# BLIND MODEL BASED FUSION OF MULTIBAND IMAGES USING IMAGE ENHANCMENT AND A NOVEL FUSION ALORITHM

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**Abstract:** This paper suggests a blind model-based fusion method to combine a low-spatial resolution multi-band image and a high-spatial resolution image. This method is blind in the sense that the spatial and spectral reactions in the degradation model are unknown and estimated from the observed data pair. The Gaussian and overall variation priors have been used to legalize the disadvantaged fusion problem. Experimental results, including qualitative and quantitative ones show that the fused image can combine the spectral information from the multi-band image and the high spatial resolution information from the panchromatic image effectively with very competitive computational time.

**Key words:** Image fusion, image enhancement, multiband images, MATLAB.

## I. INTRODUCTION

In computer vision, Multi sensor Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images.

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. But, the standard image fusion techniques can distort the spectral information of the multispectral data, while merging.

In satellite imaging, two types of images are available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will be usually, two or four times lower. At the receiver station, the panchromatic image is merged with the multispectral data to convey more information.

Many methods exist to perform image fusion. The very basic one is the high pass filtering technique. Later techniques are based on DWT, uniform rational filter bank, and Laplacian pyramid.

In general fusion means, an approach to extract information that is in several domains. The image fusion process is to integrate multi sensor or multi view or multi focus information into a new image that contains better quality features and is more informative of all the individual input information[1][2]. With rapid advancements in technology, it is now possible to obtain information from multi source images to produce a high quality fused image[3]. In the field of sensing technologies multi sensor systems have become a reality in a growing number of fields such as remote sensing, medical imaging, machine vision and the military applications for which they were first developed [4].

The result of the use of these techniques is a great increase of the amount available. Image fusion provides an effective way of reducing this increasing volume of information while at the same time extracting all the useful information from the source of images. Image fusion methods can be broadly classified into spatial domain and transform domain fusion [5]. Wavelet transform and laplacian transform is transform domain fusion. Principal component analysis (PCA), Intensity hue saturation (IHS), And High pass filtering etc. methods fall in spatial domain fusion techniques.

Spatial image fusion work by combining the pixel values of the two or more images. The simplest is averaging the pixel values of input images [6]. Wavelet transform and laplacian transform come in the transform domain. In the transform domain method the multi scale decomposition of the images is done and the composite image is constructed by using fusion rule. Then inverse multiscale transform is applied to achieve the fused image. Discrete wavelet transform (DWT), principal component analysis (PCA), Morphological techniques, combination of DWT and PCA, have been popular techniques of image fusion [7] [8][4].

The formulated optimization problem associated with the image fusion can be attacked efficiently using a recently developed robust multi-band image fusion algorithm in [9]. Multi-band imaging generally suffers from the limited spatial resolution of the data acquisition devices, mainly due to an unsurpassable trade-off between spatial and spectral sensitivities [10]. To enhance its spatial resolution, fusing a multi-band image, more specifically, a multispectral (MS) image, with a high spatial resolution panchromatic (PAN) image, referred to as pan sharpening, has been receiving particular attention in remote sensing [11], [12]. Note that a PAN image is a one-band image which has much higher spatial resolution than a MS image. Generally, the linear degradations modelled in the observed images, including the multi-band and PAN images, with respect to (w.r.t.) the target high-spatial and high spectral image reduce to spatial and spectral transformations. Thus, the pan sharpening problem can be interpreted as restoring a three-dimensional data-cube from two degraded data cubes. A more precise description of the problem formulation is the well-admitted linear degradation model provided as

$$\begin{aligned} \mathbf{Y}_{\mathrm{M}} &= \mathbf{XBS} + \mathbf{N}_{\mathrm{M}} \\ \mathbf{y}_{\mathrm{P}} &= \mathbf{rX} + \mathbf{n}_{\mathrm{P}} \end{aligned} \qquad (1)$$

where

- $\mathbf{X} \in \mathbb{R}^{p \times n}$ is the full resolution target MS image and each row is a vector obtained by rearranging each band.

- $\mathbf{Y}_{\mathrm{M}} \in \mathbb{R}^{p \times m}$ is the spatially degraded MS image.
- $\mathbf{y}_{\mathrm{P}} \in \mathbb{R}^{1 \times n}$ is the spectral degraded PAN image.
- $\mathbf{B} \in \mathbb{R}^{n \times n}$ is a cyclic convolution operator.
- $\mathbf{S} \in \mathbb{R}^{n \times m}$ is a uniform downsampling operator.
- $\mathbf{r} \in \mathbb{R}^{1 \times p}$ is the spectral response of the PAN sensor.
- $\mathbf{N}_{\mathrm{M}} \in \mathbb{R}^{p \times m}$ and $\mathbf{n}_{\mathrm{P}} \in \mathbb{R}^{1 \times n}$ are additive terms that include both modeling errors and sensor noise.
- $p$ is the number of bands in the MS image.
- $m$ is the number of pixels in each MS band.
- $n(> m)$ is the number of pixels in the PAN image.

Since the fusion problem is usually ill-posed, the Bayesian methodology offers a convenient way to regularize the problem by defining appropriate prior distribution for the scene of interest given the observed MS and PAN images. More specifically, the posterior, which is the Bayesian inference engine, has two factors: a) the likelihood function, which is the probability density of the observed MS and PAN images given the target image, and b) the prior probability density of the target image, which promotes target images with desired properties, such as being segmentally smooth.

Computing the Bayesian estimators is a challenging task, mainly due to the large size of X and to the presence of the down sampling operator S, which prevents any direct use of the Fourier transform to diagonalize the blurring operator B. To overcome this difficulty, several computational strategies have been designed to approximate the estimators. Based on a Gaussian prior modelling, a Markov chain Monte Carlo (MCMC) algorithm has been implemented in [13] to generate a collection of samples asymptotically distributed according to the posterior distribution of X. The Bayesian estimators of X can then be approximated using these samples. Despite this formal appeal, MCMC-based methods have the major drawback of being computationally expensive, which prevents their effective use when processing images of large size. Relying on exactly the same prior model, the strategy developed in [14] exploits an alternating direction method of multipliers (ADMM) embedded in a block coordinate descent method (BCD) to compute the maximum a posterior (MAP) estimator of X. This optimization strategy allows the numerical complexity to be greatly decreased when compared to its MCMC counterpart. Based on a prior built from a sparse representation, the fusion problem is solved in [15], [16] with the split augmented Lagrangian shrinkage algorithm (SALSA) [17], which is an instance of ADMM. In [18], contrary to the algorithms described above, a much more efficient method is proposed to solve explicitly an underlying Sylvester equation (SE) associated with the fusion problem derived from (1), leading to an algorithm referred to as Fast fUsion based on Sylvester Equation (FUSE). The MAP estimators associated with a Gaussian prior similar to [13], [14] can be directly computed thanks to the proposed strategy. When handling more complex priors such as [15], [16], the FUSE solution can be conveniently embedded within a

 

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conventional ADMM or a BCD algorithm. A more robust version of FUSE algorithm, which is termed as R-FUSE has been proposed recently in [9], getting rid of the invertibility assumption of blurring kernel. Besides, the core of this fast fusion algorithm has been extended and applied in single image super-resolution [19], [20].

In terms of the spatial blurring B and spectral response r, they are very often assumed known [13], [16]. In practice, however, the information that is available about these responses is often scarce and/or somewhat inaccurate. In [15], the authors formulated a convex problem to estimate the spatial and spectral response, making only minimal assumptions, i.e., the spatial response has limited support and that both responses are relatively smooth.

In this work, we propose to first estimate the spatial and spectral responses, i.e., B and r, using the method in [15] and then fuse the offered MS and PAN images using the method in [9], leading to a blind multi-band image fusion method.

## II. METHODOLOGY

Image fusion treats the different combinations of images sensed from different sensors which include multi-spectrum and high-spectrum, multi-angle viewing and multi-resolutions. This enhances the scope for accomplishing the quality of images. Multi sensor images are used in several fields such as machine vision, remote sensing and medical imaging. It is likely to combine various images of the same scene captured with verities of sensors giving different details. If it is possible to combine the relevant information acquired by different sensors to get an original and enriched image, then a new fused image is produced and this mechanism is called fusion. To support more accurate clinical information for physicians to deal with medical diagnosis and assessment, multimodality medical images are required such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), or Positron Emission Tomography (PET) etc. For example, the CT image can provide dense structures like bones and implants with less distortion but cannot detect physiological changes. But the MRI can provide information of normal and pathological soft tissues and it cannot support the bone information. In this circumstance, a single image cannot be appropriate to deliver perfect clinical requirements for the physicians. Hence the fusion of the multimodal medical images is essential and it has become a promising and very challenging research area in recent years.  Image fusion broadly defined as the representation of the visual information with more than one input image, as a single fused image without the introduction of distortion or loss of information. The fusion of different images can reduce the ambiguity related to a single image.

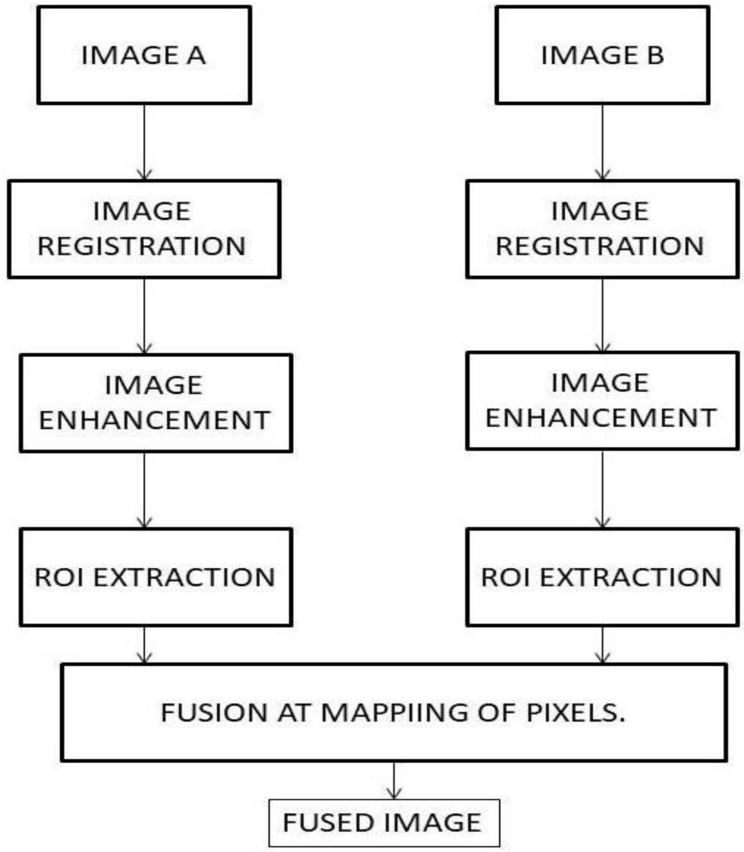


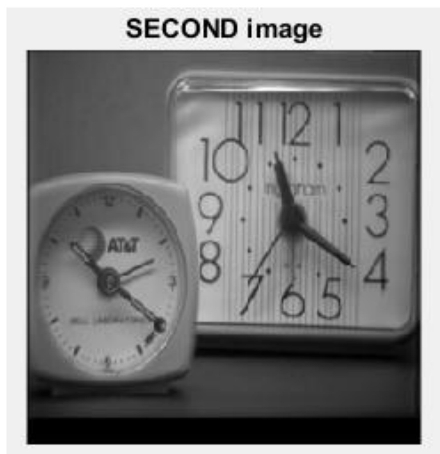

Figure 1 Implementation of image fusion

**Pixel-level image fusion** is the information fusion that is implemented directly using the basic data of the images needed to be fused. This kind of image fusion integrates the information of multi source images on the premise of strict registration. In the proposed image fusion technique, Image will be enhanced first and then will be calculated the region of interest, and pixels mapping will be at the level of pixels.

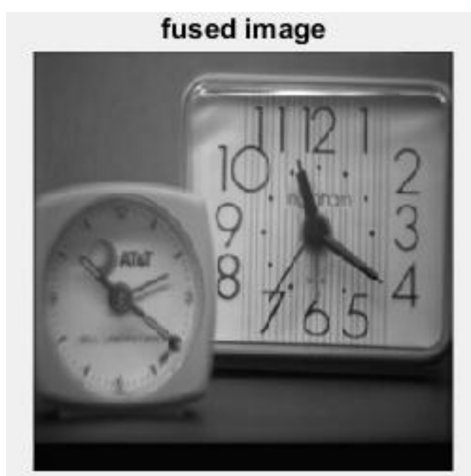
## III. SIMULATION RESULTS

Figure 2 shows the two images used for fusion and fused image and figure 3 shows the simulation results of the proposed fusion technique. Code has been written in MATLAB and also executed in MATLAB.


(a)




(b)




(c)

Figure 2 Two images and their fused image.

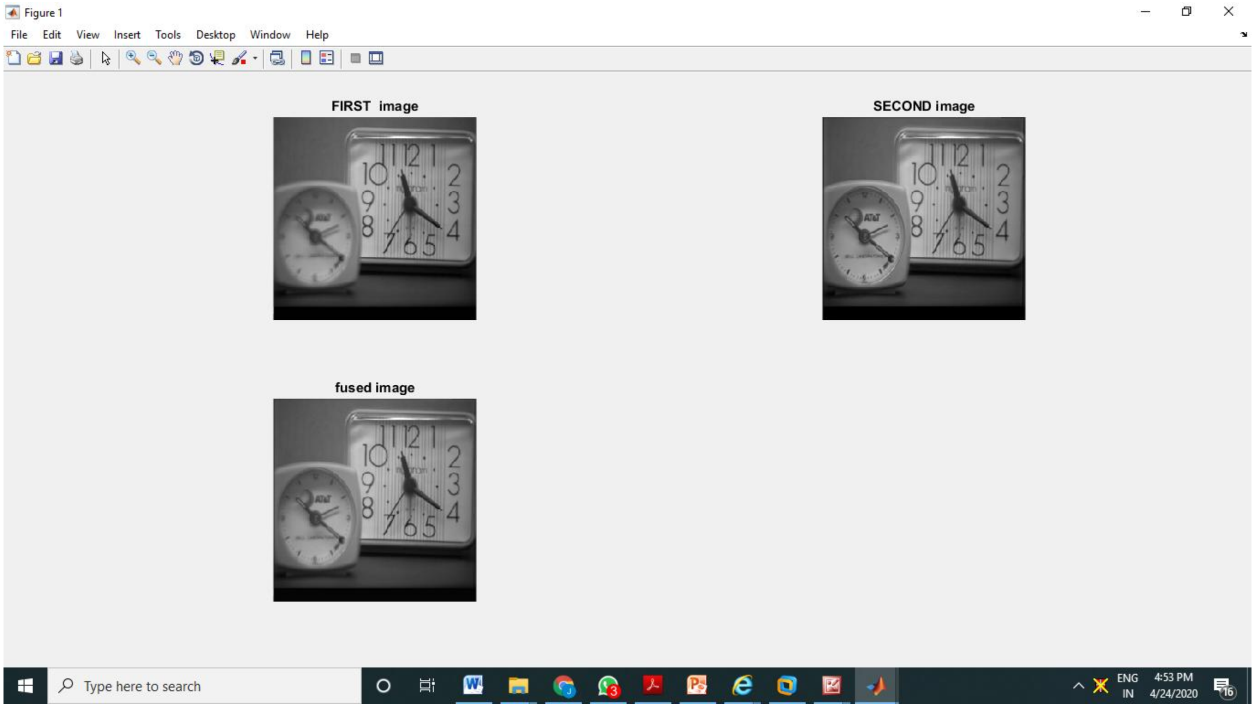



Figure 3. Simulation result of the proposed system

## IV. CONCLUSION

Depending upon the type of application and the requirement of the user that one might have desire to obtain the visually beautiful image someone else may require the more details of the colors for getting more detailed accurate results about the image. The PCA method provides better enhanced fused images and has better fused image without much change in the spectral and spatial information of the original image. The research activities are mainly in the area of developing fusion algorithms that improves the information content of the composite imagery, and for making the system robust to the variations in the scene, such as dust or and night. We proposed a fusion technique at pixel level based mapping of pixels which is very flexible.

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