A Novel Approach for Image Fusion Using Total Variation and Markov Random Field

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Abstract

In this paper, a novel approach based on total variation and markov random field is proposed for pixel-level image fusion. In the proposed approach, fusion is posed as an inverse problem and an image formation model is used as the forward model. Considering the spatial correlation of sensor selectivity factor, total variation (TV) and markov random field (MRF) model are employed to estimate the fused image. To evaluate the performance of the proposed approach, several types of multisensor images are used. The experimental results demonstrate that the proposed fusion approach provides superior performance.

Keywords: Image Formation Model, Image fusion, Total Variation (TV), Markov Random Field (MRF)

1. Introduction

Image fusion is a process of integrating redundant information present in two or more input images into a single image. It aims at the integration of disparate and complementary data to enhance the information apparent in the images as well as to increase the reliability of the interpretation [1]. Image fusion has a wide variety of applications in remote sensing [1], medical diagnosis [2], nondestructive evaluation [3], etc.

Image fusion is performed at three different levels, i.e., pixel level, feature level, and decision level [1]. Pixel-level fusion refers to the image processing directly based on the original pixel information from input images. Compared with the feature level fusion and decision level fusion, advantage of pixel level fusion is more time efficient and easy to implement [4]. This paper aims at proposing a novel approach for pixel-level image fusion.

Many pixel-level image fusion approaches have been proposed in recent years. These approaches can be classified into several categories, such as simple mathematic approaches, multiscale transforms (MT) based approaches, and probabilistic based approaches, etc. Referring to the simple mathematic approaches, the averaging method, which directly takes the average of the input images pixel by pixel, is stated as an instance. This approach increases the signal to noise ratio, but reduces the contrast. In contrast, The MT based fusion methods including the pyramid transform methods [5]-[6], and the wavelet transform methods [7]-[8] are rendered at full contrast. But these methods are sensitive to sensor noise. Involving with the probabilistic based approach, Sharma et al. [9] have proposed an image formation model and used a Bayesian fusion method to solve the model, which is based on estimation theory and assumes all distortions follow a Gaussian density. Yang et al. [10] have presented an expectation-maximization (EM) algorithm with the assumption that all distortions best fit Gaussian and non-Gaussian. Kumar et al. [11] have proposed a total variation (TV) based approach in conjunction with principal component analysis to solve the image formation model and estimate the fused image. The TV seminorm preserves discontinuity and is robust to sensor noise [12]. However, the TV method neglects the spatial correlation of the sensor selectivity factor

To address this problem, a novel approach based on TV method is proposed, which adopts the MRF model to incorporate the spatial correlation of the sensor selectivity factor. Markov Random Field (MRF) theory, which is utilized to find a priori distribution function of an image, provides a basis for modeling contextual constraints in visual processing and interpretation [13]. Since the proposed
algorithm based on MAP criterion cannot obtain solution directly, the simulating annealing (SA) algorithm is applied to stochastically search the result [14].

This paper is organized as follows. In section 2, image fusion problem based on the forward model is formulated. Section 3 presents the proposed algorithm, while the experimental results are reported in section 4 and section 5 concludes the paper.

2. Problem formulation

Assume that the input images are generated from a true scene, which is an image acquired under uniform conditions including lighting, unlimited visibility and perfect sensors [9]. Let \( f_0(x, y) \) denote the true scene, which is inspected by \( n \) different sensors and \( f_1(x, y), f_2(x, y), \ldots, f_n(x, y) \) are the corresponding \( n \) observed sensor images. \((x, y)\) is the pixel coordinate. The image formation model is given by [9]

\[
f_1(x, y) = \beta_1(x, y)f_0(x, y) + \eta_1(x, y) \quad \text{for} \quad i = 1, 2, \ldots, n
\]

where \( \beta_1(x, y) \) and \( \eta_1(x, y) \) are the sensor selectivity factor and sensor noise of the \( i^{th} \) sensor at location \((x, y)\). \( \beta_1(x, y) \in [0, 1] \) determines whether the true scene contributes to the \( i^{th} \) input image. For instance, \( \beta_1(x, y) = 1 \) indicates the \( i^{th} \) sensor may be able to “see” certain object, contrarily, it indicates the sensor may fail to “see” the object. The goal of fusion is to estimate \( f_0(x, y) \) from \( f_1(x, y), \ldots, f_n(x, y) \).

In order to estimate \( f_0(x, y) \), assume that 1) \( f_0(x, y), f_1(x, y), \ldots, f_n(x, y) \geq 0 \) \( (1 \leq i \leq n) \); 2) the sensor noise \( \eta_1(x, y), \eta_2(x, y), \ldots, \eta_n(x, y) \) are zero mean, independent and identically distributed (i.i.d) random variables. The standard deviation of \( \eta_i(x, y) \) is denoted as \( \sigma^2 \), and \( \sigma^2 \) is assumed to be known a priori and independent of spatial location [11]. From eq. (1),

\[
f = \beta f_0 + \eta
\]

where \( f = [f_1, \ldots, f_n]^T \), \( \beta = [\beta_1, \ldots, \beta_n]^T \), \( \eta = [\eta_1, \ldots, \eta_n]^T \), and \((x, y)\) is omitted for simplicity of notation.

Obviously, the goal of image fusion problem is to estimate \( \beta \) and \( f_0 \). If \( \beta \) is known, the pixel of the fused image can be directly obtained by a Least Squares (LS) techniques, that is to minimize the cost function \( \| f_0 - f \|_2^2 \) which is the \( L_2 \) norm of \( \| f_0 - f \| \). Since \( \beta \) and \( f_0 \) are obtained pixel by pixel here, the solution is sensitive to noise. As mentioned earlier, the TV seminorm is more robust to sensor noise compared to the LS approach. Moreover, it is a data driven approach and does not require knowledge of the probability function of the fused pixels [12]. Therefore, the solution to eq. (1) can be obtained via minimizing its TV seminorm under suitable constraints as follows:

\[
\min_{f_0} g(f_0) = \min_{f_0} \frac{\lambda}{2} \| f_0 - f \|_2^2 + \alpha TV(f_0) \quad (3)
\]

\[
TV(f_0) = \int_W \| \nabla f_0 \| dx dy \quad (4)
\]

the expression \( TV(f_0) \) is the total variation regularization term, where \( \| \nabla f_0 \| = \sqrt{\| f_{0x} \|^2 + \| f_{0y} \|^2} \). \( f_{0x} \) and \( f_{0y} \) are the first derivatives of \( f_0 \) in \( x \) and \( y \) direction, correspondingly. Further, the parameter \( \lambda, \alpha \) control the trade-off between the residual term and the regularization term of the \( f_0 \). Apparently, solving eq. (3) requires estimating \( \beta \) first.

Referring to the acknowledgement of \( \beta \), MRF is proposed to model the spatial correlation of \( \beta \) as mentioned earlier. Let \( S = \{ s(i, j) ; 1 \leq i \leq M, 1 \leq j \leq N \} \) be a set of sites in an image with size of \( M \times N \). Assume that the sensor selectivity factors \( \beta(S) \) follow MRF properties with respect to the
neighborhood system [13]: For a pixel site $s$ and its neighborhood system $L_s$, there $P(\beta | \beta_{s-(i)}) = P(\beta, \beta_s)$, which means the pixel site $s$ is determined by its neighborhood system other than any other pixel sites in the image. In this paper, a 4-neighborhood system is used.

In general, the fusion problem can be divided into two parts: 1) A TV seminorm is applied to estimate the fused image; 2) Motivated by the fact that the sensor selectivity factors are spatially correlated, the MRF model is employed to model the spatial correlation. A detailed solution to this fusion problem is presented in section 3.

3. Fusion with TV and MRF approach

In this study, an MRF approach is utilized to obtain the sensor selectivity factor first and then a TV seminorm is used to estimate the fused image. Thus the overall approach consists of two parts.

A. Estimation of $\beta$ based on MRF model

As it is discussed before, the sensor selectivity factor $\beta$ follows MRF model. Thanks to the Hammers-Clifford theory [15], it provides us equivalence between MRF and Gibbs distribution. From the theorem, an MRF is of the form:

$$P(\beta) = \frac{1}{Z} \exp\left[-\sum_{c \in S} U_c(\beta)\right]$$

(5)

where $c$ is a clique which consists of a set of neighboring sites; $Z$ is normalization constant; and $U_c(\beta)$ is called Gibbs potential. As mentioned in section 2, cliques have been categorized into 4 types: $c_2, c_1, c_4, c_5$, involved with the vertical pairs, horizontal pairs, left-diagonal pairs, and right-diagonal pairs, respectively. Thus, Gibbs potential function is defined as [13],

$$\sum_{c \in S} U_c(\beta) = a^T L$$

(6)

where $a=[a_2, \cdots, a_5]^T$ is a smooth parameter used for describing correlation of neighborhood system and $L=\left[\sum_{(x,y)\in c_2} I(\beta(x),\beta(y)), \cdots, \sum_{(x,y)\in c_5} I(\beta(x),\beta(y))\right]$ is the coefficient potential vector associated with clique types. Here function $I$ is defined as $I(a,b)=1$, if $a=b$; and $I(a,b)=-1$, otherwise. From MAP criterion and Bayesian theory [13], $\beta$ can be estimated via eq. (5):

$$\hat{\beta} = \arg\{\max_{\beta} [P(f|\beta, f_0)P(\beta)]\}$$

(7)

In the model given in eq. (1), sensor noise $\eta_i(x,y), \eta_j(x,y), \cdots, \eta_k(x,y)$ follows an i.i.d Gaussian distribution with the same variance $\sigma^2$, therefore the conditional probability density function of the input images $f$ given $\beta$ and $f_0$ is given by,

$$P(f|\beta, f_0) = \sqrt{\frac{1}{2\pi\sigma^2}} \exp\left[-\frac{1}{2\sigma^2}(f-\beta f_0)^T(f-\beta f_0)\right]$$

(8)

Then substituting eq.(5), (7), (8) and taking the constant term out,

$$\hat{\beta} = \arg\{\min_{\beta} \{E(\beta)\}\}$$

(9)

where $E(\beta) = \frac{1}{2\sigma^2}(f-\beta f_0)^T(f-\beta f_0) - \sum_{c \in S} U_c(\beta)$.
Since the optimal estimate for $\beta$ cannot be obtained directly, simulated annealing algorithm is applied to stochastic search for the optimal solution. SA is a Monte Carlo approach for minimizing such function and a computationally efficient mathematical tool for the implementation of MAP estimator. The idea of the SA algorithm is to generate a random sequence of configurations that eventually converges to solution of the MAP problem [14].

### B. TV regularization for image fusion

Since the estimation of $\beta$ have been obtained, $\beta$ can be applied in the process of estimating fused image from eq. (3). In order to solve eq. (3) numerically, the first derivative of $g(f_0)$ should be set to zero. That is:

$$\frac{\partial g(f_0)}{\partial f_0} = \lambda \nabla^\top (\beta f_0 - f) - \alpha \nabla \cdot \left( \frac{\nabla f_0}{|\nabla f_0|} \right) = 0 \quad (10)$$

The approach proposed by Rundin et al. in [16] may be used to derive the following iterative solution to solve eq. (10)

$$f_{0}^{i+1} = f_{0}^{i} + \tau \left[ \lambda \beta (f - \beta f_{0}^{i}) + \alpha \nabla \cdot \left( \frac{\nabla f_{0}^{i}}{|\nabla f_{0}^{i}|} \right) \right] \quad (11)$$

where $k$ is the iteration number and $\tau$ is the time step.

The flowchart of the proposed image fusion approach is addressed as follows:

**Input:** Two co-registered sensor images $f_1, f_2$

**Output:** Fused image $f_0$

1. Initial $f_0^0$ and $\beta_0$; // set $f_0^0$ as the average of $f_1$ and $f_2$; initial $\beta_0$ using LS approach.
2. Get $\beta$ with SA algorithm:
   a. Set the initial temperature $T_0$, frozen temperature $T_{\text{min}}$ and iteration number $K$; $\beta_{\text{new}} = \beta_0$, $E_{\text{new}} = E(\beta_{\text{new}})$ energy function;
   b. Do while $T(i) > T_{\text{min}}$
      1. Obtain a new estimation of $\beta_{\text{new}}$, then $E_{\text{new}} = E(\beta_{\text{new}})$, $\Delta E = E_{\text{new}} - E_{\text{new}}$;
      2. If $\Delta E \leq 0$; then $\beta_{\text{new}} = \beta_{\text{new}}$; else if $\Delta E \geq 0$; then $p = \exp(-\Delta E / T(i))$;
         2.1) If $c = \text{random [0,1]} < p$, then $\beta_{\text{new}} = \beta_{\text{new}}$, otherwise $\beta_{\text{new}} = \beta_{\text{new}}$;
      3. Repeat (1) ~ (2) for $K$ times.
   c. $\beta = \beta_{\text{new}}$;
3. Get $f_0(x, y)$ via solving eq. (11) iteratively.

### 4. Performance analysis

In this section, performances of the proposed fusion algorithm are presented. 15 pairs of multisensor images which have been pre-registered are utilized to evaluate the performance of the proposed approach. These images are captured by various types of sensors, including Daedalus scanner, hyper-spectral scanner, low-light-television (LLTV) and forward-looking-infrared (FLIR) etc., as listed in Table 1. Moreover, it includes a variety of medical, industrial, urban and natural scenes, as show in Figure 1 from left to right and from top to bottom respectively. Here, sensor noise is simulated by adding zero mean white Gaussian noise to the input images. These input images are available online [17].

To evaluate the performance of the proposed method, we compare the proposed method with the EM algorithm [10], wavelet fusion [8], Laplacian pyramid [5], and TV based approach [11]. Difference, mean squared error (MSE), mutual information (MI), relative difference (RD) and union entropy (UE) are used as quantitative measures. Moreover, a universal image fusion evaluation method integrating...
both subjective and objective factors [18] (called Universal Index (UI)) is used to evaluate the fusion performance based on the Human Visual System. A larger value of UI indicates less loss of information of the fused image compared with the input images.

Table 1. Input images details

<table>
<thead>
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First, the fusion results of aircraft navigation images for SNR=23 dB by Laplacian pyramid, wavelet, EM algorithm, TV based approach and the proposed method are presented in Figure.3, respectively. From the Figure 3, we know that the proposed approach provides the results with best visual appearance. Furthermore, the quantitative measures of these five approaches for SNR=23 dB are given in Table.2. We can conclude that the proposed approach has achieved the best results of difference, MSE and RD compared with other methods.

Next, we apply the five fusion methods to the aircraft navigation images for SNR=3 dB and the fusion results are shown in Figure 4, correspondingly. From the Figure 4, it is evident that the proposed method maintains the image features while reducing the sensor noise when compared with other methods. Moreover, the objective metric of the five methods are listed in Table 3. The highest quality measures of difference, MSE, RD and UI indicate that the proposed method still have obtained better performance with the increasing of sensor noise.

From the experimental results of aircraft navigation images at different SNR levels, which are presented in Figure 3, Table 2, Figure 4 and Table 3, we can conclude that our approach is better than other fusion approaches and less influenced by sensor noise.

Another set of images are captured by Daedalus scanner at two SNR levels: 23dB and 3dB. The fusion results obtained by Laplacian pyramid, wavelet, EM algorithm, TV based approach and the proposed method are presented in Figure 5, Table 4, Figure 6, and Table 5, respectively. From Figure 5 and Table 4, we also see that the proposed approach has the better result compared with the other four algorithms, and still gets the best performance on difference, MSE and RD. Further, with the increasing of sensor noise, the proposed method performs more robust and has achieved best values of more assessments, including difference, MSE, MI, RD, and UI. It is clear to conclude that our proposed approach performs effective on dataset, even at the low SNR level.

In general, we can draw a conclusion that the proposed approach achieves superior fusion performance and is more robust to noise as compared to other approaches.

5. Conclusion
In this paper, we have studied the pixel-level image fusion problem based on a forward model. Based on the fact that the sensor selectivity factor, which determines whether the true scene contributes to the input image, has significant correlation within its neighborhood, MRF is utilized to model the spatial correlation of sensor selectivity factor. Motivated by that, a novel approach employs MRF model in the TV based approach is proposed. Applying the proposed approach to a variety of multisensor images, visual inspection and quantitative performance metrics both demonstrate that the proposed approach has achieved a superior performance than the traditional pixel-level fusion approaches.

Acknowledgement

This work was supported by the project of graduate innovation of Chongqing University (Grant No.200909C1011), the Science and Technology Project of Ministry of Transport with Grant No. 2011318740.

Reference

Figure 2. Aircraft navigation images, SNR=23 dB: (a) LLTV image, (b) FLIR image, (c) Laplacian pyramid fusion, (d) Wavelet fusion, (e) EM algorithm, (f) TV fusion, (g) fused image: Proposed approach.

Table 2. Aircraft navigation images, SNR=23 dB: Performance summary of fusion approaches

<table>
<thead>
<tr>
<th>LLTV/FLIR(SNR=23 dB)</th>
<th>Difference↓</th>
<th>MSE↓</th>
<th>MI↑</th>
<th>RD↓</th>
<th>UE↑</th>
<th>UI↑</th>
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<td>Lap-pyramid</td>
<td>46.8667</td>
<td>11.0783</td>
<td>25.1440</td>
<td>31.1584</td>
<td>25.9063</td>
<td>0.3592</td>
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<tr>
<td>Wavelet</td>
<td>64.4965</td>
<td>11.5131</td>
<td>24.7314</td>
<td>37.1795</td>
<td>26.8437</td>
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<tr>
<td>EM-GM</td>
<td>63.0354</td>
<td>10.6437</td>
<td>25.5172</td>
<td>38.2584</td>
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<tr>
<td>TV</td>
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<td><strong>29.2762</strong></td>
<td><strong>25.2276</strong></td>
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Figure 3. Aircraft navigation images, SNR=3 dB: (a) LLTV image, (b) FLIR image, (c) Laplacian pyramid fusion, (d) Wavelet fusion, (e) EM algorithm, (f) TV fusion, (g) fused image: Proposed approach.

Table 3. Aircraft navigation images, SNR=3 dB: Performance summary of fusion approaches

<table>
<thead>
<tr>
<th>LLTV/FLIR(SNR=3 dB)</th>
<th>Difference↓</th>
<th>MSE↓</th>
<th>MI↑</th>
<th>RD↓</th>
<th>UE↑</th>
<th>UI↑</th>
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<td>Lap-pyramid</td>
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<td>27.0736</td>
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<td>Wavelet</td>
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<td>EM-GM</td>
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<td>12.2515</td>
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<td>TV</td>
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Figure 4. Daedalus images, SNR=23 dB: (a) Daedalus image, (b) Daedalus image, (c) Laplacian pyramid fusion, (d) Wavelet fusion, (e) EM algorithm, (f) TV fusion, (g) fused image: Proposed approach.

Table 4. Daedalus images, SNR=23 dB: Performance summary of fusion approaches

<table>
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<tr>
<th>Daedalus/Daedalus (SNR=23 dB)</th>
<th>Difference↓</th>
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Figure 5. Daedalus images, SNR=3 dB: (a) Daedalus image, (b) Daedalus image, (c) Laplacian pyramid fusion, (d) Wavelet fusion, (e) EM algorithm, (f) TV fusion, (g) fused image: Proposed approach.
<table>
<thead>
<tr>
<th>Daedalus/Daedalus (SNR=3 dB)</th>
<th>Difference↓</th>
<th>MSE↓</th>
<th>MI↑</th>
<th>RD↓</th>
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