Pixel-level image fusion: A survey of the state of the art

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Highlights

- This review provides a survey of various pixel-level image fusion methods according to the adopted transform strategy.
- The existing fusion performance evaluation methods and the unresolved problems are concluded.
- The major challenges met in different image fusion applications are analyzed and concluded.

Pixel-level image fusion: A survey of the state of the art

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Abstract

Pixel-level image fusion is designed to combine multiple input images into a fused image, which is expected to be more informative for human or machine perception as compared to any of the input images. Due to this advantage, pixel-level image fusion has shown notable achievements in remote sensing, medical imaging, and night vision applications. In this paper, we first provide a comprehensive survey of the state of the art pixel-level image fusion methods. Then, the existing fusion quality measures are summarized. Next, four major applications, i.e., remote sensing, medical diagnosis, surveillance, photography, and challenges in pixel-level image fusion applications are analyzed. At last, this review concludes that although various image fusion methods have been proposed, there still exist several future directions in different image fusion applications. Therefore, the researches in the image fusion field are still expected to significantly grow in the coming years.

Keywords: Image fusion, Multiscale decomposition, Sparse representation, Remote sensing, Medical imaging

1. Introduction

Image fusion can be performed at three different levels, i.e., pixel level, feature level, and decision level. Compared with others, pixel-level image fusion directly combines the original information in the source images, which aims at synthesizing a fused image that is more informative for visual perception and computer processing. Many applications that require analysis of two or more images of a scene have been benefited from image fusion. For instance, in remote sensing applications, the synthesis of a low resolution multispectral (MS) image and a high resolution panchromatic (PAN) image is used to obtain a fused image containing the spectral content of the MS image with enhanced spatial resolution. In medical imaging applications, images from multiple modalities can be fused together for a more reliable and accurate medical diagnosis. In surveillance applications, image fusion can fuse the information across the electromagnetic spectrum, (e.g., visible and infrared band) for night vision.

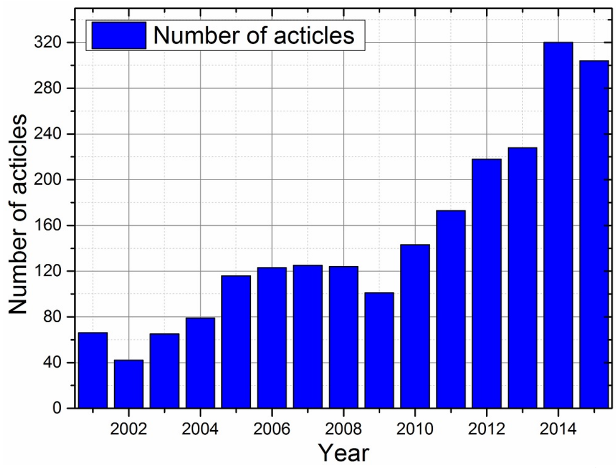

Figure 1: The number of scientific journal articles with topic of image fusion. (Statistics with Web of Science [1]).

In response to the requirements in real applications, the researchers have been very active in proposing more effective image fusion methods. As shown in Fig. 1, the number of scientific papers published in the international journals increases dramatically since 2010, and reaches to the peak 320 at 2014. 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 instance, in recent years, many powerful signal processing tools such as sparse representation [2, 3] and multi-scale decomposition [4] have been proposed, which bring opportunities to further improve the performance of image fusion. 3) The growing amount and diversity of obtained complementary images in different applications. For example, in remote sensing application, an increasing number of satellites are acquiring remote sensing images of the observed scene with different spatial, spectral, and temporal resolutions. This situation is similar in other applications such as medical imaging. For the full exploitation of these complementary images, a lot of image fusion algorithms have been developed.

For survey of early proposed image fusion methods, Zhang and Blum give a categorization of the multi-scale decomposition based image fusion methods in [5]. Another excellent source that follows the development of image fusion methods is the special issue published on the Information Fusion journal organized by Goshtasby and Nikolov [6]. Furthermore, the surveys of the image fusion methods in some specific application fields also have been published in recent years [7, 8]. For example, in remote sensing, the early proposed remote sensing image fusion methods are reviewed in [7]. A critical comparison among the recently proposed remote sensing image fusion algorithms can be found in [8]. Jixiang Zhang reviews current techniques of multi-source remote sensing data fusion (including pixel, feature, and decision level fusion) and discusses their future trends and challenges [9]. In the medical imaging field, James and Dasarathy summarize the state-of-the-art image fusion methods in [10]. Different from these previous surveys, the objective of this paper is to cover relevant fusion approaches and applications introduced recently and in this way give new insights to the current development of image fusion theory and applications. Classical image fusion methods published early that introduced key ideas are still included to give complete view of image fusion research. However, the details of particular algorithms or results of comparative experiments will not be described. More efforts will be spent on summarizing main approaches and pointing out the interesting ideas of the existing image fusion methods and applications.

In Section 2, we will provide a taxonomical view of the field into four main families of pixel-wise image fusion methods. Section 3 reviews the existing algorithms for measuring the fusion performance. Section 4 investigates the main challenges and problems in different applications. Finally, the major comments and the future directions on image fusion methods are concluded and discussed.

2. Pixel-level image fusion methods

Pixel-level image fusion, as mentioned above, is widely used in remote sensing[8], medical imaging[10], and computer vision [6]. Although it is impossible to design an universal method applicable to all image fusion tasks due to the diversity of images to be fused, the majority of the image fusion methods can be summarized by the three main stages shown in Fig. 2, i.e., image transform, fusion of the transform coefficients, and inverse transform. Based on the adopted transform strategy, the existing 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. In addition to the signal transform scheme, the other key factor affecting fusion results is the fusion strategy. The fusion strategy is the process that determines the formation of the fused image from the coefficients or pixels of the source images. Table 1 shows the summary of the major pixel-level image fusion methods, the adopted transforms and fusion strategies.

2.1. Multi-scale decomposition based methods

Multi-scale transform is a recognized tool that has been demonstrated to be very useful for image fusion and other image processing applications. Fig. 3 illustrates the schematic diagram of a generic multi-scale decomposition based image fusion scheme. First, multi-scale transform is used to obtain the multi-scale representations of the input images, in which the image features are represented in a joint space-frequency domain. Then, a fused multi-scale representation is obtained by fusion of the multi-scale representations of different images according to a specific fusion rule, in which the activity

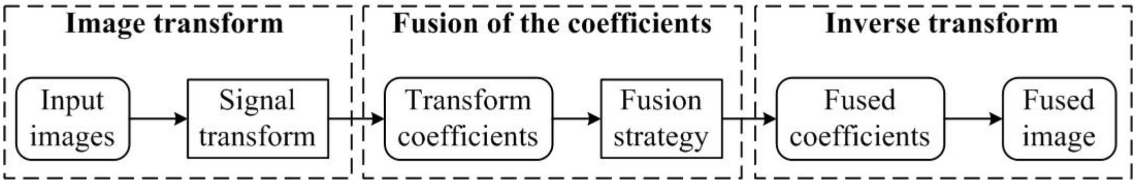

Figure 2: The summary of the main stages for a generic pixel-level image fusion method.

Table 1: Major pixel-level image fusion methods, the adopted transforms and fusion strategies.

Methods	Transforms	Fusion strategies
Multi-scale decomposition	pyramid[4], wavelet [5, 11, 12], complex wavelet [13], curvelet[14, 15], contourlet [16–23], shearlet [24–26], edge-preserving decompositions[27–29], anisotropic heat diffusion[30], log-Gabor transform[31], support value transform [32, 33], optimal scale transform [34, 35]	coefficient [4, 17], window[18], and region[13] based activity level measurement, choose-max[28], optimization based method[36], weighted-average[4, 37, 38], and substitution[12, 15] based coefficients combining, window and region based consistency verification[5, 39], cross-scale fusion rule [40], guided filtering based weighted average [41]
Sparse representation (SR)	orthogonal matching pursuit[42, 43], group SR [44], gradient constrained SR [45], simultaneous OMP (SOMP) [46], joint sparsity model [47–49], SR with over-complete dictionary [50–53], structural subdictionary [54], spectral and spatial details dictionary [55]	window based activity level measurement[42, 46], choose-max [42, 46, 51] and weighted average [54] based coefficients combining, substitution of sparse coefficients [52, 56], spatial context based weighted average[57]
Methods in other domains	spatial domain (non transforms) [58–73], intensity-hue-saturation transform (IHS) [74–77], principal component analysis (PCA) [78], Gram-Schmidt (GS) transform[79], matting decomposition[80], independent component analysis (ICA) [81], gradient domain[82], and fuzzy theory [83]	machine learning based weighted average[59, 60, 72], block [61–63] and region [64, 65] based activity level measurement, spatial context based weighted average [66–71], model based method[73], component substitution [74–80]
Combination of different transforms	hybird wavelet-contourlet [84], multi-scale transform-SR[85], morphological component analysis-SR[86], contourlet-SR[87], IHS-retina-inspired models [88], IHS-wavelet[89]	coefficient and window based activity level measurement[85–87], choose-max and weighted-average based coefficient combining method[85–87], component substitution[89], integration of component substitution and weighted average [88]

level of coefficients, and the correlations among adjacent pixels and coefficients of different scales may be considered. Finally, the fused image is obtained by taking an inverse multi-scale transform on the fused representation. This image fusion framework involves two basic problems, i.e., the choice of the multi-scale decomposition method, and the adopted fusion strategy used for the fusion of the multi-scale representations. Recently, many works attempt to solve these two problems, which are detailed as follows.

1) Multi-scale decomposition methods

In previous research, the most commonly used multi-scale decomposition methods for image fusion are the pyramid and wavelet transforms, such as the Laplacian pyramid[4], discrete wavelet decomposition (DWT)[5, 36], and stationary wavelet decomposition[12]. Pajares and Cruz [11] give a tutorial

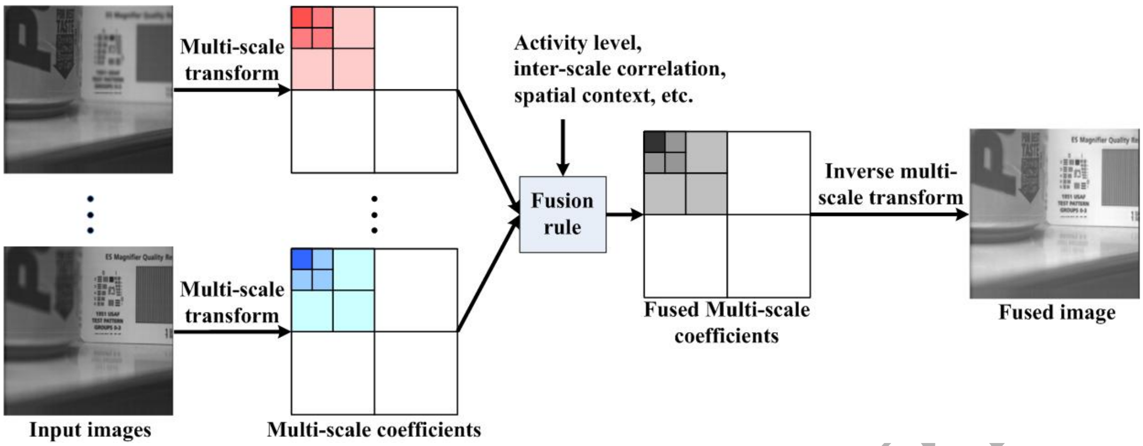

Figure 3: The main stages for a generic multi-scale based image fusion method.

of the wavelet-based image fusion methods, in which they present a comprehensive comparison of different pyramid merging methods, different resolution levels, and different wavelet families. Zhang and Blum give a categorization of the early proposed multi-scale decomposition based image fusion methods [5] including most of the pyramid based methods and the classical wavelet based methods. Besides the pyramid and wavelet transform, in recent years, some new multi-scale transforms such as dual-tree complex wavelet[13], curvelet[15], contourlet[17, 18], and shearlet [25, 26] are introduced for image fusion. In the following, these newly introduced multi-scale decomposition methods will be briefly reviewed.

It is known that the discrete wavelet transform suffers from some fundamental shortcomings, e.g., shift variance, aliasing, and lack of directionality[5]. As a solution to these problems, the dual-tree complex wavelet transform is successfully applied for image fusion[13]. The key advantages of the dual-tree complex wavelet over the DWT are its shift invariance and directional selectivity, and thus can reduce the artifacts introduced by DWT. However, a common limitation of the methods in the wavelets family is that they cannot well represent the curves and edges of images. To represent the spatial structures in the images more accurately, some novel multi-scale geometric analysis tools are introduced into image fusion. For example, Candeś and Donoho propose the curvelet bases to represent the images [14]. Nencini successfully applies the curvelt transform for the fusion of remote sensing images [15]. In addition to curvelet, contourlet is another transform that can capture the intrinsic geometrical structure of the images, and it is preferable for processing two-dimensional signals[16]. In the contourlet transform, the Laplacian pyramid is first used to capture the point discontinuities, and then a directional filter bank is used to link point discontinuities into linear structures. Due to its effectiveness in representing spatial structures, contourlet transform has been successfully applied in medical imaging [19], surveillance [20, 21], and remote sensing[22, 23] applications. However, since contourlet contains downsampling processes in the transform process, it has no shift-invariant property.

The nonsubsampled version of the contourlet is a possible solution to this problem, while it will be more time consuming. Furthermore, the directional filter bank used in the contourlet is fixed, which means that it cannot well represent complex spatial structures with many different directions [23]. Recently, the shearlet also has been successfully applied for image fusion[25]. Compared to the contourlet, the implementation of shearlet is more computationally efficient, and there are no restrictions on the number of directions for the shearing, as well as the size of the supports[24].

In recent years, edge-preserving filtering also has been successfully applied to construct multi-scale representations of images. For example, Farbman *et al.* construct edge-preserving multi-scale image decompositions with weighted least squares filter for fusion of multi-exposure images[27]. Hu *et al.* combine bilateral and directional filters to construct the multi-scale representations for medical and multi-focus image fusion[28]. Zhou *et al.* combine Gaussian and bilateral filters together for the fusion of infrared and visible images[29]. Li *et al.* introduce a guided filtering based image fusion method which achieves state-of-the-art performance in several image fusion applications[41]. Besides edge-preserving filtering, other powerful computer vision tools such as anisotropic heat diffusion[30], log-Gabor transform[31], and support value transform [32, 33] also have been successfully applied for multi-scale decomposition based fusion. Generally, the major advantage of these kinds of methods is their ability to accurately separate fine-scale texture details, middle-scale edges, and large-scale spatial structures of an image. This property helps to reduce halo and aliasing artifacts in the fusion process, and thus, is able to achieve fusion results good for human visual perception.

At last, besides the determination of the multi-scale decomposition method, the number of decomposition levels also influences the quality of the fused images dramatically. If fewer decomposition levels are applied, the spatial quality of the fused images may be less satisfactory. If excessive levels are applied, the performance and computing efficiency of the method also may decrease. Thus, some researchers attempt to determine the optimal number of decomposition levels which yields the optimal fusion quality. For example, Li *et al.* investigate the effect of decomposition levels to different filters used for different image fusion applications in [34]. Pradhan *et al.* estimate the optimal number of decomposition levels for fusion of multi-spectral and panchromatic images with a particular resolution ratio[35].

2) Strategies used for fusion of multi-scale representations

In order to enhance the fusion quality, another direction can be explored in muti-scale decomposition based fusion: using effective fusion strategies. In [5], Zhang and Blum review some classical fusion schemes, e.g., coefficient, window, and region based activity level measurement, choose-max and weighted-average based coefficient combining method, window and region based consistency verification, etc. In recent years, some novel fusion schemes have been designed to achieve better fusion results. For example, Ben Hamza *et al.* formulate the image fusion as an optimization problem and propose an information theoretic approach in a multiscale framework to obtain the fusion results[36]. In [37], the base components are fused using the principal component analysis based method. For the detail coefficients (the other three quarters of the wavelet coefficients) at each transform scale, a choose-max scheme is used and followed by a neighborhood morphological processing step, which can increase the consistency of coefficient selection thereby reducing the distortion in the fused image. Jiang *et al.* propose a novel weighted average method to fuse the multi-scale decompositions, in which the weight parameters in different scales are determined by combing global and local weighting, making the method insensitive to noise and able to well preserve image details[38]. Gemma Piella first make a multi-resolution segmentation based on the input images and then use the segmentation to guide the fusion process [39]. Recently, Shen *et al.* propose a novel cross-scale fusion rule for multiscale-decomposition-based fusion of medical images taking into account both intrascale and interscale consistencies. Moreover, the weights of different scales are optimized by using a generalized random walkers method which can effective exploit the spatial correlation among adjacent pixels[40]. Instead of using a global optimization method, Li *et al.* propose a guided filtering based weighted average method to fuse the multi-scale decompositions of the input images[41].

In conclusion, most of the researches in this field focus on developing novel methods for multi-scale decomposition, and this direction is still very hot now. Compared with the development of the decomposition methods, the fusion rules have not got enough attention in the early years. However, in recent years, researchers find that advanced fusion rules can address many limitations of the multi-scale transforms, and thus, providing state-of-the-art fusion performances [40, 41]. Although the traditional fusion rules are usually quite simple, such as the widely used choose-max and averaging schemes, these rules may introduce visual artifacts when the images are not perfectly registered or contain noise. Through making full use of the strong correlation among adjacent pixels and the dependency among the coefficients of different scales, these problems actually can be effectively addressed now.

2.2. Sparse representation based methods

By simulating the sparse coding mechanism of human vision systems, sparse representation[2] is a novel image representation theory, which has been successfully applied to many image processing problems, such as denoising, interpolation, and recognition[3]. The sparse representation 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 exist in the sparse coefficients to efficiently represent the saliency information of the original images. By exploiting the characteristics of the sparse coefficients, Yang and Li [42] first apply the sparse representation theory to image fusion. Specifically, to 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 coefficients. After that, a fusion process (e.g., choose-max) is applied on the coefficients from multiple sources. Finally, the image is reconstructed using the fused coefficients and dictionary. The outline of the sparsity based image fusion framework is illustrated in Fig. 4. In general, the sparsity based fusion framework has two key problems: 1) sparse coding to obtain the coefficients. 2) dictionary construction. Recently, many works attempt to solve these two problems, which are detailed as follows.

1) Sparse coding to obtain the coefficients

To obtain the sparse coefficients, in [42], Yang and Li apply the orthogonal matching pursuit (OMP) [43] algorithm to image patches of multiple sources. The nonzero coefficients obtained by the OMP algorithm distribute randomly. Recent studies show that the distribution of non-zero elements may exhibit some special structures. In [44], Li *et al.* incorporate a group sparse constraint to ensure that the obtained sparse coefficients have group sparsity. In [45], Chen *et al.* add a gradient sparsity constraint into the sparse solution, which enables sparse coefficients to more accurately reflect the sharp edges. Since images of multiple sources are acquired from the same scene, strong correlations are existed in these images. To exploit the correlations, Yang and Li [46] utilize the simultaneous OMP (SOMP) to jointly decompose the patches from multiple sources on the same dictionary, which can make the non-zero coefficients of different sources occur at the same locations. In addition, works in [47–49] design a joint sparsity model to describe image patches of different sources as a combination of common sparse coefficients and innovation coefficients.

2) Dictionary construction

The building of the dictionary generally has two ways: 1) based on mathematical models (e.g., discrete cosine transform, wavelet and curvelets). 2) based on example learning (e.g., K-SVD and method of optimal direction)[3]. The original sparsity based fusion work [42] adopts one class of mathematical functions to construct the dictionary. Since each mathematical model is only designed for one specific structure, such a dictionary has poor representation ability for the nature images. Work in [46] utilizes multiple kinds of mathematical models to construct a hybrid dictionary. The hybrid

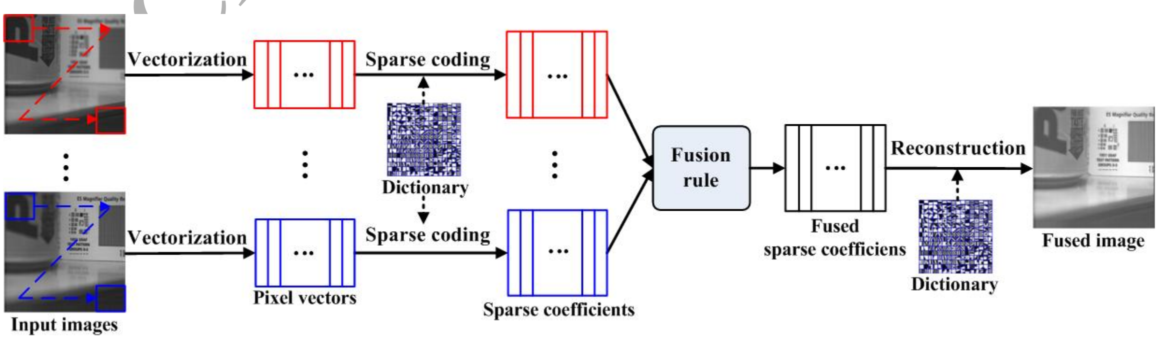

Figure 4: The main stages for a generic sparsity based image fusion method.

dictionary can well reflect several specific structures, but still lack the adaptability for representing different types of image. In [50–53], an over-complete dictionary is learned from a large set of training samples similar to the input images, thus adding adaptability for the representation. However, only one general dictionary cannot accurately reflect the complex structures in the input image. Therefore, in [54], Kim *et al.* first cluster training samples into many structural groups and then train one specific sub-dictionary on each group. In this way, each sub-dictionary can best fit a particular structure and the whole dictionary has stronger representation ability. Similarly, Wang *et al.* separately construct the spectral dictionary and spatial details dictionary for fusion of multi-spectral and panchromatic images[55].

In sparse representation based image fusion, novel sparse coding and dictionary learning schemes have been researched in recent years. However, most of these methods are designed based on traditional fusion strategies, such as window based activity level measurement[42, 46], choose-max and weighted average based coefficients combining[42, 46, 51], and substitution of sparse coefficients (a widely used scheme for fusion of remote sensing images with different spatial resolutions)[52, 56]. Similar to the multi-scale decomposition based method, fusion strategies also make an important role in improving the fusion performances of the sparsity based methods. For example, Zhang *et al.* design an effective sparse representation based mutli-focus image fusion method which considers not only the detailed information regarding each image patch and its spatial neighbors[57]. Therefore, designing more advanced fusion rules for sparse representation based fusion is expected to be another interesting direction of this field.

2.3. Methods performed in other domains

There are also many other image fusion methods which are not based on multi-scale decomposition and sparse representation. Some of these methods directly calculate the weighted average of the pixels in the input images to construct the fused image, or are applied in other transform domains. In this subsection, all of these methods are classified into two general classes.

1) Methods performed in pixel domain

A straightforward approach to image fusion is to take each pixel in the fused image as the weighted average of the corresponding pixels in the input images. Generally, the weights are determined according to the activity-level of different pixels[58]. For instance, in [59, 60], the support vector machines and neural networks are used to choose the pixels with the highest activity, in which the wavelet coefficients are used as features. In order to make full use of the spatial context information, Li *et al.* first partition the input images into uniform blocks and maximize the spatial frequency in each block [61]. In order to determine the optimal block size adaptively, De and Chanda make use of a quad-tree structure to obtain an optimal subdivision of blocks [62]. However, this kind of approaches may generate block artifacts on object boundaries[61–63]. Instead of performing the block-wise fusion, region based image fusion methods perform fusion to the regions with irregular shapes which are obtained by image segmentation [64, 65]. A common limitation of segmentation based methods is that they rely heavily on an accurate segmentation of the input images, which is another hard image processing topic.

Another way to make full use of the spatial correlation of adjacent pixels can be achieved by the post-processing of the initial pixel-wise weight maps. For example, Li *et al.* first calculate the weights based on local features, then refine the weights based on image matting [66, 67]. Liu *et al.* measure the activity level of source image patches to obtain an initial decision map, and then the decision map is refined with feature matching and local activity-level comparison [68]. In [69], an edge-preserving filtering based method is applied for the refinement of the initial weights, which will be more efficient compared with the matting scheme. Rui *et al.* take neighborhood information into account through using random walker based optimization [70]. In [71], this method is further improved by deriving the optimal fusion weights using Maximum A Posteriori (MAP) estimation in a hierarchical multivariate Gaussian conditional random field model. Zhang *et al.* first decompose the source images into principal component matrices and sparse matrices with robust principal component analysis, and then estimate the weights by taking the local sparse features as the inputs of a pulse-coupled neural network[72]. Instead of performing a weighted average of pixels, Kummar and Dass propose a total variation based approach to fuse images acquired by multiple sensors, in which the imaging process is modeled as a locally affine model and the fusion problem is posed as an inverse problem [73].

Generally, pixel-domain image fusion methods perform the fusion directly in the spatial domain, leading to advantages and limitations. On one hand, compared with transform based methods, most of pixel-level weighted average based fusion methods are fast and easy to implement. On the other hand, this kind of methods rely heavily on the accurate estimation of the optimal weights for different pixels. Otherwise, the fusion performance will be quite limited.

2) Methods performed in other transform domains

Besides the fusion methods based on muli-scale decomposition or sparse representation, color space and dimension reduction based transforms also have been successfully applied for image fusion, such as the intensity-hue-saturation (IHS) transform [74, 75], principal component analysis (PCA) [78], and Gram-Schmidt (GS) transform [79] based methods. These methods have been widely used for fusion of low resolution mutli-spectral and high resolution panchromatic images in remote sensing, which is also known as the "pansharpening" problem. For these kinds of methods, the fusion is usually achieved by substituting the intensity or first principal component of the multi-spectral image with the high resolution panchromatic image. This component substitution strategy operates in the same way on the whole image, which can be considered as a global approach. On one hand, the global fusion strategy ensures that the spatial details of the other input image can be well preserved in the fused image. On the other hand, this kind of methods have not considered the local dissimilarities between the input images, and thus, may produce significant color distortions in the fused images. In order to solve this problem, some researchers aim at estimating the optimal component to be substituted adaptively[76, 77, 80]. For instance, through minimizing the difference between the intensity component and the panchromatic image, Rahmani *et al.* estimate the global weights for different bands adaptively to construct the optimal intensity component[76]. For the same objective, Choi *et al.* generate the synthetic components by using a linear regression model. Moreover, the component will be only partially replaced according to the correlation between the intensity component and the panchromatic image[77]. Besides using the common IHS and PCA based transforms, Kang *et al.* apply the matting model to decompose the input images into the spectral foreground, spectral background, and alpha components for component substitution based fusion of remote sensing images[80].

Although various color space and dimension reduction based image fusion methods have been proposed, these methods are usually designed for fusion of color and gray-scale images, and thus, are limited to some specific applications, such as the pansharpening problem mentioned above. For other image fusion applications, some novel transforms and fusion strategies also have been developed. For example, in [81], the multi-focus images are fused in the independent component analysis (ICA) transform domain using pixel-based and region-based fusion rules. In [82], the salient structures of the input images are first fused in the gradient domain. Then, the fused image is reconstructed by solving a Poisson equation which forces the gradients of the fused image to be close to the fused gradients. Balasubramaniam and Ananthi apply the intuitionistic fuzzy set theory in image fusion, in which the input images are first transferred into the fuzzy domain, and then fused using maximum and minimum operations [83].

2.4. Methods combining different transforms

Different transforms have their special advantages as well as some shortcomings. The multi-scale transform based fusion can extract the spatial structures of different scales in the image. However, they are not able to represent the low-frequency component sparsely. In this situation, if the low-frequency coefficients are integrated using simple fusion rules such as averaging or choose-max, it may degrade the fusion performance because the low-frequency coefficients contain the main energy of the image. The sparse representation based fusion can give more meaningful representations of source images by dictionary learning, which are more finely fitted to the data. However, due to the limited number of atoms in a dictionary, it is difficult to reconstruct the small-scale details of the source images. Furthermore, the other transforms, such as the IHS and PCA transforms are fast and effective for fusion of remote sensing images with the corresponding fusion rules. However, these kinds of methods cannot be directly used for other image fusion applications, such as multi-focus and multi-exposure image fusion.

In order to combine the advantages of different transforms, there are various fusion methods that are based on the combination of different transforms. For instance, Li *et al.* propose a hybrid multiresolution method by combining wavelets and contourlets [84]. Experiments show that the hybird method performs better than the individual wavelets or contourlets based method. Liu *et al.* propose a general image fusion framework based on multi-scale transform and sparse representation[85]. Specifically, the source images are first decomposed using multi-scale decomposition methods. Then, the low frequency components are fused using the sparse representation method, while the high frequency details are fused with traditional fusion rules. Finally, an inverse multi-scale transform is performed to obtain the fused image. Instead of using the traditional multi-scale transforms, Jiang *et al.* propose a fusion method based on morphological component analysis and sparse representation, in which the source images are first decomposed with morphological component analysis, and then fused with sparse representation based method[86]. Wang *et al.* propose a fusion method based on the nonsubsampled contourlet transform and sparse representation[87]. To avoid the weak points of the IHS fusion technique and those of the retina-inspired multi-scale decomposition technique, Daneshvar and Ghassemian propose an IHS and multi-scale decomposition integrated approach for the purpose of medical image fusion [88]. Similarly, Zhang and Hong propose a fusion method that integrates the advantages of both IHS and wavelet techniques to reduce the color distortion in remote sensing image fusion[89].

3. Objective fusion evaluation metrics

Generally, a good fusion algorithm should have the following properties: (1) the fused image should be able to preserve most of the complementary and useful information from the input images. (2) the fusion algorithm does not produce any visual artifacts which may distract the human observer or the further processing tasks. (3) the fusion algorithm should be robust to some imperfect conditions such as mis-registration and noise. In most image fusion applications, it is often very difficult to obtain a ground truth that the perfect fused image should be, making evaluations often subjective. Thus, after the consideration of the fusion algorithms themselves, another important issue for image fusion is how to assess the fusion performance objectively.

Here, the existing objective fusion evaluation metrics are divided into two major classes, in which one class requires a reference fused image, while the other does not.

3.1. Objective evaluation metrics requiring a reference image

In some applications, an "ideal" fused image may be available or manually constructed, which can then be used as a ground-truth to test the performance of image fusion. For example, in remote sensing image fusion, the input multi-spectral (MS) and panchromatic (PAN) images can be first degraded. Then, the degraded images are fused and compared with the original observed MS images to evaluate the fusion performance [90]. In some special cases of multi-focus image fusion, a reference all-in-focus fused image can be constructed by performing manual segmentation and combination of the focused regions of each input image[66].

When the reference fused image is available, various objective fusion metrics could be used (known as full-reference quality metrics). The root-mean-square error (RMSE) and the peak-signal-to-noise-ratio (PSNR) are two classical ones. However, the two methods have been demonstrated to be not well correlated with human perception in some special cases [91]. During the last decade, a number of new objective metrics have been proposed as better alternatives [92–97]. For example, the *erreur relative globale adimensionnelle de synthèse* (ERGAS) index [93] is used to evaluate the spectral quality of the fused image in remote sensing applications, which is based on calculating the global RMSE in different bands. Instead of measuring the pixel difference between the fused image and the reference image, Wang *et al.* propose an alternative complementary framework for quality assessment through measuring the degradation of structural information[94]. In [95], this method is further improved by measuring the significance of local structures with the phase congruency. In [96], pixel-wise gradient magnitude similarity and a standard deviation based pooling scheme are combined to construct a novel full reference image quality metric. Instead of only considering the loss of structural information, Capodiferro *et al.* propose a quality metric which is based on two diverse measures, in which one measures the loss based on the Fisher information about the positions of the structures, and the other indicates the type of distortion that images underwent [97]. In order to investigate how humans interpret visible and infrared images, Toet *et al.* [98] design an interesting experiment to test the performances of different image fusion algorithms. In the test, a reference contour image is first constructed by manually segmenting a set of input images. The resulting reference images are then used to evaluate the manual segmentation results of the fused images.

Although a number of full-reference image fusion metrics have been proposed, there are still many unresolved problems, including the following: First, some metrics may be superior for evaluating one image distortion type produced in the fusion process but inferior for others, which limits the use of these metrics in different image fusion applications. Second, there have not been good solutions for cross-resolution image quality evaluation. For instance, in remote sensing applications, the full-reference image fusion metrics can be only used in a reduced-resolution environment. Third, for images with multiple channels, which include color, multispectrum, hyperspectrum, and three-dimensional volume, most of existing full-reference image fusion metrics cannot be directly used.

3.2. Objective evaluation metrics without requiring a reference image

In most image fusion applications, the "ideal" fused image is not always available. Therefore, objective image fusion quality assessment metrics without assuming the availability of a "ground truth" fused image (known as no-reference quality metrics) are highly desirable. Generally, the existing no-reference fusion metrics can be categorized into two major groups: 1) information theory based metrics, which only consider how much information is transferred from inputs to the fused image, and 2) local feature based fusion metrics, which evaluate the relative amount of features (sensitive to human vision system) that is transferred from the input images to the fused image.

In order to measure the amount of information that is preserved in the fused image, many solutions have been proposed. For instance, Qu *et al.* develop a mutual information based metric, in which mutual information (MI) is a quantitative measure of the distance between joint statistical distributions for two variables [99]. Hossny *et al.* propose a normalized version of the MI metric, which also considers the entropy difference between different source images in the evaluation process [100]. In order to more accurately model the transfer of information from input images to the fused output, Cvejic *et al.* suggest using Tsallis entropy to define the mutual information metric [101]. In [102], instead of calculating the MI value globally, a localized MI metric based on quadtree decomposition is investigated. Furthermore, Wang *et al.* introduce a nonlinear correlation coefficient for fusion quality evaluation, which is similar to the definition of mutual information [103].

A common limitation of information theory based metrics is that they lack in estimating the transfer of local features from source images into the fused image. Therefore, as alternatives of information theory based metrics, considerable efforts have been made to develop local feature based objective performance measures. For instance, Xydeas and Petrović propose a gradient-based fusion metric which estimates the amount of edge information that is transferred from the inputs to the fusion result [104]. Similarly, Zheng *et al.* propose a metric based on spatial frequency, in which the edge information is modeled as the gradients along different directions [37]. Liu *et al.* use phase congruency to measure the amount of image features transferred from the input images to the fused image[105]. Furthermore, a number of structural similarity index (SSIM) based image fusion metrics have been built in recent years to measure the preservation of structural information in the fused image [106–108]. Specifically, the pixel-by-pixel SSIM maps between each source image and fused image are first calculated. Then, a spatial pooling scheme could be used to obtain a global measure of fusion performance [107]. Since the human visual system is highly adapted to structural information, and thus, a measurement of the loss of structural information in the fusion process can provide a good approximation of the real fusion performance. Considering the diversity of the input images, improved SSIM based quality metrics have been proposed for different image fusion applications including remote sensing image fusion [109], multi-modal image fusion[110], and multi-focus image fusion [108]. Besides the SSIM index, other powerful tools based on the human vision system also have been widely investigated. For instance, Chen and Varshney first employe the contrast sensitivity function (CSF) on the entire image and then estimate the transferred local spatial information on a region-by-region basis [111]. Han *et al.* propose an image fusion metric based on visual information fidelity (VIF), that has shown high performance for image quality prediction[112].

Besides the increasing interests in developing non-reference objective fusion metrics, comprehensive evaluation and comparison of these metrics also have been investigated in recent years. For instance, Liu *et al.* conduct a comparative study on different image fusion metrics for night vision image fusion applications [113]. Wei and Blum perform theoretical analysis for different quality measures applied to the weighted averaging fusion algorithm [114]. Ma *et al.* test the performance of different fusion metrics on a multi-exposure image database [115]. As concluded in these previous studies, there are still many challenging problems to be solved for the existing non-reference objective fusion metrics. First, most existing objective fusion metrics work with gray images only. For color images with multiple channels, proper accounting for color distortions may improve the performance of fusion metrics dramatically. Second, in some applications, the input images may be captured in dynamic scenes, or contain noise and image blurring. Therefore, it is useful to generalize the existing metrics for these imperfect situations. At last, how to implement the quality assessment methods in real-time is also a challenging problem.

4. Major applications

In recent years, pixel-level image fusion has been used in a wide variety of applications, such as remote sensing [7, 116], medical diagnosis[10], surveillance[29], and photography[70] applications. In this section, the data sources and challenging problems of the major application domains will be discussed and concluded.

4.1. Remote sensing applications

Fig. 5 shows two examples of image fusion in remote sensing applications, i.e., fusion of multi-spectral (MS) and panchromatic (PAN) images, and fusion of multi-spectral and hyperspectral images. The first fusion application is an important problem in remote sensing, which is known as *pansharpening* [7]. It has been successfully applied to produce the imagery seen in the popular Google Maps/Earth products. Furthermore, other remote sensing applications, e.g., change detection [117] and classification [118] can be also benefited from pansharpened imagery. More recently, hyperspectral (HS) imaging which acquires a scene with several hundreds of contiguous spectral bands has demonstrated to be very useful for land-cover classification[119] and spectral unmixing[120]. However, the disadvantage of HS images is that they usually have lower spatial resolution than MS images, due to the complexity of the sensors and cost issues. In this situation, a need has arisen for fusion of HS, MS, and PAN images to improve the spatial resolution of hyperspectral images [121]. Compared with pansharpening, this is a more difficult problem, since the multichannel MS image contains both spectral and spatial information, and thus, the existing pansharpening methods are inapplicable or inefficient for the fusion of HS and MS images. In addition to the modalities mentioned above, there are several other imaging methods such as synthetic aperture radar (SAR), light detection and ranging (LiDAR), and moderate resolution imaging spectroradiometer (MODIS, a multi-temporal hyperspectral sensor) that have been applied in image fusion applications. For instance, Alparone *et al.* extend several representative pansharpening methods for the fusion of MS images and the high resolution

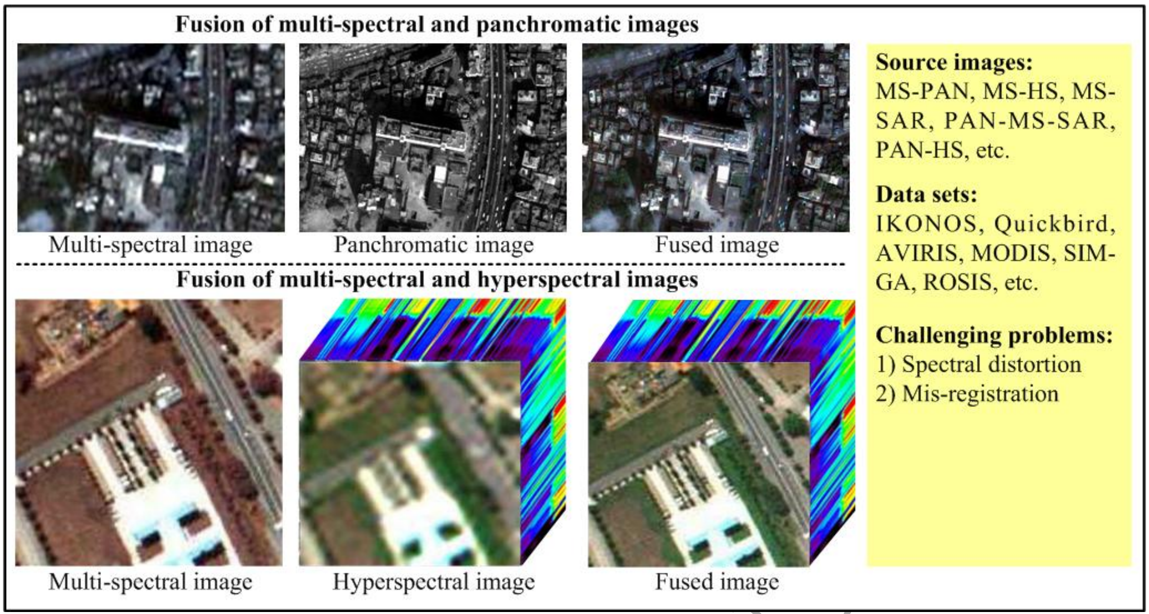

Figure 5: Examples of image fusion in remote sensing applications. (In this figure, the fusion of MS with PAN and hyperspectral images are achieved using the matting model based method[80] and the sparse representation based method [125], respectively.)

SAR images[122]. Byun *et al.* propose an area-based image fusion scheme for the integration of PAN, MS, and SAR images[123]. Wu *et al.* propose a high spatial and temporal data fusion approach to generate daily synthetic Landsat imagery by combining Landsat and MODIS data. Furthermore, the fusion of air-bone hyperspectral and LiDAR data is also researched in recent years since it allows the integration of spectral and elevation information [124].

In Fig. 5, the data sources widely used in remote sensing image fusion applications are listed. For instance, data sets captured by typical Earth imaging satellites, such as the IKONOS[126], Quickbird[126], and Worldview-2[127], are available for pansharpening applications. Compared with the MS and PAN images, co-registered HS and MS images are more difficult to obtain. Most of existing fusion solutions are built on synthetic multi-spectral images obtained by selected bands of hyperspectral images, such as images captured by airborne visible infrared imaging spectrometer (AVIRIS), and reflective optics system imaging spectrometer optical sensor (ROSIS). However, this problem will be addressed in future remote sensing platforms. For instance, the Advanced Land Observation Satellite 3 (ALOS-3) will install the Hyperspectral Imager SUIte (HISUI) sensor, a hyper-multi spectral radiometer, which able to capture HS and MS images with different spatial resolutions[128]. Furthermore, air-bone hyperspectral and LiDAR data sets are also available now. For instance, the 2013 and 2015 IEEE GRSS Data Fusion Contests have distributed several hyperspectral, color, and LiDAR data for research purposes [129, 130].

The major challenging problems in the remote sensing image fusion field are concluded in Fig. 5:

1) spectral and spatial distortions. As mentioned above, the data sets used in remote sensing image fusion usually exhibit many dissimilarities in spectral and spatial structures. In this situation, the fusion process may produce distortions to these structures, and thus, introduce spectral and spatial artifacts in the fused image. 2) Mis-registration. The second major problem in remote sensing image fusion is how to reduce the effect of mis-registration. The source images used in remote sensing are usually obtained from different times, different spectral bands or different acquisitions. Even for the PAN and MS data sets captured by the same platform, the two sensors do not exactly aim at the same direction and their acquisition moments are also not precisely identical. In order to solve this problem, most of the existing image fusion methods require a precise registration of the source images before the fusion step. However, registration is quite challenging due to the significant difference between the input images, especially for images captured with different acquisitions.

4.2. Medical diagnosis applications

Fig. 6 shows two examples of image fusion in medical diagnosis applications, i.e., fusion of magnetic resonance imaging (MRI) and positron emission tomography (PET) images, and fusion of MRI and computerized tomography (CT) images. The major advantage of MRI images is that it is able to capture the soft issue structures in organs such as brain, heart and eyes. Different from MRI imaging, the CT imaging is able to capture the bone structures in the human body with high spatial resolutions. The PET imaging is a useful type of nuclear medicine imaging, while the captured images usually has

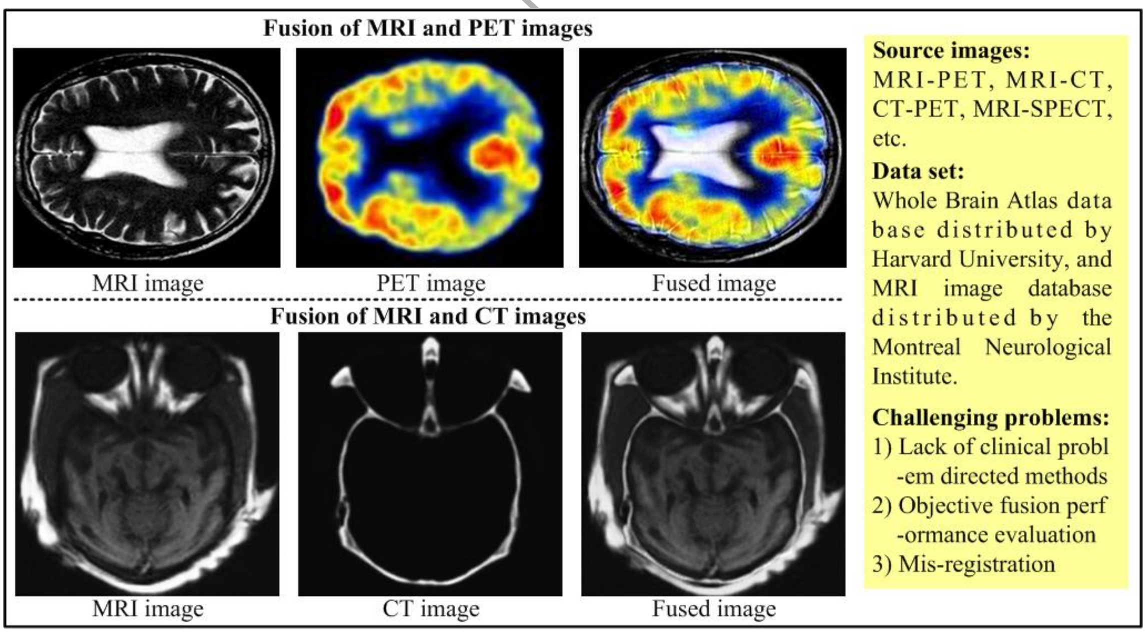

Figure 6: Examples of image fusion in medical diagnosis applications. (In this figure, the fusion of MRI with PET and CT images are achieved using the shearlet transform based method[25] and the guided filtering based method [41], respectively.)

a low spatial resolution. The MRI, CT, and PET images can be used together with image fusion techniques, which have shown advantages in improving the imaging accuracy, and practical clinical applicability [10]. Furthermore, other medical imaging methods such as single photon emission computed tomography (SPECT) scan [131] and ultrasound imaging [132] can find applications through image fusion.

In Fig. 6, the data sources widely used in medical image fusion applications are listed. For instance, a brain image data set [133] which contains registered MRI, PET, and CT images has been distributed by the Harvard Medical School. This data set has been widely used in related image fusion works [26, 54, 88]. Furthermore, the McConnell Brain Imaging Centre of the Montreal Neurological Institute also has distributed a MRI image database [134] for research purposes.

The major challenging problems in the medical image fusion field are also concluded in Fig. 6: 1) The lack of clinical problem oriented fusion methods. As mentioned above, the major objective of medical image fusion is to aid for better clinical outcomes. However, designing methods targeting a specific clinical problem is still a challenging and nontrivial task, since it require both medical domain knowledge and algorithmic insights. 2) Objective fusion performance evaluation. The second major problem in medical image fusion is how to evaluate the fusion performance objectively. Similar to the first problem, there are many different clinical problems of image fusion, in which the desired fusion effect may be quite different. 3) Mis-registration. Similar to the problem met in the remote sensing filed, the inaccurate registration of the objects between the images is also highly linked to the poor performance of medical image fusion algorithms.

4.3. Surveillance applications

Fig. 7 shows two examples of image fusion in surveillance applications, i.e., fusion of visible and infrared (IR) images, and fusion of daytime and nighttime images. The infrared image is sensitive to objects which have higher temperature than the background, making it able to "see in night" without illumination. The disadvantage of IR image is its poor spatial resolution. This problem can be addressed easily by fusion of the IR and visible images[29, 135]. Fusion of daytime and nighttime images, usually known as denighting, is another important technique for surveillance applications[136]. Due to low illumination, nighttime images usually have lower contrast and higher noise than their corresponding daytime images of the same scene. Through fusing the nighttime images with the daytime images, the quality of nighttime images can be improved significantly. Furthermore, in recent years, the fusion of visible, near-infrared, and infrared images also has been investigated for other surveillance problems, such as image dehazing [137], face recognition[138–140], and military reconnaissance[141].

In Fig. 7, the data sources widely used in surveillance image fusion applications are listed. For instance, some widely used infrared and visible image pairs can be downloaded from `http://www.ece.lehigh.edu/SPCRL/IF/image_fusion.htm` and `http://www.metapix.de/indexp.htm`. For

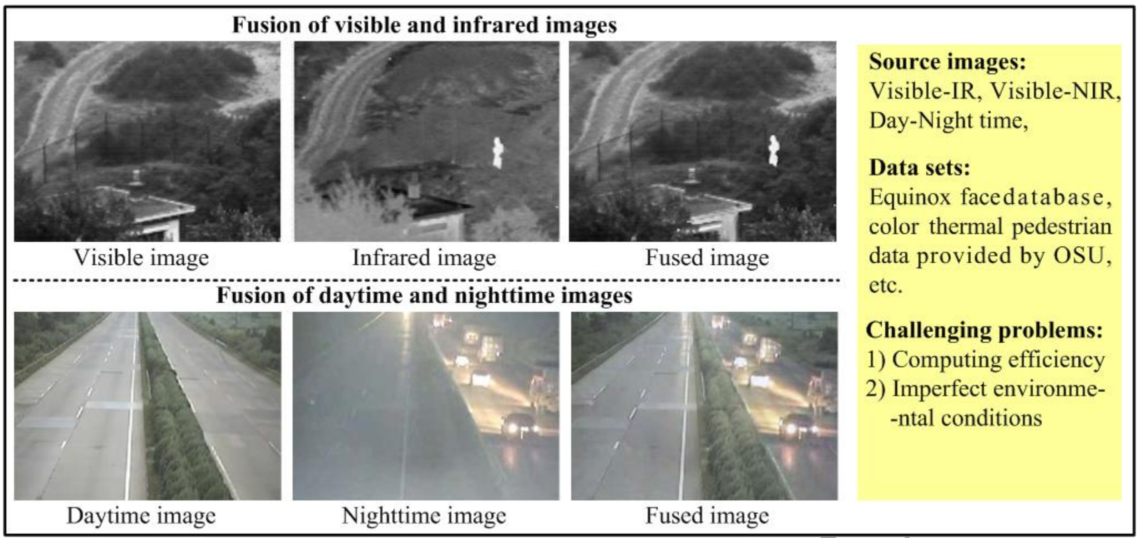

Figure 7: Examples of image fusion in surveillance applications. (In this figure, the fusion of visible and infrared images, and the fusion of day-time and night-time images are achieved using the image matting based method[66] and the gradient blending based method [143], respectively.)

face recognition, the Equinox face database gives a collection of both Long Wave Infrared and visible face images[142]. Furthermore, a color-thermal pedestrian data base can be found in `http://vcipl-okstate.org/pbvs/bench/` which is provided by the Oklahoma State University (OSU). For image denighting, a data set consists of daytime and nighttime images of the same scene can be downloaded at `http://web.media.mit.edu/~raskar/NPAR04/`

The major challenging problems in the surveillance image fusion field are also concluded in Fig. 7: 1) Computing efficiency. In surveillance applications, effective image fusion algorithms should well combine the information of the original images and make the fused image clear. More importantly, surveillance applications usually involve continuous real-time monitoring. Therefore, an interesting direction in surveillance applications is how to improve the speed of image fusion. 2) Imperfect environmental conditions. Another important problem in the surveillance image fusion field is that the images may be acquired at imperfect conditions. For instance, the source images may contain serious noise, and under-exposure due to the weather and illumination condition. Developing image fusion methods robust to such imperfect conditions is an important topic of this field.

4.4. Photography applications

Fig. 8 shows two examples of image fusion in photography applications, i.e., fusion of multi-focus images, and fusion of multi-exposure images. Due to the limited depths of field of cameras, it is impossible to have all objects with quite different distances from the camera to be all-in-focus within one shot. In order to solve this problem, mutli-focus image fusion merges multiple images of the same scene but with different focus points to create an all-in-focus fused image[53, 68]. The

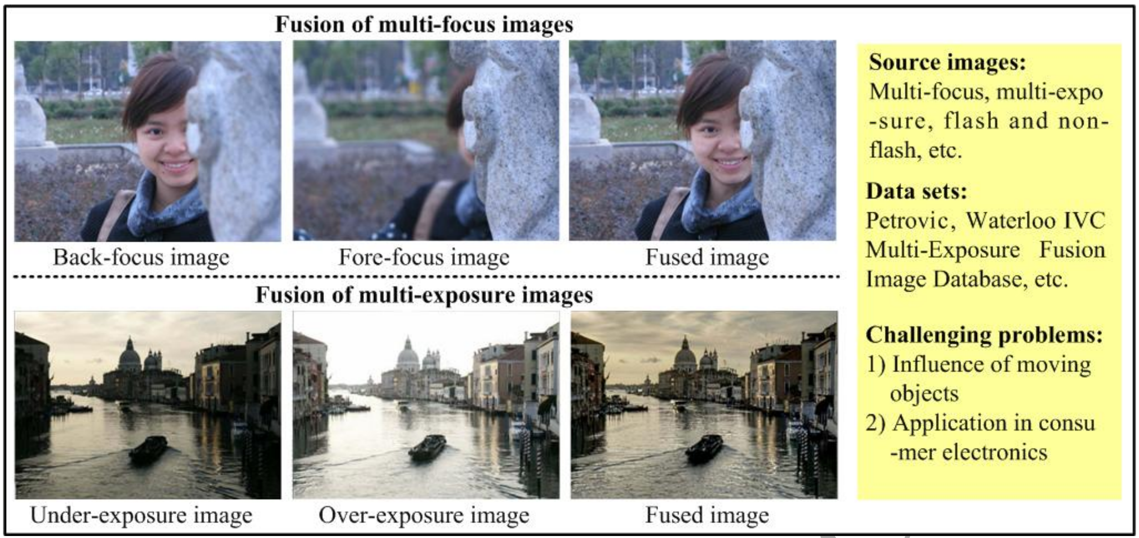

Figure 8: Examples of image fusion in photography applications. (In this figure, the fusion of multi-focus images, and the fusion of multi-exposure images are achieved using a guided filtering based method[41] and a recursive filtering based method [69], respectively.)

fused image can well preserve the relevant information from the original data, and thus, is highly desirable in many machine vision and image processing tasks. Similar to the idea of multi-focus image fusion, multi-exposure image fusion aims at constructing an all-well-exposed image by combining multiple images taken with different exposures [70, 71]. Besides setting the exposure degree, another photography technique is using flash under dark illumination. However, flash photography also brings some unacceptable artifacts, e.g., red eyes, flat, and harsh lighting, and distracting sharp shadows at silhouettes. As a solution of this problem, flash and non-flash image fusion is an interesting research topic in this field [144].

In Fig. 8, the data sources widely used in photography applications are listed. For instance, a multi-focus image data set can be found at `http://dsp.etfbl.net/mif`, which is distributed by Savic. Some multi-exposure images widely used in related researches can be downloaded at `http://www.easyhdr.com`. Recently, Ma *et al.* develop a multi-exposure database consists of 17 high quality multi-exposure image sequences, which is named as the Waterloo IVC Multi-Exposure Fusion Image Database [115]. Furthermore, the well-known Petrović image fusion database [145] also contains several pairs of multi-focus images and multi-exposure images.

At last, the major challenging problems in the photography image fusion field are concluded in Fig. 7: 1) Influence of moving targets. In photography applications, the multi-focus and mutli-exposure images are always captured at different times. In this situation, moving objects may appear at different locations during the capturing process. The consequence on fusion is that moving objects might create ghost artifacts to the fused image. 2) Application in consumer electronics. In the photography field, the imaging process involves taking several shots with different camera settings, which is quite time consuming. Therefore, how to integrate the multi-focus and multi-exposure image fusion algorithms into consumer electronics to capture high quality fused image in real-time is another challenging problem.

5. Future trends

Although various image fusion and objective performance evaluation methods have been proposed, at the present time, there are still many open-ended problems in different applications. In this section, the future trends in different application domains, i.e., remote sensing, medical diagnosis, surveillance, and photography, are analyzed.

In remote sensing, the major problem is how to decrease visual distortions when fusing multi-spectral, hyperspectral, and panchormatic images. Furthermore, although the input images are usually captured with the same platform, different imaging sensors do not exactly focus on the same direction and their acquisition moments are also not precisely identical. In this situation, precise registration is challenging due to the significant resolution and spectral difference among the source images. At last, due to the fast development of remote sensing sensors, developing novel algorithms for fusion of images captured by novel aircraft or satellite sensors will be a hot research topic.

In medical diagnosis field, the precise registration is also a challenging topic since the medical images are usually captured with different acquisition modalities. More importantly, designing methods targeting specific clinical problems is a challenging and nontrivial task of medical diagnosis. The reason is that the design of fusion methods requires both medical domain knowledge and algorithmic insights. Moreover, since the desired fusion performances may be not the same as those of general image fusion, the objective evaluation of the medical image fusion methods is also a challenging topic.

In surveillance applications, two major requirements should be considered. On one hand, fusion methods are expected to be computationally efficient, so as to be used for real-time surveillance applications. On the other hand, since the image acquisition conditions may vary dramatically in the outdoor environment, designing fusion methods robust to imperfect conditions such as noise, under- or over-exposure is a very important topic.

In photography field, since the input images are always captured at different times, moving objects may appear at different locations during the capturing process, and thus, produce ghost artifacts in the fused image. In order to solve this problem, designing methods insensitive to such mis-registration is a challenging topic of this area. Furthermore, another research direction is how to apply image fusion algorithm into embedded consumer camera systems for practical photography applications.

6. Conclusions

Pixel-level image fusion is one of the most important techniques to integrate and analyze information from multiple sources. It allows a more comprehensive analysis of the captured scene, which is not available while looking at images from a single modality or camera setting, and thus, has been widely used in feature extraction, object detection, recognition, and other related applications. In this paper, we have presented a survey of various pixel-level image fusion methods, which are coarsely divided into fusion *methods based on multi-scale decomposition*, *sparse representation*, *methods performed in other domains*, and *methods based on combination of different transforms*. Here, some conclusions about the main categories of image fusion methods are given as follows.

In the first category, most of researches focus on representing the image spatial structures with different multi-scale decompositions, such as pyramid, wavelets, multi-scale geometrical analysis, edge-preserving filtering, etc. Furthermore, various novel fusion rules which consider the high correlation among adjacent pixels, have been developed to further improve fusion performance.

In the second category, the sparse representation based methods have been reviewed. It is found that novel sparse coding and dictionary learning schemes have been researched seriously and successfully applied in different image fusion applications. In the future, designing more advanced fusion rules for sparse representation based fusion methods will be an interesting research topic of this area.

In the third category, the pixel-domain image fusion methods and methods based on color and PCA transforms are reviewed. It is found that the pixel-domain methods usually require advancing fusion rules to achieve satisfactory performance, while the color and PCA transform based methods are usually designed for specific applications, such as remote sensing and medical imaging.

In the fourth category, several image fusion methods have been proposed to combine the advantages of different transforms. Among these works, the combination of multi-scale decomposition and sparse representation has become a hot topic of this area.

Besides the fusion methods, the objective evaluation of the fusion methods' performances is also a challenging topic. In this paper, these fusion quality metrics are divided into two major classes, i.e., metrics requiring a reference or not. For the first class, most of methods focus on measuring the difference between the reference and the fused image more accurately. Some state-of-the-art methods are usually developed based on the perception function of human vision. For the second class, a very important topic is how to measure the complementary information (including the complementary spatial structures, global contrast, etc.) and the visual artifacts appeared in the fused image (including edge, color artifacts, etc.). Furthermore, in different applications, the choose of an optimal fusion quality metric also should consider the actual requirement is specific applications.

In conclusion, the significant progress in pixel-level image fusion research indicates the importance of this research in various real applications. The prominent approaches include multi-scale decomposition, sparse representation, etc. Moreover, combining multiple image fusion methods is also observed to be successful in this field. However, there still exist many challenges in image fusion and objective fusion performance evaluation, resulting from image noise, resolution difference between images, imperfect environmental conditions, computational complexity, moving targets, and limitations of the imaging hardware. Therefore, it is expected that novel researches and practical applications based on image fusion would continue to grow in the upcoming years.

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