The Effect of Fusion Rule in Sparse-Based Infrared-Visible Image Fusion with Blotless-Update Dictionary Learning Algorithm

Lalit Kumar Saini[1, 3] and Pratistha Mathur[2]
Research Scholar, Department of Information Technology, Manipal University Jaipur, Jaipur, 302007, India[1]
Professor, Department of Information Technology, Manipal University Jaipur, Jaipur, 302007, India[2]
Assistant Professor, Department of CSE, Sobhasaria Group of Institutions, Sikar, 332001, India[3]

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Abstract
Image fusion is the combination of information from multiple images to a single image for various benefits. These benefits are in the form of reducing time, cost, and resources. from many image fusion methods, transfer domain methods had the extra benefit of solving complex problems easily. It is also quite popular due to the wide range of new development in the same domain from time to time. Among the wide range of image fusion applications and types, infrared-visible image fusion is one of the important image fusion techniques. It’s also so much popular due to its various application areas. Security, surveillance, and industrial safety are some of its application areas. Safe driving is one of its application areas by producing high-quality fused infrared-visible images for drivers. In this study, different experiments are done by applying modifications in the basic image fusion rule of the recently proposed sparse representation (SR) based image fusion technique for medical image fusion. The approach is based on the use of the BLOTLESS-update dictionary learning technique as a modification in the SR-based general image fusion framework. The experimental results also confirm that for different-different applications the same fusion rule could not be applied in the same way. So the study and experiments on fusion rule variation are quite interesting and inclined us to develop new fusion rules for infrared-visible image fusion applicable in day and night driving conditions.

Keywords:-Infrared-visible Image fusion, Sparse Representation, Dictionary learning, fusion rule, Safe driving

1.Introduction

Road transport is the primary mode of transport these days and it is also affected by the different weather conditions. Due to the limitation of the human visual system when looking through fog, snow, rain, and smoke, this mode of transport requires an automated visual system (AVS) which particularly works well in all weather conditions [1]. Different automobile companies already introduced a supplementary visual system in trucks and cars for the betterment of the visual system. Famous automobile companies working on camera technology like FLIR for the last five decades and developed low-cost camera systems for the same purpose [2]. So, if the internal algorithms are discussed infrared-visible image fusion plays an important role in developing the same type of camera systems for many years.

In bad weather conditions, whether it's day or night, the drivers need a supplementary visual system. That can easily achieve by fusing infrared-visible images [3]. Infrared images are the images in which the temperature of an object is measured. All objects emit electromagnetic radiation, mostly in the infrared (IR) range, which is invisible to the unaided eye. On the other hand, IR radiation can be perceived as heat on the skin. Objects generate more infrared radiation when they are hotter. On the other hand, visible images are the general images captured like HVS in the visible range in the wavelength spectrum.

So infrared-visible image fusion is one of the main technologies that play an important part in developing these types of solutions. Image fusion is the technology used for combining the information from multiple images produced by different types of image-capturing sensors. It has many types depending on the application type, sensor type, and source image type Spatial domain and transfer domain image fusion are the two most used terminologies as their type. Furthermore, the transfer domain methods can be classified as deep learning and sparse-based image fusion techniques [4]. In recent years SR- based image fusion techniques are also quite popular due to their beneficial properties like space reduction and better performance compared to other benchmark image fusion methods.

As the Sparse representation is discussed it is the signal modelling technique used as a tool in signal processing and image processing applications [4]. Sparse representation is the representation of signal or data in which only a few coefficients or parameters are non-zero and mostly others are zeros. "This means it is a linear combination of data or signals with linear combinations of a few dictionary elements called atoms" [5]. The whole idea of the sparse representation is given in figure 1 as shown below. So the dictionary D here is used to produce the final signal S with the help of a sparse representation of S in the form of α.

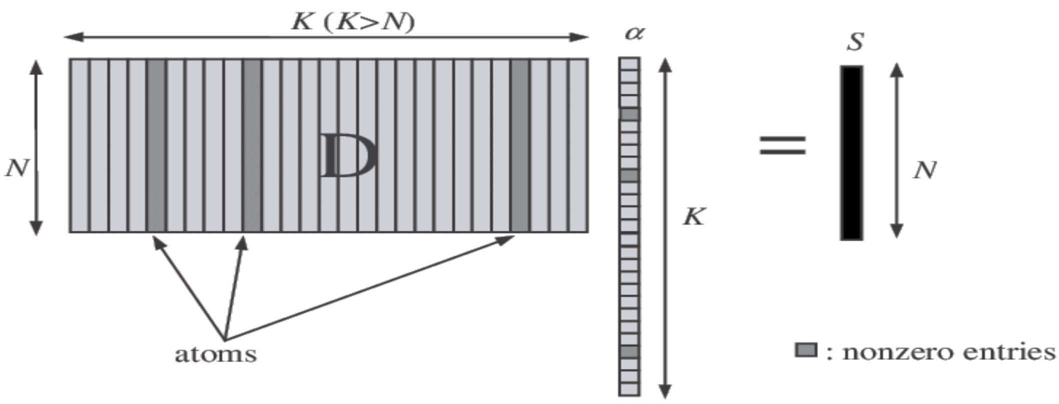

Figure 1 Principal idea of sparse representation

Dictionary learning is one of the unique sub-domains of sparse approximation [6]. The basic purpose of dictionary learning is to provide the best possible dictionary for finding sparse coefficients for a signal. As shown in figure 1 the dictionary is a matrix where each column is treated as an atom. Initially, some basic transforms like cosine, contourlet, and curvelet are used for dictionary learning but the trained dictionary performs well according to the research. In the case of image processing with SR, the input images are used as training images are the best option for better performance [5].

But the fusion rule is one of the important factors in digital image fusion. How efficiently the coefficient is merging, whether it is in the spatial domain or transfer domain, is directly dependent on the fusion rule. In many years so many fusion rules are proposed, some of the fusion rules are "choosing-max, choosing min, min-max, average, mean, threshold-based adaptive fusion rule, PCA –weighted fusion rule [7]. So in some methods fusion rules are applied according to the requirement of the application of fusion.

The current manuscript is divided into some sections. The literature survey on infrared-visible Image fusion with sparse representation with various applications is included in section 2. A proposed study on the fusion rule and its effect on SR-based infrared visible image fusion with the BLOTLESS-update dictionary learning technique [8] is discussed in section 3. Experimental results including detailed analysis are included in section 4. In the last section, the conclusion of this study is given with future work.

2.Literature Survey

Deep research is done on infrared-visible image fusion due to the heavy demands of these algorithms for industrial purposes. These algorithms are been proposed in the last three to four decades from the beginning of sensor development for specialized photography. Most importantly these algorithms are the main part of satellite imagery also. Yang, Wen Liu, et al. [9] In 2013, a color fusion method was proposed for infrared and low-light images using sparse representation applied to the fused image of a specific channel. In 2014, Wang [10] introduced an intriguing method for fusing visible and infrared images called NNSP, in which the characteristics of the source images are extracted using non-negative sparse representation. However, the ASR (Adaptive sparse representation) model for simultaneous picture fusion and denoising was presented by Liu and Wang [11] in the same year. The approaches of IR-VI image fusion with a sparse-based compressed sensing technique were proposed in 2015 by Liu, Yin, et al. [12]. By significantly reducing computational complexity, the CS-based fusion strategy can also improve the quality of the fused image. The difficulty of SR-based fusion stated above is recovered by a simple-yet-effective fusion framework based on CSR, which was developed by Liu, Chen, et al. in 2016 [13].

A fusion technique based on spatial convolutional sparse representation is proposed by Luling Shao et al. [14]. It can perform global representation on local image patches with a gradient constraint, effectively extracting the details and intensity information of the source image, and improving the quality of the fused image as a result. A fusion approach for infrared and visible images was developed by Duan, Liu, et al. in 2021 [15] using a truncated Huber penalty function (THPF) smoothing-based image decomposition, a visual saliency-based threshold optimization (VSTO) fusion strategy, and a sparse representation (SR) fusion strategy. Deep learning techniques, in particular, have become increasingly popular in recent years for the fusion of infrared and visible images [16].

A lot of work is also done as a targeted application area of infrared-visible image fusion as developing Advanced Driver Assistance Systems (ADAS) for automobiles. Poor weather conditions are the main cause of road accidents on Indian roads. According to the National crime record bureau (NCRB) published report of "Accidental Deaths and Suicides in India-2021" (ADSI-2021) [17] a total of 2.8% means 11,110 cases out of 4,03,116 accidents were due to poor weather conditions. That needs to be reduced by technological advancements like infrared imagery and the development of low-cost image processing devices. Image fusion is one of the main contributors in the direction of achieving the milestone of reducing in minimal numbers. Lots of work is done by many automobile companies in the development of ADAS to recover from unwanted accidents and losses of lives. In recent years some of the works are quite impressive with the help of image fusion with transfer domain techniques and deep learning techniques. The visible-NIR image fusion approach is used by Vanmali, Gadre, et al. [18] to address this issue rather than using the traditional imaging methodology. Weight maps generated local entropy, local contrast, and visibility used as metrics that influence the fusion result are used to direct the proposed algorithm's Laplacian-Gaussian pyramid-based multi-resolution fusion process. A learning-based technique for fusing visible and thermal images was proposed by Shopovska, Jovanov, et al. [19] in 2019 to create fused photos with a high degree of visual similarity to RGB images while incorporating new educational elements in pedestrian areas. The objective is to produce natural, intuitive visuals that would be more instructive to a human driver in poor visibility situations than a standard RGB camera.

In 2021 an enhance vehicle recognition performance in adverse weather situations, Wang, Zhan, et al. [20] provide the most recent vehicle detection system based on multi-sensor fusion. First, a method for effectively extracting vehicle targets from the radar is suggested, using supervised learning to train a LightGBM-based classifier. With the help of this technique, the target extraction may be converted into a data-driven classification without the need for sophisticated prior information to define the target segmentation threshold. Whereas in the current year, He and Liu [21] proposed a feature fusion method that is intended to enhance the camera sensor's performance in driving obstacle identification in foggy conditions. The explanation for the camera sensor's decreased detection ability in foggy situations is discovered by comparing the differences in image attributes of the same traffic scene on sunny and foggy days. The collection of foggy images is created, and YOLOv3 is used to realize the feature fusion of the detecting object in both foggy and sunny conditions.

3. Proposed fusion rule variation for infrared-visible image fusion

3.1Use of modified fusion framework

In the proposed study and experiments the recently proposed sparse-based modified fusion framework for medical image fusion is used. That modification is done with the help of the BLOTLESS-update dictionary learning algorithm [8]. As discussed in the introduction part the dictionary learning techniques are the key factor in the sparse-based fusion methods. In the last two decades, some of the benchmark dictionary learning algorithms are proposed like MOD [22], KSVD[23][24], SIMCO [25], etc.

By Qi Yu et al.[8] in 2020, the Dictionary algorithm with BLOTLESS updating is presented. The Block Total Least Squares (BLOTLESS) algorithm updates the dictionary blocks and accompanying sparse coefficients simultaneously. The prerequisites for reliable dictionary recovery are noted and explained. The bilinear nonconvex blocks update issue is converted into a linear least squares problem in the procedure, which is subsequently successfully solved.

Thus, the entire dictionary D is split up into several sub-dictionaries as a solution to the problem above. These sub-dictionaries are updated one at a time, with the other dictionaries and corresponding coefficients remaining fixed. All sub-dictionaries have undergone this updating process. The sub-dictionaries are treated as separate blocks.

3.2 The fusion rule variation

As per the modified framework used in proposed by Saini & Mathur [26], the normal mean method is used for the meaning of image sparse coefficients. But for better results, some variations on the fusion rule are proposed in this general fusion framework for a set of day fusion and night fusion conditions.

The modified fusion framework proposed by Saini & Mathur [26] used this framework for medical image fusion so they used the same fusion rule for all kinds of medical images. In the SR-based image fusion framework, patch-based coefficient fusion is done. Initially, mean_1 of path 1 (patch from the first image) is calculated followed by calculation mean_2 of patch 2 (patch from the second image). The w1 and w2 are also generated with the help of the OMP algorithm and learned dictionary by the BLOTLESS-update dictionary learning algorithm [8]. Then fusion goes like that:

Basic Fusion Rule:

```
If (sum (abs (w1))>sum (abs (w2)))
{
   W_f=w1
   Mean_f =mean_1
}
else
{
  W_f=w2
  Mean_f =mean_2
}
```

After that final fuse patch is generated by multiplying dictionary D and final W_f (W_fused) followed by adding Mean_f (Mean_fused). This same process is also applied for infrared-visible image fusion with the FLIR dataset [27] for both fusion conditions of day and night fusion but the results are impressive but not satisfactory. So the variation in fusion rules is applied to get better fusion results. These variations are different for day and night conditions. The key factor is we need wisely choose the W_fused and Mean_fused for day and night conditions.

From mean_1 and mean_2 calculations followed by calculations of w_1 and w_2 the process are same. But after that, the fusion rules follow as:

Modified fusion rule:

```
If (sum (abs (w1))>sum (abs (w2)))
{
   W_f=w1
   Mean_f =mean_2 // Change
}
else
{
   W_f=w2
```

Mean_f =mean_2

}

Left all processes are done as same as the basic modified framework. In day conditions mean_2 is applied for calculating Mean_fused in both conditions.

4.Experiments and result analysis

In this section, the experiment and their findings are shown for both the steps of all experiments. The whole experiment is processed in two phases.

Phase 1: Infrared-visible image fusion by basic modified SR-based fusion framework with BLOTLESS-update dictionary learning algorithms [8].

Phase 2: After getting the results of phase 1 the modified results are getting using phase 2. In phase 2 the infrared-visible image fusion by a modified SR-based fusion framework with fusion rule variations and BLOTLESS-update dictionary learning algorithms [8][26] for fusion in day and night driving conditions.

The source image pairs of 5 pairs of infrared-visible image pairs in the day driving conditions and 5 pairs of infrared-visible image pairs in night driving conditions from 180 image pairs from the FLIR image dataset [27].

4.1 Hardware and software resources

As described above the experiments are done in two phases. In both phases, the dictionary is learned by 16 natural random grayscale images with dimensions of 256x256 of type uint8. The dictionary is learned with BLOTLESS-update dictionary learning algorithms with a patch size of 16x16. The algorithm runs up to 10 iterations. For both phases, All fusion methods the day and night public benchmark dataset FLIR [27] are used. It had 180 Infrared-visible image pairs for experimental purposes of 128x128 dimensions. All the experiments are done with randomly selected 5-5 image pairs of day and night driving conditions. These 10 selected images are shown in figure 2. All the experiments are performed by MATLAB R2018a with the hardware configuration of Intel(R) Core™ i5-2450 CPU@2.50GHZ and 8 GB RAM.

Table 1 The random five sets of IR-VI image infrared-visible image fusion in day and night driving conditions from the FLIR dataset

S.no	**Day Conditions**		**Night Conditions**	
	Visible Image	**Infrared Image**	**Visible Image**	**Infrared Image**
1				

2				
3				
4				
5				

4.2 Results and Discussions

Results Phase 1:

The image fusion results of phase 1 are shown in figure 2 as the ten fused images. The first row shows the fused images at night conditions whereas the results of day conditions are shown in row 2. The fusion results are fine but not satisfactory. The fine details are missing in the images in all the images as shown in figure 2. Also, the day-condition fused images are looking like night images. Some crucial information in fused images is also not transferred from source images to single fused images like:

(a.) Object corners information is not sharp.
(b.) Edge information
(c.) Lightening information is not up to date.
(d.) Power cables across the road are not visible infused.
(e.) Objects are not distinctly identified

Result Phase 2:

All the problems of output fused images of phase 1 are recovered in the results of phase 2. These resulting fused images are shown below in figure 2. By qualitative analysis anyone can easily identify the benefit of phase 2 variations in final fused images like all objects are easily identified, edges are sharp, lightning information is better, and corners information is better.

Figure 2 Phase 1 results of infrared-visible image fusion in Day and Night driving conditions using a recently proposed modified SR-based general fusion framework with BLOTLESS-update dictionary learning algorithm

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Figure 3 Phase 2 results of infrared-visible image fusion in Day and Night driving conditions by proposed variations in fusion rule for a day and night conditions.

5.Conclusion and future work

In this paper, the recently proposed modified fusion framework by the BLOTLESS-update dictionary learning algorithm, which has application in medical image fusion, is applied to Infrared-visible image fusion. For the same, we learned an over-complete dictionary with the help of the BLOTLESS-update dictionary learning algorithm. As an input image for dictionary learning, sixteen random natural grayscale images are used. Then for the fusion process input images are divided into small patches of dimension 8x8 followed by lexicological order arrangement. A standard FLIR dataset containing infrared-visible image pairs is used as testing the framework. The results are good but not satisfactory. In fused images, the transferred information has some sort of problem. This all is done in the first phase of experiments. In the second phase, the framework used in the first phase is modified with variations in the fusion rule. The proposed modification with the fusion framework is tested with the same dataset used in phase 1. The proposed fusion rule variations in the first phase framework. The results of phase 2 are quite impressive and better than phase 1. So it is easily identified by experiments that for the different input images the same framework can't work efficiently with the same fusion rule. We need to modify it according to the requirements of the application domain

The current work is extendable with variations with various datasets like a satellite image dataset with different bands and the current variation is also compared with standard infrared-visible image fusion methods with quantitative analysis

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Conflicts of interest

The authors have no conflicts of interest to declare.

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Lalit Kumar Saini is a research scholar at Manipal University Jaipur, Jaipur (India). He received his BE and M.Tech degrees in Computer Engineering from the University of Rajasthan and RTU, Kota, respectively. His current research interests include Digital Image Fusion, Sparse Representation, Dictionary learning, and Compressed sensing algorithms.
Email:lalitkumar20april@hotmail.com

Dr. Pratistha Mathur is a Professor in the Department of Information Technology at Manipal University Jaipur. She has done her Ph.D. and M.Tech in Computer Science from Banasthali Vidyapith in 2012 and 1998. Her research areas are Digital Image Processing, Soft Computing, and Machine Learning. She has published more than 40 papers in international and national journals and conferences.
Email:pratistha.mathur@jaipur.manipal.edu