

Analysis and Evaluation of Image Fusion Algorithms

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ABSTRACT

There is an increasing need for performance tools or quality assessment in order to compare the results obtained with different algorithms of image fusion. This analysis can be used to select a specific algorithm for a defined fusion dataset. The image quality is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect picture). Imaging systems may introduce a certain amount of distortion or artifacts in the signal, hence the quality assessment is an important problem. There are several techniques and measures that can be objectively measured and evaluated automatically by a computer program. Therefore, they may be classified as complete reference methods (FR) and the No-reference methods (NR). In the methods of image quality assessment FR, the quality of a test image is evaluated by comparing a reference image that is supposed to have perfect quality. NR measures attempt to assess the quality of an image without any reference to the original.

Keywords : Image Fusion, Wavelets.

1. INTRODUCTION

Image fusion is a type of information fusion. Multiple images from different image sensors are fused to obtain a new image that contains more information and more positive description of the same scene image. Image fusion has so far been widely used in some military applications such as object detection and tracking, sensitivity to context and so on fields, and recently also in many areas including civil navigation airport security check, intelligent traffic, geographic information system, medical imaging, and human visual aids.

Fusion research began in the nineties. After the Gulf War, the image fusion technology caused a great attention in China. Since then, some universities and research institutions have conducted research in this

area, but most are part of the theoretical study. At present, image fusion study in China is still in a state of diffident, especially in the practical aspects of engineering research.

The design and implementation of system for image fusion, that merging images from multiple sources using traditional wave, multiple wavelets, and pulse couple neural networks (PCNN) to pixel level image. It is well known that image fusion can be performed at three levels: pixel level, feature level and decision level.

2. IMAGE FUSION CATEGORIES

Image fusion methods can be grouped into three categories: Pixel or sensor level, feature level and decision level.

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2.1 Pixel Level

In pixel level fusion the source images are fused pixel-by-pixel followed by the information/feature extraction. To implement the pixel level fusion, arithmetic operations are widely used in time domain and frequency transformations are used in frequency domain.

The main goal of pixel level fusion is to enhance the raw input images and provide an output image with more useful information than input image. Pixel level fusion is effective for high quality raw images but not suitable for images with unbalanced quality level because information from one physical channel might

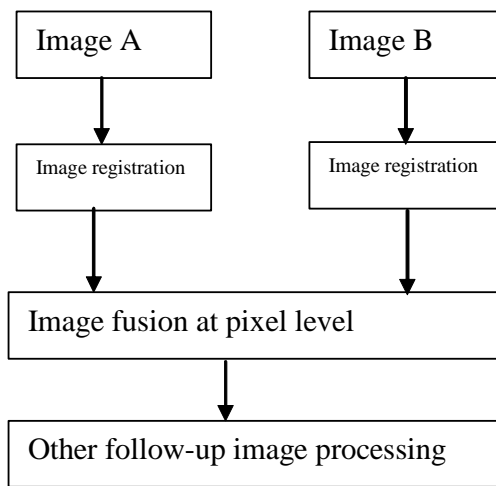


Fig.1. Pixel Level Fusion

be impeded by the other. The scheme of pixel level fusion is shown in Figure 1.

2.2 Feature Level

In feature level fusion the information is extracted from each image source separately then fused based on features from input images. The feature detection is typically achieved through edge enhancement algorithms, artificial neural networks, and knowledge based approaches. Feature level fusion is effective for raw images with unbalanced quality level. It requires a feature extraction algorithm effective for

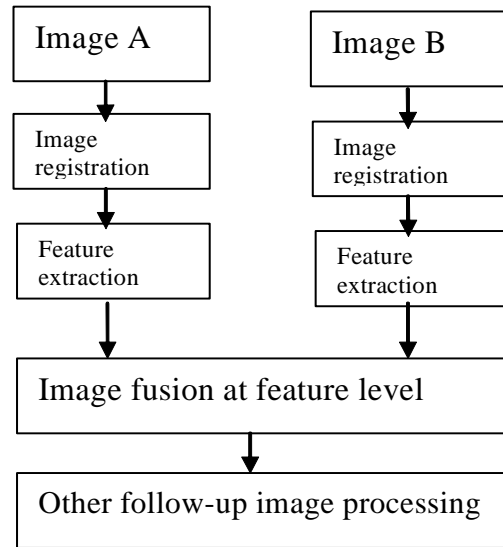


Fig.2. Feature Level Fusion

both physical channels. The scheme of feature level fusion is shown in Figure 2.

2.3 Decision Level

In decision level fusion information is extracted from each source image separately and then decisions are made for each input or source channel. Finally these decisions are fused to generate the final decision or image. Decision level fusion is effective for complicated systems with multiple true or false

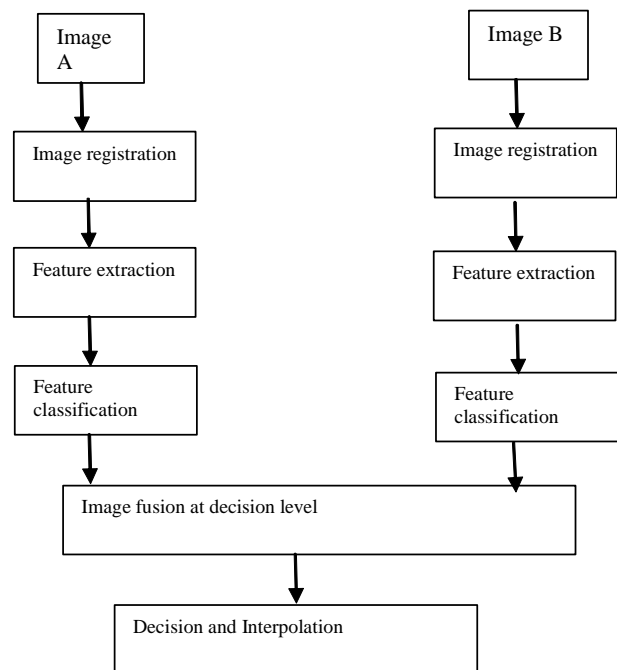


Fig.3. Decision Level Fusion

decisions but not suitable for general applications. The scheme of decision level fusion is shown in Figure 3.

3. STANDARD IMAGE FUSION METHODS

Image fusion methods are broadly classified into two groups - spatial domain fusion and transform domain fusion. The fusion methods like averaging, Bovey method, Principal Component Analysis (PCA) and IHS transform based methods fall under spatial domain approaches. Another important spatial domain fusion method is the high pass filtering based technique. Here the high frequency details are injected into up sampled version of multiple sources images. The disadvantage of spatial domain approaches is to produced spatial distortion in the fused image. Spectral distortion becomes a negative factor while going for further processing, such as classification problem. Spectral distortion can be very well handled by frequency domain approaches on image fusion. The multiresolution analysis has become a very useful tool for analyzing remote sensing images. The discrete wavelet transform has become a very useful tool for fusion.

Some other fusion methods are also there, such as Laplacian pyramid based, curvelet transform based etc. These methods show a better performance in spatial and spectral quality of the fused image compared to other spatial methods of fusion.

- High pass filtering technique
- IHS transform based image fusion
- PCA based image fusion
- Wavelet transform image fusion
- Pair-wise spatial frequency matching

3.1 Remote Sensing Image Fusion

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such

data convincingly. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. However, the standard image fusion techniques can distort the spectral information of the multispectral data while merging. In satellite imaging, two types of images are available.

Image fusion in remote sensing has several application domains. An important domain is the multi-resolution image fusion (commonly referred to pan-sharpening). In satellite imagery we can have two types of images:

3.1.1. Panchromatic images

An image collected in the broad visual wavelength range but rendered in black and white.

3.1.2 Multispectral images

Images optically acquired in more than one spectral or wavelength interval. Each individual image is usually of the same physical area and scale but of a different spectral band.

The SPOT PAN satellite provides high resolution (10m pixel) panchromatic data while the LANDSAT TM satellite provides low resolution (30m pixel) multispectral images. Image fusion attempts to merge these images and produce a single high resolution multispectral image.

The standard merging methods of image fusion are based on Red-Green-Blue (RGB) to Intensity-Hue-Saturation (IHS) transformation. The usual steps involved in satellite image fusion are as follows:

1. Resize the low resolution multispectral images to the same size as the panchromatic image.
2. Transform the R, G and B bands of the multispectral image into IHS components.
3. Modify the panchromatic image with respect to the multispectral image. This is usually performed by histogram matching of the panchromatic image with Intensity component of the multispectral images as reference.

4. Replace the intensity component by the panchromatic image and perform inverse transformation to obtain a high resolution multispectral image.

3.2 Medical Image Fusion

Medical Imaging has become a vital component of a large number of application, including diagnosis, research and treatment. Image fusion has become a common term used within medical diagnostics and treatment. The term is used when multiple patient images are registered and overlaid or merged to provide additional information. Fused images may be created from multiple images from the same imaging modality, or by combining information from multiple modalities, such as C. All these modalities used for different purposes and information for example CT image provide dense structure like bones and MRI provide normal and pathological soft tissues but not provide information about bones. In this case one kind of image will not provide the sufficient and accurate clinical information for physician therefore fusion of multimodal medical image is required.

4. EVALUATION OF IMAGE FUSION ALGORITHM

There is an increasing need for performance or quality assessment tools in order to compare the results obtained with different image fusion algorithms. This analysis can be used to select a specific fusion algorithm for a particular type of data set. The image quality indices try to figure out the some or the combination of the various factors that determine the quality of the image. Some of the critical factors that the image quality metrics try to project are:

4.1 Sharpness

Determines the amount of detail an image can convey. System sharpness is affected by the lens (design and manufacturing quality, focal length, aperture, and instance from the image center) and sensor (pixel count and anti-aliasing filter). In the field,

sharpness is affected by camera shake (a good tripod can be helpful), focus accuracy, and atmospheric disturbances (thermal effects and aerosols). Lost sharpness can be restored by sharpening, but sharpening has limits. Over sharpening can degrade image quality by causing “halos” to appear near contrast boundaries. Images from any compact digital cameras are over sharpened.

4.2 Noise

Is a random variation of image density, visible as grain in film and pixel level variations in digital images. It arises from the effects of basic physics—the photon nature of light and the thermal energy of heat—inside image sensors. Typical noise reduction (NR) software reduces the visibility of noise by smoothing the image, excluding areas near contrast boundaries. This technique works well, but it can obscure fine, low contrast detail.

4.3 Dynamic Range

Dynamic range (or exposure range) is the range of light levels a camera can capture, usually measured in f-stops, EV (exposure value), or zones (all factors of two in exposure). It is closely related to noise: high noise implies low dynamic range.

4.4 Tonal Response

The relationship between light and pixel level.

4.5 Contrast

It is also known as gamma, is the slope of the tonal response curve. High contrast usually involves loss of dynamic range—loss of detail, or clipping, in highlights or shadows—when the image is displayed.

4.6 Color accuracy

It is an important but ambiguous image quality factor. Many viewers prefer enhanced color saturation; the most accurate color isn't necessarily the most pleasing. Nevertheless it is important to measure a camera's color response: its color shifts,

saturation, and the effectiveness of its white balance algorithms.

4.7 Distortion

It is an aberration that causes straight lines to curve near the edges of images. It can be troublesome for architectural photography and metrology (photographic applications involving measurement). Distortion is worst in wide angle, telephoto, and zoom lenses. It is often worse for close-up images than for images at a distance. It can be easily corrected in software.

4.8 Light falloff

Also known as vignetting, darkens images near the corners. It can be significant with wide angle lenses.

4.9 Exposure Accuracy

You can usually determine it quickly with the help of the histogram, to alter the accuracy you can change the exposure compensation or the way you meter. Exposure accuracy can be an issue with fully automatic cameras and with video cameras where there is little or no opportunity for post-exposure tonal adjustment. Some even have exposure memory: exposure may change after very bright or dark objects appear in a scene.

4.10 Lateral Chromatic Aberration

LCA, also called “color fringing” is a lens aberration that causes colors to focus at different distances from the image center. It is most visible near corners of images. LCA is worst with asymmetrical lenses, including ultrawides, true telephotos and zooms. It is strongly affected by demosaicing.

4.11 Veiling Glare

It is stray light in lenses and optical systems caused by reflections between lens elements and the inside barrel of the lens. It predicts the severity of lens flare, image fogging (loss of shadow detail and color) as well as “ghost” images that can occur in the presence of bright light sources in or near the field of view.

4.12 Color moiré

It is artificial color banding that can appear in images with repetitive patterns of high spatial frequencies, like fabrics or picket fences. It is affected by lens sharpness, the anti-aliasing (low pass) filter (which softens the image), and demosaicing software. It tends to be worst with the sharpest lenses.

4.14 Artifacts

Software (especially operations performed during RAW conversion) can cause significant visual artifacts, including Data compression and transmission losses (e.g. Low quality JPEG), over sharpening “halos” and loss of fine, low-contrast detail. The various Image quality metrics studied and developed, as a part of this project, to assess the quality of the fused images, either project one or combination of some of the above factors with respect to a perfect image. The Full Reference (FR) methods are discussed in the following sections.

Quantitative quality analysis of fusion algorithm carries out using following methods:

4.15 Peak Signal to Noise Ratio (PSNR)

It computes Peak Signal to Noise Ratio in decibels between two images. This ratio is used as a quality measurement between the original and reconstructed image.

Higher the PSNR value, better the quality of reconstructed image. PSNR of an $M \times N$ image is calculated by following formula:

$$\text{PSNR} = 10 * \log_{10} (R^2 / \text{MSE})$$

R = is the maximum fluctuation in input image data type. MSE = mean squared error.

4.16 Root Mean Squared Error (RMSE)

RMSE calculate cumulative squared error between re-constructed and original image. Lower the RMSE lower the error. RMSE of an $M \times N$ image is calculated as:

$$MSE = \frac{1}{MN} \sum_{m,n=1}^{M,N} [I(m,n) - R(m,n)]^2$$

$$RMSE = \sqrt[2]{MSE}$$

4.17 Standard Deviation (STD)

The standard deviation of an image with size of $M \times N$ is defined as [4]

$$STD = \frac{1}{MN} \sum_{m,n=1}^{M,N} \text{sqr}[R(m,n) - \mu]^2$$

μ = mean of the fused or reconstructed image

$R(m,n)$ = reconstructed image

4.18 Cross Entropy (CE)

The cross entropy is used to measure the difference between the source images and the fused image. Small value corresponds to good fusion result obtained:

$$CE = \sum_{l=0}^{L-1} P_l \log_2 \frac{P_l}{Q_l}$$

Where P_l and Q_l denote the gray level histogram of the source image and fused image, respectively [5].

4.19 Entropy (ENTR)

The formulation of the classical information entropy of an image is defined as

$$H = -\sum_{l=0}^{L-1} P_l \log_2 P_l$$

Where L is the number of gray level, and P_l equals the ratio between the number of pixels whose gray value is l ($0 \leq l \leq L-1$) and the total pixel number contained in the image. The information entropy measures the richness of information in an image. Thus, higher the entropy better the performance [5].

4.20 Spatial Frequency (SF)

Spatial frequency is used to measure the overall activity level of an image (Eskicioglu and Fisher, 1995). For an $M \times N$ image F , with the gray value at pixel position (m, n) denoted by $F(m, n)$, its spatial frequency is defined as [6]

$$SF = \sqrt{RF + CF}$$

Where RF and CF are the row frequency and column frequency

$$RF = \sqrt{\frac{1}{MN} \sum_{m=1, n=2}^{M,N} (F(m,n) - F(m, n-1))^2}$$

$$CF = \sqrt{\frac{1}{MN} \sum_{m=2, n=1}^{M,N} (F(m,n) - F(m-1, n))^2}$$

5. CONCLUSION

This analysis can be used to select a specific fusion algorithm for a particular type of data set. The image quality indices try to figure out the some or the combination of the various factors that determine the quality of the image. Some of the critical factors that the image quality metrics try to project.

Image fusion is one of the most required techniques to merge images with good qualities. In a field of medical images, above criteria improves diagnosis process. A remote sensing image gives good result if considered above criteria.

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