# Advanced Minimum Method for fusion of True Color Images

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***Abstract*—**Image fusion has always been an interesting topic to fuse two or more images using various techniques. Researchers have always been trying to innovate techniques and algorithms so as to increase the entropy of the fused image so that minimum information is lost during the fusion process. Among several algorithms such as DCT, DWT, wavelet functions, minimum method etc., the author proposes an advanced minimum method. In this method, duty cycle concept is used to vary the fused content of the two images. This variation is done by sinusoidal variation. The results obtained are promising.

**Keywords—**Advanced minimum method, image fusion, sinusoidal variation

## I. INTRODUCTION

The process of merging two or more than two images with similar features into one fused image with the highest distinct visual effects is known as image fusion (IF)[1]. When these images are united, they provide info that would otherwise be difficult to obtain when viewed independently.[2],[3],[4],[5]. In count to the digital CCD, additional imaging sensors are carefully chosen that collect images at other frequencies, along with those of infrared cameras. Results are enhanced when multiple sensors collect images of same site[6].

A solo imaging sensor is not enough to arrest the real-time scene information and specific deductions cannot be drawn from a sole imaging sensor alone. Consequently, different imaging sensors are employed to capture the image information. The imaging sensors arrest the scene information and show it in a lower dimensional space based on the basis images captured.IF is classified as MFIF[7], [8], [9], MEIF [10], [11], [12]MMIF [13], and MTIF [14] or MVIF. Theamount of general-purpose research manuscripts with general-purpose impact evaluations has grown rapidly since more than 15 years.

The frequency domain, also called transform domain method, falls under the category of MSD. There are three phases in the MSD process: Decomposition, fusion, and reconstruction. Following MSD, transforms like DWT[13] are used. Fusion guidelines are functional to the constants by taking into account the link between together pixels. The final effect of the fused image is attained by the inverse wavelet transform.

The widely used TD techniques are PT and WT. TD methods include PT, DWT, DFT, SWT[15], WT [16], Curve [17] and Contour Transform (CT)[18].Fusion algorithms are classified into different groups according to their purpose and the methods used to attain the input images. All of these methods are elucidated below in the forthcoming subsections:

Camera manipulation was anability when there were cameras that worked with rolls of film. The key reason for this is that it was difficult to focus the image with the camera. The camera uses a single or lens system, so each camera has a focus. The full use and integration of multi-source or multi-temporal isolated sensing imagery is needed for much conceivable tenacity in urban, agricultural, emergency and natural settings to leverage additional information and improve detection performance. Objects below the focal length of the visual sensor are in sharp focus and clear, while other parts of the image are blurry. A solo camera (visual sensor) cannot provide perfectly all the details of a scene. [19]. Cameras are also fundamentally different and can have different focal emphasis and focal lengths. The IF of many visual sensors is known as the MMIF. A specimen of MRI and CT IF to improve disease diagnosis. Operative combination of imaging data from diverse modalities provides more detail than imaging evidence from each discrete mode. Due to which interpretation increases and provides more consistent results. Its job is to intelligently combine multimodal images. This improves the visibility of objects with protracted information. If images are acquired with diverse cameras with different focal points, IF is performed to obtain more informative images.

Digital images encompass very large dynamic ranges in terms of intensity, color and depth. The human visual system can capture these statistics of scenes. The human brain convolutes signals proficiently and provides natural insight. But discrete visual sensor is not capable of capturing intensity, colour and wisdom in a solo photograph. Due to the increasing variety and availability of satellite sensor data, the high-resolution detection and classification of the Earth's surface changes have attracted extensive interest. The full use and integration of multi-source or multi-temporal isolated sensing imagery is needed for much conceivable tenacity in urban, agricultural, emergency and natural settings to leverage additional information and improve detection performance. Therefore, various exposure settings are managed to capture multiple images of the identical scene. The exposure of each shot is different. Few images have well exposed areas. However, some areas may be more exposed to bright light or less exposed, and some discrete facts may be lost. Some areas may show up better in some images than others. MEIF algorithms excerpt and syndicate well-exposed areas from entire images to create a visual matrix of which well-exposed areas. MEIF has lately been used to keep the details of micro-organisms intact found in both low and high-light areas [20]. Factors considered in the MEIF are obscuration of objects caused by concealment.

The IF of many visual sensors is known as the MMIF. A specimen of MRI and CT IF to improve disease diagnosis. Operative combination of imaging data from diverse modalities provides more detail than imaging evidence from each discrete mode. Due to which interpretation increases and provides more consistent results. Its job is to intelligently combine multimodal images. This improves the visibility of objects with protracted information. A specimen of MRI and CT IF to improve disease diagnosis[21]. CT scans find applications to produce high dpi images of bone assemblies, and MRI scans of soft tissue assemblies such as the small organs, on the other hand, IF techniques can be employed in aggregation with CT scans and MRI scans to upsurge precision and medical benefits. MMIF is a process to combine data from different sensors to lessen the ambiguity of the given data and provide enough information compared to the individual quality of respective sensor [22]. Image quality enhancement techniques have been broadly investigated due to essential camera limitations. Since photos taken with a comparable camera can sometimes differ in many ways, no single photo is sufficient to judge the exact situation [5], [23].

In practice, multiple photographs are combined to generate a more comprehensive image that can be employed for subjective as well as objective investigation. Effective integration of imaging data from different modalities provides more detail than imaging proof from individual modality. This causes upsurge in interpretation and provides more consistent results. Its job is to intelligently combine multimodal images. This improves the visibility of objects with extended information. Typically, multiple sensors take two or more photos, and a composite image is proliferated based on comprehensive object and scene visual information. The details of the resulting composite image are clearer, more visible and more recognizable [24], [25]. This technique resolves to excerpt valuable and complementary info from the source. Due to which, hyper spectral imagery has wide applications in isolated sensor detection, face identification, medical image diagnosis, etc. These photos are apposite for use in many places. Biomedicine [26], [27] astronomy [28] and others are important fields of IF.

In some cases, a similar scenery is photographed at several time epochs. In MTIF, images developed at various time intermissions are united to sense any variation [29]. The variances among the pixels of items are perceived by investigating the pictures.The frequency domain, also called transform domain method, falls under the category of MSD. As per the research done by Pan et al. [30], a merged matrix of visual data will include additional data andwill be better for assessing land exterior features.This improves the visibility of objects with extended information.

MVIF combines photos of the same scene from several different angles to get a more accurate image. It helps to create a volume structure of objects based on multiple two-dimensional images. Three-dimensional surface rebuilding is employed in countless applications, for example, industrial plan design, real-time virtual environments, terrain maps and medical imagery. Typically, multiple sensors take two or more photos, and a composite image is proliferated based on comprehensive object and scene visual information. The details of the resulting composite image are clearer, more visible and more recognizable. Bhatnagar et al. [8] [32] developed a scheme to combine the utmost relevant information from multiple imaging modalities into a useful final result for biomedical diagnosis. MVIF combines photos of the same scene from several different angles to get a more accurate image[33].

Due to the increasing variety and availability of satellite sensor data, the high-resolution detection and classification of the Earth's surface changes have attracted extensive interest. The full use and integration of multi-source or multi-temporal isolated sensing imagery is needed for many conceivable tenacities in urban, agricultural, emergency and natural settings to leverage additional information and improve detection recital. In the current context, many Earth observation satellites can collect multi-sensor images of the identical scenery at the same instant, and multispectral (MS) and panchromatic (PAN) images are the utmost widely used data fusion in real-time applications. A Hyper-Spectral Imaging (HSI) sensor can collect numerous spectral frequency bands in a wide range. Since materials often have different reflectivity at multiple wavelengths, Inappropriately, it does not covers the complete investigation of the recently proposed HSI and MSI fusion techniques.

Due to which, hyper spectral imaging has wide applications in isolated sensing, face identification, medical image diagnosis, etc. However, there is some trade-off between spectral accuracy and spatial resolution due to the limitations of imaging equipment. Typically, multiple sensors take two or more photos, and a composite image is proliferated based on comprehensive object and scene visual information. Owing to the limitations of image detectors, HSIs with high spectral resolution often face insufficient spatial dpi.

Image fusion is a competent and gainful way to increase the coordinate density of HSI by fusing it along with an advanced spatial dpi resolution multispectral image (MSI) of the identical scene. In recent years, numerous HSI and MSI fusion techniques have been nurtured to achieve high-dpi HSI. Inappropriately, it does not covers the complete investigation of the recently proposed HSI and MSI fusion techniques.

## II. Related Work Done

The spatial/ magnitude variation approach operates on the magnitude of pixels of the input images, employing the images to achieve the looked-for result. SDIF achieves the results using methods clearly at the pixel magnitude level. Pixel-level proceduresfrequently exploit the ability to createaccurate weight matrices from input images before combining them using biased/weighted fusion. This approach is a simple process that syndicates a minimum/ maximum/ other-criteria pixel value algorithm, a maximum pixel value technique, pixel replacement algorithm, etc.

• Maximum pixel value technique

It selects the highest-intensity pixels from the source images and creates an output result. This has a benefit for images with light tones.

$$F(a,b) = \sum_{a=1}^{M}\sum_{b=1}^{N} \max\big(A(a,b), B(a,b)\big) \quad (1)$$

where A, B are source images and F is the output image.

• Averaging method

The scientific slant of IF encompasses averaging the corresponding pixels of two images and adding them to the correct pixel location in the resulting image. It is a composite technique that averages a combination of pixels into images. This approach emphasises on all pixels of the image and works fine if double type visual data is taken from the same kind of sensor. This improves the visibility of objects with extended information.

$$F(a,b) = \sum_{a=1}^{M}\sum_{b=1}^{N} \frac{A(a,b)+B(a,b)}{2} \quad (2)$$

• Minimum pixel value technique

It selects the lowest intensity pixels from the visual data and creates a printable image. This has a lead for images with dark tones.

$$F(a,b) = \sum_{a=1}^{M}\sum_{b=1}^{N} \min\big(A(a,b), B(a,b)\big) \quad (3)$$

• Max-min technique

The visual matrix can be divided into maximum and minimum pixel values using filters, and the final filter values can be calculated by considering the magnitude difference amongst the maximum in additionwith minimum filter outputs. It processes the smallest and largest pixels of each source photo and creates a composite image as a result.

$$F(a,b) = \sum_{a=1}^{M}\sum_{b=1}^{N} \left(\max\big(A(a,b), B(a,b)\big) - \min\big(A(a,b), B(a,b)\big)\right) \quad (4)$$

Fig 1. shows the structural classification of spatial methods.

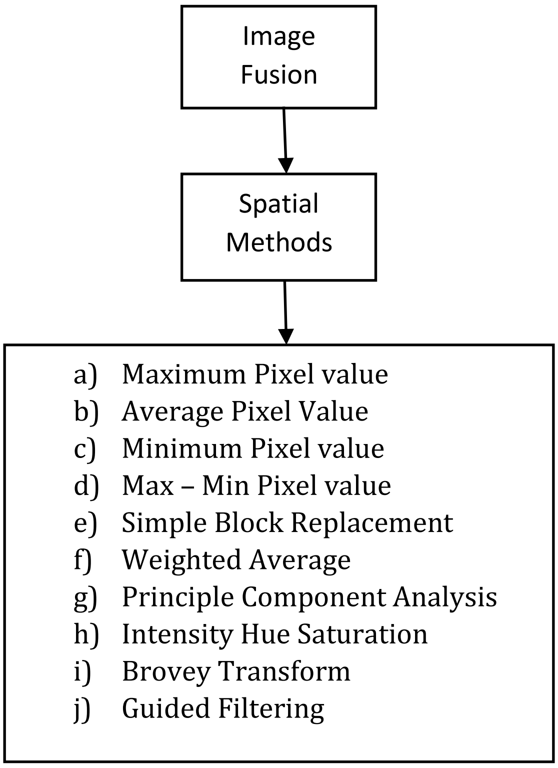


**Fig. 1 Structural Classification of Spatial methods**

**III.Proposed Work Done**

Using the above method, the authors propose an Advanced Minimum (AM) method in which the duty is varied sinusoidally.

The conceptual formula for AM method is as follows:

$$F(a,b) = \sum_{a=1}^{M}\sum_{b=1}^{N} \sin^2 k * A(a,b) + \cos^2 k * B(a,b)$$

Here k is varied from 0 to 360 so as to count all the sinusoidal variations that may vary the duty cycle. Here, the concept of employing duty cycle arises from state space averaging method, usually used in power electronic DC-DC converters. The algorithm of the proposed method is as follows:

- Input the images
- Convert their data types from uint8 to double
- Measure the entropy of the input images
- Now run the iteration as per the formula given in (5)
- Store the entropy values for all the fused image combinations and find the maximum of those entropy values.
- Note down the value of k for which that max entropy was calculated.
- Now using that k value, use the (5) again to retrieve the fused image with max entropy.

## IV.Results

Following two images (Fig. 2(a) and Fig. 2(b)) have been inputted to the algorithm. The output image of the algorithm is show in Fig. 2(c)

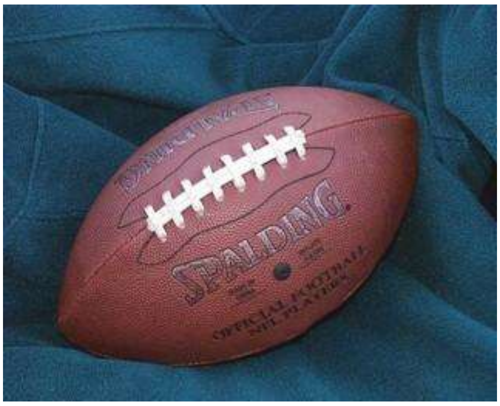


**Fig.2(a)**

**Fig.2(b)**


**Fig.2(c)**

**The entropy values of the visual results are as follows:**

**Table 1. Shows the input and output images along with their entropy values.**

| S. No. | Fig. No. | Entropy Value |
|---|---|---|
| 1. | Fig. 2(a) | 7.1585 |
| 2. | Fig. 2(b) | 7.4042 |
| 3. | Fig. 2(c) | 7.4177 |

## V. Conclusion

This method of fusing two or more images is very easy to implement and is also one of the optimization ways to get the fused image with maximum entropy. It can be observed in Table 1 that the entropy value of fused image is higher than the two input images which means the fused output image has more visual information than the two individual images.

Another advantage of using this algorithm is that the duty cycle is calculated using simple trigonometric identity. As there are other similar identities also so multiple method can be created according to the application or required output.

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