Proceedings of the Seventh International Conference on Machine Learning and Cybernetics, Kunming, 12-15 July 2008

# IMAGE FUSION ALGORITHM IN INTELLIGENT TRANSPORT SYSTEM

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**Abstract:**

**Traffic congestion has been increasing world-wide as a result of increased motorization, urbanization, population growth and changes in population density. Interest in Intelligent Transport System (ITS) comes from the problems caused by traffic congestion and a synergy of new information technologies for simulation, real-time control and communications networks. Successful implementation of ITS depends upon complete and accurate vehicle information. An image fusion algorithm based on Lifting Wavelet Transform (LWT) is presented in this paper to combine an infrared image and a visible light image into a single composite image. A new image fusion method is proposed in this paper: after lifting wavelet transform, mean gradient are used to determine the coefficients in fusion formula for low frequency component. Local deviation rules are applied to merge the high frequency coefficients. Experimental results have shown that most of the final composite images have better quality than either of the source images. The results indicate that application of this algorithm improves performance of ITS.**

**Keywords:**

**Image fusion; lifting wavelet transform; Intelligent Transport System (ITS)**

## 1. Introduction

The development of Intelligent Transport System (ITS) concept is based on the application of advanced computer systems, communication, sensing, traffic control and information processing technologies to surface transportation facilities. ITS technologies are applied to improve travel safety standards, reduce congestion, improve energy efficiency, and enhance economic productivity. This paper presents a new image fusion scheme for the real-time traffic data collection system in ITS.

A number of studies have shown that infrared images and visible light images forming from identical scene contain lots of complementary information due to disparate image-forming mechanism between them. For instance, infrared images offer higher performance than visible light images when it is rainy, foggy or in dark space. But infrared images are usually less clear-cut. The proposed image fusion method utilizes lifting wavelet decomposition and wavelet domain fusion rules to combine an infrared image and a visible light image into a higher quality composite image. Experimental results have shown that the composite image has more complete information content and better perceptual quality than the individual source image. High quality composite images are transmitted from the real-time traffic data collection system to traffic control centre, which can improve the performance of ITS.

The rest of this paper is organized as follows. In Section 2, we introduce the framework of ITS. Section 3 gives details about the fusion scheme of the visible light image and the infrared image. In Section 4, we illustrate our experimental results with some real examples. Finally, in Section 5, the conclusions are presented.

## 2. Framework of ITS

The framework of Intelligent Transport System is illustrated in Fig. 1. First of all, visible light images and infrared images captured by cameras are combined into composite images by local detecting equipments. Then these equipments extract useful traffic information, vehicle information and characteristics from these composite images. These characteristics and useful information are sent to the traffic control centre to control the traffic lights. The traffic information centre processes the real-time traffic information and then transmits useful message to On-Board Unit on vehicles by GPS or communication towers to provide available information to different drivers.

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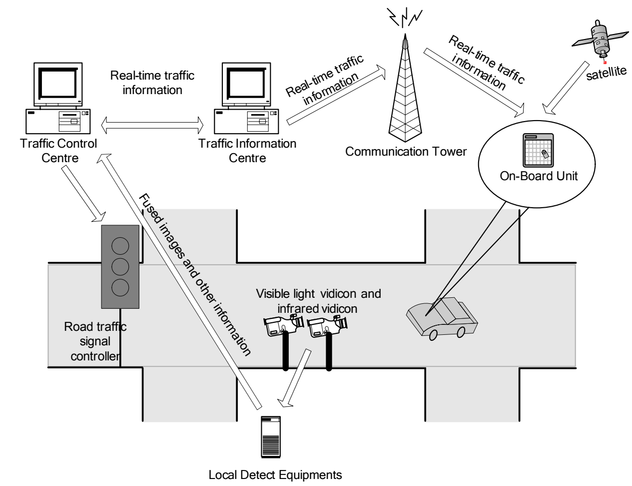



Figure 1. Framework of ITS

## 3. Lifting Wavelet Based Image Fusion Algorithm

In this section, we propose the lifting wavelet based image fusion algorithm. Suppose a visible light image and an infrared image forming from identical scene has identical spatial resolutions. Lifting wavelet transform is applied to visible light image and infrared image respectively. An original image may be decomposed to several levels. Coefficients at the same decomposition level of two original images are merged to new multi-scale coefficients of the fused image. Inverse lifting wavelet transform is finally applied to transform these new coefficients to the final fused image.

### 3.1. Lifting Wavelet Transform

Lifting wavelet transform is a multi-resolution analysis method used for the construction of the second generation wavelet [1]. It is an efficient implementation of the traditional wavelet transform algorithm. Suppose the source signal is $C_j, j \in Z$. After wavelet transform the low and high frequency components are $C_{j-1}$ and $D_{j-1}$. The lifting scheme consists of the following three steps:

Step1 - Split: This step divides the source signal into two subsets $C_{j-1}$ and $D_{j-1}$.

Step 2 - Predict: This also termed as dual lifting. In this step, the odd coefficients are predicted from the neighboring even coefficients using a predictor, and the wavelet coefficients or details are generated as the error in predicting the odd samples from the even ones using prediction operator.

Step 3 - update: This is also termed as primal lifting. This step updates the even set using the wavelet coefficients to compute the scaling function coefficients. It applies an update operator to detail coefficients obtained in Step 2.

See more detail about lifting wavelet transform in reference [1].

### 3.2. Image Fusion Algorithm

Suppose $V$ describes an original visible light image, $IR$ expresses a corresponding original infrared image, and $F$ expresses the fused image. Lifting wavelet decomposition is applied to $V$ and $IR$ respectively. Two different fusion algorithms and operators are applied to low frequency components and high frequency components because of their different information and characteristics. After all of the coefficients are obtained, inverse lifting wavelet transform is performed to get the final fused image.

#### 3.2.1. Low Frequency Components

After lifting wavelet decomposition, low frequency components are forward transform results, which indicate rough distribution of image energy. Larger values of low frequency components express more information entropy. Therefore, we divide the wavelet coefficients of two images $V$ and $IR$ into several blocks in the size of 5*5 and calculate the mean gradient of each block. Mean gradient are used to determine the coefficients in fusion formula.

Suppose low frequency components of $V$ and $IR$ are $C_{j,V}(m,n)$ and $C_{j,IR}(m,n)$ after $J$ levels lifting wavelet decomposition, where $j$ expresses different resolutions.

For each $C_{j,V}(m,n)$ and $C_{j,IR}(m,n)$, suppose $C_{j,V}(m,n)$ is in the 5*5 block $B_{j,V}$ and $C_{j,IR}(m,n)$ is in the 5*5 block $B_{j,IR}$. $G_{j,V}$ and $G_{j,IR}$ are the mean gradient of $B_{j,V}$ and $B_{j,IR}$ [2]. The fusion function is as follows:

$$C_{j,F}(m,n) = \frac{|G_{j,V}|}{\sqrt{G_{j,V}^2 + G_{j,IR}^2}} C_{j,V}(m,n) + \frac{|G_{j,IR}|}{\sqrt{G_{j,V}^2 + G_{j,IR}^2}} C_{j,IR}(m,n), \tag{1}$$

#### 3.2.2. High Frequency Components

After lifting wavelet decomposition, high frequency components contain lots of details. We apply local deviation rules to merge the high frequency coefficients because directional deviations adequately express local remarkable characteristics in different directions. Suppose high frequency components of $V$ and $IR$ are $D_{j,V}(m,n)$ and $D_{j,IR}(m,n)$ after $J$ levels lifting wavelet decomposition, and $j$ expresses different resolutions. Corresponding fusion rules are three steps:

1. To decompose $D_{j,V}(m,n)$ and $D_{j,IR}(m,n)$ to several blocks (size of M*N, ex. 3*3) and calculate directional deviation of each block. Statistical functions are

$$\sigma_\varepsilon^2(m,n) = \frac{1}{M*N}\sum_{i=1}^{M}\sum_{k=1}^{N}\begin{bmatrix} D_j^\varepsilon(m+i-\frac{M+1}{2}, n+k-\frac{N+1}{2}) \\ -E_\varepsilon(m,n) \end{bmatrix}, \quad (2)$$

where,

$$E_\varepsilon(m,n) = \frac{1}{M*N}\sum_{i=1}^{M}\sum_{k=1}^{N} D_j^\varepsilon(m+i-\frac{M+1}{2}, n+k-\frac{N+1}{2}), \quad (3)$$

and $\varepsilon = 1,2,3$ (horizontal, vertical and diagonal, respectively).

2. To decide the weighted coefficient $k_V$ and $k_{IR}$ for each block. If the directional deviation of one block of image $V$ is larger than the value of corresponding block of image $IR$, we apply $k_V \geq k_{IR}$. Contrarily, we apply $k_V \leq k_{IR}$. (We adopt $k_V, k_{IR} \in \{0.4, 0.6\}$ in our experiments).
3. Fusion rule for each block is

$$D_{j,F}(x,y) = k_V D_{j,V}^\varepsilon(m,n) + k_{IR} D_{j,IR}^\varepsilon(m,n), \quad (4)$$

Repeat three steps above and calculate the coefficients of all high frequency blocks.

## 4. Experimental Results

We have developed a real-time traffic data collection and signal process system which applies the fusion scheme described in Section 3. The proposed vehicle images fusing simulation framework is applied in it. In our experiments, a visible light camera and an infrared camera are fixed to screen the vehicles on road. Both of them are placed proximately at the same spot.

We have designed a test strategy according to the following steps:

*(1) Perform a comparative study for each lifting wavelet family:*

We have considered seven decomposition levels and have implemented the coefficient combining methods in Section 3. In our experiments we have chosen several couples of visible light image and infrared image. We have used the coefficient-based activity measures, which consider each coefficient separately.

The lifting wavelets families analyzed are[3,4] Daubehies (dbN, N = 1..40), Symlets (symN, N = 2..45), Biorthogonal (bior$(\tilde{N},N)$ with $(\tilde{N},N)$ given in Table 1), Reverse Biorthogonal (rbior$(\tilde{N},N)$ with $(\tilde{N},N)$ as in bior) and Morlet (morlN with number of voices N = 2..4), Coiflets (coifN, N = 1..5). We firstly select the member of each family with the best results and this member is used as the representative member for this family so that it can be compared against the remaining representative lifting wavelets family members.

Table 1 Result for the lifting wavelets Biorthogonal family

| Factors $(\tilde{N},N)$ | | | | | | |
|---|---|---|---|---|---|---|
| bior | (1, 2) | (1, 3) | (2, 1) | (2, 4) | (3, 1) | (3, 4) |
| Level | 2 | 3 | 2 | 2 | 4 | 3 |
| Mean Gradient | 5.8902 | 5.2949 | 5.0593 | 5.9927 | 5.4368 | 5.5274 |
| Standard Deviation | 51.9343 | 54.9892 | 53.3817 | 53.1943 | 52.3692 | 53.2906 |
| Entropy | 5.3742 | 5.4308 | 5.6831 | 5.7292 | 5.6941 | 5.5853 |

Table 2 Result for different lifting wavelet families

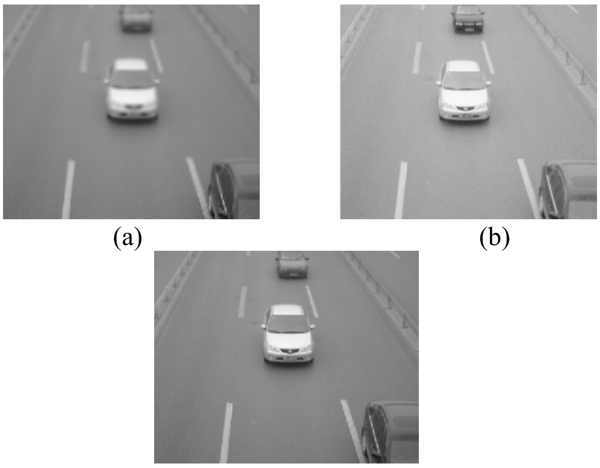
| families | db12 size 6 | sym5 size 4 | bior(2, 4) size 4 | rbior(2, 3) size 6 | morl3 size 5 | coif5 size 4 |
|---|---|---|---|---|---|---|
| Mean Gradient | 4.4893 | 5.3782 | 5.9927 | 4.9097 | 5.3204 | 5.8294 |
| Standard Deviation | 43.2247 | 50.6832 | 53.1943 | 54.2105 | 53.4514 | 52.7035 |
| Entropy | 5.2305 | 5.4326 | 5.7292 | 5.2536 | 5.7048 | 5.6624 |

We have used Matlab wavelet toolbox [4, 5] as the reference for the lifting wavelet transform with different families. Table 1 gives only the best results obtained for the Biorthogonal family. The pairs of factors $(\tilde{N},N)$, first row, are ordered in the second row according to the increasing size of the filter. The decomposition level is in the third row. The fourth row and fifth row appear the mean gradient and standard deviation [6] of the fused image. Finally, in the sixth row the entropy [7] of fused image is given.

We select the bior(2, 4) (the best of this family) as the respective member for this family in order to compare it against other representative family members. The members selected as the best for each family are then given in Table 2. Similarly, for the remainder of the families, the selected members are given in the first row of Table 2.

(2) *Comparison of the fused image against original individual source image images:*

We have done lots of experiments. The following example illustrates the fusion of a visible image which is captured in foggy situation, Fig. 2(a) with the synchronous infrared image, Fig. 2(b). The fused image, Fig. 2(c), includes the detailed information of visible image and the functional information from infrared image. In the fused image, the relative position of the functional information with respect to the details and edges of vehicle far away from the camera is clearly displayed.



(a) (b) (c)

Figure 2. (a) visible light and (b) infrared images; (c) fused image from (a) and (b)

## 5. Conclusions

In this paper, we presented an image fusion algorithm based on lifting wavelet transform for ITS. The number of fusion possibilities with different lifting wavelets families, resolution levels and coefficient combinations becomes very high. We give quantitative results for different lifting wavelet families and compare them with each other. From Table 1, Table 2 and Fig. 2 the following conclusions can be inferred:

(1) From Table 1, the best results are obtained with bior(2, 4) with a decomposition level of 2.
(2) From Table 2, the best results are also bior(2, 4), One important conclusion is that the results concerning lifting wavelets families are obtained with filter sizes ranging from 4 to 6, but there is no direct relation between the size and the results, as can be seen from the sizes shown in Table 2.
(3) In Fig. 2, comparing with single source image, fused image shows higher performance. It is indicated that image fusion scheme above is able to improve qualities of images in real-time traffic data collection system in ITS.

From the above conclusions, we have the behavior and performance of the reported fusion method. Because this paper is a pixel-level-based approach, our following study is how to extend our algorithm to the other two fusion-level schemes, namely [8]: feature and symbol. How to improve the operation speed of image fusion module is also the following discussion.

**Acknowledgements**

This paper is supported by Natural Science Foundation of Tianjin number 07JCZDJC05800.

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