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A Survey on Image Fusion Techniques

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Abstract

Image fusion techniques have interest within the remote sensing community. The reason of this is that in most cases the new generation of remote sensors with very high spatial resolution acquires image datasets in two separate modes: the highest spatial resolution is obtained for panchromatic images (PAN) whereas multispectral information (MS) is associated with lower spatial resolution. Usually, the term 'fusion' gets several words to appear, such as merging, combination, synergy, integration and several others that express more or less the same meaning the concept have since it appeared in literature. Image fusion techniques can be classified into three categories depending on the stage at which fusion takes place; it is often divided into three levels, namely: pixel level, feature level and decision level of representation. This paper describes the concept of image fusion and its relevant methods.

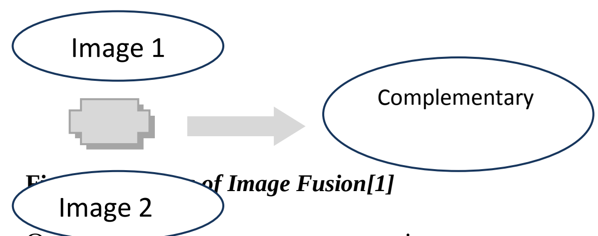
Keywords: Image Fusion, Pixel Based, Decision Based, Feature Based

Introduction

Image Fusion is a process of combining the relevant information from a set of images of the same scene into a single image and the resultant fused image will be more informative and complete than any of the input images. Input images could be multi sensor, multimodal, multifocus or multi temporal. There are some important requirements for the image fusion process [1]:

- The fused image should preserve all relevant information from the input images.
- The image fusion should not introduce artifacts which can lead to a wrong diagnosis.

In the Image fusion process it combines relevant information of two images and then generates the output into a single relevant image. The resulting image will be more informative than any of the input images.



Fi... of Image Fusion[1]

One of the important pre-processing steps for the fusion process is image registration. Image registration is the process of transforming different sets of data into one coordinate system. Image fusion find application in the area of navigation guidance, object detection and recognition, medical diagnosis, satellite imaging for remote sensing, military and civilian surveillance, etc. Image fusion algorithms can be categorized into different levels: pixel, feature, and decision levels. Pixel level fusion works directly on the pixels of source images while feature level fusion algorithms operate on features extracted from the source images. There are so many applications of image fusion which requires the high spatial and spectral resolution in a single image.

Image fusion classification

Image Fusion is a mechanism to improve the quality of information from a set of images. Important applications of the fusion of images include medical imaging, microscopic imaging, remote sensing, computer vision, and robotics .Use of the Simple primitive technique will not recover good fused image in terms of performance parameter like peak signal to noise ratio (PSNR), Normalized correlation (NC), and Men square error (MSE) [2]. Recently, Discrete Wavelet Transform (DWT) and Principal Component Analysis(PCA),Morphological processing and Combination of DWT with PCA and Morphological techniques have been popular fusion of image. These methods are shown to perform much better than simple averaging, maximum, minimum.

Simple Average

It is a well documented fact that regions of images that are in focus tend to be of higher pixel intensity. Thus this algorithm is a simple way of obtaining an output image with all regions in focus [2]. The value of the pixel P (i, j) of each image is taken and added. This sum is then divided by 2 to obtain the average. The average value is assigned to the corresponding pixel of the output image which is given in equation (1). This is repeated for all pixel values

$$K(i, j) = \{X(i, j) + Y(i, j)\}/2 \quad (1)$$

Where X (i , j) and Y (i, j) are two input images.

Select Maximum

The greater the pixel values the more in focus the image. Thus this algorithm chooses the in-focus regions from each input image by choosing the greatest value for each pixel, resulting in highly focused output. The value of the pixel P (i, j) of each image is taken and compared to each other. The greatest pixel value is assigned to the corresponding pixel [4] [5].

Need of Image Fusion

- To extract all the useful information from the source images by combining two images and to get the relevant information.
- Fusion do not introduce artifacts or inconsistencies which will distract human observers.
- Reliable and robust to imperfections such as miss-registration
- Image fusion Improve reliability

Fusion also Improve the capability by complementary information. In simpler terms, the main condition for successful fusion is that "all" visible information in the input images should also appear visible in the fused images [3].

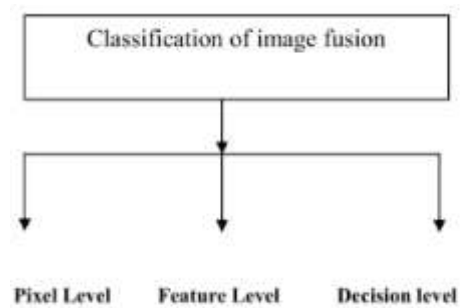


Figure 2: ***Image Fusion Classification***

Pixel-based image fusion

Image fusion is a sub area of the more general topic of data fusion [6]. Generally, Image fusion techniques can be classified into three categories depending on the stage at which fusion takes place; it is often divided into three levels, namely: pixel level, feature level and decision level of representation [7, 8]. The pixel image fusion techniques can be grouped into several techniques depending on the tools or the processing methods for image fusion procedure. It is grouped into four classes: 1) Arithmetic Combination techniques (AC) 2) Component Substitution fusion techniques (CS) 3) Frequency Filtering Methods (FFM) 4) Statistical Methods (SM).

Overview Of Pixel-Level Fusion Methods

In this section, we provide a brief overview of existing methods for the pixel-level fusion of spatially registered images. Most of these methods have been developed for the fusion of static imagery, so temporal aspects arising in the fusion of image sequences, e.g. temporal stability and consistency, are usually not addressed [9].

Weighted Superposition and Principal Component Analysis:

The straightforward way to build a fused image of several input frames is to perform the fusion as a weighted superposition of all input frames. The optimal weighting coefficients, with respect to information content and redundancy removal, can be determined by a principal component analysis (PCA) of all input intensities. By performing a PCA of the covariance matrix of input intensities, the weightings for each input frame are obtained from the eigenvector corresponding to the largest eigenvalue.

Color Space Fusion:

A method similar to the one above is the linear combination of all inputs in a pre-chosen colorspace, leading to a false color representation of

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the fused image. Nicholson et al. [10] perform the fusion of three different infrared bands by a superposition in the R-G-B colorspace. To attain an enhanced contrast in the fused image Toet [11] proposes the combination of a false color representation with a nonlinear preprocessing for the fusion of FLIR and LLTV imagery. Waxman et al. [12] combine the color space fusion approach with an artificial neural network.

Markov Random Fields and Simulated Annealing:

In the Markov Random Field (MRF) approach to image fusion, the fusion task is expressed as an optimization problem: The MRF is used to define an appropriate cost function, which describes the fusion goal and a global optimization strategy such as simulated annealing is employed in search of the global optimum of this cost function. Usually the input images are described as sets of coupled random fields: One MRF lattice is used to describe the local smoothness of image intensities and a second lattice, often called line or edge lattice, is introduced to describe the region boundaries. Due to the fact that the pixel intensities of the several input images are approximately independent while the edges of all inputs are correlated, the cost function for the fusion process is mainly based on the demand for homogenous regions with congruent edges of all input frames.

Artificial Neural Networks:

Inspired by the fusion of different sensor signals in biological systems, artificial neural networks (ANNs) have recently been employed in the fusion process. The most popular example for the fusion of different imaging sensors in biological systems is described by Newman and Hartline: Rattlesnakes (and the general family of pit vipers) possess so called pit organs which are sensitive to thermal radiation through a dense network of nerve fibers. The output of these pit organs is fed to the optical tectum, where it is combined with the nerve signals obtained from the visual sensors, i.e. the eyes. Newman and Hartline distinguished six different types of bimodal neurons merging the two signals, which they categorized as: AND, OR, Visible-Enhanced-Infrared, Visible-Suppressed-Infrared, Infrared-Enhanced-Visible and Infrared-Suppressed-Visible neurons [9].

Image Pyramids:

Image pyramids have been initially described for a multi-resolution image analysis and as a model for the binocular fusion in human vision. A generic image pyramid is a sequence of images where each image is constructed by low-pass filtering and subsampling from its predecessor. Due to subsampling, the image size is halved in both spatial directions at each level of the decomposition process, thus leading to an multiresolution signal representation. The difference image between the input image and the filtered image at each decomposition level is necessary to allow an exact image reconstruction from the pyramidal representation. The pyramid decomposition thus performs a signal representation in two pyramids: The smoothing pyramid called 'gaussian pyramid' containing the averaged pixel values, and the difference pyramid called 'laplacian pyramid' containing the pixel differences, i.e. the edges. The fusion process is performed by a combination of the laplacian pyramids of all input frames, leading to a composite laplacian pyramid from which the fused image is constructed.

Wavelets:

A method similar to the image pyramid fusion scheme is based on the discrete wavelet transform [9]. The main difference is that while image pyramids lead to an overcomplete signal representation, the wavelet transform results in a nonredundant signal representation. Ranchien et al. [13] describe the utilization of the wavelet fusion method for the fusion of several spectral bands of SPOT satellite images. Due to the different spatial resolutions of the SPOT image data, they make explicit use of the multi-resolution properties of the wavelet transform in the fusion process. Li et al. [14] use this method for the fusion of synthetic aperture radar and multispectral image data.

Feature level methods

Feature level methods are the next stage of processing where image fusion may take place [15]. Fusion at the feature level requires extraction of features from the input images. Features can be pixel intensities or edge and texture features. The Various kinds of features are considered depending on the nature of images and the application of the fused image. The features involve the extraction of feature primitives like edges, regions, shape, size, length or image segments, and features with similar intensity in the images to be fused from different types of images of the same geographic area. These features are then combined with the similar features present in the other input images through a pre-determined selection process to form the final fused image . The feature level fusion should be easy. However, feature level fusion is difficult to achieve when the feature

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sets are derived from different algorithms and data sources.

Classification Of Feature Level

Segment Based Image Fusion(SF):

The segment based fusion was developed specifically for a spectral characteristics preserving image merge. It is based on an IHS transform coupled with a spatial domain filtering. The principal idea behind a spectral characteristics preserving image fusion is that the high resolution of PAN image has to sharpen the MS image without adding new gray level information to its spectral components. An ideal fusion algorithm would enhance high frequency changes such as edges and high frequency gray level changes in an image without altering the MS components in homogeneous regions. To facilitate these demands, two prerequisites have to be addressed. First, color and spatial information have to be separated. Second, the spatial information content has to be manipulated in a way that allows adaptive enhancement of the images. The intensity ILPF of MS image is filtered with a low pass filter (LPF) whereas the PAN image is filtered with an opposite high pass filter (HPF). HPF basically consists of an addition of spatial details, taken from a high-resolution Pan observation, into the low resolution MS image [15].

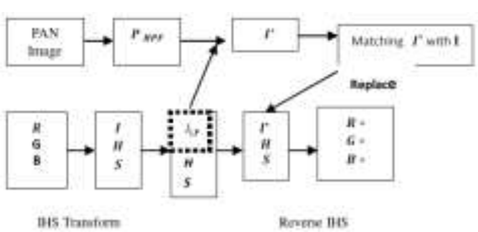

Figure 3: ***Segment Based Image Fusion[15]***

PCA-based Feature Fusion

The PCA is used extensively in remote sensing applications. It is used for dimensionality reduction, feature enhancement, and image fusion. The PCA is a statistical approach that transforms a multivariate inter-correlated data set into a new un-correlated data set. The PCA technique can also be found under the expression Karhunen Loeve approach. PCA transforms or projects the features from the original domain to a new domain (known as PCA domain) where the features are arranged in the order of their variance. The features in the transformed domain are formed by the linear combination of the original features and are uncorrelated. Fusion process is achieved in the PCA domain by retaining only those features that contain a significant amount of information. The main idea behind PCA is to determine the features that explain as much of the total variation in the data as possible with as few of these features as possible. The PCA computation done on an N-by-N of MS image having 3 contiguous spectral bands is explained below. The computation of the PCA transformation matrix is based on the eigenvalue decomposition of the covariance matrix Σ is defined as:

$$\Sigma = \sum_{i=1}^{N^2}(\vec{X}_i - \vec{m})(\vec{X}_i - \vec{m})^T \quad (1)$$

Where $\vec{X}_i$is the ith spectral signature, $\vec{m}$ denotes the mean spectral signature and N2 is the total number of spectral signatures. In order to find the new orthogonal axes of the PCA space, Eigen decomposition of the covariance matrix $\sum$ is performed. The eigen decomposition of the covariance matrix is given by

$$\sum \overrightarrow{a_k} = \lambda_k \vec{a}_k \quad (2)$$

where λ denotes the kth eigenvalue, $\vec{a}_k$ denotes the corresponding eigenvector and k varies from 1 to 3. The eigenvalues denote the amount of variance present in the corresponding eigenvectors. The eigenvectors form the axes of the PCA space, and they are orthogonal to each other. The eigenvalues are arranged in decreasing order of the variance. The PCA transformation matrix, A, is formed by choosing the eigenvectors corresponding to the largest eigenvalues. The PCA transformation matrix A is given by

$$A = |\vec{a}_1|\vec{a}_2 \ldots . |\vec{a}_j \quad (3)$$

Where $A = |\vec{a}_1|\vec{a}_2 \ldots . |\vec{a}_j$ are the eigenvectors associated with the J largest eigenvalues obtained from the eigen decomposition of the covariance matrix Σ . The data projected onto the corresponding eigenvectors form the reduced uncorrelated features that are used for further fusion processes. The PCA based feature fusion is shown in Figure 4. The input MS are, first, transformed into the same number of uncorrelated principal components. Its most important steps are:

a. perform a principal component transformation to convert a set of MS bands (three or more bands) into a set of principal components.

b. Substitute the first principal component PC1 by the PAN band whose histogram has previously been matched with that of the first

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principal component. In this study the mean and standard deviation are matched by :

$$P_{new} = \bar{M}_k + (Pc1 - \overline{PC1})\frac{\sigma_M}{\sigma_{PC1}} \quad (4)$$

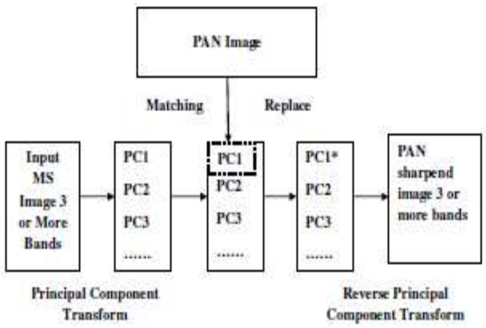

Figure 4: ***Schematic flowchart of PCA image fusion***

Decision-level fusion

Decision-level fusion consists of merging information at a higher level of abstraction, combines the results from multiple algorithms to yield a final fused decision. Input images are processed individually for information extraction. The obtained information is then combined applying decision rules to reinforce common interpretation [16]. Decision fusion or classifier combination can be interpreted as making a decision by combining the outputs of different classifiers for a test image. In our case, instead of different type of classifiers, we combined outputs of nearest neighbor classifiers trained by different blocks that correspond to different regions on a face image. For 16x16 blocks, we have 16 different block positions and a separate nearest neighbor classifier is trained by using the features extracted over the training data for that block. From a given test image, 16 feature vectors each corresponding to a different block are extracted. For each test image, local feature vector is given as an input to the corresponding classifier and the outputs of the classifiers are then combined to make an ultimate decision for the test image [17].

Unlike fixed combination methods, trainable combiners use the outputs of the classifier, class posterior probabilities, as a feature set. From the class posterior probabilities of several classifiers each corresponding to a block, a new classifier is trained to provide an ultimate decision by combining the posteriors To train a combiner, training dataset is divided into two parts as train and validation data. Individual classifiers are trained using the training data part [17]. Then, the class posterior probabilities for each block are calculated on the validation data. For each image, these posterior probabilities are concatenated into a long vector $([p(C_1|x_1),(C_2|x_1),....p(C_{N-1}|x_B)(C_{N-1}|x_B),(C_N|x_B)]^T)$ Which is then used to train the combiner. However, the length of input feature vectors of the combiner, makes it difficult to train a classifier for multi-class classification problems. Therefore, we did not prefer to build a conventional trainable combiner for decision fusion. In sum rule, the posterior probabilities for one class from each classifier are summed. Similar to the sum rule, one can also perform weighted summation of posterior probabilities.

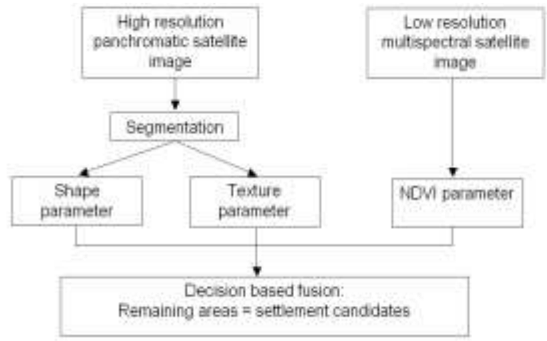

Figure 5: ***Decision based fusion process***.

Texture and shape parameters are calculated from the high resolution panchromatic data, whereas the multispectral data are used to calculate vegetation indices.Contrary to the iconic image fusion techniques, the images were rectified to ground coordinates but otherwise left in their original format. Parameters such as texture and shape are extracted from the high resolution panchromatic data, vegetation information from the multispectral images i.e figure 5

Table 1 Comparison of existing techniques

Author	Reference	Description

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Manfred Ehlers et al.	[8]	The author proposed a method for decision based fusion to automate the delineation of new residential and commercial built-up area. The procedure is based on fusion techniques at the decision level using differently weighted parameters for texture, shape, and spectral characteristics. This method, accuracies exceeds 90% .
Firouz Abdullah Al-Wassai et al.	[6]	The author said NRMSE gave the same results for some methods; but the DI gave the smallest different ratio between those methods, therefore , it is strongly recommended to use the DI because of its mathematical more precision as quality indicator
Berkay Topcu et al.	[17]	The autors proposed three novel weighting schemes for assigning weights in the weighted sum rule over class posterior probabilities of patches. The 85.69% recognition accuracy is achieved.
Oliver Rockinger et al.	[9]	The author proposed a novel fusion method for the pixel level fusion of spatially registered images and image sequences. This fusion method is based on a shift invariant extension of the discrete wavelet transform which yields an over complete signal representation. Due to the shift invariant signal representation the fusion results obtained by this method are temporal stable and consistent
Xiaoli ZHANG et al.	[18]	The author proposed a new color-gray image fusion algorithm based on MorphologicalComponent Analysis (MCA). The proposed fusion algorithm is the ability of preserving Textural information

Morphological Component Analysis

MCA is a novel image (signal) decomposition method based on sparse representation. The basic idea is separating various morphological characteristics included in the image (signal) on the basis of image (signal) morphological composition differences (which can be sparsely represented by different dictionaries). The theory of MCA can be applied in image compression, reconstruction, noise suppression and feature extraction, and it's extremely useful in the respect of image segmentation and image inpainting. For a given n-sample image X, we assume that it consists of a sum of K different signals, which are corresponding to K different morphologies {xi }i=1;2;..;K respectively. Each xi is called a morphological component, and the linear superposition of the K morphological components will form image X, that is $X = \sum_{i=1}^{k} x_i$, possibly contaminated with noise$Y = \sum_{i=1}^{k} x_i + \varepsilon$. The MCA framework aims at recovering the components $\{x_i\}i = 1,2 \dots k$ from their observed linear combination. MCA assumes that each morphological component xi can be sparsely represented in an associated basis Φ_i.

$$x_i = \Phi_i a_i \quad i = 1,2, \dots, k$$

Where αi is a sparse coefficient vector (sparse means that only a few coefficients are large and most are negligible, this way, the key message of signals and images can be expressed by the least non-zero coefficients possible). The independent orthogonal bases Φ_i $(i = 1,2 \dots k)$ amalgamated build the over-complete dictionary $\Phi = [\Phi_1 \dots \dots, \Phi_k]$ for each i, the representation of xi in Φi is sparse and not, or at least not as sparse in other$\Phi_1 (i \neq j)$. Thus, the dictionary Φi plays an important part in discrimination between content types, preferring the

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component xi over other parts. This is a key observation for the success of the MCA-based separation algorithm. Taking advantage of this feature of dictionary Φ, we can achieve the purpose that decomposing the images (signals) morphological component [18].

Conclusion

Image Fusion is a process of combining the relevant information from a set of images into a single image, where the resultant fused image will be more informative and complete than any of the input images. Image fusion techniques can improve the quality and increase the application of these data. This paper presents a literature review on some of the image fusion techniques for image fusion.

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