International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 3, Issue 9, September 2014

IMAGE ENHANCEMENT OF GRAY AND COLOR IMAGES USING IMAGE FUSION METHOD

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ABSTRACT

Image enhancement can improve the perception of information. An image taken from a real scene can be divided into several regions according to the need for enhancement. This paper proposes a method to improve the enhancement result with image fusion method with image fusion algorithm for both grayscale and color images. The experiment results show that the fusion improves the enhancement results. Fusion algorithm can be optimized for speed in future research.

Index Terms: Digital image processing, Image Enhancement, Image Fusion, Histogram equalization

1. INTRODUCTION

1.1 Image Enhancement

Image enhancement is among the simplest and most appealing areas of digital image processing. The fundamental goal of image enhancement is to process the input image in such a way that the output image is more suitable [1] for interpretation by the humans as well as by machines. The process of image enhancement is application specific, thereby meaning that a method which is suitable for enhancing images for one type of application might not be suitable for other. There are numerous available techniques in the literature that can use for image enhancement. Improvement in quality of these degraded images can be achieved by using application of enhancement technique

Image enhancement techniques can be broadly classified into two categories:

- spatial domain
- frequency domain

1.1.1 Spatial Domain

Spatial domain methods directly process the pixels of an input image. An expression for spatial domain processing is given by the equation shown below:

$$g(x, y) = T[f(x, y)] \qquad (1.1.1)$$

Here, f(x, y) is the original image, g(x, y) is the processed image and T is an operator over neighborhood of (x, y). The principal approach in defining a neighborhood about a point (x, y) is to use a square or rectangular sub image area centered at (x, y). The center of the sub image is moved from pixel to pixel. The operator T is applied at each location to yield the output at that location. The process utilizes only the pixels in the area spanned by the neighborhood. The smallest possible size of the neighborhood is 1 × 1. Then depending upon the area selected, a larger matrix of higher order is formed. In this case spatial domain processing is called intensity transformation. There are numerous techniques available in the literature for image enhancement depending on the specific application. Contrast enhancement by histogram equalization is one such technique.

1.1.2 Frequency Domain

Frequency domain image enhancement involves modifying the Fourier transform of the image [1]. In frequency domain methods the original input image is first transformed into frequency domain using 2D Fourier transforms. The image is then processed in frequency domain. Finally, the output image is obtained using 2D inverse Fourier transforms.

The block diagram showing the main steps in frequency domain image processing is shown below:

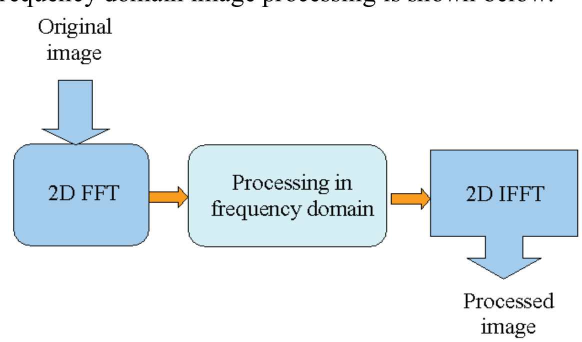

Figure: Frequency domain image processing [1]

2. Literature Review

This describes the comprehensive literature review of many fusion techniques, image gradient and histogram equalization techniques.

- Histogram equalization is an important image enhancement technique commonly used for contrast enhancement and to stretch the histogram of the given image. Greater is the histogram stretch greater is the contrast of the image.
- Image fusion is the combination of two or more different images to form a new image by using a certain algorithm.
- Image gradient is used to get the edge information.

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In order to measure the performance of fusion algorithms subjective and objective analysis is carried out. Some performance parameters have also been discussed in the literature survey.

2.1 Literature Survey

C. H. Hsieh et al. presented an approach to detail aware contrast enhancement with linear image fusion. Two main stages are involved in this approach: Conventional histogram equalization (CHE) and Linear image fusion (LIF).

The CHE has problem of over enhancement, it is noted that the details which is not obvious in the original image are generally revealed after the CHE. The details shown in the original image and in the equalized image are of a kind of complementary property.It is called **detail complementary property (DCP)** between the original image and the equalized image. The DCP suggests that the details in the original image and the equalized image may be combined to form an image with better contrast and visual quality.Result after the simulation indicates that the enhanced image proposed by the DACE/LIF approach has better visual quality than that in the original image and that by the compared HE based approach. **A. Saleem et al.** presented a fusion based contrast enhancement technique which integrates information to overcome the limitations of different contrast enhancement algorithms. Fusion is performed in a multi-resolution fashion using Laplacian pyramid decomposition to account for the multi- channel properties of the human visual system. The proposed method balances the necessity of local and global contrast enhancements and a faithful representation of the original image appearance, an objective that is difficult to achieve using traditional enhancement methods. For this purpose, metrics are defined for contrast, image brightness and saturation. The performance of the proposed method is evaluated using visual assessment and quantitative measures for contrast, luminance and saturation. The results show the efficiency of the method in enhancing details without affecting the color balance or introducing saturation artifacts and illustrate the usefulness of fusion techniques for image enhancement applications. **X. Fang et al.** also projected a technique which improves the result with image fusion method with evaluation on sharpness. Image enhancement can improve the perception of information. An image taken from a real scene can be divided into several regions according to the need for enhancement. One exacting development method improves some regions and actually deteriorates the other regions which have no need for such enhancement or any enhancement at all. Several different assessment methods and fusion policies are discussed and compared. Experiment shows that the fusion improves the enhancement results.

J. Sarup et al. compares various fusion techniques and their accuracies have been evaluated on their categorization. The Image fusion techniques are helpful in providing classification accurately. The satellite images at different spectral and spatial resolutions with the aid of image processing techniques can improve the quality of information. Particularly image fusion is very helpful to extract the spatial information from two images of different spatial, spectral and temporal images of same area.An function of image analysis such as image classification on fused images provides better results in comparison of original data. **B. Khaleghi et al.** proposed a review of the data fusion state of the art, exploring its conceptualizations, benefits and tough aspects, as well as accessible methodologies..**U. Patil et al.** proposed image fusion algorithm using hierarchical PCA. Image fusion is a process of combining two or more images (which are registered) of the same scene to get the more revealing image. Hierarchical multi-scale and multi-resolution image processing techniques, pyramid decomposition are the basis for the greater part of image fusion algorithms. **Principal Component Analysis (PCA)** is a well known scheme for feature extraction and dimension reduction and is used for image fusion. The image fusion algorithm has also been made by combining pyramid and PCA techniques and carryout the quality analysis of proposed fusion algorithm without reference image. Also describes fusion using pyramid, wavelet and PCA fusion techniques and carry out their performance analysis for these four fusion methods using different quality measures for variety of data sets and show that proposed image fusion using hierarchical PCA is better for the fusion of multimodal imaged. Visible inspection with quality parameters are used to arrive at a fusion results. **S. Li, B. Yang et al.** compare various multi-resolution decomposition algorithms, especially the latest developed image decomposition methods, such as curvelet and contourlet, for image fusion. The investigations include the effect of decomposition levels and filters on fusion performance. It describe image fusion that combines information from multiple images of the same scene to get a composite image that is more suitable for human visual perception or further image-processing tasks.The results show that the shift-invariant property is of great importance for image fusion.

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P. Du et al. proposed the impacts of different information fusion techniques on change detection; a sequential fusion strategy combining pan sharpening with decision level fusion is introduced into change detection from multi-temporal remotely sensed images. Normally, change map from multi-temporal remote sensing images using any single method or single kind of data source may contain a number of omission errors, degrading the detection accuracy to a great extent. To take advantage of the merits of multi-resolution image and multiple information fusion schemes, the proposed procedure consists of two steps: first is the change detection from pan sharpened images and Final change detection map generation by decision level fusion.

S. Krishnamoorthy et al. discuss the performance of three categories of image fusion algorithms:-

1. the basic fusion algorithms,
2. the pyramid based algorithms and
3. the basic DWT algorithms,

developed as an **Image Fusion Toolkit- ImFus**, using Visual C++6.0. The fused images were assessed using Structural Similarity Image Metric, Laplacian Mean Squared Error along with seven other simple image quality metrics that helped to determine the various image features which were also implemented as part of the toolkit. The readings produced by the image quality metrics, based on the image quality of the fused images were used to assess the algorithms. **Z. Wang, Y. Tie and Y. Liu** introduced the basic principles of image fusion at the level of pixel, feature and decision. Various image processing tools like Multi wavelets; Pulse Couple Neural Network has also been described. Image fusion system based on GUI is then designed and implemented. Functions like image de-noising, image enhancement, image registration, image segmentation, image fusion, and fusion evaluation. It gives the framework of the overall design of the system and explains its usage method.

S. H. Yun, J. H. Kim et al. proposed an image enhancement method based on a modified Laplacian pyramid framework that decomposes an image into band-pass images to improve both the global contrast and local information. For the global contrast, a novel robust HE is proposed to provide a well balanced mapping function which effectively suppresses the quantum jump. For the local information, noise-reduced and adaptively gained high-pass images are applied to the resultant image. In qualitative and quantitative comparisons through experimental results, the proposed method shows natural and robust image quality and suitability for video sequences, achieving generally higher performance when compared to existing methods.

K. X. Wu, C. H. Wang et al. introduced the idea of the image fusion technology and its distribution level. Image fusion by the different levels of information abstraction can be divided into three levels: **P**ixel level fusion,**F**eature level fusion and **D**ecision level fusion.It gives the idea about image fusion at pixel level technology and probes into the form of image fusion method of evaluation criteria. Fundamentally, it gives the development direction of image fusion.

Z. Youzhi and Q. Zheng compare the performance of different image fusion algorithms.A structural resemblance metric that does not use a reference image for image fusion evaluations. The metric is based on the universal image quality index and addresses not only the similarities between the input images and the fused image, but also the similarities among the input images. The evaluation process distinguishes between balancing and outmoded information using similarities among the input images. The metric uses the information classification to estimate how much structural similarity is preserved in the fused image.

K. G. Nikolakopoulos compare the efficiency of nine fusion techniques and more specifically the efficiency of IHS, Modified IHS, PCA, Pansharp, Wavelet, LMM (Local Mean Matching), LMVM (Local Mean and Variance Matching), Brovey, and Multiplicative fusion techniques for the fusion of QuickBird data. The suitability of these fusion techniques for various applications depends on the spectral and spatial quality of the fused images. All the fusion techniques improve the resolution and the visual result.**Y. Niu and L. Shen** presented a novel approach to image fusion based on multi-objective optimization which could achieve the optimal fusion indices through optimizing the fusion parameters.First the uniform model of image fusion in DWT (Discrete Wavelet Transform) domain was established, then the proper evaluation indices of image fusion were given; and finally the adaptive multi objective particle swarm optimization was introduced to search the optimal fusion parameters..**V. Vijayaraj, V. Younan et al.** proposed the idea of pixel level and feature level fusion. Co-registered Quick-Bird multispectral and panchromatic image data sets were used to examine the advantages of pixel level and feature level fusion schemes. Object-based classification was used to classify the images.In object-based method the data is segmented into image objects based on shape, color, homogeneity and compactness. The image is then analyzed in the image object domain instead of the pixel domain. **eCognition** an object oriented image analysis software was used to perform the classification. Three different classifications were

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done and compared. The multispectral data was classified based on features from the raw multispectral data alone. The image was segmented into image objects based on color and shape parameters in the multispectral image. A mask indicating the training and test areas was created to aid in supervised classification and accuracy evaluation. **C. Wang and Z. Ye** proposed a novel accumulation of histogram equalization, actually histogram requisite, to overcome such drawback as HE. To make best use of the entropy is the essential idea of HE to make the histogram as flat as possible. Following that, the essence of the proposed algorithm, named **B**rightness **P**reserving **H**istogram **E**qualization with **M**aximum **E**ntropy (BPHEME), tries to find, by the variation approach, the target histogram that maximizes the entropy, under the constraints that the mean brightness is fixed, and then transforms the original histogram to that target one using histogram specification. Comparing to the existing methods including HE, **B**rightness preserving **B**i-**H**istogram **E**qualization (BBHE), equal area **D**ualistic **S**ub-**I**mage **H**istogram **E**qualization (DSIHE), and **M**inimum **M**ean **B**rightness **E**rror **B**i-**H**istogram **E**qualization (MMBEBHE), experimental results show that BPHEME can not only enhance the image effectively, but also preserve the original brightness quite well, so that it is possible to be utilized in consumer electronic products. **B. E. Ramirez** worked on a multi channel model based on the scale space theory. This model is encouraged in biological insights and includes some important properties of human vision such as the Gaussian derivative model. The image transform that the author proposed in this work uses analysis operators similar to those of the Hermite transform at multiple scales, but the synthesis scheme of the approach integrates the responses of all channels at different scales. The advantages of this scheme are: Both analysis and synthesis operators are Gaussian derivatives. This allows for simplicity during implementation and the operator functions possess better space frequency localization. A discrete approximation is also derived from an asymptotic relation between the Gaussian derivatives and the discrete binomial filters .**G. Piella** presents a summary on image fusion techniques by means of multi-resolution decompositions..The basic idea is to make a multi-resolution segmentation based on all different input images and to use this segmentation in guiding the fusion process. The projected several activity level measures including the absolute value, the median, or the contrast to neighbor's measures.

S. D. Chen and A. Ramli anticipated a overview of BBHE referred to as **R**ecursive **M**ean-**S**eparate**H**istogram **E**qualization(RMSHE) to provide not only better but also scalable brightness conservation. BBHE separates the input image's histogram into two based on its mean before equalizing them independently. While the separation is done only once in BBHE,it is analyzed mathematically that the output image's mean brightness will converge to the input image's mean brightness as the number of recursive mean separation increases. Besides, the recursive nature of RMSHE also allows scalable brightness preservation, which is very useful in consumer electronics. Simulation results show that the cases which are not handled well by HE, BBHE and Dualistic Sub Image Histogram Equalization (DSIHE), have been properly enhanced by RMSHE.**L. Chan, S. Der** investigates the probable benefits of fusing two bands of forward-looking infrared (FLIR) data for target detection and clutter rejection. The proposed method consist a similar set of neural based clutter rejecters and target detectors, each of which consists of an eigen space transformation and a simple multilayer perception. The same architecture is used to operate on either single band or dual band FLIR input images, so that the net effects of dualband fusion can be demonstrated. When the dualband inputs are used, the component bands are combined at either pixel or feature level, thus providing insight into methods of performing data fusion in this particular application.A large set of real FLIR images is used in two series of experiments, one for clutter rejection tasks and the other for target detection tasks.

In both series, the results indicate that the dual band input images do improve the performance of the clutter rejecters and target detectors over their single band counterparts. **D. Rajan and S. Chaudhuri** offered two new techniques of using data fusion, based on the modality of the data generation process, to generate a super resolved image from a sequence of low resolution image intensity data. First, we develop a generalized interpolation scheme wherein an image is decomposed into appropriate subspaces, interpolation is carried out in individual subspaces and subsequently the interpolated values are transformed back to the image domain. Various structural properties of the image, such as 3D shape of an object, regional homogeneity, local variations in scene receptivity can be better preserved during the interpolation process. In the second method, the data to be fused consist of a sequence of decimated, blurred and noisy versions of the high resolution image. The high resolution image is modelled as a Markov random field and a maximum a posterior estimation technique is used to fuse the data to obtain

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a super-resolved image. The proposed technique did not require sub-pixel registration of given observations. **Y. Wang, Q. Chen** offered a novel histogram equalization technique equal area dualistic sub image histogram equalization, is put forward in this paper. First, the image is decomposed into two equal area sub images based on its original probability density function. Then the two sub images are equalized respectively. After the processed sub images are composed into one image.The reproduction result indicates that the algorithm can not only enhance image information effectively but also keep the original image luminance well enough to make it possible to be used in video system directly. **L. G. Shapiro** proposed the idea about relational models that are commonly used in scene analysis systems. Most such systems are experimental and deal with only a small number of models. Unknown objects to be analyzed are usually sequentially compared to each model. Some ideas for organizing a large database of relational models have been proposed that how simple relational distance measure, prove it is a metric, and using this measure, describe two organizational/access methods: clustering and binary search trees. **D. L. Hall** gave the idea of Multisensory data fusion. An rising technology applied to Department of Defense areas such as automated target, recognition, battle-field surveillance, and guidance and control of autonomous vehicles, and to non DoD applications such as monitoring of complex machinery, medical diagnosis, and smart buildings.Techniques for multisensory data fusion are drawn from a wide range of areas including artificial intelligence, pattern recognition, statistical estimation, and other areas.

Y. T. Kim proposed a novel extension of histogram equalization to overcome such drawback of the histogram equalization. The essence of the proposed algorithm is to utilize independent histogram equalizations separately over two subimages obtained by decomposing the input image based on its mean with a constraint that the resulting equalized subimages are bounded by each other around the input mean. It could be showed mathematically that the proposed algorithm preserves the mean brightness of a given image significantly well compared to typical histogram equalization while enhancing the contrast and thus provides much natural enhancement that can be utilized in consumer electronic products.

A. Toet presented an adaptive contrast enhancement technique based on a hierarchical image representation.First linear multi-scale image decomposition is obtained by computing a ratio of low pass pyramid. The input image is reconstructed by non linear multiplication of successive pyramid layers. The recombination process adaptively stretches local image contrast at all levels of resolution. This results in an overall contrast enhancement of the recombined image. Moreover, the reconstructed image can become independent of changes in lighting and luminance gradients.

Z. Zhang and R.S. Blum proposed a generic image fusion framework based on multi-scale decomposition. This structure provides freedom to choose different multi-scale decomposition methods and different fusion rules. The frame includes all of the existing multi-scale decomposition based fusion approaches which did not assume a statistical model for the source images. Different image fusion approaches are investigated based on this framework.

3. HISTOGRAM EQUALIZATION

Histogram equalization is an important image enhancement technique commonly used for contrast enhancement. The histogram equalization technique is used to stretch the histogram of the given image. Greater is the histogram stretch greater is the contrast of the image. In other words if the contrast of the image is to be increased then it means the histogram distribution of the corresponding image needs to be widened. Histogram equalization is the most widely used enhancement technique in digital image processing because of its simplicity and elegancy. In an image processing context, the histogram of an image normally refers to a histogram of the pixel intensity values. This histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8-bit grayscale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those grayscale values.Histograms can also be taken of color images - either individual histogram of red, green and blue channels can be taken, or a 3-D histogram can be produced, with the three axes representing the red, blue and green channels, and brightness at each point representing the pixel count. The exact output from the operation depends upon the implementation, it may simply be a picture of the required histogram in a suitable image format, or it may be a data file of some sort representing the histogram statistics. The operation of HE is performed by remapping the gray levels of the image based on the probability distribution of the input gray levels. It flattens and stretches the dynamic range of the image's histogram and resulting in overall contrast enhancement. Contrast enhancement by histogram equalization is one such technique.

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4. IMAGE FUSION

Data fusion is a process dealing with data and information from multiple sources to achieve refined/improved information for decision making. Image fusion is the combination of two or more different images to form a new image by using a certain algorithm.In data fusion the information of a specific scene acquired by two or more sensors at the same time or separate times is combined to generate an interpretation of the scene not obtainable from a single sensor. Image fusion is a component of data fusion when data type is strict to image format. Image fusion is an effective way for optimum utilization of large volumes of image from multiple sources. Multiple image fusion seeks to combine information from multiple sources to achieve inferences that are not feasible from a single sensor or source. It is the aim of image fusion to integrate different data in order to obtain more information than can be derived from each of the single sensor data alone.

Image fusion can be performed roughly at four different stages: **signal level, pixel level, feature level, and decision level**.

The concept of the four different fusion levels is described below:

- **Signal level fusion**: In signal-based fusion, signals from different sensors are combined to create a new signal with a better signal-to noise ratio than the original signals.
- **Pixel level fusion**: Pixel-based fusion is performed on a pixel-by-pixel basis. It generates a fused image in which information associated with each pixel is determined from a set of pixels in source images to improve the performance of image processing tasks such as segmentation.
- **Feature level fusion**: Feature-based fusion at feature level requires an extraction of objects recognized in the various data sources. It requires the extraction of salient features which are depending on their environment such as pixel intensities, edges or textures. These similar features from input images are fused.
- **Decision level fusion**: It 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.

The most popular image fusion techniques are:

- **Fusion using Principle Component Analysis:** The PCA image fusion method simply uses the pixel values of all source images at each pixel location, adds a weight factor to each pixel value, and takes an average of the weighted pixel values to produce the result for the fused image at the same pixel location. The optimal weighted factors are determined by the PCA technique. The PCA technique is useful for image encoding, image data compression, image enhancement, pattern recognition (especially for object detection), and image fusion. It generates a new set of axes which is orthogonal. By using this method, the redundancy of the image data can be decreased.
- **Multiresolution image fusion:** The IHS fusion converts a color MS image from the RGB space into the IHS color space. Because the intensity (I) band resembles a panchromatic (PAN) image, it is replaced by a high-resolution PAN image in the fusion. A reverse HIS transform is then performed on the PAN, together with the hue (H) and saturation (S) bands, resulting in an IHS fused image.
- **Fusion using Laplacian pyramid method:** The Laplacian pyramid fusion consists of an iterative process of calculating the Gaussian and Laplacian pyramids of each source image, fusing the Laplacian images at each pyramid level by selecting the pixel with the larger absolute value, combining the fused Laplacian pyramid with the combined pyramid expanded from the lower level, and then expanding the combined pyramids to the upper level.
- **Fusion using gradient pyramid method:** A gradient pyramid is obtained by applying a set of 4 directional gradient filters (horizontal, vertical, and 2 diagonal) to the Gaussian pyramid at each level. At each level, these 4 directional gradient pyramids are combined together to obtain a combined gradient pyramid that is similar to a Laplacian pyramid. The gradient pyramid fusion is therefore the same as the fusion using the Laplacian pyramid method except replacing the Laplacian pyramid with the combined gradient pyramid.
- **Fusion using filter-subtract-decimate pyramid method:** The FSD pyramid fusion method is conceptually identical to the Laplacian pyramid fusion method. The only

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difference is in the step of obtaining the difference images in creating the pyramid. In a Laplacian pyramid, the difference image L_k at level k is obtained by subtracting an image up-sampled and then low-pass filtered from level k+1 from the Gaussian image G_k at level k, while in the FSD pyramid, this difference image is obtained directly from the Gaussian image G_k at level k subtracted by the low pass filtered image of G_k. Hence FSD pyramid fusion method is computationally more efficient than the Laplacian pyramid method by skipping an up-sampling step.

- **Fusion using discrete wavelet transforms method**: In the DWT based fusion method, the source images are first transformed by DWT to their corresponding wavelet coefficient images at each scale level. Corresponding approximation coefficients and detail coefficients of the source images at each level are then fused, respectively, based on a certain fusion rule. This rule can be a simple addition or averaging, or a PCA-based weighted averaging. The fused approximation and detail coefficients at each level are used in the final reconstruction of a single output fused image by an inverse DWT.
- **Exposure Fusion method:** Exposure fusion computes the desired image by keeping only the “best” parts in the multi-exposure image sequence. This process is guided by a set of quality measures, which we consolidate into a scalar-valued weight map. It is useful to think of the input sequence as a stack of images. The final image is then obtained by collapsing the stack using weighted blending. Quality measures are used for assigning weights. Many images in the stack contain flat, colorless regions due to under- and overexposure. Such regions should receive less weight, while interesting areas containing bright colors and details should be preserved.

$$W_{ij,k} = (C_{ij,k})^{\omega_c} \times (S_{ij,k})^{\omega_s} \times (E_{ij,k})^{\omega_e} \qquad (4.1)$$

With C, S and E, being contrast, saturation, and well exposedness, resp., and corresponding weighting exponents ω_c, ω_s, and ω_e. The subscript ij, k refers to pixel (i, j) in the k-th image. If an exponent ω equals 0, the corresponding measure is not taken into account. A weighted average along each pixel to fuse the N images, using weights computed from our quality measures. To obtain a consistent result, we normalize the values of the N weight maps such that they sum to one at each pixel (i, j):

$$\hat{W}_{ij,k} = \left[\sum_{k'=1}^{N} W_{ij,k'}\right]^{-1} W_{ij,k} \qquad (4.2)$$

The resulting image R can then be obtained by a weighted blending of the input images:

$$R_{ij} = \sum_{k=1}^{N} \hat{W}_{ij,k} I_{ij,k} \qquad (4.3)$$

With I_k the k-th input image in the sequence. Unfortunately, just applying Eq. (4.3) produces an unsatisfactory result. Wherever weights very quickly, disturbing seams will appear. This happens because the images we are combining contain different absolute intensities due to their different exposure times. We could avoid sharp weight map transitions by smoothing the weight map with a Gaussian filter, but this results in undesirable halos around edges, and spills information across object boundaries. An edge aware smoothing operation using the cross-bilateral filter seems like a better alternative. However, it is unclear how to define the control image, which would tell us where the smoothing should be stopped. Using the original grayscale image as control image does not work well, also, it is hard to find good parameters for the cross-bilateral filter (i.e., for controlling the spatial and intensity influence).

- **Fusion using local contrast:** For each point x in each channel I_n, the local contrast is defined as:

$$C_i(x) = \max(N_i(x)) - \min(N_i(x)) \qquad (4.4)$$

Where $N_i(x)$ is a 3×3 neighborhood centered at x, and max (·) and min(·) represent the maximum and minimum value in the neighborhood, respectively. Based on the local contrast above, we present the fusion approach for two images as follows. Let D be the difference of C_1 and C_2, i.e., $D(x) = C_1(x) - C_2(x)$ for each point x. Then the fusion weight is defined by the sigmoidal function as follows (and let the sum of x_1 and x_2 be 1):

$$s_1 = \frac{1}{1+e^{-a(\hat{D}-b)}}, s_2 = 1 - s_1 \qquad (4.5)$$

where a=5, b=−min(D)/(max(D)−min(D)) are constants, which control the steepness and center position of the sigmoidal function, and

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$\hat{D}$ =(D−max(D))/(max(D)−min(D)) is the normalized difference.

Fusion of three or more images with complementary advantages is also feasible. Let the definition of $C_i(x, y)$ be the same as that of the case of two. The exponential of C_i is $E_i(x) = e^{cC_i(x)}$, where c is a constant. The fusion weight, which is an extension of Eq. (4.5), is defined as

$$s_i(x) = \frac{E_i(x)}{\sum_{i=1}^{N} E_i(x)} \quad (4.6)$$

- **Image enhancement by gradient fusion:** This method is an extension of the method discussed above. In this method a structure of the multiple images is calculated based on the gradient of the image and the weight values described above. This structure tensor represents the geometrical information contained in the multiple images and hence represents the edges of the desired image. The output fused image can be reconstructed from this structure tensor.
- **Detail Aware Contrast Enhancement using linear image fusion:** In this linear image fusion is used to enhance the image. Linear image fusion of two images is given by the formula:

$$I_f(x, y)=w*I_1(x, y)+(1-w)*I_2(x, y) \quad (4.7)$$

Here I_1 and I_2 are the two images. Specifically only one image is used and the second image is obtained using conventional histogram equalization on the source image. The two images are then fused using the above equation. Here, the value of w needs to be entered manually. The advantage of using this algorithm is that it is simple to implement both in hardware and software but one disadvantage could be that value of w needs to be manually entered for getting good results.

Gradients

For a function f(x, y), the gradient of f at (x, y) is defined as the two dimensional column vector

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \quad (4.8)$$

The magnitude of this vector is given by

$$|\nabla f| = \left[\left(\frac{\partial f}{\partial x} \right)^2 + \left(\frac{\partial f}{\partial y} \right)^2 \right]^{1/2} \quad (4.9)$$

The first order derivative of a one dimensional function f(x) is the difference

$$\frac{\partial f}{\partial x} = f(x+1) - f(x) \quad (4.10)$$

For color images following equations are used [1] for calculating the gradient and hence the edges of the image:

$$g_{xx} = \left(\frac{\partial R}{dx}\right)^2 + \left(\frac{\partial G}{dx}\right)^2 + \left(\frac{\partial B}{dx}\right)^2 \quad (4.11)$$

$$g_{yy} = \left(\frac{\partial R}{dy}\right)^2 + \left(\frac{\partial G}{dy}\right)^2 + \left(\frac{\partial B}{dy}\right)^2 \quad (4.12)$$

$$g_{xy} = \frac{\partial R}{dx}\frac{\partial R}{dy} + \frac{\partial G}{dx}\frac{\partial G}{dy} + \frac{\partial B}{dx}\frac{\partial B}{dy} \quad (4.13)$$

$$\theta = \frac{1}{2}\tan^{-1}\left[\frac{2g_{xy}}{g_{xx} - g_{yy}}\right] \quad (4.14)$$

$$F(\theta) = \left\{ \frac{1}{2}\left[\left(g_{xx} + g_{yy}\right) + \left(g_{xx} - g_{yy}\right)\cos 2\theta + 2g_{xy}\sin 2\theta \right] \right\}^{1/2} \quad (4.15)$$

Here g_{xx}, g_{yy}, g_{xy} are the gradients in x, y and x-y directions respectively and θ is the direction of maximum gradient. F (θ) represents the gradient of the color image.

AIM

Using image enhancement techniques like histogram equalization one can get images which are complementary in the sense that they enhances some parts of the original image while distorting information of other parts of the image. In this kind of scenario, the image fusion technology can be utilized to retain the important information from both the images. In other words, the two images can be combined in such a way that the information from both the images is preserved in the final fused image. So our aim is- Image Enhancement using Image Fusion.

Objectives

The image fusion technology can be used to enhance the original image. Using image enhancement techniques like histogram equalization, we can get images which are complementary in the sense that they enhances some parts of the original image while distorting information of other parts of the image. To retain the important information from both the images, the two images can be combined in such a way that the information from both the images is preserved in the final fused image.

So the objectives of present work are:

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- Study various histogram equalization techniques in order to obtain a complementary image of the original image.
- Study various fusion techniques for combining two or more images.
- To study image gradients in order to calculate the edge information of both greyscale and color images and utilize this information for fusing images.
- To develop and implement an algorithm for image enhancement based on histogram equalization, gradients and image fusion.
- To measure the performance of the fusion algorithm using subjective and/or objective analysis.

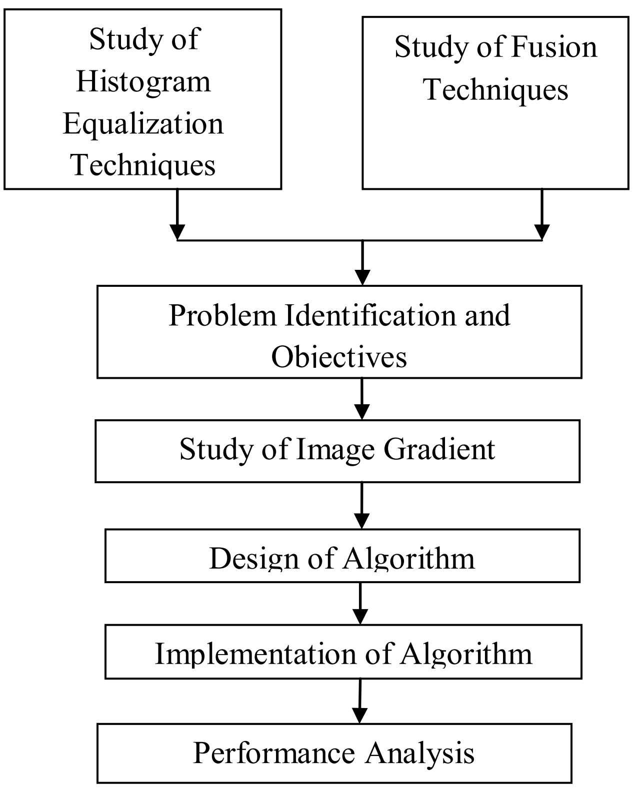

Figure: Research Approach.

Proposed Algorithm

Flowchart of Image Fusion

Image fusion algorithm could be applied on grayscale images or color images. The fusion algorithms for both grayscale as well as color images are described below:

For Grayscale Images

The outline of the fusion algorithm for grayscale images is as follows:

- Let the input image is I_1.
- Compute the conventional histogram equalized image I_2 from I_1.
- Calculate magnitude gradient of I_1 using Sobel operator to get the edge map S_1.
- Calculate magnitude gradient of I_2 using Sobel operator to get the edge map S_2.
- Calculate $S = S_1 – S_2$.
- Calculate the absolute maximum value of matrix S.
- Normalize the matrix S with the absolute maximum value.

For each pixel located at position (x, y) repeat the following steps:

- Calculate $w = \dfrac{1}{1+10^{-S(x,y)}}$.

This function is used for weighting each pixel based on the strength of edges of I_1 and I_2. If $S_1(x, y) > S_2(x, y)$, then $I_1(x, y)$ is given the higher weightage and $I_2(x, y)$ the lower weightage. But if $S_2(x, y) > S_1(x, y)$, then $I_2(x, y)$ is given the higher weightage and so on.

- Use the value of w in Eq. (4.7) to find the fused image $I_f(x, y)$.

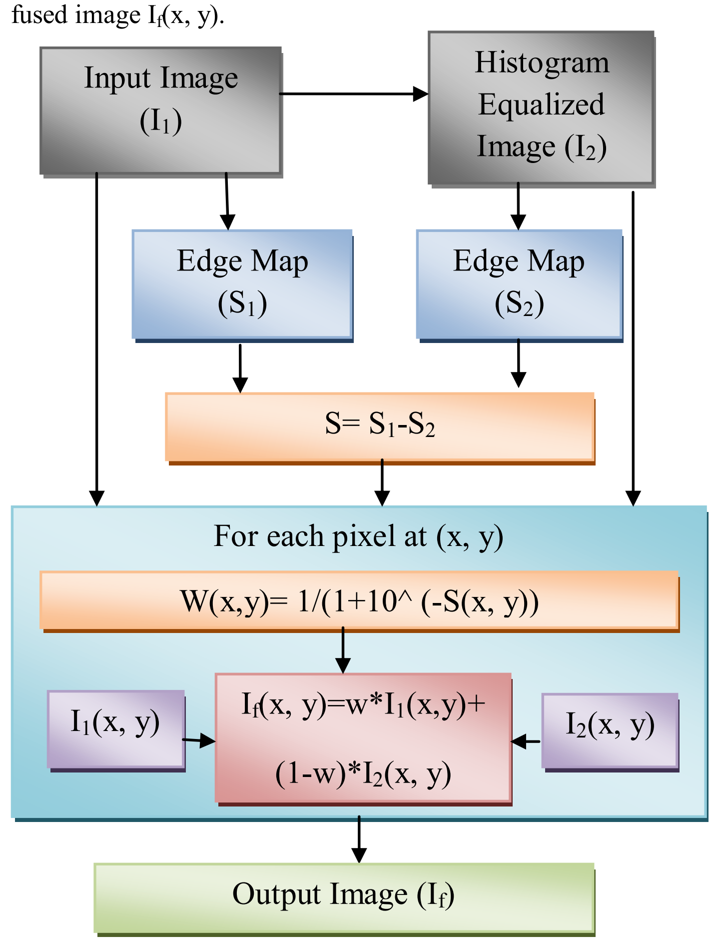

Figure : Flowchart for grayscale images

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For Color Images

For color images the process is outlined below:

- Let the input image is I_1.
- Compute the conventional histogram equalized image I_2 from I_1. For this step histogram equalization is carried out for each of the channels i.e. R, G and B channels are equalized independently and finally combined.
- Calculate the gradient of I_1 using Eq. (4.15) to get the edge map S_1.
- Calculate the gradient of I_2 using Eq. (4.15) to get the edge map S_2.
- Calculate $S = S_1 - S_2$.
- Calculate the absolute maximum value of matrix S.
- Normalize the matrix S with the absolute maximum value.

For each pixel located at position (x, y) repeat the following steps:

- Calculate $w = \dfrac{1}{1+10^{-S(x,y)}}$.
- Use the value of w in Eq. (4.7) to find the fused image $I_f(x, y)$. This step is repeated for each R, G and B channel.

Finally combine the R, G and B channels to get the output fused image. The flowchart for color image fusion is same except the fusion is carried out on the three channels simultaneously.

CONCLUSION

For grayscale images the disadvantage of using histogram equalization is that it over enhances the original image. Because of this the key information that was present in the original image gets lost in the histogram equalized image. In other words, original image and histogram equalized image contains complementary information. We can utilize this complementary relation between the two images by using the fusion algorithm The information in the output fused image is the weighted sum of information in the original source image and histogram equalized image. Our claim that the fused image is the enhanced version of the original image is supported by the objective analysis of original image and the fused image. Similar arguments can be given for the enhancement of color images. The enhancement in case of color images involves variation in color information and it is this variation in color information which is responsible of input image enhancement. Fusion of the histogram equalized image with the original image keeps the color change within limits.

REFERENCES

[1] R. Gonzalez and R. Woods, "*Digital Image Processing*", 2nd ed., Prentice Hall, Jan. 2002, pp. 75-102, 134-137, 572-581.

[2] Cheng-Hsiung Hsieh, Bo-Chang Chen, Chih-Ming Lin, Qiangfu Zhao,"*Detail Aware Contrast Enhancement with Linear Image Fusion*", International Symposium on Aware Computing, 2010, pp. 1-5.

[3] Y. Wang, Q. Chen, B. Zhang, "*Image enhancement based on equal area dualistic sub-image histogram equalization method*," IEEE Trans. on Consumer Electronics, vol. 45, no. 1, pp. 68-75, Feb. 1999.

[4] Xiaoying Fang, Jingao Liu, Wenquan Gu, Yiwen Tang, "*A Method to Improve the Image Enhancement Result based on Image Fusion*", International Conference on Multimedia Technology, 2011, pp. 55-58

[5] P. Du, S. Liu, J. Xia and Y Zhao, "Information fusion techniques for change detection from multi-temporal remote sensing images", *Information Fusion 14*, pp. 19-27, 2012.

[6] www.mathworks.com

[7] L.Chan, S. Der and N. M. Nasrabadi. "*Dualband FLIR fusion for automatic target recognition*", Information Fusion, 4, 35-45, 2003.

[8] D.Rajan and S.Chaudhuri. "*Data fusion techniques for super-resolution imaging*", Information Fusion, 3, 25-38, 2002.

[9] G.Piella, "*A General Framework for Multiresolution Image Fusion: from Pixels to Regions*". Information Fusion 4 (2003) 259-280, 2003.

[10] M. L. Williams, R.C. Wilson, E.R. Hancock, "*Deterministic search for relational graph matching*", Pattern Recognition 32, 1255-1516, 1999.

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