

Multi-scale Analysis based Image Fusion

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Abstract

Image fusion provides a better view than that provided by any of the individual source images. The aim of multi-scale analysis is to find a kind of optimal representation for high dimensional information expression. Based on the nonlinear approximation, the principle and ways of image fusion are studied, and its development, current and future challenges are reviewed in this paper.

Keywords: image fusion, multi-scale analysis, beyond wavelet.

1. Introduction

Imaging sensors provide a system with useful information regarding some features of interest in the system environment⁽¹⁾. However, a single sensor cannot provide a complete view of the scene in many applications. The fused images, if suitably obtained from a set of source sensor images, can provide a better view than that provided by any of the individual source images for post-processing, such as image segmentation, computer vision. In recent decades, growing interest has focused on the use of multiple sensors to increase the capabilities of intelligent machines and systems. As a result, multi-sensor fusion has become an area of intense research and development in the past few years. Given the limited scope of imaging systems, clearly displaying the goals of visible-light imaging system is difficult. Image fusion technology can solve this problem by repeatedly focusing the same imaging lens on the targets and imaging the clear part of these fused images into a new image to facilitate human observation or computer processing.

Recently, a variety of image fusion techniques have been developed, which can be roughly divided into two groups: *multi-scale decomposition*-based fusion methods such as, pyramid algorithms, wavelet, wedgelet, bandelet, curvelet, and contourlet transform methods, as well as *non-multi-scale decomposition*-based fusion methods, such as, weighted average, nonlinear, estimation theory-based

methods, et al.

For analysis multi-scale decomposition based fusion methods, the pyramid method initially constructs the input image pyramid and takes some feature selection approach to form the fusion value pyramid. The pyramid of the image can be reconstructed using the inverter of the pyramid to produce fusion images. The pyramid method is relatively simple but it also has some drawbacks, such as noise impact in pyramid reconstruction. The themes of classical wavelets include terms such as compression and efficient representation. The wavelet transform method decomposes the image into a series of sub-band images with different resolutions, frequencies, and directional characteristics. However, the use of classical wavelets to represent images poses problems such as their efficient representation in two dimensions. And then the different resolution image fusion is performed. But because of limited directional of wavelets, it cannot express line- or curve-singularities in two- or higher dimensional signal. So, other excellent MRA methods are proposed in recent years to overcome the drawbacks of wavelets. Several theoretical papers have called attention to the benefits of beyond wavelets. The beyond wavelets have signified benefits in image representation and denoising. The spectral characteristics and spatial characteristics of image are completely separation. Minh N. Do and Martin Vetterli proposed contourlet transform in 2002. They first develop a transform in the continuous domain and then discretize for sampled data. After that, Y. Lu and Minh N Do modify a new multiscale decomposition method in the frequency domain, called sharp frequency localized contourlet transform (SFLCT)⁽²⁾. However, due to upsamplers and downsamplers presented in the directional filter banks (DFB) of SFLCT, Unfortunately, the downsampling of SFLCT leads to the lack of translation invariance.

In this paper, we summarize the recent multi-scale based methods in session 2. For a guidance, in session 3, we review the quantitatively indexes for image fusion. Finally, we conclude the paper in session 4.

2. Multi-scale Image Fusion Methods

The themes of classical wavelets are compression and efficient representation. The important features in the analysis of functions in two variables are dilation, translation, spatial and frequency localization, and singularity orientation. Important singularities in one dimension are simply points. One-dimensional singularities are important in two-dimensional signal or higher. Smooth singularities in two-dimensional images often occur as boundaries of physical objects. Efficient representation in two dimensions is a hard problem. So, we introduce beyond wavelets transform for solving these problems.

2.1 Pyramid Transform

The Laplacian pyramids⁽³⁾ are many used in different application systems. Generally, the pyramid transform contains Laplacian, gradient and morphological pyramids et al. Among all of these pyramids, the Laplacian is the first introduced as a model for binocular fusion, where the implementation used a Laplacian pyramid and a maximum selection rule at each point of the pyramid transform. The source image is blurred by low-pass filtering, then in the second step, it takes sub-sampling to reduce size, after that, an interpolation operation is used. Finally, subtract two image pixel by pixel. In the Laplacian pyramid, the lowest level of the pyramid is constructed from the original image.

2.2 Wavelet Transform

The discrete wavelet transform (DWT)⁽⁴⁾ is widely used for image fusion. The discrete wavelet transform is a multi-scale analysis method. At first, two source images are decomposed into DWT coefficients. The coefficients consist of four parts: approximation, horizontal detail, vertical detail and diagonal detail. Then, the coefficients of two source images are fused pixel by pixel. After inverse DWT, the fused image is obtained.

2.3 Wedgelet Transform

The multi-scale wedgelet transform is the first step towards explicitly capturing the geometric structure of images⁽⁵⁾. There are two parts in the multiscale wedgelet framework: decomposition and representation. Each wedgelet by itself simply and succinctly represent a straight edge within a certain region of the image. Wedgelets can take a good approximation of singularities and simultaneously maintain the edge feature and smoothing of the homogeneous region.

2.4 Bandelet Transform

The bandelets transform is defined as anisotropic wavelets that are warped along the geometric flow⁽⁶⁾, which is a vector field indicating the local direction of the regularity along the edges. The dictionary of bandelet frames is constructed using dyadic square segmentation and parameterized geometric flows. The ability to exploit image geometry makes its approximation error decay optimal asymptotically for piecewise regular images. In image surfaces, the geometry is not a collection of

discontinuities but areas of high curvature. The bandelet transform recasts these areas of high curvature into an optimal estimation of regularity direction. In real applications, the geometry is estimated by searching for the regularity flow and then for a polynomial to describe that flow.

2.5 Curvelet Transform

In the single scale ridgelet or local ridgelet transform, curvelets can be constructed to describe the singularity of the boundary with curved objects. Curvelet transform⁽⁷⁾ combines the beneficial abilities of ridgelet transform, which is good at expressing the line characteristic and wavelet transform and has the advantage of expressing point features. In fact, this method is the multi-scale transformation of local ridgelet transform. Curvelet transform has the advantage of direction. Curvelet transform also has the exact reconstruction property and gives stable reconstruction under perturbations of the coefficients.

2.6 Contourlet Transform

Recently, Do and Vetterli proposed an efficient directional multi-resolution image representation called contourlet transform. Contourlet is a “true” two-dimensional transform that can capture the intrinsic geometrical structure, and has been applied to several tasks in image processing. Contourlet transform better represents the salient features of the image such as, edges, lines, curves, and contours, than wavelet transform because of its anisotropy and directionality. Two steps are involved in contourlet transform, subband decomposition and the directional transform. Contourlet transform uses the Laplacian pyramid (LP) transform to decompose the image in multiscale form before adopting the directional filter banks (DFB) to decompose the high frequency coefficients and obtain details with different directions of the directional subband. Contourlet transform accurately expresses directions. However, because of the non-subsampled process in LP and DFB, it causes frequency aliasing, which creates larger changes in decomposition coefficient distribution with a small shift in the input image. However, if we fuse the decomposition coefficients, the process results in edge aliasing or the pseudo-Gibbs phenomena. Therefore, non-subsampled contourlet transform (NSCT)⁽⁸⁾ was created simply by turning the downsampler units in the subsampled contourlet by considering some aliasing issues.

3. Performance Evaluation

There is no universally measurement for evaluating image fusion performance until now. Usually, image fusion results were evaluated by human vision. Quantitatively assessing is a complicated and difficult issue in practical applications because the image fusion is a blind operation. In this paper, we summarize fidelity assessment to the reference requires computation of several indexes. These

indexes are on spectral consistency, spatial consistency or on the both together. Spectral consistency assumes that fused data have increased spatial resolution with spectral properties of the original image. We conducted some quantitative analysis, mainly from the perspective of mathematical statistics aspect and the image's statistical parameters are calculated, which include Peak Signal to Noise Ratio (PSNR), mean squared error (MSE), fusion quality index (Q), weighted fusion quality index (Q_w), edge-dependent fusion quality index (Q_E), Structural SIMilarity (SSIM), Multi-scale Structural SIMilarity (MS-SSIM).

Let x_i and y_i be the i -th pixel in the original image \mathbf{x} and the distorted image \mathbf{y} , respectively. The MSE and PSNR between the two images are given by

$$MSE = \frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2, \quad (1)$$

$$PSNR = 10 \log_{10} \left(\frac{L^2}{MSE} \right) \quad (2)$$

In the work, use a sliding window, from the top-left of the two images A, B . The sliding window is with a fixed size. For each window w , the local quality index $Q_0(A, B | w)$ is computed for the values $A(i, j)$ and $B(i, j)$, where pixels (i, j) lies in the sliding window w .

$$Q_0(A, B) = \frac{1}{|W|} \sum_{w \in W} Q_0(A, B | w), \quad (3)$$

where W is the family of all windows and $|W|$ is the cardinality of W . In practice, the Q_0 index also defined as

$$Q_0(A, B) = \frac{\sigma_{AB}}{\sigma_A \cdot \sigma_B} \cdot \frac{2\bar{A} \cdot \bar{B}}{[\bar{A}]^2 + [\bar{B}]^2} \cdot \frac{2\sigma_A \cdot \sigma_B}{(\sigma_A^2 + \sigma_B^2)} \quad (4)$$

where, σ_{AB} denotes the covariance between A and B , \bar{A} and \bar{B} are the means, σ_A^2 and σ_B^2 are the variances of A and B , respectively.

Piella et al. redefined the useful quality index Q_0 as $Q(A, B, F)$ for image fusion assessment. Here A, B are two input images and F is the fused image. They denoted by $s(A|w)$ some saliency of image A in window w . This index may depend on contrast, sharpness, or entropy. The local weight $\lambda(w)$ is defined as

$$\lambda(w) = \frac{s(A | w)}{s(A | w) + s(B | w)} \quad (5)$$

where $s(A|w)$ and $s(B|w)$ are the local saliencies of input images A and B , $\lambda \in [0,1]$. The fusion quality index $Q(A, B, F)$ as

$$Q(A, B, F) = \frac{1}{|W|} \sum_{w \in W} (\lambda(w)Q_0(A, F | w) + (1 - \lambda(w))Q_0(B, F | w)) \quad (6)$$

They also defined the overall saliency of a window as

$C(w) = \max(s(A|w), s(B|w))$. The weighted fusion quality index is then defined as

$$Q_w(A, B, F) = \sum_{w \in W} c(w) (\lambda(w)Q_0(A, F | w) + (1 - \lambda(w))Q_0(B, F | w)) \quad (7)$$

where $c(w) = C(w) / (\sum C(w'))$. Using edge images A', B', F' inside of original images A, B , and F , and combine $Q_w(A, B, F)$ and $Q_w(A', B', F')$ into an edge-dependent fusion quality index by

$$Q_E(A, B, F) = Q_w(A, B, F) \cdot Q_w(A', B', F')^\alpha \quad (8)$$

where α is a parameter that expresses the contribution of the edge images compared to the original images.

A multi-scale SSIM method for image quality assessment is proposed. Input to signal A and B , let μ_A, σ_A and σ_{AB} respectively as the mean of A , the variance of A , the covariance of A and B . The parameters of relative importance α, β, γ are equal to 1. The SSIM is given as follow:

$$SSIM(x, y) = \frac{(2\mu_A\mu_B + C_1)(2\sigma_{AB} + C_2)}{(\mu_A^2 + \mu_B^2 + C_1)(\mu_A^2 + \mu_B^2 + C_2)} \quad (9)$$

where C_1, C_2 are small constants. The overall multi-scale SSIM (MS-SSIM) evaluation at the j -th scale with Scale M is obtained by

$$MS-SSIM(A, B) = [l_M(A, B)]^{\alpha M} \cdot \prod_{j=1}^M [c_j(A, B)]^{\beta j} [s_j(A, B)]^{\gamma j} \quad (10)$$

where $l(A, B), c(A, B), s(A, B)$ are the luminance, contrast and structure comparison measures, respectively.

The following figure shows an example for comparing the different multi-scale analysis fusion methods. Table 1 shows the statics results of these methods.

Table 1. COMPERATION OF DIFFERENT MULTIMODAL MEDICAL IMAGE FUSION METHODS

Methods	EN	AG	PSNR	Q	SSIM
Average	4.6863	3.1444	22.281	0.5014	0.82750
PCA	3.3630	4.7380	22.447	0.5015	0.83345
Wavelet	5.1089	8.1707	24.223	0.2412	0.80555
Curvelet	2.7608	5.8818	15.365	0.4966	0.51964
Contourlet	5.1635	8.2360	25.295	0.4617	0.77268
Proposed	5.3622	7.8162	24.818	0.5217	0.83619

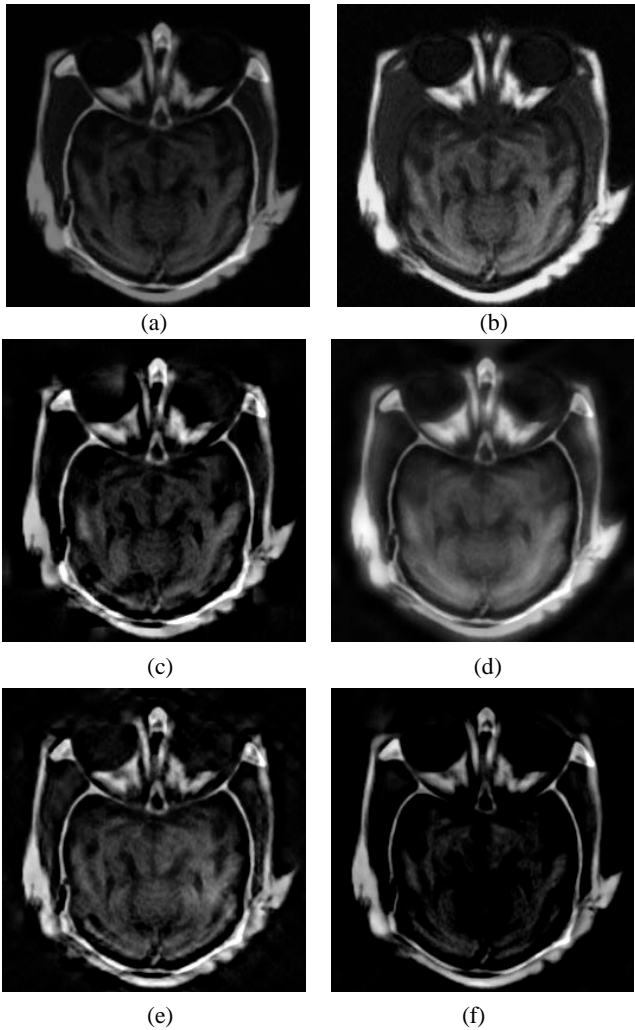


Figure Test T1/T2-MR images fused results with different method.
 (a) Average method. (b) PCA. (c) Wavelet. (d) Curvelet. (e) Contourlet. (f) SFLCT.

4. Conclusions

In this paper, we summarized the techniques and methods on multi-scale image fusion. Multi-scale image fusion performs better than non-multi-scale image fusion methods in edge approaching, directional et al. However, because of the most of the transforms cost a lot of computing time. The multi-scale image fusion method cannot be applied in industry right now. Consequently, it has some challenges for regarding to developing intelligent fusion methods.

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