	6.43	40.05

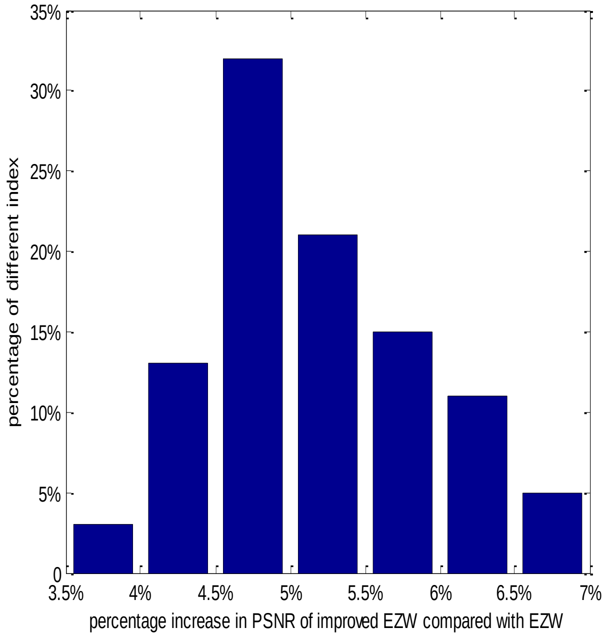

Fig.8. Distribution of percentage increase in PSNR of improved EZW algorithm compared with EZW algorithm

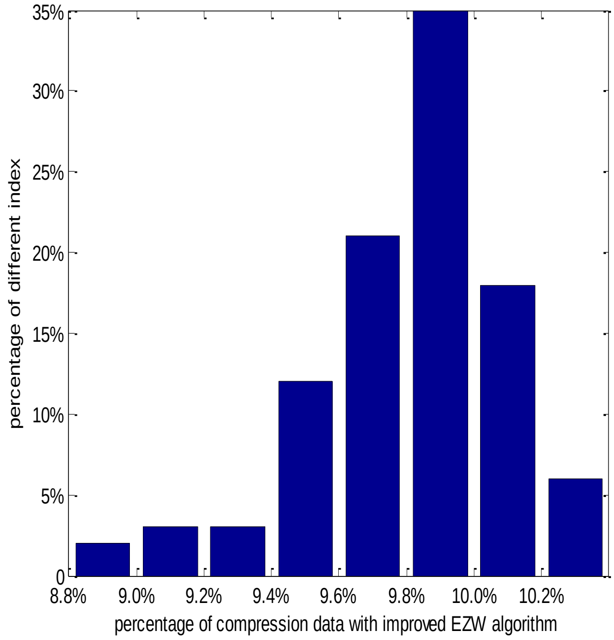

Fig.9. Distribution of percentage of compression data with improved EZW algorithm

TABLE Ⅱ compares the MSE and the PSNR for the basic and the improved EZW algorithm for a selection of example images. The example data shows how the improved EZW algorithm significantly improves the mean square error over the basic algorithm. At the same time, the PSNR is slightly, but significantly, reduced as well. Figure 8 gives a more comprehensive view of the performance of the improved EZW algorithm by showing a histogram of the relative PSNR improvement for the 100 images selected. And percentage increase in PSNR (P_G) of every image by a contrast between improved EZW algorithm and EZW algorithm can be gotten by Equation (7).

$$P_G = \frac{PSNR_{\text{improved EZW}} \text{-} PSNR_{\text{EZW}}}{PSNR_{\text{EZW}}} \times 100\% \tag{7}$$

The results indicate that one can expect an improvement of the compression quality in the order of 5%.At the same time, the data volume of the original image is compressed into about one-tenth of its original size as shown in Fig.9.

The distribution of percentage increase in total encoding and decoding time of improved EZW compared with EZW algorithm is shown in Figure 10. And percentage increase in time (P_T) of every encoding and decoding by a contrast between improved EZW algorithm and EZW algorithm can be gotten by Equation (8).

$$P_T = \frac{T_{\text{improved EZW}} \text{-} T_{\text{EZW}}}{T_{\text{EZW}}} \times 100\% \tag{8}$$

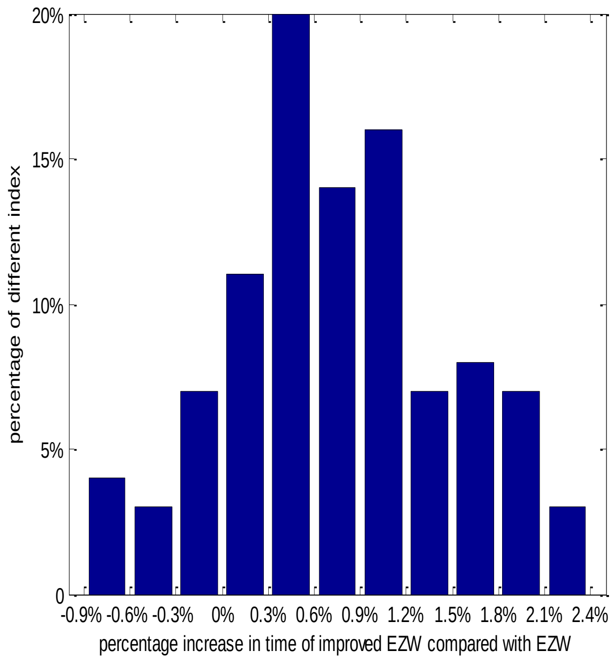

Fig.10. Distribution of percentage increase in total encoding and decoding time of improved EZW compared with EZW

These results indicate that the reduced scanner time can mainly make up for the time of recalculating the threshold. The avoidance of superfluous rescans is likely to reduce the total encoding and decoding time of improved EZW algorithm over that of the basic EZW algorithm.

The experiments show that PNSR is improved about 5%, compression performance is at most 10% while the cost of time is less than 2.5%. In Summary, the improved EZW algorithm achieves higher-quality images with high compression efficiency at only marginally higher CPU cost.

V. CONCLUSION

In this paper we present an improved EZW algorithm that uses image pretreatment, dynamic thresholding, and the addition of new symbols to describe zerotrees. The experiments show that the proposed algorithm improves the scanning accuracy and reduces the resulting data volume, while at the same time only marginally increasing computation cost. We consider the improved EZW algorithm an excellent candidate to meet the requirements of upcoming intelligent transportation systems.

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