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A survey on region based image fusion methods

Bikash Meher[a], Sanjay Agrawal[a], Rutuparna Panda[a,*], Ajith Abraham[b]

[a] Department of Electronics and Telecommunication Engineering, VSS University of Technology, Burla, Odisha, India
[b] Machine Intelligence Research Labs, Washington, United States

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ABSTRACT

Image fusion has been emerging as an important area of research. It has attracted many applications such as surveillance, photography, medical diagnosis, etc. Image fusion techniques are developed at three levels: pixel, feature and decision. Region based image fusion is one of the methods of feature level. It possesses certain advantages – less sensitive to noise, more robust and avoids misregistration. This paper presents a review of region based fusion approaches. A first hand classification of region based fusion methods is carried out. A comprehensive list of objective fusion evaluation metrics is highlighted to compare the existing methods. A detailed analysis is carried out and results are presented in tabular form. This may attract researchers to further explore the research in this direction.

1. Introduction

Image fusion is the method of merging information from many images of the same scene taken from various sensors, different positions or different time. The fused image retains all the complementary and redundant information of the input images that are very useful for human visual perception and image processing task. The objective of image fusion is to fuse the details of the important information extracted from the two or multiple images. In order to meet these objectives, the fused result should meet the following requirements: (a) the fused image should retain the most complementary and significant information of the input images, (b) the fusion technique should not generate any synthetic information which may divert the human observer or the advance image processing application, (c) it must avoid imperfect states, for instance, misregistration and noise [1]. It is observed from the literature that image fusion approaches are classified into two types, spatial based and transform based. In spatial based methods, the pixels of the images to be fused are combined in a linear or non-linear manner. The fused image is expressed mathematically as $I_F = \phi(I_1, I_2, \ldots, I_N) = \alpha_1 I_1 + \alpha_2 I_2 + \cdots + \alpha_N I_N$, where $I_1, I_2, \ldots, I_N$ are registered input images, ϕ denotes the fusion rule, α is a constant such that $\sum_{n=1}^{N} \alpha_n = 1$.

On the other hand, in transform based techniques, the input images to be combined are transformed from the space domain to some other domain by applying appropriate transforms such as wavelets or pyramids. A suitable fusion rule is utilized to fuse the transformed images. The inverse transform is utilized to reconstruct the original image. The fused image is represented mathematically as $I_F = T^{-1}(\phi(T(I_1), T(I_2), \ldots, T(I_N)))$, where T is the forward transformation operator and T^{-1} is the inverse transformation operator. A model of an image fusion concept is presented in Fig. 1.

As discussed above, the fused image will retain both the complementary and the redundant information from the input images.

On the basis of levels of abstraction, image fusion algorithms are applied at three stages: pixel, feature and decision level. In pixel level, images are combined directly using individual pixels to form the fusion decision. A comprehensive survey on pixel level image fusion is found in [2–6]. The feature level image fusion is achieved by region based fusion scheme [7–9]. In region based image fusion, initially an image is partitioned into a set of regions. The different features of these regions are extracted. The appropriate features from all the source images are merged to get the fused image. They are less responsive to noise and more robust. Further, the feature information is used for considering more intelligent semantic fusion rules. A first hand survey on region based image fusion is presented in Section 2. Decision level image fusion techniques are based on the outputs of initial object detection and classification task [10–12]. Usually, a preliminary decision from the feature based image fusion serves as the input to the decision level fusion. A generic classification of image fusion methods is shown in Fig. 2.

Most of the fusion applications need analysis of multiple images of the same scene for improved results. For instance, in the medical imaging applications, computer tomography (CT), magnetic resonance (MR) and positron emission tomography (PET) images are fused

* Corresponding author.
E-mail addresses: r_ppanda@yahoo.co.in (R. Panda), ajith.abraham@ieee.org (A. Abraham).

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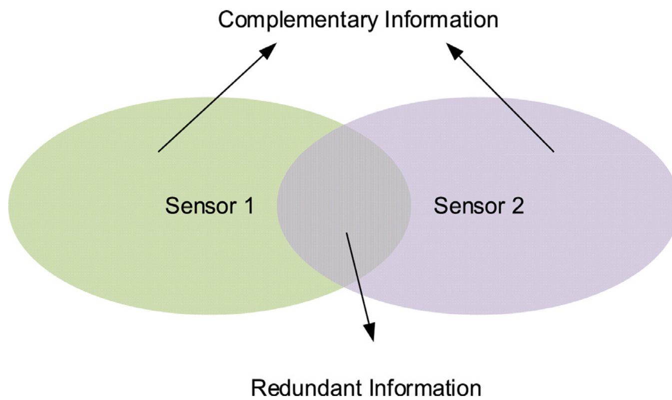

Fig. 1. Image fusion example.

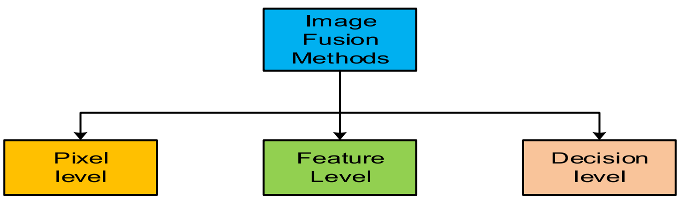

Fig. 2. A generic classification of image fusion methods.

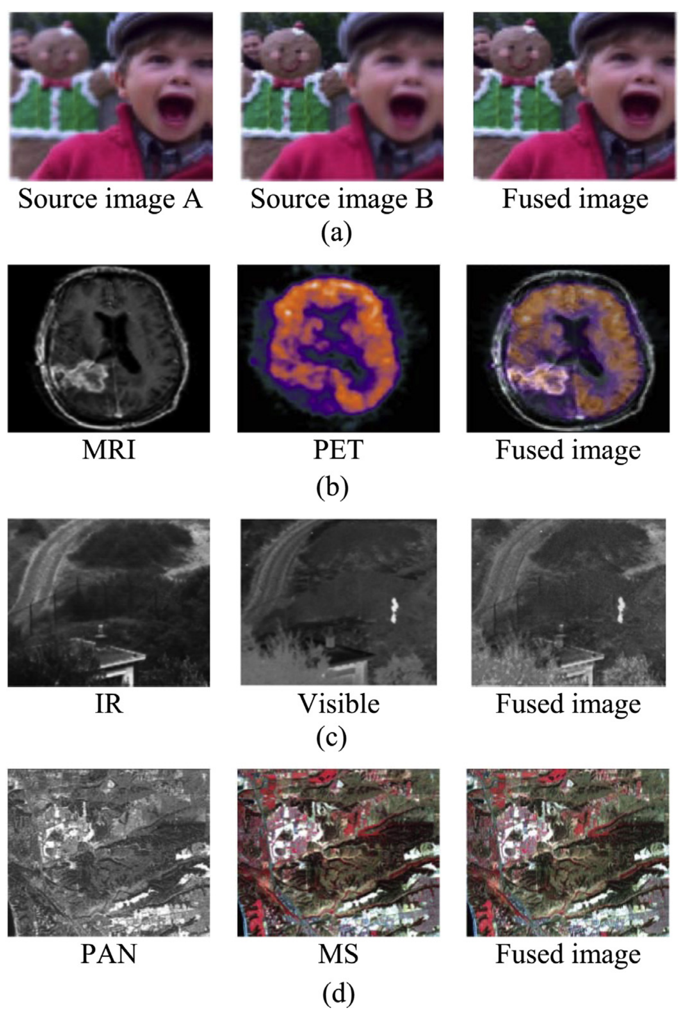

Fig. 3. Example images of different image fusion applications, (a) Photography (Multifocus) [13] (b) Medical diagnosis [14] (c) Surveillance [15] (d) Remote sensing [16].

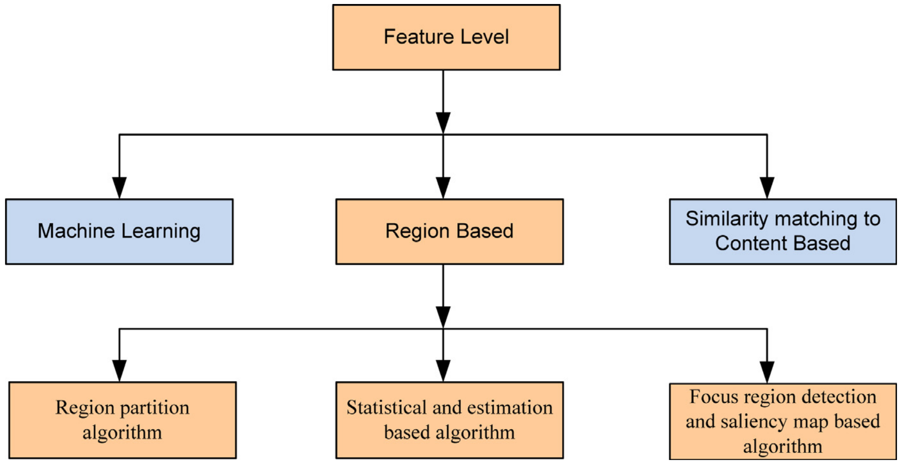

Fig. 4. Classification of region based image fusion methods.

together for better analysis and diagnosis of the diseases. Similarly, in the remote sensing applications, multispectral (MS) images, which have low resolution and high spectral density are fused with panchromatic (PAN) images possessing high resolution and low spectral density, to obtain the spectral contents of the MS image with high spatial resolution. In surveillance applications, the different images (infrared, visible, near infrared) are taken from different sensors and fused for detection or for night vision. In photography applications, the multifocus images, multi-exposure images, etc. are fused to get the image which is better perceived to the human vision and computer processing. Some of the examples of the different image fusion applications are illustrated in Fig. 3. The methods used are described in [13–16]. The following methods are used in Fig. 3– a) deep convolutional neural network based fusion [13], b) optimum spectrum mask based fusion [14], c) non-subsampled contourlet transform and intensity-hue-saturation transform based fusion [15], and d) fuzzy integral based fusion [16]. Some of the applications of image fusion are carried out in real time. This has inspired the researchers to develop more effective techniques for image fusion. The number of articles published has increased rapidly since 2010 [5].

A survey on different image fusion methods is done by many researchers. A classification of image fusion methods based on multi-scale decomposition technique is described in [17]. A review of image fusion techniques in remote sensing is presented in [18–20]. Solanky and Katiyar [18] focussed on pixel based fusion methods in remote sensing. Ghassemian [19] has carried out the survey on pixel, feature, and decision level with more emphasis on pixel level method. Vivone et al. [20] presented a comparison among different remote sensing image fusion algorithms, particularly focussing on multiresolution analysis and component substitution methods. Wang et al. [21] presented a review of image fusion methods based on pulse coupled neural network (PCNN). An overview of multimodal medical image fusion is described in [22,23]. The authors in [22] have used different image reconstruction and decomposition techniques, namely multiresolution based, sparse representation based and salient feature based. They have experimented with different fusion rules and compared the results using different image quality assessment parameters.

Most of these methods describe the image fusion techniques based on pixels. However, it has several limitations: (i) blurring effects, (ii) high sensitivity to noise and (iii) misregistration. These limitations may be reduced by deploying the region based image fusion techniques. These techniques have the capability to utilize intelligent fusion rules. As far as our knowledge is concerned, a survey on region based image fusion methods is not available in the literature. This has motivated us to carry out a survey on different region based image fusion methods. In this context, we present a survey on image fusion methods based on the regions. Mainly, the paper focusses on different approaches and ideas of the existing region based fusion practices. The results of the different techniques are summarized. An elaborate discussion is presented at the end, comparing the various fusion methods. This may clearly set a path for more investigations into region based fusion techniques. This may open doors to new unsolved problems in the domain of image fusion.

The remainder of the manuscript has been structured as follows. Section 2 explains the different region based image fusion methods. Section 3 presents the performance evaluation parameters. An elaborate discussion on a comparison of various methods is presented in Section 4. Finally, Section 5 draws the conclusion giving a brief summary and critique of the findings.

2. Region based image fusion methods

It is observed from the literature that the feature level image fusion technique can be further classified into machine learning, region based and similarity matching to content based. In the machine learning method, the features are extracted and a suitable classifier is used for fusion. In region based method, the input images are divided into different regions using some segmentation techniques. The features are extracted from the regions and suitable fusion rules are used to get the fused image. The similarity matching to content based image retrieval technique uses the visual contents of an image, for instance, shape, texture, colour, and spatial layout to denote the index. The relevant indices are combined to get the fused image. A first hand classification of region based image fusion methods is proposed here. It is classified as shown in Fig. 4.

The region based image fusion is carried out in three different approaches – (i) the region partition approach is based on partitioning the source images into distinct regions by using standard segmentation methods. The characteristics of the regions are used to get the fused image; (ii) the statistical and estimation based approach partitions the source images into regions using advanced region segmentation algorithms followed by a statistical image formation model. A joint region map is developed by analysing the region map of each source image to produce the fused image; (iii) the focus region detection and saliency map based approach aims at the separation of the significant foreground object from the background leading to perceptually coherent regions. The advantages and disadvantages of these three approaches are mentioned later in this section.

A generic block diagram of the region based image fusion scheme is presented in Fig. 5. The region based image fusion procedure reads two or more input images. The images are segmented into different regions using various segmentation algorithms. The various features like edge, texture, contour, etc. are extracted from each of the regions using

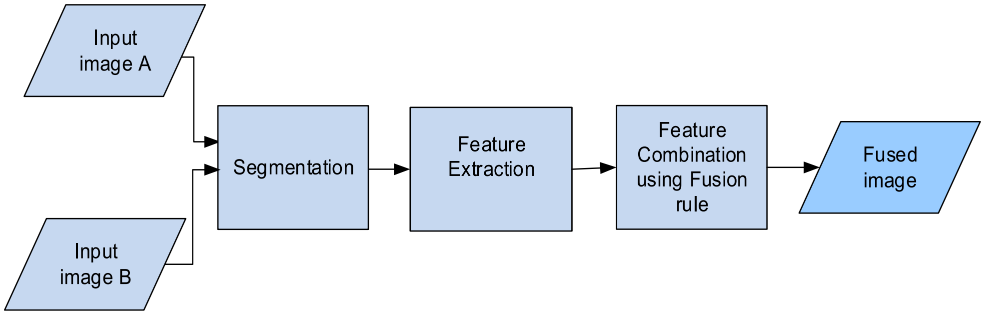

Fig. 5. A schematic block representation of region based image fusion method.

Table 1
Classification of various region based image fusion algorithms.

Algorithm	Method	References
Region partition algorithm	DWT	[24,25]
	dual-tree complex wavelet transform (DT-CWT)	[28]
	DWT and highboost filter	[29]
	nonsubsample contourlet transform (NSCT)	[30,31]
	shift invariant shearlet transform (SIST)	[32]
	discrete wavelet frame transforms (DWFT)	[33]
	independent component analysis (ICA)	[34-38]
	Chebyshev-ICA	[39]
	ICA-support vector machine (SVM) (ICA-SVM)	[40]
	artificial neural network (ANN)	[43]
	PCNN	[46]
	fuzzy logic and particle swarm optimization (FPSO)	[47]
	differential evolution (DE)	[48]
	bi-dimensional empirical mode decomposition (BEMD)	[49]
	region segmentation and spatial frequency (RSSF)	[50]
	region fusion structural similarity index (RF-SSIM)	[51]
	compressed sensing (CS)	[52]
	image matting	[53]
	sparse representation (SR)	[54]
Statistical and estimation based algorithm	expectation maximization (EM)	[58]
	energy evaluation model	[61,62]
	bivariate alpha-stable (BαS)	[63]
	non expectation maximization (NEM) and bootstrap sampling	[64]
Focus region detection and saliency map based algorithm	lifting stationary wavelet transform (LSWT)	[70]
	NSCT and LSWT	[71]
	quaternion wavelet transform (QWT) and normalized cut	[72]
	NSCT and Focus area detection	[73]
	Surface area based	[74]
	shearlet and graph based visual system (GBVS)	[75]
	NSCT and Frequency Tuned (FT)	[76]

suitable feature extraction techniques. The features are joined using relevant fusion rules to get the fused image.

Based on the vast information available in the literature, the various region based image fusion procedures are categorized into three classes as shown in Table 1.

In the region partition based algorithms, the first step is to partition the input images into distinct regions by employing standard segmentation techniques. By considering the characteristics of the regions, fusion rules are employed to get the fused image. In general, the different approaches of multiresolution, ICA based transform, optimization etc. are incorporated with the segmentation algorithms. Some flow diagrams of the existing methods are shown. The flow diagram of region partition algorithm based method explained in [49] is depicted in Fig. 6.

The region based image fusion technique was firstly suggested by Zhang and Blum [24]. The authors in their work combined synergistically the pixel and feature based fusion. The wavelet transform of the source images is merged to produce the fused image. The authors identified edges and region of interest (ROI) as the important features for guiding the fusion process. It is to be noted that this approach involves division of a series of images at discrete resolutions. This problem was addressed by Piella [26,27]. The author proposed a general framework for pixel and region based image fusion utilizing multiresolution approach. The segmentation stage is improved by performing a single segmentation from all the source images in a multiresolution fashion. The images are fused following the additive or weighted combination fusion rule. However, the author has not optimized the performance and investigated the effect of different parameters on the fusion process. Further, the regions are combined based on simple region property like average activity. The DWT lacks shift invariance and directionality property.

To overcome these problems, Lewis et al. reviewed a lot of pixel level fusion algorithms (using averaging, pyramids, DWT, DT-CWT). The authors compared their findings with a new region based technique [28]. The authors used DT-CWT for segmentation of the features of the input images to develop a region map. The properties of every region are determined, and the fusion is performed region by region utilizing region based approach in the wavelet domain. However, the authors pointed towards the improvement of higher level region based fusion rules. The quality of the fused image may deteriorate due to the inverse

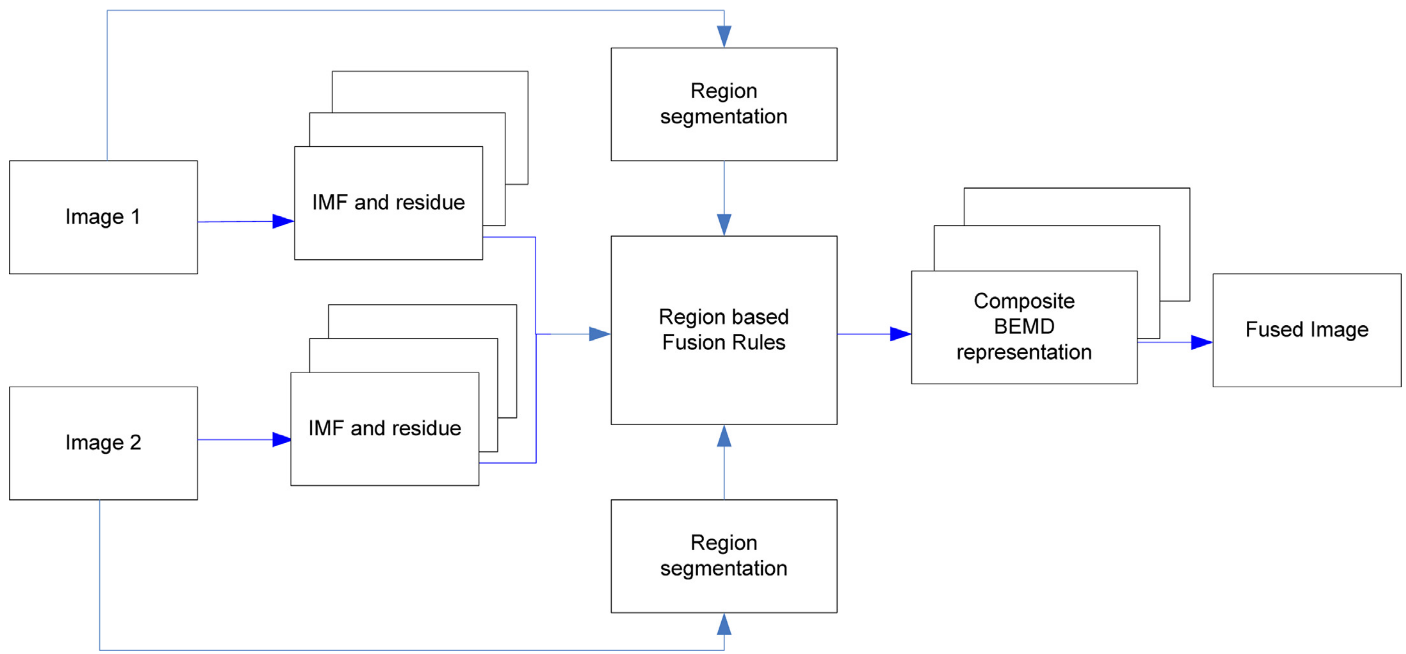

Fig. 6. Flow diagram of region based BEMD fusion scheme [49].

DT-CWT transform. To improve the fusion results, Zaveri and Zaveri [29] used highboost filter concept with DWT for the fusion. Their proposed technique overcomes the shift variance problem; as inverse wavelet transform is not needed in the algorithm. The highboost filter is used to get accurate segmented image. The segmented image is utilized for obtaining the regions from the input images. The extracted regions are fused using the fusion rule i.e. mean max standard deviation and spatial frequency. However, they concluded that, to enhance the robustness of the method, complex fusion rules may be developed.

Many researchers have also used the NSCT approach to image fusion. A region based image fusion procedure for infrared (IR) and visible image using NSCT is suggested by Guo et al. [30]. The features of the target region are used to segment the IR image. The input images are divided using NSCT. The target region and the background regions are merged using different fusion rules. The inverse NSCT is used to get the fused image. However, the fusion process involved has a high computational complexity. Zheng et al. used NSCT and fuzzy logic for the fusion of IR and visible image [31]. Firstly, the required input images are segmented using the live wire segmentation method followed by decomposition using NSCT transform. The fuzzy fusion method is used in the low frequency domain and region based rule is used in high frequency domain. The inverse NSCT is applied to get the fused image. To effectively analyse the geometric structure of remote images with computationally efficient approach, a SIST and regional selection algorithm is suggested by Luo et al. [32] for remote sensing image fusion application. The feature vectors from MS and PAN images are divided into regions using fuzzy c-means (FCM) clustering. Based on the regional similarity, an adaptive multi-strategy fusion rule of high frequency band is suggested. Finally, the fused image is found by taking the inverse SIST and inverse entropy component analysis.

The local features of an image are usually not considered for fusion. To resolve this, Wang et al. suggested a fusion procedure based on the DWFT and regional characteristics [33]. The transform coefficients are found from the two input images using the DWFT. Taking the mean of the transform coefficients, an average image is obtained which represents the approximate features of the input images. The average image is segmented based on the region features to get the region coordinates. The coefficients and the region coordinates are mapped. The fused image is produced by combining the coefficients of each region using suitable fusion rules. However, it needs a relatively long time for processing due to the image segmentation process involved.

Researchers have extensively used ICA for image fusion [34–42]. Mitianoudis and Stathaki [34] used ICA for region based image fusion. The authors investigated the effectiveness of a transform utilizing ICA and topographic ICA bases in image fusion. The fused image in ICA domain is obtained by utilizing new pixel and region based fusion rules. The suggested method demonstrated better performance as compared to conventional wavelet approaches at the cost of slightly more computational load. Contrary to the suggested framework, Cvejic et al. used ICA bases for region based multimodal image fusion [35,36]. The authors used different training subsets to identify the most significant regions in the source images. Subsequently, they combined the ICA coefficients utilizing the fusion metrics for enhanced results. In [35], a combined approach is used to obtain the most significant regions from the source images. The fused image is obtained by merging the ICA coefficients from the obtained regions. The authors used the Piella metric to enhance the quality of results. The performance improved with an increase in the computational complexity.

These proposed methods exhibit the following drawbacks: (i) the approaches cannot be easily extended to multiple sensor fusion application, (ii) there is no theoretical justification for the presence of the global optimum of the objective function derived from the Piella index. To overcome this, in [37], the authors used optimization of the Piella index for multiple input sensors. To get the optimal solution, the authors revisited the previously proposed work in [34] and further suggested a method to find the optimum intensity range through optimization of a fusion index. The suggested method improves the original ICA-based framework and produces a better fused image. In [38], the authors extended their work to a more advanced region based fusion approach. A group of fusion rules using textural info is presented. The suggested method enhances the performance than the max-abs fusion rule in case of multifocus images. On the contrary, it was not so good for multimodal image fusion. The reason may be the various modality images have different texture properties. In [39], Omar et al. used the combination of Chebyshev polynomial (CP) and ICA depending on regional information of source images. The proposed method used segmentation technique to identify features such as texture, edge, etc. The fused image is found using distinct fusion rules as per the selected regions. The advantage of this method is that it offers an autonomous denoising property, combining the benefits of both CP and ICA. Nirmala et al. proposed a region based multimodal (visible and Infrared) image fusion scheme using ICA and SVM [40]. The source images are jointly segmented in the spatial domain. The significant features of every region are calculated. The ICA coefficients of the particular regions are combined to form the fused ICA representation. As the ICA bases are computed and SVM is trained, the suggested technique may seem to multiply the computational load.

In recent studies, many optimization methods have been utilized by researchers for image fusion. Neural networks (NN) have been extensively employed for image fusion [43–45]. Hsu et al. suggested a multi-sensor image fusion method using ANN, which merges the features of the feature and pixel level fusion scheme [43]. The basic concept is to segment only the far infrared image. The information from each segmented region is added to the visual image. The different fused parameters are determined according to the different regions. In [46], PCNN has been utilized for the fusion of multi-sensor images. The procedure begins with the segmentation of source images using PCNN and the output is used to direct the fusion process. The suggested method outperforms the pixel based methods in terms of blurring effect, sensitivity to noise and misregistration. Saeedi and Faez [47] proposed a fusion of visible and IR image using fuzzy logic and PSO. The high frequency wavelet coefficient of IR and visible images is fused using fuzzy based approach. The PSO is suggested for the low frequency fusion rule. The low frequency and high frequency parts of the wavelet coefficient are fused. The authors have not considered noise in their work. It is evident that for noisy images, the segmentation process will result in over segmentation with inaccurate regions. Aslantas et al. described a new method for thermal and visible images [48]. Instead of using a single weighting factor, the authors have used multiple weighting factors for distinct regions to get the fused image. The weighting factors are optimized using DE. A new image fusion metric – sum of correlation difference is formed to assess the performance of the fused images during the optimization procedure.

Some other methods have also been proposed by many researchers. Zheng and Qin used BEMD technique for region based image fusion [49]. The source images are partitioned into several intrinsic mode functions and a residual image. The process of fusion is carried out as per the segmentation of the source images, which produces a combined BEMD representation. The fused image is found by using the inverse BEMD. Because of the finite length of wavelet function, DWT induces energy leaking. This problem does not occur in BEMD because it is considered as an adaptive highpass filter. Li and Yang [50] proposed a novel method for multifocus images utilizing region segmentation and spatial frequency. The normalized cut method is utilized to segment the intermediate fused image. The two input images are segmented as per the segmenting results of the intermediary fused image. The fused image is obtained by merging the segmented regions using spatial frequency. The advantage of the suggested technique is that it does not use the multiresolution approach, as few information of the input image may be missed while performing the inverse multiresolution operation. The limitation of the proposed method is that the computational time is more as compared to the wavelet based approaches, as the segmentation procedure takes more time.

In most of the papers, a common segmentation technique for different input images taken from distinct sensors have not been used for region based image fusion. These approaches are restricted to the particular input images only. Luo et al. proposed the method of region partition strategy in which the segmentation is performed on the similar features of input images (irrespective of the kind of input images) [51]. The complementary and redundant correlations of the source images are distinguished by using fusion methods. On the basis of the similar components, the small homogeneous regions are merged. The final region map is obtained by comparing the resemblance between the images. The method has several advantages like the generality of application, superior visual perception and simple realization without parameter setting.

Chen and Qin [52] used CS theory in the region based fusion framework. The authors considered both compression capabilities of sensors and the intelligent understanding of the image features for fusion. In dynamic scene, it is very hard to accurately determine whether a pixel or region is blurry or not by utilizing only the focus information only. Besides, another limitation of the pixel based method is that the fusion results obtained is not accurate when the image patterns become complex. In contrast to this, Li et al. proposed image matting fusion technique for the fusion of multifocus images in dynamic scenes [53]. The algorithm uses morphological filters to get rough segmentation results followed by image matting to obtain the accurate focussed regions. The fused image is found by merging the focussed regions. Chen et al. [54] used the SR method for the fusion of multifocus images. The suggested technique merges the advantages of regional and sparse representation based fusion to obtain the fused image. The fusion of high resolution images using mean shift segmentation method is described in [55]. The authors used SSIM for the measurement of regional similarity.

These methods need a precise selection of segmentation technique. The choice of segmentation technique is crucial to obtain a fused image. In these approaches, the regions are chosen and fused based on some regional characteristics. The significance of the statistical characteristics of the regions has not been considered, which is utilized to enhance the precision of the decision process in image fusion applications.

Most of the region based image fusion procedures suggested by different researchers have not applied the estimation theory approach rigorously. In the statistical and estimation based algorithms, first the input images are partitioned into regions by using some sophisticated region segmentation algorithms. A joint region map is developed by analysing the region map of each source image to produce the fused image. A statistical image formation model is developed for every region in the joint region map. The estimation procedure is utilized in combination with the model to build an iterative fusion process to determine the model constraints and to generate the fused image. A typical flow diagram of statistical and estimation based algorithm explained in [58] is shown in Fig. 7.

Sharma et al. [56] suggested a Bayesian fusion scheme inspired by estimation theory. A statistical signal processing method to image fusion is suggested by Yang and Blum in [57]. Many researchers have proposed image fusion using the EM algorithms [58–60]. In [58], the authors used the EM algorithm, which utilizes the features of regions for fusion in an optimal way. Each region is built by a statistical image formation model. The region-level EM algorithm is developed by using the EM fusion procedure in combination with the model to produce the fused image. Zhang and Ge [61,62] proposed image fusion method employing energy estimation approach. To partition the source images into regions on the basis of homogeneity, piecewise smooth Mumford and Shah Model is used. To speed up convergence, a level set based optimization procedure is combined with it. The fusion quality is determined using an energy model. The methods proposed in [27,28,58], fail to consider the importance of the statistical features of regions, which is utilized to enhance the precision of the decision process in image fusion applications. In some of the research articles, statistical model for fusion and the segmentation of images are integrated. Wan et al. integrated the multi-scale image segmentation technique and statistical feature extraction in the suggested framework [63]. A region map of input images is obtained using DT-CWT and statistical region combining algorithm. The source images are divided into significant regions that contain salient information using symmetric alpha stable distribution. By employing the BαS technique, region features are modelled. The fused image is obtained by applying a segmented driven approach in the complex wavelet domain.

In most of the practical applications, the dimensions of the training data set are too large which accounts for a large computation time in statistical image fusion. This constraint requires data reduction. This is achieved by choosing a suitable subset of the prime training data set without compromising the image fusion precision appreciably. Zribi [64] proposed a non-parametric and region based image fusion method following the principle of bootstrap sampling. This brings down the dependence effect of pixels in true image and also reduces the fusion time. The image sensors are expressed as a real scene degraded by distortion in the statistical image formation model. The authors used a non-parametric EM procedure to determine the model constraints and the fused image. However, the proposed method utilized only two source images for fusion.

These methods characterized the segmented regions using the statistical and estimation approaches. The quality of image segmentation is vital for determining accurate segmented regions. The ROI and boundary detection of focused regions is not accurately obtained with

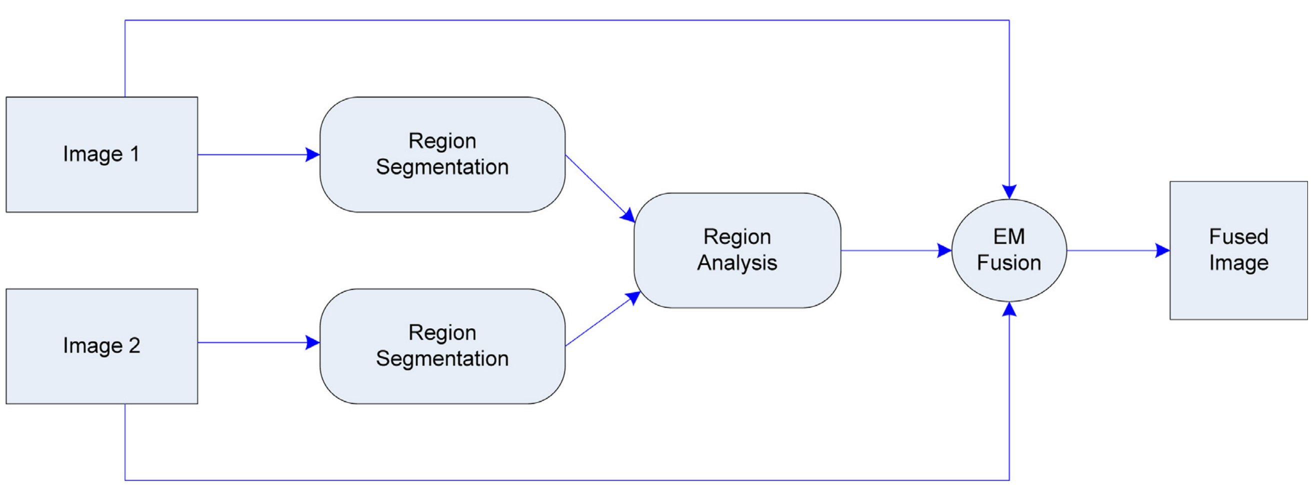

Fig. 7. Flow diagram of region based EM fusion scheme [58].

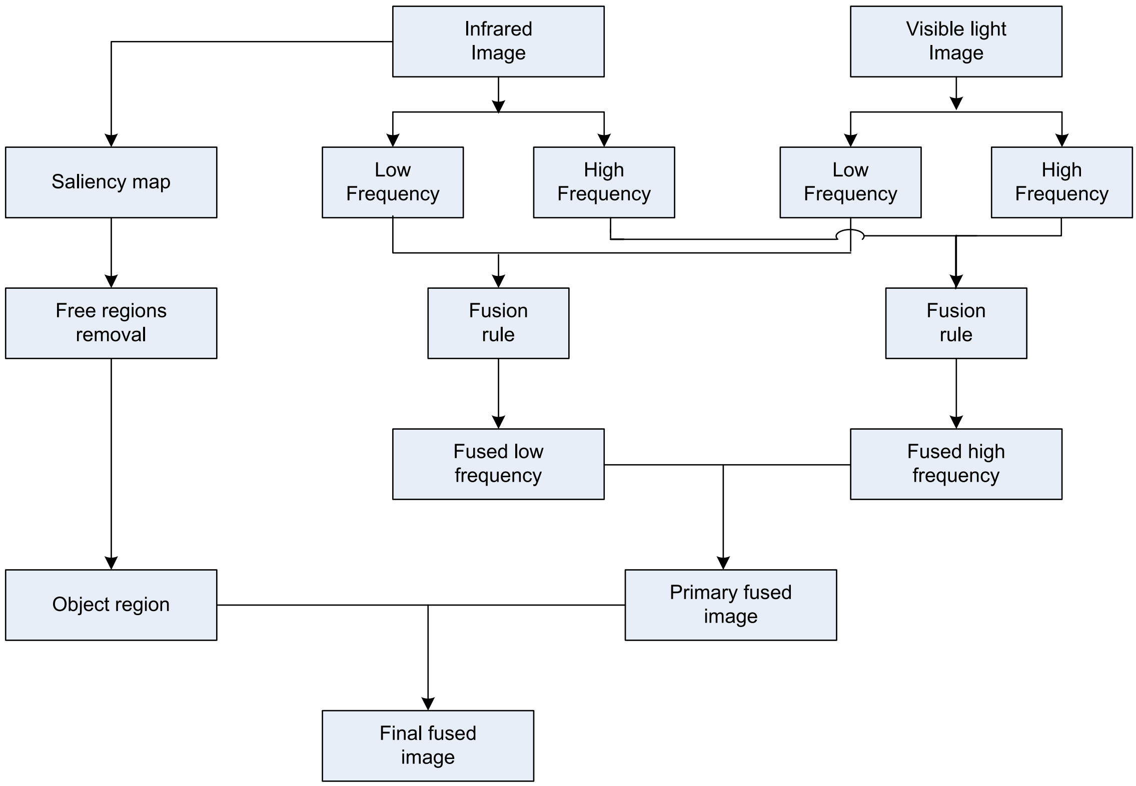

Fig. 8. Flow diagram of region based image fusion scheme of NSCT based method [76].

the methods discussed above. Many researchers have also used saliency map based algorithms for region based image fusion. In general, salient object detection is an image/background segmentation problem and aims at the separation of the significant foreground object from the background. It is marginally different from the conventional segmentation procedure in which image is segmented into the perceptually coherent regions. To select an optimal region extraction method, researchers have compared many saliency analytical methods [65–69]. Fig. 8 shows the flow diagram of focus region detection and saliency map based algorithm described in [76].

The problem of the spatial domain based methods is that they may generate artefacts or imprecise results at the focused border areas, as the boundary of focused areas cannot be estimated correctly. This problem is solved by the use of multi-scale transform method. However, the problem with this method is to choose the proper fusion rule. Additionally, some information of the input image may be lost while implementing the inverse multi-scale transform. So as to avoid these problems, the authors proposed methods combining the benefits of spatial region based and transform domain [70,71]. Chai et al. suggested a multifocus image fusion technique utilizing the focus region detection and multiresolution approach [70]. The authors have used the focus region detection and LSWT to combine the benefits of spatial and transform domain based fusion approaches. The idea of local visibility (LV) in LSWT domain is used for the fusion of the lowpass subband coefficients. The sum modified Laplacian inspired local visual contrast rule is applied for the fusion of the highpass subband coefficients. However, the fused image consists of several imprecise results at the boundary of the focused region. To overcome this, the authors proposed a multifocus image fusion method based on NSCT and focus region detection [71].

The image visibility rule in NSCT domain is used for the fusion of lowpass subband coefficients. The local area spatial frequency rule is employed for the fusion of highpass subband coefficients. The limitation of the methods is that the post- processing phase utilizing morphological procedure is not robust. In order to avoid this problem, Liu et al. suggested a multifocus image fusion utilizing QWT [72]. Initially, the authors used the local variance of the phases to identify the focus or defocus for each pixel. They segmented the focus detection result using normalized cut to eliminate the detected errors. Finally, the fused image is found utilizing the spatial frequency as fusion weight along the edge of the focus region. However, the method may create false information and irregular phenomenon at the boundaries of the focused areas, as the boundary cannot be estimated precisely. To perfectly determine the boundaries of the focused region, Yang et al. suggested a novel hybrid multifocus image fusion method based on NSCT and focus area detection [73]. The authors modified their work in the sense that they used the log Gabor filter for high frequency subband coefficients. The limitation of the method is that the NSCT procedure is consuming more time. Nejati et al. proposed a new focus measure depending on the surface area of the region surrounded by juncture points for multifocus image fusion [74]. The objective of this metric is to differentiate focus regions from blurred regions. The juncture points of the source images are computed and segmented utilizing these juncture points. The surface area of every region is used as a quantity to get the focused regions. An initial selection map for the fusion is obtained using this measure which is refined using morphological operations.

The most challenges task in region based image fusion is the proper image segmentation. In recent years, numerous state-of-the-art saliency region detection approaches have been suggested. Still, there are some shortcomings with them. The most noticeable among them is the salient region detection approaches which may focus the object region as well as some of the background region. Detection of the visual salient region has been an ongoing research process for a long time. The saliency map is an emerging technique to identify the salient region, which can overcome the above problem. Zhang et al. suggested a multifocus image fusion technique based on focus region extraction. The authors used saliency analysis [75]. The GBVS procedure is utilized to identify the focused region in the input image. Subsequently, watershed and morphological techniques are employed to find the bounded area of saliency map and eliminate the pseudo focus area. In the final step, the

Table 2
Objective fusion evaluation metrics with reference image.

Sl. no.	Quality metric	Description	Formula	Reference
1	PSNR	It is calculated as the ratio of number of intensity levels in the image to the related pixels in the ideal and the fused image. A higher PSNR value indicates superior fusion.	$PSNR = 20\log_{10}\left(\frac{L^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_r(i,j) - I_f(i,j)\right)^2}\right)$	[79]
2	RMSE	It estimates the quality of the fused image by relating the ideal and the fused image. The value of RMSE should be lower i.e. close to zero for a good fused image.	$RMSE = \sqrt{\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=1}^{N-1}(R(i,j) - F(i,j))^2}$	[80]
3	MI	The similarity of image intensity between ideal and fused image is measured using mutual information. MI should be high for a better fusion performance.	$MI_F^{AB} = MI_{FA} + MI_{FB}$	[81]
4	SSIM	The SSIM is employed to calculate the quality of one image compared with the other image, provided that the other image is of perfect quality. SSIM should be high between [− 1, 1].	$SSIM(x,y) = \frac{\left(2\mu_x\mu_y + C_1\right)(2\sigma_{xy} + C_2)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)(\sigma_x^2 + \sigma_y^2 + C_2)}$	[82]
5	CC	It is used to compute the spectral feature similarity between the reference and the fused image. The value of CC should be high i.e. close to 1.	$CC = \frac{\sum_{i,j}[(X_{i,j} - \bar{x})\cdot(\hat{X}_{i,j} - \bar{\hat{x}})].}{\sqrt{\sum_{i,j}[(X_{i,j} - \bar{x})^2]\cdot\sum_{i,j}\left[(\hat{X}_{i,j} - \bar{\hat{x}})^2\right]}}$	[83]
6	UQI	The UQI is used to calculate how much amount of relevant data is transformed from ideal image into the fused image. The value of this metric ranges between − 1 to 1.	$UQI = \frac{\sigma_{xy}}{\sigma_x\sigma_y}\frac{2\bar{x}\bar{y}}{(\bar{x})^2 + (\bar{y})^2}\frac{2\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2}$	[84]

focused area is fused straight and the residual area are fused using shearlet transform.

In [76], Meng et al. suggested a new procedure based on object region detection and the NSCT. The FT saliency detection map is used to acquire the saliency map for the IR image. The significant object region is extracted from the IR image using free regions removal method. The input images are divided via NSCT and distinctive fusion rules are applied for the lowpass and highpass subband coefficients. The inverse NSCT is utilized to produce a primary fused image. At last, the final fused image is found by combining the primary fused image with the object region. Again in [77], Meng et al. presented the region based image fusion technique to merge IR and visible image by employing the saliency map and interest point. A saliency map is built using a saliency detection process for IR image. Further, it is explored to identify interest points. To get the salient region, a convex hull of the salient interest point is computed. The first saliency map is developed by merging the convex hull of the salient interest points. Finally, the various fusion rules are employed for object region and background. In [78], Han et al. proposed a saliency aware fusion procedure for multimodal image fusion (IR and visible image) to enrich the visualization of the visible image. The process is used for saliency recognition followed by a bias fusion. The information of these two sources is combined using the Markov random fields. The following fusion phase is used to bias the end result favouring the visible image, excepting when a region has distinct IR saliency. The fused image represents both salient foreground from the IR image and background as provided by the visible image. The fused image obtained with these methods has significant improvement compared to other methods, because it avoids the traditional segmentation process. The transform used in these methods may consume more time. Still, the different methods have their own importance. The further improvement in the fusion quality may require a suitable selection of the regional features.

The region partition based algorithms are simpler than the other two approaches – statistical and estimation based, focus region detection and saliency map based. The region partition based algorithms need a precise selection of segmentation technique. The choice of segmentation technique is crucial to obtain a fused image. In these approaches, the regions are selected and fused based on certain regional characteristics. However, the importance of the statistical characteristics of the regions are not considered, which is utilized to enhance the precision of the decision process in image fusion applications. The statistical and estimation approach uses the statistical characteristics to improve the precision of the decision process. It is needed to choose an efficient image segmentation technique for determining accurate segmented regions. However, the ROI and boundary detection of focused regions is not accurately obtained with these approaches. The focus region detection and saliency map approaches uses the ROI and boundary detection to accurately obtain the fused image. The selection of segmentation technique is not vital in these approaches. However, these approaches are complex and application specific.

3. Performance evaluation

There are two methods in which the quality of the fused image is computed i.e., qualitative or subjective and quantitative or objective. Qualitative analysis means visual analysis in which the fused image is matched with the source images by a group of observers. The analysis of the fused image considers different optical parameters like spatial details, the size of the object, colour etc. The qualitative analysis is typically accurate if it is done correctly. However, these methods are inconvenient, expensive and consumes more time. It is a very difficult task in most of the image fusion applications due to lack of availability of a ground truth image that is perfectly fused. So, another technique to calculate the fusion performance is the quantitative or objective evaluation. But again, it remains an issue as how to measure the performances of the fused image objectively. In this survey, the quantitative fusion assessment metrics are classified in two groups based on the presence or absence of a reference fused image.

3.1. Objective fusion evaluation metrics with reference image

The reference image is the ideal fused image that is taken as a ground truth image for validating the image fusion algorithm. The ground truth image may be available or manually constructed. A list of commonly used objective fusion evaluation metrics with reference image is illustrated in Table 2. The quality metrics employed to compute the fusion performance are peak signal to noise ratio (PSNR), root mean square error (RMSE), mutual information (MI), structural similarity index measure (SSIM), correlation coefficient (CC) and universal quality index (UQI). The symbols used in the expressions carry the same meaning as depicted in the corresponding reference papers mentioned in Tables 2 and 3.

3.2. Objective fusion evaluation metrics without reference image

In very rare case, the ground truth image is available. Hence, it is highly desirable to assess the quality of the fused image without taking the ideal image. The meaning of quality metric with the reference

Table 3
Objective fusion evaluation metrics without reference image.

Sl. no.	Quality metric	Description	Formula	References
1	SD	The change in intensity variation in the fused image is measured using standard deviation. The SD value should be high.	$SD = \sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(f(i,j)-\bar{\mu})^2/MN}$	[85]
2	H	The information content of the fused image is computed using entropy. The fused image containing rich information has high entropy value.	$H = -\sum_{i=0}^{L-1} P_i \log P_i$	[85]
3	CE	To know the resemblance in information content between the input and fused image, cross entropy is employed. The cross entropy should be low.	$CE(A, B, F) = \frac{D(h_A \parallel h_F) + D(h_B \parallel h_F)}{2}$	[86]
4	SF	Spatial frequency is measured only using the fused image. It is measured by calculating the row and column frequency of the fused image. The value of SF should be high.	$SF = \sqrt{(RF)^2 + (CF)^2}$	[87]
5	FMI	It is utilized to compute the level of dependency between the input and the fused image. A larger value of FMI indicates an improved quality of the fused image.	$FMI = I_{FA} + I_{FB}$	[86]
6	SCD	The sum of the correlation of differences indicates how much of information is transmitted from source images to the fused image. For better fusion performance, the SCD should be high.	$SCD = r(D_1, S_1) + r(D_2, S_2)$	[88]
7	Piella metric (Q_O, Q_W, Q_E)	Piella's metric estimates the way the salient information is presented in the fused image using the local measurement i.e., image correlation coefficient, mean luminance and contrast. It includes the significance of edge information. The dynamic range of Piella's metric is [0,1] and the value should be near to 1 for improve fusion performance.	$Q_0(a, b) = \frac{1}{\lvert W\rvert}\sum_{w\in W}(\lambda(w)Q_0(a, f\vert w) + (1-\lambda(w))Q_0(b, f\vert w))$ $Q_W(a, b, f) = \sum_{w\in W} C(w)(\lambda(w)Q_0(a, f\vert w) + (1-\lambda(w))Q_0(b, f\vert w))$ $Q_E(a, b, f) = Q_W(a, b, f)\cdot Q_W(a', b', f')^{\alpha}$	[89]
8	Petrovic metric ($Q^{AB/F}$)	It provides the matching between the edges transmitted in the fusion procedure. The dynamic range of $Q^{AB/F}$ is [0, 1].	$Q^{AB/F} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} Q^{AF}(n,m)w_A(n,m) + Q^{BF}(n,m)w_B(n,m)}{\sum_{i=1}^{N}\sum_{J=1}^{M}(w_A(i,j) + w_B(i,j))}$	[90]

image is that either the ground truth image or the ideal image is available. The meaning of quality metric without the reference image is that either the ground truth image or the ideal image is not available. In such cases the quality metric is computed using the source or input images and the output or fused image. A commonly used list of the objective fusion evaluation metrics without ideal/reference image is illustrated in Table 3. The quality metrics used to evaluate the fusion performance are standard deviation (SD), entropy (H), cross entropy (CE), spatial frequency (SF), fusion mutual information (FMI), sum of the correlation of difference (SCD), Piella metric and Petrovic metric.

4. Discussions

Image fusion is very important and beneficial for various image processing steps such as object extraction, identification and computer vision. It is a tedious job due to misregistration, distortion and other artefacts. Recently, in many applications like photography [91–93], medical diagnosis [94–96], surveillance [97–99], remote sensing [100–102], etc., the region based image fusion has been widely used. Different methods are proposed in the literature for region based image fusion, as discussed in Section 2. A comparison among various methods is quite a difficult task, as they use different modalities, databases and performance indices. The assessment of quality of fused image is carried out in two ways i.e. qualitative and quantitative. In this paper, a comparison of various methods is carried out for different applications using quantitative and qualitative analysis. This comparison would benefit the researchers to apply different methods in the various applications.

The quantitative assessment for the existing methods is provided in form of tables. The different tables are prepared after considering different references using similar test conditions, same application and using the same source images. The symbol '–' in all the tables represent unavailability of the particular information. The particular performance metric is not evaluated due to non-availability of the fused image. A comparison of different methods for multifocus image fusion application is illustrated in Table 4.

Table 4
Comparison of different methods for multifocus images (Reference: Clock Image).

Method	MI	$Q^{AB/F}$	H	SF	Q_O	Q_w	Q_E
RSSF [29]	6.9279	0.7119	8.7813	10.3350	0.7138	0.8312	0.6618
BEMD [49]	5.9016	0.6250	7.4562	8.8864	0.6170	0.7690	0.6500
RF-SSIM [51]	7.0572	0.4285	7.4262	9.1006	0.7608	0.8516	0.6652
BEMD [51]	6.1665	0.4830	7.3462	9.1925	0.7133	0.8342	0.6632
RSSF [51]	8.6973	0.7032	7.3691	8.9858	0.7628	0.8212	0.6516
DWT and highboost filter [29]	7.7344	0.7018	8.8066	10.0048	0.7608	0.8119	0.6521
SR [54]	5.6106	0.7533	7.0657	8.4682	0.6911	0.7814	0.5918
CS [52]	4.7918	0.4261	7.4123	8.5618	0.6124	0.7764	0.4939
LSWT [70]	8.5518	0.7246	7.1549	8.0456	0.6818	0.7631	0.5825
QWT and normalized cut [72]	8.9971	0.7443	7.3419	8.3981	0.7632	0.8428	0.6649
NSCT and focus area detection [73]	8.6580	0.7502	7.2906	8.4729	0.7529	0.8341	0.5823
Surface area based [74]	8.8280	0.7400	–	13.6500	–	–	–
Shearlet and GBVS [75]	7.8397	0.7168	7.4337	8.7078	0.6812	0.7355	0.5862

It is seen that most of the methods perform well for the multifocus fusion example in terms of MI. However, the methods listed under the focus region detection group performs better as compared to other methods. A similar trend is observed for the parameter $Q^{AB/F}$. For instance, QWT and normalized cut, NSCT and focus area detection and Surface area based methods give a value of 8.9971, 8.6580, and 8.8280 respectively for MI. The reason may be (i) presence of superiorities such as multiresolution, multidirection and shift-invariance, (ii) use of the detected focus area as a fusion decision map to drive the fusion process, (iii) preventing artefact and imprecise results at the boundary of the focus region. Further, few researchers have computed the remaining metrics. So, these metrics may be calculated for the given methods for a

Table 5
Comparison of different methods for IR and visible images (Reference: UN Camp Image).

Method	$Q^{AB/F}$	MI	H	SD	Piella	Q_w
ICA-SVM [40]	0.6100	7.1700	7.1800	31.4100	0.9500	0.7118
DT-CWT [40]	0.4900	2.9800	6.8300	32.9900	0.9100	0.6512
Region based ICA [40]	0.5700	4.1600	6.5300	30.4100	0.9200	0.6602
BαS[63]	0.5106	3.0889	6.5181	42.1618	0.9210	0.7087
DT-CWT [63]	0.5069	2.6980	6.4490	41.0710	0.8912	0.6829
Region based ICA [36]	0.6000	3.0519	6.5657	33.6952	0.9300	0.7018
DT-CWT [36]	0.4600	3.0173	6.6727	34.1523	0.9100	0.6835
FPSO [47]	0.5520	2.7028	7.4100	32.3155	0.9128	0.6918
DT-CWT [47]	0.5030	3.1603	6.6600	36.9536	0.8910	0.6721

Table 6
Comparison of different methods for medical images (Reference: CT and MRI).

Method	MI	$Q^{AB/F}$	Q_O	Q_w	Q_E	H
RF-SSIM [51]	5.6274	0.6259	0.8928	0.8027	0.6283	6.8614
RSSF [51]	3.4326	0.5017	0.4372	0.4034	0.4128	5.4359
BEMD [51]	2.1028	0.4604	0.5293	0.7145	0.5612	6.8879
CS [52]	2.8958	0.5195	0.5634	0.7231	0.6275	6.3807
BαS [63]	–	0.6808	–	0.7541	–	–
DT-CWT [63]	–	0.6339	–	0.6722	–	–

fair comparison. A comparison of various methods for IR and visible image fusion application is illustrated in Table 5.

It is observed that the ICA based methods outperform other methods in the IR and visible image fusion application. For instance, the ICA-SVM method gives a value of 0.61 for $Q^{AB/F}$, 7.1700 for MI, 7.1800 for H, 31.4100 for SD, 0.9500 for the Piella metric and 0.7118 for Q_w which is better as compared to other methods. The reason may be the ICA based methods perform segmentation and uses numerous statistical properties of the regions to make intelligent decisions. The researchers have not computed most of the metric values. Therefore, these values may be computed for the above mentioned methods for a fair comparison. A comparison of different methods for medical image fusion application is depicted in Table 6.

The results indicated in the table shows that the region partition based algorithms perform better than the other methods. For example, the RF-SSIM method gives a value of 5.6274 for MI, 0.8928 for Q_{O}, 0.8027 for Q_w, 0.6283 for Q_E and 6.8614 for H which is better than the other methods. The reason may be the methods merge the homogenous regions based on SSIM. The statistical and estimation based algorithms also show promising results but using other metrics. So researchers may compute these metrics for a fair comparison.

The subjective or qualitative evaluation reflects the visual perception of the image, which varies from viewer to viewer. It is evaluated properly by the experts who have long experience in the field. However, this type of evaluation is not always preferred, as it is inconvenient and time consuming. The fused images for different image fusion applications are depicted below. The experimental results obtained for clock images carried out by different researchers are shown in Fig. 9.

As shown in Fig. 9, the input images are represented in (a) and (b). In (a), the left clock is out of focus and in (b) the right clock is out of focus. The fused images of different methods are illustrated in fig (c)-(p). It is observed that almost all the images look similar. Therefore, the subjective evaluation, in general, is treated as an ineffective tool for comparison. However, it is seen that the visual quality of the images in (c), (e), (f) and (g) is better as compared to other methods. The image in (c) and (f) contain sharp edges at the upper portion of the right clock. The fused image obtained with these methods have retained more

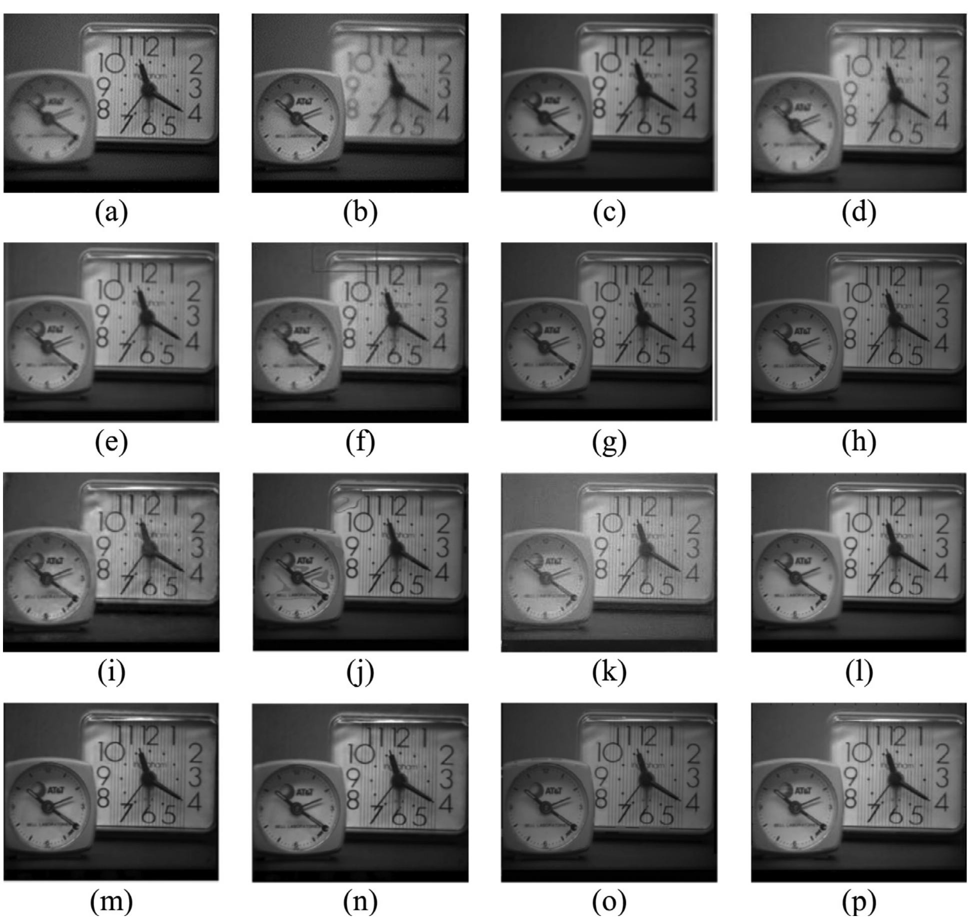

Fig. 9. Experimental results for clock images, (a) right focus, (b) Left focus, (c) QWT and normalized cut [72], (d) CS [52], (e) shearlet and GBVS [75], (f) NSCT and focused area detection [73], (g) LSWT [70], (h) SR [54], (i) BEMD [49], (j) BEMD [51], (k) DWFT [33],(l) RSSF [29], (m) RF-SSIM [51], (n) RSSF [51], (o) RSSF [54], (p) DWT and highboost filter [29].

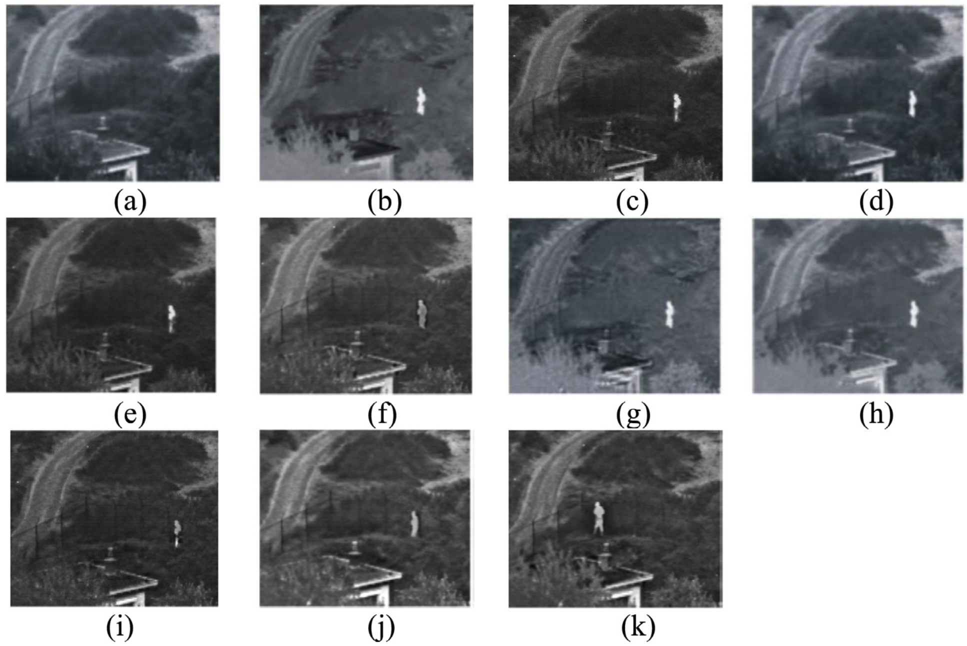

Fig. 10. Experimental results for IR and visible image fusion application, (a) Visible image, (b) IR image, (c) FPSO [47], (d) ICA-SVM [40], (e) BαS [63], (f) Region based ICA [36], (g) Region based ICA [40], (h) DT-CWT [40], (i) DT CWT [63], (j) DT-CWT [47],(k) DT-CWT [36].

relevant information of the source images. In (i) and (j), the edge at the top of the right clock is not sharp i.e. fractional edge information is lost. Further, the images in (d) and (k) have blurry clock hands. The experimental results obtained for IR and visible image fusion application carried out by different researchers are shown in Fig. 10.

As shown in Fig. 10, (a) represents the visible image and (b) represents the IR image. The fused images from different methods are shown in (c)-(j). It is observed that the person is identifiable in (b) and trees and fence are visible in (a). The fused images in (d),(f),(g), (h) and (k) are demonstrating more details as compared to other methods. However, the images in rest of the methods do not show the details clearly. In some cases such as (i), the person's image is blurry. The experimental results obtained for medical image fusion application carried out by different researchers are shown in Fig. 11.

As presented in Fig. 11, (a) represents the CT image, (b) represents the MRI image. The fused images from different methods are shown in (c)-(f). It is observed that the image in (d) is more prominent as compared to other methods. The method preserved more salient source information. In the middle portion of (e), some part is lost. Further, some artefacts are introduced at the top portion of the fused image (f). It is wise to reiterate the fact that the reason of choosing the special fusion methods for multifocus, IR, visible, and for medical images are – i) the tables in this work are prepared application wise for showing a fair comparison among different methods, ii) the respective fusion methods are chosen based on including more number of quality metrics, and iii) the fusion methods are grouped based on the results available using the same input images.

5. Conclusion

In this paper, we have presented a survey on region based image fusion methods. The region based image fusion algorithms are classified, for the first time, into three classes: region partition based, statistical and estimation based, and focus region detection and saliency map based. A comparison of different methods in terms of various metrics for different applications is done. Based on this comparison, an idea about the various image fusion methods is developed for different applications. The focus region detection and saliency map based

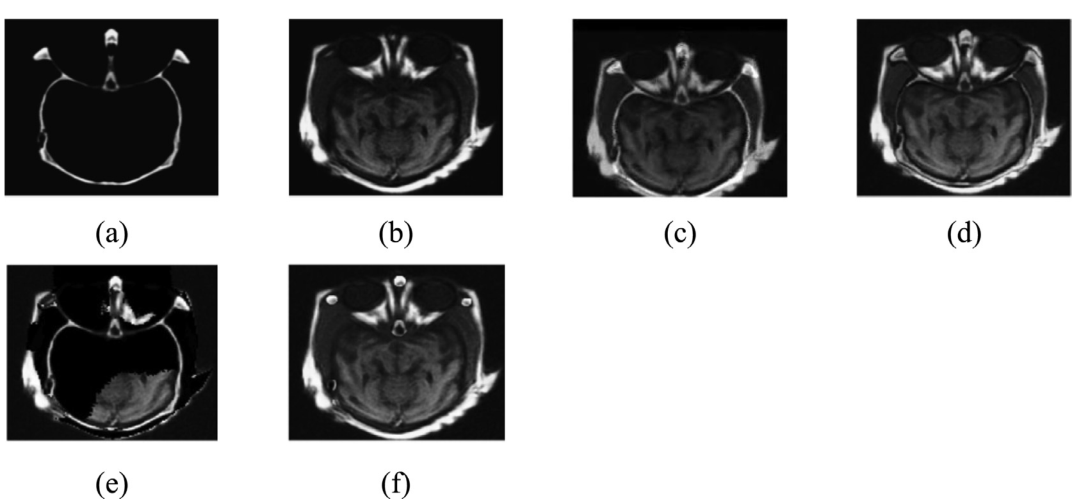

Fig. 11. Experimental results for medical image fusion application, (a) CT image, (b) MRI image, (c) CS [52], (d) RF-SSIM [51], (e) RSSF [51], (f) BEMD [51].

algorithm is mostly suitable for the multifocus image fusion applications. The ICA based methods perform better in case of the multimodality image fusion applications. The region partition algorithms are used in medical image fusion applications producing better fusion results. It is observed that the saliency map method is an emerging technique that can be used in many applications. The quality assessment metrics $Q^{AB/F}$ and MI is mostly preferred in all the applications. However, the other metrics can also be computed for a fair comparison. The problems existing in different methods is discussed. The survey carried out in this paper may help the researchers in further research in the domain of region based image fusion.

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