REGION BASED FUSION OF THERMAL AND VISIBLE IMAGE

A Dissertation submitted towards the partial fulfilment of
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Submitted by

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CERTIFICATE

This is to certify that the dissertation title "**Region based fusion of thermal and visible image**" submitted by **Mr. Sudhir, Roll. No. 2K15/SPD/17**, in partial fulfilment for the award of degree of Master of Technology in "**Signal Processing and Digital Design(SPDD)",** run by Department of Electronics & Communication Engineering in Delhi Technological University during the year 2015-2017., is a bonafide record of student's own work carried out by her under my supervision and guidance in the academic session 2016-17. To the best of my belief and knowledge the matter embodied in dissertation has not been submitted for the award of any other degree or certificate in this or any other university or institute.

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I hereby declare that all the information in this document has been obtained and presented in accordance with academic rules and ethical conduct. This report is my own work to the best of my belief and knowledge. I have fully cited all material by others which I have used in my work. It is being submitted for the degree of Master of Technology in Signal Processing & Digital Design at the Delhi Technological University. To the best of my belief and knowledge it has not been submitted before for any degree or examination in any other university.

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1 Introduction

Within the last decades substantial progress was achieved in the imagery sensor field. Improved robustness and increased resolution of modern imaging sensors and, more importantly, cheap fabrication costs have made the use of multiple sensors common in a wide range of imaging applications. This development led to the availability of a vast amount of data, depicting the same scene coming from multiple sensors. However, the subsequent processing of the gathered sensor information can be cumbersome since an increase in the number of sensors automatically leads to an increase in the raw amount of sensor data which needs to be stored and processed. This means that longer execution times have to be accepted or the number of processing units and storage devices has to be increased, leading to solutions which may be quite expensive. In addition, when imaging systems are operated by humans, presenting various images may be an overwhelming task for a single observer and may lead to a significant performance drop. One solution for these problems is to replace the entire set of sensor information by a single composite representation which incorporates all relevant sensor data. In image-based applications this plethora of techniques became generally known as image fusion and is nowadays a promising research area. Image fusion can be summarized as the process of integrating complementary and redundant information from multiple images into one composite image that contains a 'better' description of the underlying scene than any of the individual source images could provide. Hence, the fused image should be more useful for visual inspection or further machine processing. Nevertheless, fusing images is often not a trivial process, since: a) the source images may come from different types of sensors (e.g. with different dynamic range and resolution); b) they tend to exhibit complementary information (e.g. features which appear in some source images but not in all) or c) they may show common information but with reversed contrast, which significantly complicates the fusion process. Furthermore, a fusion approach which is independent of a priori information about the inputs and produces.

a composite image that appears 'natural' to a human interpreter is highly desirable. In general, the following requirements can be imposed on the fusion algorithm :

• it should preserve all relevant information contained in the input images;

• it should not introduce any artifacts or inconsistencies which can distract or mislead a human observer or any subsequent image processing task;

• it should be reliable, robust and tolerant of imperfections such as noise and misregistrations.

Image fusion may be applied to images coming from different sensors (multisensor fusion), taken at different times (multitemporal fusion), obtained using various focal lengths (multifocus fusion), taken from different viewpoints (multiview fusion) or captured under different exposure settings (multiexposure fusion).

1.1 Categorization of image fusion:

The process of image fusion can be performed at three different levels of information representation, namely pixel-, region- or decision-level “. In the following we briefly introduce each one of them.

1.1.1 Pixel-level image fusion:

Image fusion at pixel-level represents the combination of information at the lowest level of information representation, since each pixel in the fused image is determined by a set of pixels in the source images. Usually, this set consists of a single pixel or comprises of all pixels within a small window, typically of size 3×3 or 5×5. The advantage of pixel-level fusion, apart from its easy and time-efficient implementation, is that the resulting image contains the original information from the sources [7]. However, since pixel-level fusion methods are very sensitive to misregistration, co-registered images at sub pixel accuracy are required. Today, most image fusion applications employ pixel-level fusion methods.

1.1.2 Region-level image fusion:

Region-level fusion approaches typically start by extracting all salient features from the various input images. This is done by applying an appropriate segmentation algorithm which identifies all salient features within the input images with respect to certain properties such as size, shape, contrast, texture or gray-level. Based on this segmentation, a region map is created which links each pixel to a corresponding feature. Consequently, the fusion process is performed on the extracted regions (as opposed to pixel-level image fusion where the fusion result is determined by an arbitrary set of pixels). Region-level image fusion usually yields advantages compared to pixel-based techniques since some drawbacks, such as blurring effects, high sensitivity to noise and misregistration can be avoided [7]. However, the final fusion performance of region-level image fusion methods highly depends on the quality of the segmentation process. In other words, segmentation errors such as under- or over-segmentation may lead to the absence or degradation of certain features in the fused image [8].

1.1.3 Decision-level image fusion:

Fusion at decision-level allows the information from multiple sensors to be effectively combined at the highest level of abstraction. In this context, first a decision map is built for each source image by performing a decision (labeling) procedure on all input pixels. Finally, a fused decision map is constructed based on the individual decision maps. For this purpose decision rules are used which reinforce common interpretation and are able to resolve differences between the individual decision maps.

The choice of the appropriate level depends on many different criteria such as the underlying application, the characteristics of the physical sources as well as on other factors such as execution time and the available tools. However, there exists a strong inter-linkage between the different levels of image fusion. Many fusion rules which are used to determine the individual pixels in the composite image at pixel-level can, for instance, also be used at region-level to fuse the extracted features. Furthermore, decision-level fusion often resorts to the segmentation map created at region-level to aid with decision-making. In this work we are mainly concerned with the fusion of images at pixel-level. However, in Chapter 5 we introduce a fusion framework which uses concepts of both pixel- and region-level fusion to merge visible and infrared (IR) images.

1.2 Application fields

Image fusion has attracted a great deal of attention in a wide variety of different application areas in the last decades. Generally speaking, all imaging applications that require the analysis of more than one image can benefit from image fusion. In what follows we try to classify all these applications into the four main categories: military, remote sensing, medical science and industrial applications.

(a) (b) (c)

Figure 1.1: Military fusion example. (a) Visible image. (b) Infrared image. (c) Resulting image using the fusion framework of Chapter 5 with target detection and target highlighting. Source images kindly provided by Mr. David Dwyer from OCTEC Limited.

1.2.1 Military:

Historically, military appeared as one of the first application areas for image fusion. It covers applications such as concealed weapon detection [10–13], identification, detection and tracking of targets [14, 15], mine detection [16] and tactical situation assessment [17]. Fig. 1.1 illustrates how the fusion of an IR and visible image pair can be utilized to improve the situation awareness at a location with heavy smoke concentration. It can be noticed that the visible image in Fig. 1.1(a) exhibits a high degree of textural information but is not able to penetrate the smoke. On the other hand, the IR image is able to “see through” the smoke but lacks most of the details depicted in the visible image. The fused image, however, is able to provide the most salient1 information from both source images.

1.2.2 Remote sensing:

Remote sensing is defined as the measurement of object properties on the earth’s surface using data acquired from aircrafts and satellites by means of optical sensors. These systems, particularly those deployed on satellites, provide a repetitive and consistent view of the earth providing valuable information about short- and longterm changes and the impact of human activities [18]. In most remote sensing applications, due to physical constraints, a trade-off between spectral and spatial resolution has to be accepted. In other words, some satellite sensors supply the spectral bands needed to distinguish some features spectrally but not spatially (multispectral image), whereas other sensors include the spatial information needed to distinguish features spatially but not spectrally (panchromatic image). In the context of image fusion we are interested in means to merge images from various sensors into a single image which provide, both, a high spatial and spectral resolution.

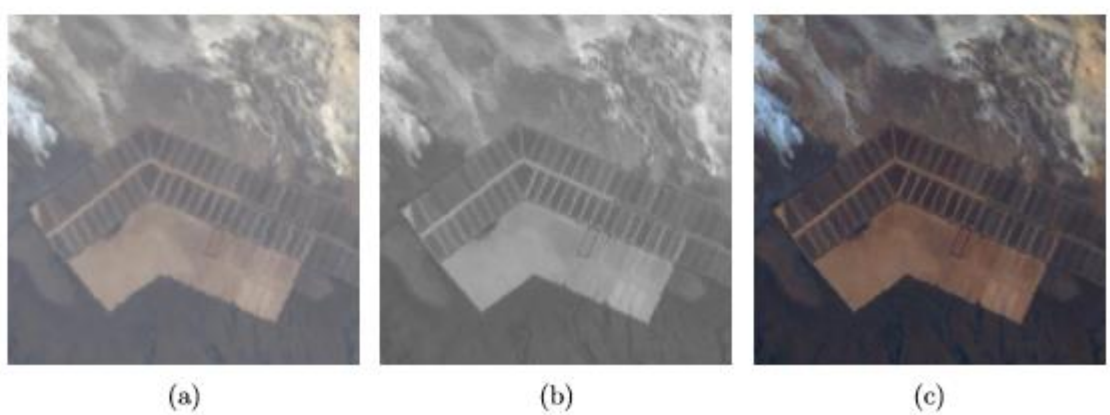


Figure 1.2: Remote sensing fusion example. (a) Multispectral image (pseudo-color). (b) Panchromatic image. (c) Resulting image using a PCA-based fusion strategy

Many image fusion methods have been proposed for this purpose, among them the intensity-hue-saturation transform [19], the Brovey transform [20, 21] and the Principal Component Analysis (PCA) [20, 21] as well as approaches based on multiscale transforms [20–25]. Fig. 1.2 exemplifies the fusion of a multispectral image (Fig. 1.2(a)), consisting of four spectral bands, with the panchromatic image of Fig. 1.2(b), using the PCA method as explained in [20]. It can be observed that the composite image in Fig. 1.2(c) provides more spatial information than Fig. 1.2(a) without losing spectral information. Note that for displaying purposes, Fig. 1.2(a) and Fig. 1.2(c) show only the first three spectral bands in the RGB color space, resulting in the depicted pseudo-color images.

1.2.3 Medical science:

Within the medical community, image fusion has gained an increasing amount of attention in the last decade. Its main application areas can be found in clinical applications such as medical diagnostics, treatment planning and during curative phases such as guided/assisted surgical procedures. The set of input data covers imaging sensors such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron-Emission-Tomography, Single Photon Emission Computed Tomography, Ultra-Sound and many variants thereof [26]. The fusion of a sample CT and MRI image pair is shown in Fig. 1.3. Here, the information provided by the CT image in Fig. 1.3(a) and the MRI image of Fig. 1.3(b) is complementary. It is well established that soft tissues are better visualized in MRI images than in CT images. Thus, MRI images are commonly used to diagnose pathological soft tissues such as brain tumors. However, the spatial accuracy of the MRI image for stereotactic2 localization (e.g. localization of the tissue bone in stereotactic surgery) is very poor due to magnetic susceptibility effects and may result in geometric shifts and distortion effects of up to 4 mm [27].

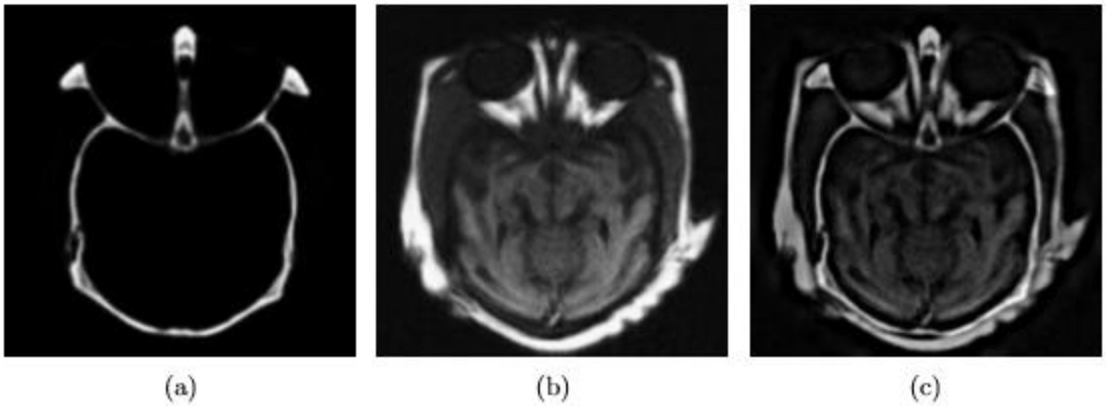


Figure 1.3: Medical fusion example. (a) CT image. (b) MRI image. (c) Resulting image using a fusion strategy based on the Dual-Tree Complex Wavelet Transform.

On the other hand, CT imagery does not suffer from this shortcoming. The fusion of CT and MRI images, as illustrated in Fig. 1.3(c), can therefore be used to remove the geometric distortions inherent in MRI imagery and improve the results in stereotactic radiotherapy.

Industrial engineering Image fusion is used in a wide variety of industrial and civil applications. In robotics, multisensor information is used to estimate the position and orientation [28, 29] as well as to navigate a robot in order to avoid collisions and stay on a preset path [28]. Moreover, image fusion is applied in computerized quality management for defect inspection of products [30, 31]. Fig. 1.4 shows an example how image fusion can be used to extend the depthof-focus of existing image capturing systems. Due to the limited depth-of-focus of individual optical lenses (see Figs. 1.4(a) and 1.4(b)), it is often impossible to get a single image with all objects in focus. One way to overcome this problem is to collect several images from the same scene but with different focus points and combine them into a single composite image which contains the focused regions of all input images. Another application of image fusion in the industrial context is the combination of multi exposure images [32–34]. A natural scene often has a high dynamic range that exceeds the capture range of common digital cameras. Therefore, a single

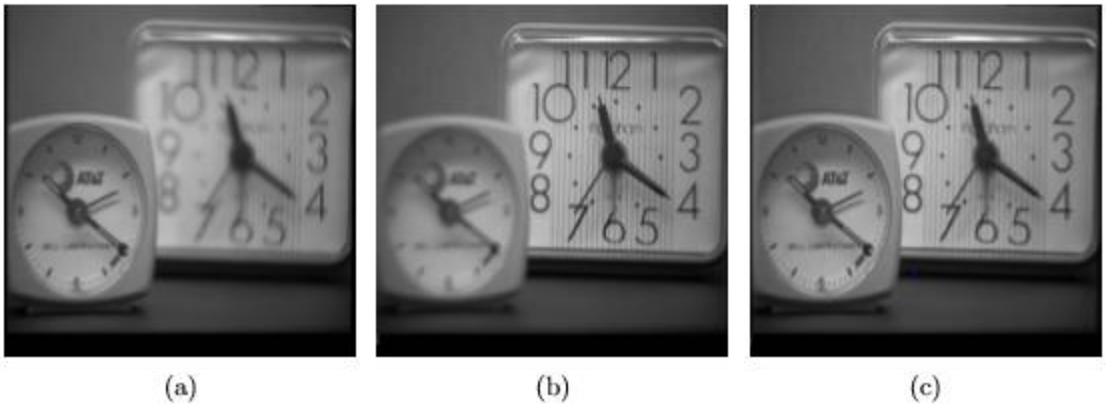


Figure 1.4: Industrial fusion example. (a) image with focus on the front. (b) image with focus on the back. (c) Resulting image using a fusion strategy based on the Non subsampled Contourlet Transform (NSCT)

captured image is usually insufficient to reveal all the details due to under- or overexposed regions. To solve this problem, images of the same scene can first be captured under different exposure settings and then be combined into a single image using image fusion techniques.

The presented list is by no means exhaustive and should merely provide an insight into the most important developments in the field of image fusion. Furthermore, we would like to point out that the image fusion research community is still very active, thus, new application fields are still explored. In this work we will be restricted to the fusion of multisensor images, exhibiting a high degree of diverging information. Hence, our main focus is placed on the fusion of IR-visible and CT-MRI image pairs as found in military and medical applications.

2 Literature Review:

Image fusion is a very wide research topic. There are many techniques in this field for fusion and a large numbers of paper are also published in this areas using various technique. The low pas contrast pyramid method is adjustable according to visual characteristics (1). The advantage of this technique is to retain the high bright and high contrast information [2]. This technique is apply on different resolution of images. The advantage of this method is that we can easily use this method but this method is slow and takes time in computation. Wavelets transformation is also the fusion technique. In this technique we convert the image in frequency domain and we got the image in four parts and tha maximum information is attain by LL part. This technique is also called as rescaling technique. Here we do fusion in frequency domain and when we got fused image we convert in to time domain using inverse discrete wavelets transformation [3]. The drawback of this technique is influenced by wavelets decomposition order no [4] and domino effect. In contrast modulation the gray image which is of less resolution is modulated by clear scale resolution [5]. In contrast modulation we required minimum two images of same time and the effect of fusion is directly related to the difference of gray scale resolution and sensors spatial [6]. In Bayesian inference method the information which contain low value or credibility is deleted by using the importance of the information because they creates only error and effect the result very much. Bayesian estimater retains the information and create the required fusion result [7]. This technique takes each snsors as a baysian classifier and give optimal output. The disadvantage of this technique is that the uncertainty expression did not give good result [8]. In template pattern recognition completes with complex relation using comparing observing data with prior templetes [9]. Parameter templatas usually contains parameter, Boolean conditions, weight cofficent, threshold, etc. ANN (artificial neural network) is a biological information processing method of our nervous system [10]. ANN contains a large no of unit which is used as data set for input and these are use as nonlinear transformation for the classification of data in to property. The theory of this method is still a good area of research .eg the number of combination present among neural network and the traditional classification method[11] and the layer of neural network ,choice among nodes numbers [12]etc. Changing color of space change is a fusion strategy in view of HIS (Intensity, Hue, Saturation) display and the handling techniques for gray pictures and color pictures [13]. As indicated by application extension and reason, color space change models can be separated into two classifications [14], which are models situated to equipment gadgets and models connected to color preparing applications. RGB show is the most usually utilized model situated to hardware [15], and HIS model is the most normally utilized model arranged to color preparing [16].

Now there are some method related to Fusion based on color space component replacement

Brovey Brovey is a fusion technique generally utilized as a part of proportion transformation of pictures improvement [17]. Brovey can't just simplify the procedure of picture color space change, additionally can keep the ghostly data of the first multispectral pictures [18].However, if the range of spectral scope of the first multispectral imageand panchromatic picture is substantial, it will cause color distortion of phantom data in fusion pictures [19]. Brovey is mainly used when multi-range pictures of low spatial determination and panchromatic pictures of high spatial determination are comparative. In addition, it will guarantee that the gray esteem scope of combination pictures after gray space extending should equivalent to that of unique multi-spectral images with various groups [20,21]. PCA is a technique that multi-dimensional orthogonal linear transformation is done in view of measurable properties [22], and can change multi-phantom and panchromatic pictures with highly relationship into unimportant factors [23]. The disadvantage of PCA is that it will misshape the otherworldly data of pictures after PCA change of panchromatic and multi-spectral images [24]. Laplace pyramid transform is used for analysis of muti resolution image fusion by this method the interpolation of sequence [27]. According to saleem [28] gave an new method for muti-source image’s sequence based on their contrast pyramid transformation. But this method has disadvantage because its ability of extraction is very poor after decomposition on multi scale [29]. After this Li [30] gave an method which improve the gradient pyramid of muti source fusion method, which gives cofficents of high band using gradient direction operator. Image fusion [34]can be performed at three different levels, i.e., pixel level, feature level, and decision level. Many applications that require analysis of two or more images of a scene have been benefited from image This fast growing trend can be attributed to three major factors: (1).The increased demand on developing low cost and high performance imaging techniques. The design of sensors with better quality or some specific characteristics may be limited by technical constraints, and image fusion has become a powerful solution to this problem by combining the images captured with different sensors or camera settings.(2)The development of signal processing and analysis theory. For survey of early proposed image fusion methods, Zhang and Blum give a categorization of the multi-scale decomposition based image fusion methods. Furthermore, the surveys of the image fusion methods in some specific application fields have been published in recent years. In the medical imaging field, James and Dasarathy summarize the state-of-the-art image fusion methods. The details of particular algorithms or results of comparative experiments will not described. More efforts will be spent on summarizing main approaches and pointing out the interesting ideas of the existing image fusion methods and applications.

Pixel-level image fusion methods Pixel-level image fusion methods can be categorized into four major families:

(1) The multi-scale decomposition based methods; (2) The sparse representation based methods; (3) The methods which perform the fusion directly to the image pixels or in other transform domains such as the principal component space or the intensity-hue-saturation color space.(4) The methods combining multi-scale decomposition, sparse representation, principal component analysis, and other transforms.

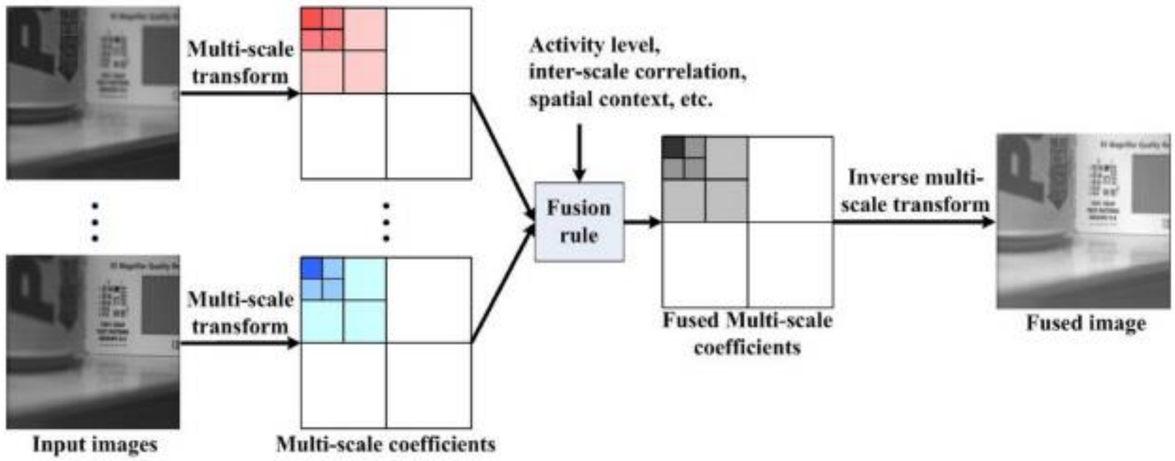


Fig. 2.1. The main stages for a generic multi-scale based image fusion method.

3. Sparse representation based methods: The sparse representation [2] can describe the images (or image patches) by a sparse linear combination of atoms selected from the over-complete dictionary. The obtained weighted coefficients are sparse, which means that only very few non-zero elements in the sparse coefficients can efficiently represent the saliency information of the original images. For capture local salient features and keep shift invariance, the input images from multiple sources are firstly partitioned into many overlapped patches. Then, patches from multiple images are decomposed on the same over-complete dictionary to obtain the corresponding sparse coef- ficients.. Finally, the image is reconstructed using the fused coefficients and dictionary.

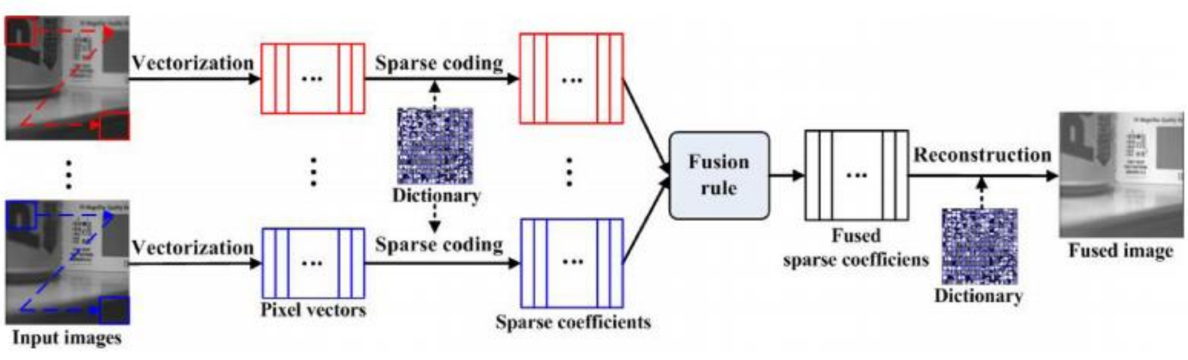


Fig. 2.2 The main stages for a generic sparsity based image fusion method.

In image fusion based on discrete wavelet transform (DWT) [35]with blurre image information, an effective visible light, infrared image fusion algorithm via feature residual and statistical matching is proposed in this study. First, the source images are divided into high-frequency coefficients and lowfrequency coefficients by DWT. The cofficent of low-frequency are fused by a local feature residual-based scheme to achieve adaptive fusion; the high frequency coefficients are accomplished by a local statistical matching-based scheme to extract the edge information effectively. Finally, the reasultant image is obtained using inverse DWT. The source images are decomposed into various scales and three directions by DWT, and the low-frequency and high frequency coefficients are obtained. Different rules are employed to create a new composite coefficient from input coefficients. For the low-frequency coefficients, the simplest method is the weighted average, but this method results in fused image with low contrast and cannot make full use of the complementary information of source images. For the high coefficients, the widely used rule is selecting the coefficients corresponding to the largest absolute value. For the image fusion based on DWT, researchers have put forward many fusion methods. have proposed DWT-based image fusion, which is pixel-based fusion approach. In order to overcome the limitation of pixel-based fusion algorithm,Chu have proposed a window-based algorithm for image fusion, which selected the low-frequency coefficients through the local gradient. In recent years, non-negative matrix factorisation (NMF) has been introduced to image fusion. Although the NMF-based image fusion method can improve the quality of fused image, it suffers from the complexity of algorithm and time consuming. To obtain a clear fused image, an effective fusion method is proposed in this paper. DWT is employed to decompose the source images. For the low-frequency coefficients, local feature residualbased scheme (LFRS) is employed, which can extract source image textural structure by the residual of local feature. The adaptive fusion could be achieved through the extracted local structure. For the high-frequency coefficients, local statistical matching-based scheme (LSMS) is applied. The mutual matching and selfmatching are used to extract the edge information. Experiments show that our approach outperforms previous ones, and could produce more accurate fusion results both in visual effect and in objective evaluation.

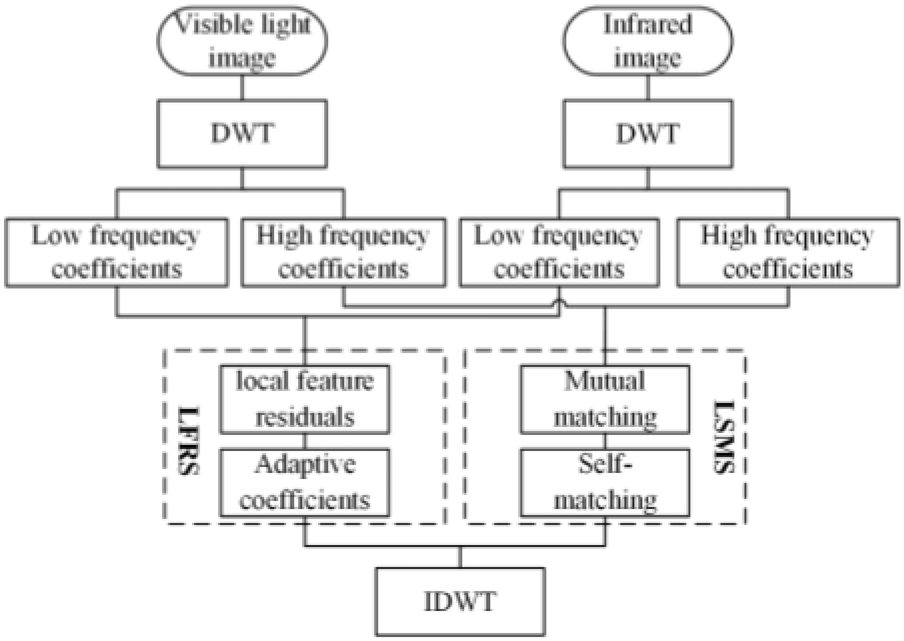


Fig. 2.3 Frame work of fusion algorithm based on DWT

This paper presents an overview on image fusion techniques using multi resolution decompositions. The aim is twofold: (i) to reframe the multi resolution-based fusion methodology[36] into a common formalism and, within this framework, (ii) to develop a new region-based approach which combines aspects of both object and pixel-level fusion. To this end, we first present a general framework which encompasses most of the existing multi resolution-based fusion schemes and provides freedom to create new ones. Then, we extend this framework to allow a region-based fusion approach. The basic idea is to make a multi resolution segmentation based on all different input images and to use this segmentation to guide the fusion process. Performance assessment is also addressed and future directions and open problems are discussed as well.

Extraordinary advances in sensor technology, microelectronics and communications have brought a need for processing techniques that can effectively combine information from different sources into a single composite for interpretation. In image-based application fields, image fusion 1 has emerged as a promising research area. In this paper we are concerned with the fusion of visual information. Indeed, as many sources produce images, image processing has become one of the most important domains for fusion. Image fusion can be broadly defined as the process of combining multiple input images into a smaller collection of images, usually a single one, which contains the relevant' information from the inputs, in order to enable a good understanding of the scene, not only in terms of position and geometry, but more importantly, in terms of semantic interpretation. In this context, the word relevant' should be considered in the sense of relevant with respect to the task the fused images will be subject to', in most cases high-level tasks such as interpretation or classification. In the sequel, we will refer to this relevant' information as salient information. The images to be combined will be referred to as input or source images, and the resultant combined image (or images) as fused image. The actual fusion process can take place at different levels of information representation. A common categorization is to distinguish between pixel, feature and symbol level, although indeed these levels can be combined themselves [2]. Image fusion at pixel-level means fusion at the lowest processing level referring to the merging of measured physical parameters.

Conclusions: In this paper, we have introduced a general framework for MR image fusion. The proposed framework not only encompasses most of the existing MR image fusion schemes, but also allows the construction of new ones, either pixel or region-based approaches. The region-based MR fusion scheme presented in this paper is an extension of the classical pixel-based schemes. The basic idea is to perform a MR/MS segmentation of the various input images in order to guide the fusion process. For this purpose, we developed a MR/MS segmentation method based on pyramid linking and suggested some combination algorithms which make use of the resulting segmentation. Experimental results have also been shown. The implementation of our region-based fusion approach is still in a preliminary stage and in the experiments performed we did not attempt to optimize its performance. However, the results obtained so far suggest that our approach may be useful for several image fusion applications. We need to investigate this more thoroughly in the future. In particular, we plan to study the effect of the different parameters and functions in the scheme on the final fusion process. We also intend to design new combination algorithms and replace the MR/MS segmentation by pyramid linking by some other techniques, such as a hierarchical watershed from mathematical morphology. A substantial part of our efforts will be devoted to the design of objective measures for fusion performance assessment. We intend to use such measures to evaluate and demonstrate the capacities of our region-based fusion approach, as well as to compare its performance with other MR fusion schemes. We also plan to study how these objective measures can be used to guide the fusion and improve the fusion performance. According to the types of source images involved in fusion, fusion methods of multi-spectral image can be divided into three categories: fusion of multi-bands images, fusion of multi-spectral [37] and panchromatic images, and fusion of hyper spectral images. This paper provides a scientific reference for the development offusion technique offmulti-spectral image, including the above three categories.

Fusion of multi-bands images: Fusion of multi-bands images is the process of generating or composing new images of multi-bands images using certain algorithm in uniform geographic coordinate system. In this section, several common fusion methods are introduced, followed by discussion of their characteristics.

Low-pass contrast pyramid: Low-pass contrast pyramid is compatible with human visual characteristics. The advantage of low-pass contrast pyramid is to preserve the high contrast and high bright information, which can be applied to different resolution images fusion Wavelet transformation: Wavelet transformation is to resample fusion images, and to decompose sub-images with different resolutions. New high frequency sub-images can be obtained by processing high frequency sub-images. Fusion results can be computed by wavelet transformation. The disadvantages of the approach are having a domino effect, and influenced by wavelet decomposition order number.

Contrast modulation: Contrast modulation modulates low resolution gray images using clear gray images. Contrast modulation is suitable for the pairs of images, and the fusion effect is proportional to the difference of sensor spatial and gray-scale resolution.

Bayesian inference: Bayesian inference deletes error information with low credibility by analyzing the compatibility of information, Bayesian estimates the retained information, and then generate the optimal fusion results. On the basis of it, multi-Bayesian classification inference is proposed. It regards each sensor as a Bayesian classifier, and then generates the optimal fusion results. The disadvantages of multi-Bayesian classification inference are that the uncertainty expression is not very good, and the calculation is complicated.

Parameter template: Parameter template completes pattern recognition with complex correlation by comparing observing data with prior template. Parameter templates usually contain Boolean conditions, parameter table, threshold, weight coefficient, etc.

Clustering analysis: Clustering analysis groups the similar predefined data .Clustering analysis is to group data into classification table, not using the statistical theory. Clustering analysis is very useful for interpreting properties and analyzing observed data. It is mainly used for target classification and recognition.

Artificial neural network: Artificial neural network contains multiple units, which is used to input data as a nonlinear transformation for the classification from data to property.

Color space transformation: Color space transformation is a fusion method based on IHS (Intensity, Hue, Saturation) model and the processing methods of gray images and color images. Fusion methods of multi-spectral and panchromatic images can be divided into two categories, which are fusion methods based on color space component replacement and fusion methods based on multi-resolution analysis. In this section, several common fusion methods are introduced. Fusion methods based on color space component replacement Fusion methods based on color components are to linear separate and replace images of each band. Final fusion images are obtained by band restructuring.

HIS: IHS is one of the most typical color component replacement fusion methods of multispectral and panchromatic image fusion [38]. It is noted that the fusion results using IHS may produce spectral distortion more or less.

Brovey: Brovey is a fusion method usually used in ratio transformation of images enhancement. Brovey cannot only simplify the process of image color space conversion, but also can keep the spectral information of the original multispectral images. However, if the spectral range of the original multispectral image and panchromatic image is large, it will cause color distortion of spectral information in fusion images. Brovey is mainly used when multi-spectrum images of low spatial resolution and panchromatic images of high spatial resolution are similar. In addition, it will ensure that the gray value range of fusion images after gray space stretching should equalto that of original multi-spectral images with different bands.

PCA: PCA is a fusion method that multi-dimensional orthogonal linear transformation is carried out based on statistical properties, and can transform multi-spectral and panchromatic images with highly correlation into irrelevant variables. The disadvantage of PCA is that it will distort the spectral information of images after PCA transformation of panchromatic and multi-spectral images.

Fusion methods based on multi-resolution analysis [39] can be divided into fusion methods based on pyramid transform, fusion methods based on wavelet transform, and fusion methods of multi scale geometric transform. Fusion methods based on pyramid transform: Laplace pyramid transform is used for multi-resolution analysis of image fusion by Gaussian pyramid sequence and interpolation sequence. On the basis of it, Saleem propose an improved fusion method of multi-source images based on contrast pyramid transform. However, it has structural disadvantage such as extraction ability is poor after multi-scale decomposition. For this purpose, Li propose an improved gradient pyramid multi-source image fusion method, which obtain high band coefficient by gradient direction operator. Furthermore, Li et al improve Gaussian pyramid decomposition, and propose a fusion method based on local neighborhood window feature value selection. Fusion methods based on wavelet transform: Ranchin and Wald first introduce discrete wavelet transform (DWT) into multi-source remote sensing image fusion so that the research area has attracted increasing attention. Li et al. make prediction on multi-spectral image fusion using the method of discrete wavelet transform. Fusion method of multi-scale geometric transform: Wavelet transform has good time-frequency local features. However, characteristics of dot shape information cannot be simply extended to two-dimensional images when one-dimensional signals process. Due to the limitation of information in directions of separable wavelet frame structure generated by one-dimensional wavelet theory, we cannot use the dot shape information to capture the characteristics of optimal lines or planes, such as exotic high-dimensional functions. Concerning on disadvantages of wavelet transformation in two-dimensional images processing, Multi-scale Geometric Analysis is introduced in two-dimensional space. The basic idea is to approximate singular curve using the function of geometric regularity and the coefficient expression. Yang et al. propose a new fusion algorithm for multimodal medical images based on contour let transform. The work of Wang et al. discusses the directionality of wavelet transform and its limitation, and then summarizes state-of-the-art image coding methods based on MGA. Kaur and Singh propose a novel multimodality Medical Image fusion (MIF) method based on improved Contour let Transform (CNT) for spatially registered, multi-sensor, multi-resolution medical images. To sum up, the development of multi-scale geometric analysis tools make up for wavelet transform in two-dimensional images to some extent. In the meanwhile, it can also be able to represent characteristics of images sparsely.

Hyper-spectral images [40] have spectral resolution. However, the spatial resolution of hyper-spectral images is still lower than multi-spectral images. Accordingly, fusion of these two kinds of information can provide researchers with fusion results of high spatial resolution and high spectral resolution. Bayer develops a PC transform-based algorithm for fusion of hyper-spectral and multispectral images taking advantage of novel fusion method used for IHS transform-based algorithm for tri-band and panchromatic images. Bissett and Kohler seek to develop the technology to fuse high spatial resolution Multi Spectral Imagery (MSI) with lower spatial resolution, but higher spectral resolution. The work of uses yellow rust disease of winter wheat as a model system for testing the featured technologies. Hyper-spectral reflection images of healthy and infected plants were taken with an imaging spectrograph under field circumstances and ambient lighting conditions. Pande compare three fusion algorithms (Principal Component Transformation, Color Normalized and Gram-Scmidt Transformation) with original hyper-spectral images. [41]This paper is an endeavor to investigate the data fusion task, including its potential advantages, challenging aspects, existing methodologies, and recent advances

While several general and specific reviews of the data fusion literature [41] exist; this paper is intended to provide the reader with a generic and comprehensive view of contemporary data fusion methodologies, as well as the most recent developments and emerging trends in the field. A discussion of new developments on high level fusion methodologies may be insightful; nonetheless, as the focus of this paper is on low level fusion, such presentation is left to a future work.

Multisensor data fusion:

It defines data fusion as a ‘‘multilevel, multifaceted process handling the automatic detection, association, correlation, estimation, and combination of data and information from several sources.

Challenging problems of multisensor data fusion:

Data imperfection, Outliers and spurious data, Conflicting data, Data modality, Data correlation, Data alignment/registration, Data association, Processing framework, Operational timing, Static vs. dynamic phenomena.

There are a number of areas in the data fusion community that will most likely be highly active in the near future. For instance, the ever-increasing demand for data fusion on extremely large scales, such as sensor networks and the Web, will drive intense research on highly scalable data fusion algorithms based on distributed architectures. In addition, the availability and abundance of non-conventional data in the form of human-generated reports or Web documents will lead to the development of new and powerful fusion frameworks capable of processing a wide variety of data forms. As a result, the fusion community will be driven towards development and widespread adoption of such protocols in the future. This trend is also anticipated to motivate more extensive research on topics related to the performance of data fusion systems in practice such as fusion security and belief reliability. It is our hope for this paper to serve as a review of advances in the breadth of work on sensor data fusion, and to provide the data fusion community with a picture of the contemporary state of fusion research.

3 Proposed method

Many image fusion techniques have been developed in recent years . They can be classified into two categories: spatial-domain and transform-domain methods. The former make use of histograms or gradient information. On the other hand, the latter employ transform coefficients The determination of valuable information inherent in each image plays a critical role in the fusion process. Human visual perception is sensitive to intensity changes like lines, edges or texture. Multi-scale transforms can efficiently emphasise this kind of information and this is why various multi-scale transforms are frequently used in this area . In this study, the discrete wavelet transform (DWT), one of the most popular multi-scale transformation techniques, was employed. In most of the transform-based image fusion methods, maximum and/or average of the transform coefficients have been utilised. These approaches are not sufficient in most cases, because they are not adaptive to varying information in the source images. Hence, the weight of each source image in the fused image has to be tuned adaptively. As a result, determining the best fused image can then be formulated as an optimisation problem. In the literature, there are some DWT-based image fusion methods that employ optimisation algorithms. In these approaches, the optimisation process is conducted only on the approximation band to determine the optimum weight of each coefficient of this band in the fusion process. Taking the approximation band only into consideration and choosing the maximum coefficient rule for the other bands are the main disadvantages of these methods. Moreover, determining the optimal weights for all the coefficients makes the problem more complex for an optimisation algorithm. Image fusion techniques can also be classified into two groups: pixel-based and region-based techniques. These techniques suffer from some drawbacks, such as blurring effects, high sensitivity to noise and misregistration. These drawbacks can be overcome by using region-based fusion techniques which have the ability to use more intelligent semantic fusion rules. Here we describes a new region-based image fusion method for thermal and visible images. After segmenting the SIs into regions by using the K-means algorithm, the corresponding regions were merged to obtain the fused image. Different regions with certain properties need to be emphasised differently in the fused image. Consequently, a single weighting factor (WF) may not be applicable for emphasising/deemphasising all the corresponding regions of the SIs. Therefore multiple WFs should be employed to weight different regions for improving the quality of the fused image. Numerous combinations of WFs are possible, and it is difficult to find optimal solutions by trial and error. Therefore optimisation of the WFs is necessary and was fulfilled by employing the differential evolution (DE) algorithm. The WFs were obtained optimally for all the bands of the DWT so as to take into account the information comprised in them. In addition to these features, the complexity of the problem was reduced since the optimisation process was conducted for a small number of regions rather than for the large number of coefficients. Furthermore, a new quality metric was also developed to measure the quality of the fused images during the optimisation process. The method which is used in the thesis is given below.

3.1 Sufficient component analysis:

The dataset used in this paper is the combination of different images taken from different websites. The input image is reduced by a novel method for dimensionality reduction that is Least Square Dimension Reduction which is a sufficient dimension method. The main purpose of sufficient dimension reduction (SDR) is to find a lower-dimensional expression of input features that is sufficient for predicting output values. Sufficient Dimension reduction method LSDR[31] not only reduces the image size but also preserve the necessary

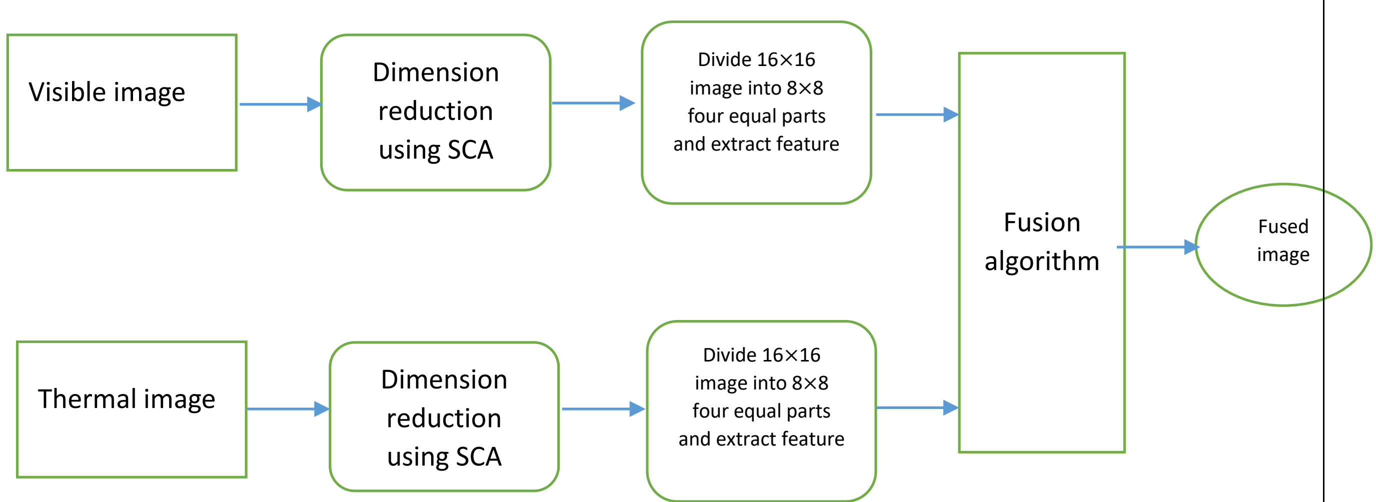


Fig :3.1 the block diagram of our purposed method features of the image and removes the redundant features. In this method, we used a novel distribution-free SDR method called sufficient component analysis (SCA), which is computationally more efficient than existing methods. In our method, a solution is computed by iteratively performing dependence estimation and maximization: Dependence estimation is analytically carried out by recently proposed least-squares mutual information (LSMI), and dependence maximization is also analytically carried out by utilizing the Epanechnikov kernel. Then a method of approximating SMI (Squared Loss Mutual Information) is adopted without going through density estimation, and elucidating the convergence properties of the SMI estimator. Through large-scale experiments on real-world image classification and audio tagging problems, the proposed method is shown to compare favourably with existing dimension reduction approaches. The sufficient dimension reduction learns the transformation matrix W from input data X to its lower dimensional representation

$z = W\mathrm{X}$

which has sufficient information for estimating the output data y. The initialization of the transformation matrix W is important. SMI is adopted to be maximized with respect to W.

$$SMI(Y,Z) = \frac{1}{2}\int \left[\frac{p_{yz}(y,z)}{p_y(y)p_z(z)} - 1\right]^2 p_z(y)p_z(z)dydz$$

where $p_{yz}(y, z)$ denotes the joint density of y and z, and $p_y(y)$ and $p_z(z)$ denote the marginal densities of y and z, respectively.

Decompose x into z and the component orthogonal to z as x = (z, $z_\perp$), i.e., z is a member of the image of W and $z_\perp$ is a member of the subspace perpendicular to the image of W.

The LSDR algorithm says

1. Initialize projection matrix W.

2. Optimize Gaussian width σ and regularization parameter λ by CV(cross-validation).

3. Update W by W ← Wε , where step-size ε may be chosen using Armijo's rule.

4. Repeat 2. and 3. until W converges.

Using this algo we can reduce the image up to 16×16 dimension.

We took both the thermal and visible image of 16×16 dimension and divide the image into four parts of 8×8. And we calculate the features of all 8 parts.

Feature extraction:

1. Mean,

2. Entropy,

3. Gradient,

4. Histogram of gradients

Mean= $\frac{\sum X}{N}$,where X is the value of all outcomes in the sample and N total no of object.

$$Entropy = \sum_{i=1}^{n} -p.log(p)$$

The table of output of all these are given in the experiment section.

3.2 Information fusion:

3.2.1 Rough sets and multi-source information systems:

An information system is the basic description of some expression of information. In general, an information system isdefinedasaquadruple*I* = (*U*, *AT* , *V*, *f*) , where *U* = { *x* 1 , *x* 2 , . . . , *x n* } is a finite non-empty set of objects (the universe of discourse), *AT* is a finite non-empty set of attributes, and *V* is the set of attribute values. For every attribute

$a \in AT$, a set of values V_a is associated with the function $f : U \times AT \rightarrow V$ such that $f(x, a) \subseteq V_a$ for every $a \in AT$, $x \in U$. For simplicity, we usually abbreviate as $I = (U, AT, f)$. This is also called an approximation space or knowledge base. For any attribute set $A \subseteq AT$, there is an associated indiscernibility relation R_A that is defined as

$$IND(A) = \{(x, y) \in U \times U \mid \forall a \in A, f_a(x) = f_a(y)\} = R_A.$$

In an information system, there is generally a lot of redundant knowledge. In the process of knowledge processing, this extra knowledge produces unnecessary computation. To reduce the computational load, the theory of knowledge reduction (attribute reduction) was proposed. Let I be an information system. For any $B \subseteq A \subseteq AT$ and $a \in A$, we have the following

same definitions. If $IND(B) = IND(A - \{a\})$, then a is said to be not necessary, or redundant, in A ; otherwise, a is a necessary attribute in A . The set of all necessary attributes in A is called the core, written as $Core(A)$. The attribute set is independent if, for any $a \in A$, a is necessary; otherwise, A is not independent. If B is an independent attribute set and $IND(A) = IND(B)$, we say B is a one-reduct of A . All reducts of A constitute the set $Red(A)$. According to the above definitions, one can easily determine the relationship between the core and reduct sets of A to be $Core(A) = \cap Red(A)$. The indiscernibility relation R_A , sometimes called the equivalence relation, divides the universe U into disjoint subsets. Such a partition is a quotient set of U , and is denoted by

$$U/R_A = \{[x]_{R_A} \mid x \in U\},$$

In view of GrC, U / R_A is a granular structure that can be represented by $K(R_A) = \{G_{R_A}(x_1), G_{R_A}(x_2), \ldots, G_{R_A}(x_n)\}$. Thus, a bi- nary indiscernibility relation R_A is regarded as a granulation method for partitioning objects. In particular, the finest granular structure on U is denoted as $K(\delta) = \{\{x_1\}, \{x_2\}, \ldots, \{x_n\}\}$, and the coarsest is denoted as $K(\omega) = \{\{x_1, x_2, \ldots, x_n\}\}$. Based on one information system, Pawlak proposed the rough set theory in which, for any $X \in P(U)$ (where $P(U)$ rep- resents the power set of U) representing a basic concept and an indiscernibility relation R induced by a subset of AT , one can characterize X by a pair of upper and lower approximations $R(X) = \{x \in U \mid [x]_R \subseteq X\}$ and $R(X) = \{x \in U \mid [x]_R \cap X \_= \emptyset\}$, respectively. Then, *pos* (*X*) = *R* (*X*) , *neg*(*X*) = ~*R* (*X*) , *bn* (*X*) = *R* (*X*) −*R* (*X*) are called the positive region, negative region, and boundary region of *X* .

With the rapid development of information science and technology, one can obtain information regarding a set of objects from different sources. Information from different sources is collected in the form of the information systems introduced above. Furthermore, a group of single information systems with the domain is named a multi-source information system. This is represented as $MI = \{ I\,i \mid I\,i = (U, AT\,i\,, \{(V\,a)\,a \in AT\,i\,, f\,i\,\})\}$, where

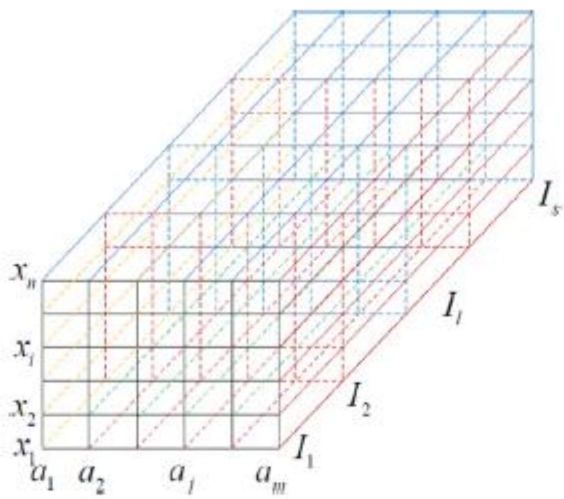


Fig. 3.2. A multi-source information box

• *U* is a finite non-empty set of objects;

• *AT i* is a finite non-empty set of the attributes of each subsystem;

• { *V a* } is the value of the attribute *a* ∈ *AT i* ;

• *f i* : *U* ×*AT i* → { (*V a*) *a* ∈ *AT i* } such that, for all *x* ∈ *U* and *a* ∈ *AT i* , *f i* (*x* , *a*) ∈ *V a* .

Table 1 A multi-source information system.

	I_1			I_2			I_3			I_4		
	a_1	a_2	a_3	a_1	a_2	a_3	a_1	a_2	a_3	a_1	a_2	a_3
x_1	1	2	1	2	2	1	2	2	2	2	2	1
x_2	0	2	1	1	1	2	2	2	1	2	1	0
x_3	1	1	2	1	0	1	2	2	2	2	1	0
x_4	1	1	2	1	0	1	2	2	1	2	0	1
x_5	1	1	0	1	1	2	2	2	1	2	1	0
x_6	0	2	2	0	1	1	0	1	0	2	0	1

Let $MI = \{ I_i \mid I_i = (U, AT_i, \{ (V_a)_{a \in AT_i}, f_i \}) \}$ be a multi-source information system that is composed of s single-source infor- mation systems, i.e., $|MI| = s$ (where $|\cdot|$ represents the cardinality of $\cdot$). In particular, if there exist some $i, j \in \{1, 2, \ldots, s\}$, and i _ $= j$ such that $AT_i = AT_j$, then all of the information systems have the structure $MI = \{ I_i \mid I_i = (U, AT, \{ (V_a)_{a \in AT}, f_i \}) \}$. In this study, we investigate multi-source information systems in which the sources have the same structure. If we let the s single-source information systems overlap, we can form an information box with s levels, as shown in Fig. 1 and considered in our previous study .

The information box is the basic structure used in the process of multi-source information fusion. More generally, there are many uncertainties in the information collection, such as equipment noise, missed data, collection time and technique, and so on. These two single information systems form a multi-source information system with a different structure. More- over, we can employ a binary relation to granulate every single-source information system from a multi-source information system, and the s granular structures can be written as $K_1, K_2, \ldots, K_s$. In terms of GrC, a multi-source information system can be represented by $MI = (U, K_1, K_2, \ldots, K_s)$.

Let $MI = \{ I_i \mid I_i = (U, AT, \{ (V_a)_{a \in AT}, f_i \}) \}$ be a multi-source information system, where the universe $U = \{ x_1, x_2, x_3, x_4, x_5, x_6 \}$ consists of six patients. Suppose there are four hospitals (I_i, $i = 1, 2, 3, 4$) that provide information re- garding attributes a_j, $j = 1, 2, 3$ of these patients, and a_{ij} denote three physical examination indicators. Every hospital can be regarded as an information source in this multi-source information system. The information provided by the four hospitals is presented in Table 1 . From this table, it is easy to calculate the granular structure for each information source:

$K1 = \{\{x1\}, \{x2\}, \{x3, x4\}, \{x5\}, \{x6\}\}$, $K2 = \{\{x1\}, \{x2, x5\}, \{x3, x4\}, \{x6\}\}$ $K3 = \{\{x1, x3\}, \{x2, x4, x5\}, \{x6\}\}$, $K4 = \{\{x1\}, \{x2, x3, x5\}, \{x4, x6\}\}$. Therefore, the multi-source information system can be described as $MI = (U, K1, K2, K3, K4)$. In addition, we can compute the granular structure induced by all attributes, which is $K = \{\{x1\}, \{x2\}, \{x3\}, \{x4\}, \{x5\}, \{x6\}\} = K(\delta)$. We will utilize these granular structures in the next section.

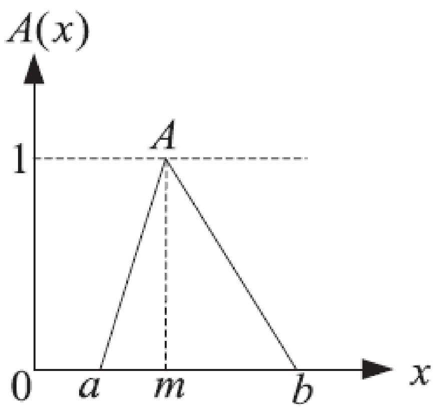


Fig. 3.3 A general triangular fuzzy number

3.2.2 Fuzzy sets and triangular fuzzy numbers

Since Zadeh first proposed the idea of fuzzy sets, in which partial membership of belonging to one or other sets is described by a membership function, fuzzy logic has made outstanding contributions to many fields. Information granules and information granulation are intuitively appealing concepts that play an important role in human cognition, pro- cessing, and communication. The information granules are generic conceptual and computing objects of GrC. Information granulation is the basis of GrC. A fuzzy set A on U is defined as a function assigning some value $A(x) \in [0, 1]$ to each element x of U . $A(x)$ is referred to as the membership degree of x with respect to the fuzzy set A . It can be described as follows:

$A = \{ < x, A(x) > | x \in U\}$.

The support set of a fuzzy set A is defined as $supp(A) = \{ x \in U | A(x) > 0 \}$. For any A , $B \in F(U)$, we say that A is contained in B , denoted by $A \subseteq B$, if $A(x) \leq B(x)$ for all $x \in U$, and we say that $A = B$ if and only if $A \subseteq B$ and $A \supseteq B$. Given A , $B \in F(U)$ and $\forall x \in U$, the union and intersection of A and B are defined as:

$(A \cup B)(x) = A(x) \vee B(x)$;

$(A \cap B)(x) = A(x) \wedge B(x)$.

where $\vee$ and $\wedge$ denote the maximum and minimum operations, respectively. Triangular, Gauss, and trapezoidal fuzzy num- bers are used in many energy fields. The triangular fuzzy number $A = (a, m, b)$ will be used later in this study, where a and b are the left and right boundary points, respectively, and m is the core of the triangular fuzzy number A). Let $A = (a\ 1\ , m\ 1\ , b\ 1\ )$ and $B = (a\ 2\ , m\ 2\ , b\ 2\ )$ be two arbitrary triangular fuzzy numbers. The Hathaway distance [10] $d\ h\ (A\ , B\ )$ of symmetric triangular fuzzy numbers A and B is defined as

$$d_{h|}^2(A, B) = (a_1 - a_2)^2 + (m_1 - m_2)^2 + (b_1 - b_2)^2.$$

Yang identified a distance that can be defined for all LR -type fuzzy numbers. Let L (and R) be decreasing shape functions from R + to [0, 1] with $L(0) = 1$, $L(x) < 1$ for all $x > 0$, $L(x) > 0$ for all $x < 1$, and $L(1) = 0$ (or $L(x) > 0$ for all x , $L(+\infty) = 0$). A fuzzy number A with the membership function

$$A(x) = \begin{cases} L\left(\dfrac{m_1 - x}{\alpha}\right), & \text{for } x < m; \\ 1, & \text{for } x = m; \\ R\left(\dfrac{x - m_2}{\beta}\right), & \text{for } x > m; \end{cases}$$

is called an LR -type triangular fuzzy number. Symbolically, A is denoted by $A = (a, m, b)$ LR , where $a > 0$ and $b > 0$ are called the left and right spreads, respectively. Given $A = (a\ 1\ , m\ 1\ , b\ 1\ )\ LR$ and $A = (a\ 2\ , m\ 2\ , b\ 2\ )\ LR$, Yang et al. defined the distance $d\ LR$ (A , B) as $d\ 2\ LR\ (A, B\ ) = (m\ 1\ - m\ 2\ )\ 2 + ((m\ 1\ - la\ 1\ ) - (m\ 2\ - la\ 2\ ))\ 2 + ((m\ 1 + rb\ 1\ ) - (m\ 2 + rb\ 2\ ))\ 2$, where $l =$ _ 1 0 $L\ -1\ (w\ )\ dw$ and $r =$ _ 1 0 $R\ -1\ (w\ )\ dw$. If L and R are linear, then $l = r = \frac{1}{2}$. Pedrycz and Yu [31,32,63] introduced a general two-phase procedure for building information granules. In the first phase, a collection of segments of numeric data is used to establish a certain level of specificity when looking at the data. In the second phase, a granular representation of the data falling within the individual segments is formed. The fuzzy information granulation aims to construct a fuzzy number on a given dataset D that includes s elements $x_1, x_2, \ldots, x_s$, where $a_i \in \mathbf{R}$.

3.2.3 Information entropy and significance of attributes

Uncertainty is an important issue in information systems and RST. Existing measures of uncertainty include information granularity, entropy theory, and the significance degree. These measures have been successfully applied in many fields. The rough entropy and information entropy are often used as uncertainty measures in information processing. Consider a given information system $I = (U, AT, V, f)$. For any $A \in AT$, $U/R_A = \{X_1, X_2, \ldots, X_m\}$, and the rough entropy of A is defined as

$$\mathrm{E_R(A)} = -\sum_{\mathrm{i=1}}^{\mathrm{m}} \frac{|\mathrm{X_i}|}{|\mathrm{Uo}|} \log_2 \frac{1}{|\mathrm{X_i}|}$$

It is obvious that there are minimum and maximum values of the rough entropy. When $U/R_A = K(\omega)$, the rough entropy of A has a minimum of 0; if $U/R_A = K(\delta)$, then the rough entropy of A has a maximum value of $log_2 |U|$. If there is some probability distribution $P_i = |X_i| / |U|$ on U , then the information entropy of information system I with respect to A can be written as:

$$H(A) = -\sum_{i=1}^{m} P_i \, log_2^{P_i}$$

In particular, if there is some $P_i = 0$, we can set $0 \cdot log_2 0 = 0$. The entropy is a measure of the disorder of the system: the greater the entropy, the higher the disorder. To measure the uncertainty in the structure of the information system, Shannon took the concept of entropy in physics and applied it to information theory. The Shannon entropy is related to the rough entropy by the expression $H(A) + E_r(A) = log_2 |U|$. Each information system has many attributes, but some of these are redundant. To measure the significance of a single attribute, the relative and absolute significance of attributes have been developed . Let $I = (U, AT, V, f)$ be an infor- mation system. For any $A \in AT$ and $a \in A$, $b \in (AT - A)$, the relative and absolute significance of attribute a in attribute set A are respectively defined as

$Sig_{in}(a, A) = Er(A - \{a\}) - Er(A)$,

$Sig_{out}(b, A) = Er(A) - Er(A \cup \{b\})$. In particular, when $A = \{a\}$, we have that $Sig_{in}(a, \{a\}) = Er(\emptyset) - Er(a) = |U| \log |U|^2 - Er(\{a\})$. According to this definition, the following properties hold for $Sig_{in}(a, A)$: 1) $0 \leq Sig_{in}(a, A) \leq |U| \log |U|^2$, 2) attribute a is necessary if and only if $Sig_{in}(a, A) > 0$, 3) $Core(A) = \{a \in A \mid Sig_{in}(a, A) > 0\}$. For a given information system I , any attribute subset $A \subseteq AT$ and A is a reduct of information system I if $Er(A) = Er(AT)$ and, for any $a \in A$, $Sig_{in}(a, A) > 0$. These concepts are commonly used to study attribute reduction, and many useful heuristic algorithms for this purpose have been proposed for various types of information systems.

3.2.4 Granular computing approach to information fusion in multi-source datasets

The rapid development of information science and technology has given rise to an unprecedented volume of freely avail- able, user-generated data. It is impossible for humans to make sense of the overall picture in a reasonable amount of time. Hence, efficient data mining has become a dominant theme within information science. There are numerous means of ob- taining data, and the number of information sources is increasing sharply. At the same time, a large amount of this data is unreliable or invalid in real-life applications. The selection of reliable information sources is a key issue in the field of information technology research, and one that can greatly improve the efficiency of information processing. Consequently, we propose two numerical characteristics that measure the validity of information sources, and discuss some of their impor- tant properties. We then describe how to find an efficient information fusion method that takes advantage of the selected information sources, with multi-source information fusion investigated in detail in terms of GrC.

Algorithm 1: Heuristic algorithm for computing the internal-confidence degree for each *I i* in *MI* .

```
Input   : A multi-source information system MI = {I_i | I_i = (U, AT_i, {(V_a)_{a∈AT_i}, f_i})} consisting of |MI| = s information
          sources.
Output  : The set reduced attributes Red(MI) = {Red(AT_1), Red(AT_2), ..., Red(AT_s)}.
1  begin
2      for i = 1; i <= s; i++ do
           Initialize: Red(AT_i) ⟵ Ø ;
3          for j = 1; j <= |AT_i|; j++ do
               Compute: Sig_in(a_j, AT_i);        // compute the absolute significance of a_j, as discussed in the Preliminaries;
4              if Sig_in(a_j, AT_i) > 0 then
5                  Red(AT_i) = Red(AT_i) ∪ {a_j};   // update the reduction by entropy and significance of attribute;
6              end
7          end
8          if E_r(Red(AT)) ≠ E_r(AT_i) then
9              for each a ∈ AT_i − Red(AT_i) do
                   Compute: a* = {a ∈ AT_i − Red(AT_i) | Sig_out(a*, Red(AT_i)) = max{Sig_out(a, Red(AT_i))}};
10             end
11             Red(AT_i) = Red(AT_i) ∪ {a*} then
12             Goto line 8;
13         else
               Compute: IC(I_i) = |Red(AT_i)|/|AT_i|;        // calculate IC(I_i) using Definition 3.1.
14             Return: The internal-confidence degree for each I_i ∈ MI.
15         end
16     end
17 end
```

3.2.5 Granular computing approach to information fusion in multi-source datasets

After completing the information source selection procedure, a number of reliable sources have been identified. There are many approaches for information fusion. In this subsection, we focus on a fusion approach based on the fuzzy granulation of information. We use the selected source to build fuzzy information granules for each $x \in U$. In fact, multi-source informa- tion fusion essentially involves processing multiple single information sources. In this study, fuzzy information granules are established to replace the object descriptions in the multi-source environment. Thus, our multi-source information fusion approach constructs a fuzzy information table instead of the original information box, and each point of this table is a fuzzy number.

Let $MI = \{ I_i \mid I_i = (U, AT_i, \{ (V_a)_{a \in AT_i}, f_i \}), i = 1, 2, \ldots, s \}$ be a multi-source information system consisting of s single infor- mation sources. All of the information sources are selected by the rules described in the previous subsection. For any $x \in U$, the value of x under any one attribute $c \in AT$ can be described as $c(x) = (c_1(x), c_2(x), \ldots, c_s(x))$. The parameters of the optimal fuzzy set A can be determined by the method in [63] . The core of the information granules consists of those elements of A that are typical of the concept conveyed by the information granule. In a triangular fuzzy set, the core of A is formed by those m that minimize the sum of the absolute differences $s\ i = 1 \mid m - c_i(x) \mid$. The solution to this optimization is a median point if s is odd, or the result is an interval from $a_{s/2}(x)$ to $c_{s/2+1}(x)$ if s is even. Consider the description of the core based on the following characterization:

• If s is odd, then m is equal to $c_i(x)$ ($m = c_i(x)$, where i satisfies $i\ j=1\ s_j < s/2 < i+1\ j=1\ s_j$;

• If s is even, then m is a real number between $a_i(x)$ and $c_{i+1}(x)$, where i satisfies $i\ j=1\ s_j = k/2$, and $m = c_i(x) + c_{i+1}(x)\ 2$.

Once the modal point or core of A has been determined, the task of building a spread splits into two independent subproblems concerning the left and right spreads for the left and right sections of A, respectively. Furthermore, because $A(x)$ is a triangular membership function, $Q(a)$ and $Q(b)$ attain maxima at $a = 2 p_1 k_1 - m$, $b = 2 p_2 k_2 - m$, where $p_1 = k_1\ i=1\ x_i$ and $p_2 = k_2\ i=1\ x_i$, and k_1, k_2 denote the number of data points located left and right of the modal value, respectively. Therefore, a fuzzy number can be obtained according to the data series $a_j(x) = (a_{j1}(x), a_{j2}(x), \ldots, a_{js}(x))$. Taking this transform operation for all attributes and each $x \in U$ This is a fuzzy number of the form $A_{ij} = (a_{ij}, m_{ij}, b_{ij})$. Next, we define the distance and similarity degree between two objects, the rough entropy and information entropy in the fusion information system

Let $MI = \{ I_i \mid I_i = (U, AT_i, \{ (V_a)_{a \in AT_i}, f_i \}) \}$ be a multi-source information system. The number of attributes in each single information system is m. For any $x_k, x_l \in U$, the relative Minkowski distance d_M between x_k and x_l can be defined as:

$$d_M(X_k, X_i) = \frac{1}{m}\sum_{l=1}^{m}(|a_{kl} - a_{il}|^p + |m_{kl} - m_{il}|^p + |b_{kl} - b_{il}|^p)^{\frac{1}{p}}$$

Table 2 Result of multi-source information fusion

	a_1	a_2	a_3
x_1	(1, 2, 2)	(2, 2, 2)	(1 ,1, 2)
x_2	(−0.5, 1.5, 2.5)	(1, 2, 2)	(0, 1, 2)
x_3	(0.5, 1.5, 2.5)	(0, 1, 2)	(−0.5, 1.5, 2.5)
x_4	(0.5, 1.5, 2.5)	(−0.5, 0.5, 2.5)	(1, 1, 2)
x_5	(0.5, 1.5, 2.5)	(1, 1, 2)	(−0.5, 0.5, 2.5)
x_6	(0, 0, 2)	(0, 1, 2)	(0, 1, 2)

Similiraty index can be calculated by $SI(X_k, X_l) = 1 - d^*(X_k, X_l)$.

The value of similrity index will be between (0,1].

The information fusion process results in the attribute value for each frame becoming a triangular fuzzy number. Based on the table, the distance and similarity degree between two objects can be computed. Furthermore, a new binary relation between any two objects can be built.

4. Experimental results:

Dimension reduction of visible image:

Fig 4.1 Reduce visible images

Dimension reduction of thermal image:

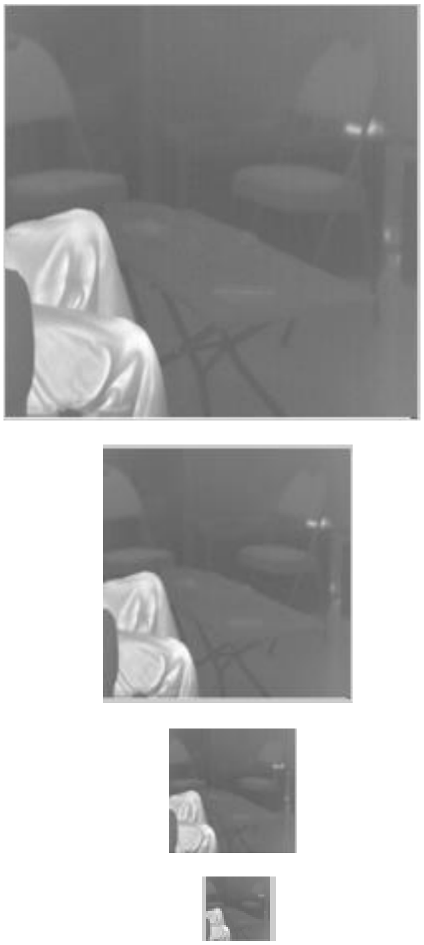
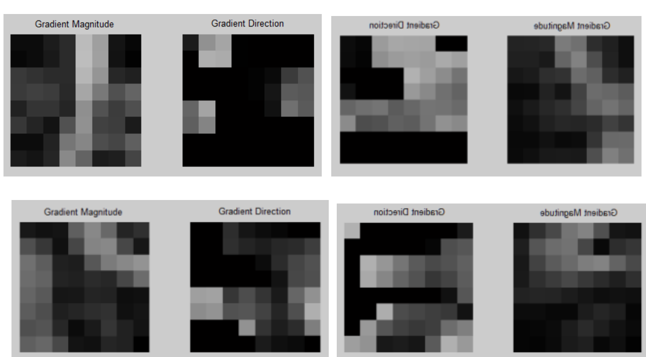
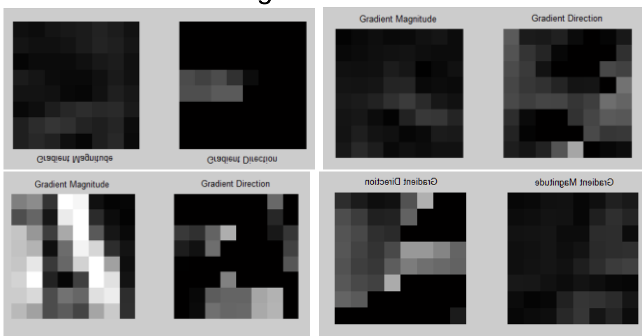


Fig 4.2 Reduce thermal image

1. output gradients (magnitude)of 8×8 images
   1.1 For visible image:



1.2 For thermal image:



2. Entopy

2.1 Value of entropy of all 8×8 region of visible image

$$\text{VI(entropy)=Ev=}\begin{bmatrix} 5.0839 & 4.9082 \\ 4.9723 & 4.7612 \end{bmatrix}.$$

2.2. After thresholding we convert into granules

$$\text{TI(entropy)=Gt=}\begin{bmatrix} 2 & 1 \\ 1 & 0 \end{bmatrix}$$

2.3. Value of entropy of all 8×8 region of thermal image

$$\text{TI(gradient)=Ev=}\begin{bmatrix} 4.2354 & 4.511 \\ 5.1582 & 4.2179 \end{bmatrix}$$

2.4. After thresholding we convert into granules

$$\mathrm{TI(entropy\ )} = \mathrm{Gt} = \begin{bmatrix} 0 & 1 \\ 2 & 0 \end{bmatrix}$$

3. Gradient

3.1. Value of gradient of all 8×8 region of visible image and thermal respectively

$$\text{VI(gradient)=Gv=}\begin{bmatrix} 4.2406 & 3.3022 \\ 3.7811 & 2.7115 \end{bmatrix}$$

$$\text{TI(gradient)=Gt= }\begin{bmatrix} 1.5296 & 1.3260 \\ 8.1874 & 1.5041 \end{bmatrix}$$

3.2. After thresholding we convert into granules

$$\text{VI(gradient)=Gv=}\begin{bmatrix} 2 & 1 \\ 2 & 0 \end{bmatrix}$$

$$TI(gradient)=Gt=\begin{bmatrix} 0 & 0 \\ 2 & 0 \end{bmatrix}$$

4. Mean

4.1. Value of mean of all 8×8 region of visible image and thermal respectively

$$VI(mean)=Mv=\begin{bmatrix} 50.256 & 45.7188 \\ 43.3594 & 49.2813 \end{bmatrix}$$

$$TI(mean)=Mt=\begin{bmatrix} 111.0781 & 118.484 \\ 159.8594 & 116.7813 \end{bmatrix}$$

After thresholding we convert into granules

$$VI(mean)=Mv=\begin{bmatrix} 2 & 1 \\ 0 & 2 \end{bmatrix}$$

$$TI(mean)=Mt=\begin{bmatrix} 0 & 0 \\ 2 & 0 \end{bmatrix}$$

Table 3

Input information table for fusion:

	Visible image			Thermal image		
Regions	Entropy(a1)	Gradient(a2)	Mean(a3)	Entropy(a1)	Gradient(a2)	Mean(a3)
X1	2	2	2	0	0	0
X2	1	2	0	2	2	2
X3	1	1	1	1	0	0
X4	0	0	2	0	0	0

Table 4

Fuzzy table:

	Entropy	Gradient	Mean
X1	(0,1,2)	(0,1,2)	(0,1,2)
X2	(1,1.5,2)	(2,2,2)	(0,1,2)
X3	(1,1,1)	(0,0.5,1)	(0,0.5,1)
X4	(0,0,0)	(0,0,0)	(0,1,2)

5. Minkowski distance $d_M =$

$$\begin{bmatrix} 0 & 1.1180 & 1.2168 & 1.4907 \\ 1.1180 & 0 & 1.6429 & 2.0522 \\ 1.2168 & 1.26429 & 0 & 1.3227 \\ 1.4907 & 2.0522 & 1.3227 & 0 \end{bmatrix}$$

6. Similarity index=1-$d *_M$=

$$\begin{bmatrix} 1 & 0.2500 & 0.1838 & 0 \\ 0.4552 & 1.0000 & 0.1995 & 0 \\ 0.2594 & 0 & 1.0000 & 0.1949 \\ 0.2736 & 0 & 0.3555 & 1.0000 \end{bmatrix}$$

Threshold $=(0.1 0.2 0.25 0.3 0.4)

Rough entropy is:

$$(1.2452 \quad 1.1462 \quad 0.8962 \quad 0.5000 \quad 0.2500)$$

5. Conclusion and future work:

The best part of this article is both dimension reduction and fusion technique. We use sufficient component ananlysis for dimension reduction which reduce the dimension of the image without losing much information and even in a small image a large number of information is present compare to first one image. The reduced image can be use in various parts of research like fusion, object tracking, shape analysis, pattern recognition etc. by using this method our fusion method computed easily because fusion have to compute low dimensionality of data and it process it very easily due small in size. The output of fusion shows that the output is good and reliable and the entropy also tells us about the randomness of the particles. Less will be the entropy good will be the output and experiment shows that tha entropy of a fused system is low so the output is reliable. We are interested on working on the SDR (sparse sufficient dimension reduction) and also want work on various new fusion techniques.

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