HYBRID FUNCTION OF IMAGE FUSION AND SUPER-RESOLUTION TECHNIQUES

J.Sapthika, T.Jemima Jebaseeli

Department of Information Technology, Karunya University, Coimbatore, India
E-mail: sapthikajebackan@gmail.com
E-mail: jemima_jeba@karunya.edu

Abstract –
The multiple source images of the similarity, signal transmission and fusion techniques integrate the underlying signal packet generation into a specific signal particularly can be termed as an image, thus gives an accurate explanation about it. Somehow, when the input or the database collected images are of poor pixel substitution, the output image will also be as the same like the original image that has the low signal quality. To make efficient the resolution of the signal, a specific step called super-resolution is to be performed. A novel workflow for the hybrid function of image fusion and super-resolution is done. This hybrid function purely depends upon the application of using signals with sparse representations. The poor-resolute input image is transformed and then decomposed into frequency differentiated components based on the sub-band separation step. Coefficients from these images are fused by implementing many algorithms. Fusion is the step of fusing/combining a signal from two or more signals generated into one hybrid image that is more resolute and quite informative. This is applicable for computer processing specifically termed to be Image Processing or Digital Signal Processing. The goal in fusion process is to get down uncertainty level gradually, eliminating redundancy while maximizing similar images and getting the similar images.

Keywords: Image fusion, Sparse Information, SR-Technique, Decomposition

INTRODUCTION
Image morphing or fusion algorithms are classified into low, mid, and high fusion levels. Pixel-classification and pixel substitution techniques are treated under some circumstances such that the pixel-level fusion is a default operation. By altering the values of pixels in the process of image enhancement in some areas, intolerable human artifacts are created in image localities such as problem in edge detection or noise...
robustness reduction, etc. When compared, edges in 2D-images have the direction. In many techniques, 1D-filtering is done as an enhancing part in horizontal and vertical directions.

A technique to overcome artifacts is to use a 2D-filter and some other morphological filters. But the problem is that the loss to signal quality is more if the edge detected goes wrong, that occurs based on the tediousness in acquisition of the images’ edges of the low resolution image. A test signal or an image is interpolated in two orthogonal sides. The results are treated as two outcomes or the validations of the sample image and adaptively fused using some fusion techniques. More specifically, dividing of the neighborhood pixels of oriented subsets of images are needed to be achieved in orthogonal directions. The outcomes are that the two tests and outcome sets will give us different occurrences; hence the missing pixel levels have greater efficiency with its neighborhood pixels in the edge detection. Each subset yields an estimation of the missing pixel levels of the signals.

ANALYSIS OF DIFFERENT ALGORITHMS AND TECHNIQUES

A. An Edge Guided Image Interpolation Algorithm via Directional Filtering and Data Fusion

The wavelet transformation is of several categories. From that, Discrete Wavelet Transform (DWT) is implemented to both input image and the enhanced image and a decomposition of each input image is brought out. This is represented in the illustrations such as horizontal, vertical, diagonal and none represent different coefficients. The two decomposition levels, such as high and low levels based on the sub band separation. The different level, regarding the decomposition level, corresponds to the same signal representation in each input signal. Only pixel values of the similar level and pixel substitution and pixel level are to be fused, so that the fused coefficients of the pixels can be obtained. In image fusion, it is essential that the signal information from all the constituents are to be aligned and registered very first combining the signals, guaranteeing that the data fusion and the image classification referring to the same pixel locations. This is a problem in image fusion, as alignment mismatch produces severe edge problems in the fused outputs. This is significant in signals where the edges are ample.

Advantages:
1. Image fusion is achieved with a greater correlation and the higher level of Mean Standard Deviation (MSD).
2. Performance validation such as Root Mean Square Error (RMSE) detection and many other parameters validation are brought out.

Disadvantages:
1. If the pixel values get distorted, the exact image fusion can’t be achieved so it depends on the pixel levels.
2. Wavelet transformation dependant – It depends on the change in pixel levels that contains pixel difference and classification.

B. Pixel- and region-based image fusion with complex wavelets

Numerous imaging cameras that acquire the face images those are with higher resolution. Images are taken in the visible signals tend to have greater accuracy in low light conditions. Thus, redundant images from a set of two or pair of dissimilar can be fused together which can be termed to the fused image. This preserves all relevant images from the original data. Image fusion techniques can be termed to be at one of various categories such as pixel, signal, feature and symbolic level. At pixel-level, images are constructed by taking out individual pixel levels. Various classifications of pixel-based fused algorithms are there. One method of accomplishing feature-level fusion is with a region-based morphological scheme. An image is segmented in some way to produce a set of regional vectors. Various properties of these pixel levels can be accounted and used to determine features from which images are included in the morphological images. The techniques have advantages over pixel-substituted algorithms as more intelligent fusion rules can be considered based on normal features in the signals. Various fusion rules are based on combining groups of pixels which form the regions of an image. Thus, more useful tests for choosing the fused image, based on various properties can be implemented. The feature information extracted from the signals could be used to register the images. Region-based fusion strategies could use estimation of object detection to track the fused features of frames to be quickly predicted from some fully fused frames.

Advantages:
1. DWT has greater accuracy; wavelet transformation gives us the exact location of image classification and the image registration.
2. Fusion rules are of greater redundancy thus it reduces the sensitivity depend on noise.

Disadvantages:
1. The evaluation factor mainly depends on the various image classification characteristics, so RMSE and other parameters depend upon the images.
2. The characteristics changes depend on the Ground Truth and the edge detection. The edges are not identified up to the tolerance.

C. Multi-focus Image Fusion using the Non Sub-sampled Contourlet transform
A number of techniques for multi-focus image fusion have been proposed during the last decade. One of the simplest approaches is to operate directly on input images, pixel-by-pixel, using operators such as the weighted averaging. This leads to many undesired effects such as loss of contrast. Many researchers have recognized that multi-scale transforms (MST) are very useful for image fusion and various MST-based fusion methods. The reconstruction of the fused image is done by taking an inverse transform. The decomposition levels of the reconstruction and the fusion rules are the needed components of MST-based image fusion algorithms. The commonly used MST methods include the Discrete Wavelet Transform (DWT) and the Laplacian pyramid (LP) transform. For 1D smooth signal, wavelets have been established, because they provide representation for these signals. This is not the case in two dimensions. As a result of a separable extension from 1D base, two-dimensional (2-D) separable wavelets are good at isolating the discredited at edge points, but cannot effectively denotes the line and the curve discontinuities. Moreover, separable wavelets can impart only limited directional information, thus cannot represent the directions of the edges accurately. The general fusion rule is the approximation level which denotes that the coefficients with standard and the absolute value are termed as the morphological multi-scale coefficients, while other coefficients are eliminated.

**Advantages:**

1. The sub-band separation depends on not only the low pass and high pass levels but also the band pass and band stop levels thus gives us the greater amount of accuracy.
2. Image fusion and the other morphological processes are carried out with the basic and fundamental algorithms of identifying the physical parameters.

**Disadvantages:**

1. The sampled and non sampled algorithms can’t give the detailed coefficient levels, so possibility of error occurrence and tolerance level can meet the desired level.
2. The optical transfer function can’t meet the requirements of the exact identification of the tolerance levels.

**D. Biological image fusion using a NSCT based variable-weight method**

The Intensity-Hue-Saturation (IHS) method derives the gray image for the intensity component of the color image and thus handles the fusion of gray level and the color image. The implementation of the GIHS method from the traditional IHS method gives the specific location. It can be extended to some methods, including many methods, the Principal Component Analysis (PCA) method and similar IHS methods. Generally, color images correspond to combination of three monochrome channels labeled as RGB image...
(red, green, blue). They can be converted to the IHS color space based on planar values, which is more consistent. The intensity component in the IHS space is termed as the mean average values of three channels in the RGB space. While the gray image, the color image and fused image are denoted, their intensity components are written as IG, IC and IF respectively. An efficient multi-scale image representation forms the foundation of many image processing tasks, such as the compression, denosing and image fusion. The contourlet transform (CT) is one of the state-of-the-art multi-scale analysis techniques. Aside from the true two-dimensional (2D) filtering for the image expansion, the flexible directional filtering makes it possible to capture the geometrical structure of the image. By allocating the redundancy, the invariance which means less sensitivity to the image shift can be targeted in the NSCT. Compared to the Counterlet Transformation, the Gibbs phenomenon due to the coefficient modification is suppressed to a great extent, since the interpolation of many filter techniques replace the image decimation.

**Advantages:**
1. The novel algorithm gives us the exact estimation of the fusion rule as it is developed with the use of Neural Networking (NN).
2. NSCT and Gibbs rules are more robust in nature.

**Disadvantages:**
1. Intensity based fusion techniques depend on the contrast level. So, the acquisition level of images can’t be leveled depend on any level of contrast.

**E. The Multi-Scale Directional Bilateral Filter and its application to multi-sensor Image Fusion**

The goal of image fusion is to integrate features from two or more input images to the fused image. Three components of image fusion algorithm are detecting, comparing and transferring the significant feature such as edge detection, detailed coefficients and directions. Finally, a method which can acquire these features is highly necessary. The algorithm possesses preserving edges and capturing directional information. Hence, the technique can be employed to identify the important features. The brightness changes responding the edge and contrast of images result in large variation of range of bilateral filter. The brightness changes to many transformation values and levels. Somehow, if the edge or object corresponds to a certain direction, the directional filter with the same direction gives large response. Thus, the transform values of this technique can be applied to measure the salience of features and the largest of absolute transform values represents these features. This filter is constructed through combining the Multi scale Bilateral Filters with
non sampled level. This is firstly applied to the original image to obtain the detail sub-bands and the approximation sub-band.

Then, the detail sub-bands are fed into a NSDFB so that the direction information is captured. It is worth noting that the combined scheme is shift-invariant used here are non sub-sampled. In addition, the Non Sub-sampled Contourlet Transform (NSCT), which has been employed for image processing applications such as image fusion is similar.

However, compared with the NSCT, our method has the following advantages. Due to the pixel substitution levels of the filters changes, the multi-scale transform is adaptive. This acquires the better capturing of all the edges in detailed manner. Next to that, there is no need to design the pyramid and the other filter techniques. At last, the reconstruction of the multi-scale transform is simpler, which only needs the operation of addition factors and the other parameters.

**Advantages:**

1. The decomposition factors are of using many transformation levels such as Complex Wavelet transformation, discrete transformation and other morphological filters, etc.
2. The tree structure and the other morphological transformations such as MBF, NSCT, SWT, etc.

**Disadvantages:**

1. The transformation techniques derive us the fusion level only. But it can’t give us the detailed levels of pixels.

**F. Image Decomposition via the Combination of Sparse Representations and a Variation Approach**

The chosen dictionaries are appropriate. It is very hard to propose a dictionary that leads to sparse representations for a wide family of signals. The decomposition level may be incompatible because it does not give us a sparse representation for the proper signals. Then for such images the separation will fail. Many techniques are obtained so for, that does not separate well between the two fundamental rules to desire to separate. Indeed it leads to sparse representations for normal values, but also known to lead to sparse representations for some texture content, clearly such values could not be used for a successful separation.
Generally we may ask whether such images exist at all. There are inner connection between the instances and the quantitative experiments. The low validated images should be attributed to the poor performance in restraining the background, blurred in nature and very poor aspect ratio, information absence and the awful artifacts. In the fusion, any gain must mean some lose its characteristics. Among the rules implemented under the Generalized Inverse Histogram Shifting frame, the IHS method replaces the intensity of images by contrasting the images based on the color levels. It can be inferred that the IHS method loses most luminance information of the images and assimilates the fused image to the phase contrast image more than any other methods, in which the substitution is performed partially.

**Advantages:**
1. The usage of Histogram technique and the sparse representation and the variance tolerance representation gives us about the hybrid function of the image fusion and the sparse representation
2. Similarities can be identified easily based on the pixel substitution technique.

**Disadvantages:**
1. Histogram technique can’t meet the basic requirements of the Gibbs phenomenon, so exact hybrid function of both can’t be achieved with greater efficiency.

<table>
<thead>
<tr>
<th>Objective</th>
<th>Methodology</th>
<th>Algorithm</th>
<th>Input</th>
<th>Output</th>
<th>Demerits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multifocus image fusion using the nonsubsampled contourlet transform</td>
<td>Increasing depth of focus</td>
<td>Fusing multifocus images</td>
<td>Camera images with different level of focussing</td>
<td>Focussed image</td>
<td>Computational complexity and high memory consumption</td>
</tr>
<tr>
<td>Biological image fusion using a NSCT based variable</td>
<td>Combining details of two or more images of a scene</td>
<td>Fusing images with variable weights</td>
<td>Fluorescent image and its corresponding contrast image</td>
<td>Fused detailed image</td>
<td>Magnetic resonance image and positron emission tomographic images cannot be used</td>
</tr>
<tr>
<td>Pixel-level image fusion with simultaneous orthogonal matching pursuit</td>
<td>Integrates image details from different scene</td>
<td>Fusing images to overlap patches in an image</td>
<td>Sparse representation</td>
<td>Sensor images</td>
<td>Enhanced information in the scene</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Super-Resolution Through Neighbor Embedding</td>
<td>High resolved image</td>
<td>Improving resolution in a low resolution image</td>
<td>Super resolution</td>
<td>Cell phone images</td>
<td>Super-resolved image</td>
</tr>
<tr>
<td>Image Super-Resolution via Sparse Representation</td>
<td>High resolved image</td>
<td>Improving resolution using sparse representation</td>
<td>Super resolution, sparse representation</td>
<td>Surveillance image</td>
<td>Super-resolved image</td>
</tr>
<tr>
<td>Matching pursuits with time frequency dictionaries</td>
<td>Matching the signal structure</td>
<td>Extracting pattern from noisy signals</td>
<td>Matching pursuit</td>
<td>Noisy signal</td>
<td>Noise free signal</td>
</tr>
<tr>
<td>Learning Low-Level</td>
<td>Estimating scenes from images</td>
<td>Improving resolution and increasing details</td>
<td>Super resolution</td>
<td>Camera image</td>
<td>Super-resolved image</td>
</tr>
<tr>
<td>An Edge Guided Image Interpolation Algorithm via Directional Filtering and Data Fusion</td>
<td>Preserving edges in a super resolution image</td>
<td>Guiding edges in an image interpolated image</td>
<td>Image interpolation</td>
<td>Digital image</td>
<td>Super-resolved image</td>
</tr>
</tbody>
</table>
CONCLUSION
The performance of image fusion and super-resolution are simultaneously dependant on sparse representation. The proposed techniques have greater merits. This technique avoids the generation of human artifacts produced by signal fusion or super-resolution as in the traditional two-stage process. Next to that, the complexity in computing the parameters is much less than performing image fusion and super-resolution separately. Studies on various types of input images exhibit the superiority of our technique over pre done fusion based on the super resolution strategies based on interpolation and representation of sparse images. This concept tells about the sparsity assumption that won’t take the structure of the sparse images into concern. The concept will derive the particular structures of different sparse images and further improved the performance of any image fusion algorithms. The hybrid function of the techniques of image fusion and the super resolution techniques gives us the much more needed output and all the parameters are evaluated.

REFERENCES

1. An Edge Guided Image Interpolation Algorithm via Directional Filtering and Data Fusion by Lei Zhang, Member, IEEE, and Xiaolin Wu, Senior Member, IEEE

2. Pixel- and region-based image fusion with complex wavelets by John J. Lewis, Robert J. O. Callaghan, Stavri G. Nikolov, David R. Bull, Nishan Canagarajah

3 Multi-focus Image Fusion using the Non Sub-sampled Contourlet transform by Qiang Zhang, Bao- longGuo.

4 Biological image fusion using a NSCT based variable-weight method by Tianjie Li, Yuanyuan Wang.

5 The Multi-Scale Directional Bilateral Filter and its application to multi-sensor Image Fusion by Jianwen Hu, Shutao Li

6 Image Decomposition via the Combination of Sparse Representations and a Variation Approach by J.L. Starck, M. Elad, D.L. Donoho.