

AN EFFICIENT MULTI-FOCUS IMAGES FUSION WITH DENSE SCALE INVARIANT FEATURE TRANSFORM

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Abstract : *a novel fusion framework is proposed for multimodal medical images based on Gradient Orientation Bracketed pairs. The source medical images are first transformed by Image separation (DOF) followed by combining background and foreground parts frequency components. The Standard Dynamic Range (SDR) device traces image details like contrasts and gradient filter direction in a series of SDR images with different levels. The image overall luminance levels are calculated with the image series, which maximizes the observable distinctions, and then the gradients embedded in these images. The fusion algorithm techniques are used for fusion of images based on Luminance and gradient level. This is done in a multi-resolution of illumination variation in the sequence. Experimental results and comparative study show that the proposed fusion framework provides an effective way to enable more accurate analysis of multimodality images.*

Keywords : *Image separation, gradient extraction, luminance extraction, fusion process.*

1. Introduction

Exposure bracketing is one of the important feature in many digital cameras in which a series of

pictures are taken in rapid succession with varying shutter speeds. The user picks up one of the best image in the set of images between color information and sharp details. Longer exposure gives good intensity and color information, but may result in blurred images; shorter exposure gives sharp details, but these images are usually dark and noisy. Increasing the brightness of the short exposure image (e.g. by global histogram matching with the long exposure image) does not solve the problem. Denoising techniques can avoid problems with the noise, but are not equipped to rectify the color issues. In the proposed approach, the visible contrast and gradient is used for the whole scene to describe scene details. Given an SDR capture device, the scene luminance is recorded under a specific exposure level as the image luminance, which is determined by the response function of the film or the charge-coupled device.

2. System Analysis

Existing System proposed the Fusion Model for Noisy and Blurred Image Pairs, unnatural restored image and unwanted ringing artifacts on the edges of the table due to the single-image-based

deconvolution. The prohibited in some places, such as museums or churches, and it can generate unwanted red eye artifacts and can dazzle the eyes during shooting. Fails in the presence of severe noise in the captured noisy image.

2.1 Depth of field Extraction

The exposure level of a photo is the total radiant energy integrated by the camera's entire sensor while the shutter is open. The exposure level can influence significantly the quality of a captured photo because when there is no saturation or thermal noise, a pixel's signal-to-noise ratio (SNR) always increases with higher exposure levels.

2.2 Luminance Extraction

A good solution to suppress halos is to apply the scene gradients to adjust the gradient of the synthesized SDR image.

To compute the quantity of the visible gradient $\psi(x, y)$ by

$$\psi(x, y) = \sum_{i=x-\frac{M}{2}}^{x+\frac{M}{2}} \sum_{j=y-\frac{M}{2}}^{y+\frac{M}{2}} T(|c(I_H(x, y). VMAX(\nabla I_H(x, y)))|) \quad (2)$$

2.3 MRI Image Fusion

Multi resolution of scale separately, sharp transitions in the weight map can only affect sharp transitions appear in the original images (e.g. edges). A Laplacian filter to the grayscale version of each image, and take the absolute value of the filter response. This yields a simple color indicator (Red, Green and Blue) for contrast. It tends to assign a high weight to important elements such as edges and

texture (color surface). A similar measure was used for multi-focus fusion for extended depth-of-field (DOF).

3. Image Separation Algorithm

The input four images are grouped into single parameter with help of vectorization concept. To load the image sequence with corresponding scaling and each image is converting into double precision. Double should be overloaded for all objects where it makes sense to convert it into a double precision value. In case of some of the images have difference scaling then the scaling is resized with appropriate size. To compute the DOF measures and combines them into a weight map. The RGB Input image vector is convert in to Grayscale vector with help of `rgb2gray` matlab in built function. Using `im filter` function: N-D filtering of multidimensional images. The output, is computed using double-precision floating point. If image is an integer or logical array, then output elements that exceed the range of the given type are truncated, and fractional values are rounded.

4. Gradient Direction Estimation

Algorithm

To compute the first order derivative of input Image vectors I in X , and in Y direction. Assign the size of image plot in the image vector space. To calculate the absolute value of X and Y coordinates. Assign the `meshgrid` function to be image plot. Process the gradient function along with the grid value of X and Y directions. To be filled the directions with help of `quiver` plot.

5. Preprocess Source, Target, And Color Images

Natural scenes always contain high dynamic range areas in comparison with the limited dynamic range capabilities of cameras or displays. The dynamic range is defined by the ratio between the maximum and minimum light intensities of the scene. An HDR image is commonly obtained by fusing multi-exposure images.

5.1 Color Image

Color images, consisting of red, green, and blue channels, can be processed by reconstructing the imaging system response curve for each channel independently. Unfortunately, there will be three unknown scaling factors relating relative radiance to absolute radiance, one for each channel. As a result, different choices of these scaling factors will change the color balance of the radiance map.

5.2 Dynamic Range

The importance of intensity ratios for image reproduction, it is natural to summarize the range of an image using a single extreme ratio between the maximum and minimum image intensities. This ratio is usually called the image dynamic range. A rendering of the image can preserve the original intensity ratios only if the dynamic range of every device within the image reproduction pipeline matches or exceeds that of the original scene.

5.3 Absolute Intensity Level

Dynamic range, by definition, eliminates any specification of the absolute intensity level. This is too extreme a summary for image rendering applications; the absolute level matters because imaging devices and observers have upper and lower bounds on their operating range. For example, suppose that an observer sees a scene through a very dark neutral density filter. The filter preserves the scene dynamic range, yet the low intensity level changes the sensitivity as well as the spatial and temporal sensitivity of the human visual system. If the absolute level is scaled too much, the entire image can move from photonic (cone) to scotopic (rod) vision.

5.4 Edge preserving Smoothing Filter

Edge Preserving Smoothing Filter in the so-called edge preserving smoothing algorithm introduced, the selection of gray-level pixels for averaging is done based on statistical principles. The pixels marked in the neighborhood are used for the following computations. The symmetrical use of 1 (a) and (b) results in eight different masks. Each of these masks includes seven points for the calculation of the new gray-level. The contrast mask (c) includes nine elements for the following computations. For each mask, we compute the variance. The mask with the lowest variance is selected. The central pixel gets the mean value of all points marked in this mask.

5.5 Image Fusion

The Infrared and visible light cameras have their own unique characteristics. Images taken in the visual spectrum tend to preserve good contextual information, while in night vision they usually show

poor perception among objects due to the low contrast. IR images are almost insensitive to the change of light condition, so it may be most reliable to distinguish the targets from the background by the thermal contrast. To improve this, the contrast histogram equalization is done before the image fusion.

5.6 Contrast Reduction

To combine multiple exposures when creating high dynamic range radiance maps. The next step consists of mapping the computed radiance values, expressed in floating point precision, and have arbitrary dynamic range in the input range (typically [0:255]) of a common display device. Problems arise from the fact that usually CRT displays are capable of representing a limited dynamic range (usually around 50, in terms of luminance values) which, furthermore, needs to be quantized into a limited number of possible gray values. Various solutions have been proposed in the literature, some of them taking into account very sophisticated features of human perception to produce ad hoc solutions. Some of these methods, the data expressed in absolute units so that the response of the human visual system HVS can be taken into account, which are usually not available to the common user. Thus, these methods cannot be applied to images rendered in fictitious raw units without any physical meaning.

5.7 Visual Sensitivity

It is widely agreed that image reproduction algorithms should aim to preserve intensity ratios.

When preserving, all ratios is impossible, certain ones are more visually significant than others and these should be preserved first. For example, it is difficult to perceive the difference between an edge whose two sides differ by 3.8 log units from an edge whose sides differ by 4 log units. On the other hand, it is very easy to discriminate between a pair of edges whose sides have intensity ratios of 0.1 log units and 0.3 log units. Hence, preserving the latter intensity ratio is much more important than the former. Visual insensitivity to image differences is always an important factor in designing algorithms, and we should rely on such insensitivity in dynamic range compression design as well.

6 Experimental Result

We Images are considered with different exposure settings under low light conditions. These images are grouped into single parameter with the help of vectorization concept. The bi-cubic interpolation technique is used to resize the image without loss of pixels in the image. Images are matched with matched database to identify high frequency regions. Peak Signal Noise Ratio is calculated for these images which gives the quality. PSNR value thus obtained is compared with the two methods of PSNR value. Fusion Based on Gradient Exposure produces the best result when compared with Variational Approach and Cross – Bilateral method. Peak Signal Noise Ratio is calculated by the under mentioned formula. The PSNR and SSIM ratio values are thus calculated and are tabulated.

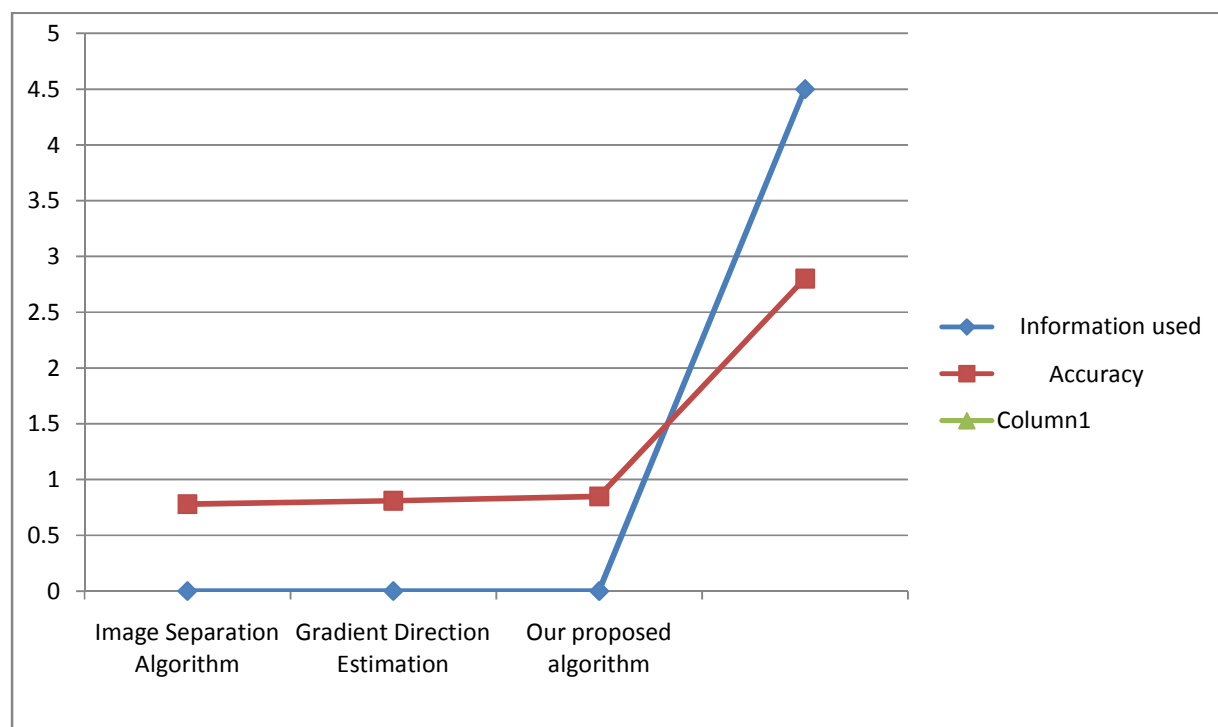


Fig. 1 Algorithms Vs Accuracy

Algorithm	Information used	Accuracy
Image Separation Algorithm	Single Image	0.78
Gradient Direction Estimation	Multiple Image	0.81
Our proposed algorithm	Single Image	0.85

Table 1. Proposed scheme Vs Existing schemes

6.1 Comparison With Existing System

Images	Variational Approach	Layer-Based Approach for Image Pair Fusion	Fusion Based on Gradient Exposure
Home	0.8551	0.8466	0.9905
Land	0.9692	0.9200	0.9998
Hall	0.9655	0.8633	0.9932
Nature	0.9509	0.9064	0.9866
Window	0.9799	0.9651	0.9922

Table 2. Calculation of Peak Signal Noise Ratio for Different Methods

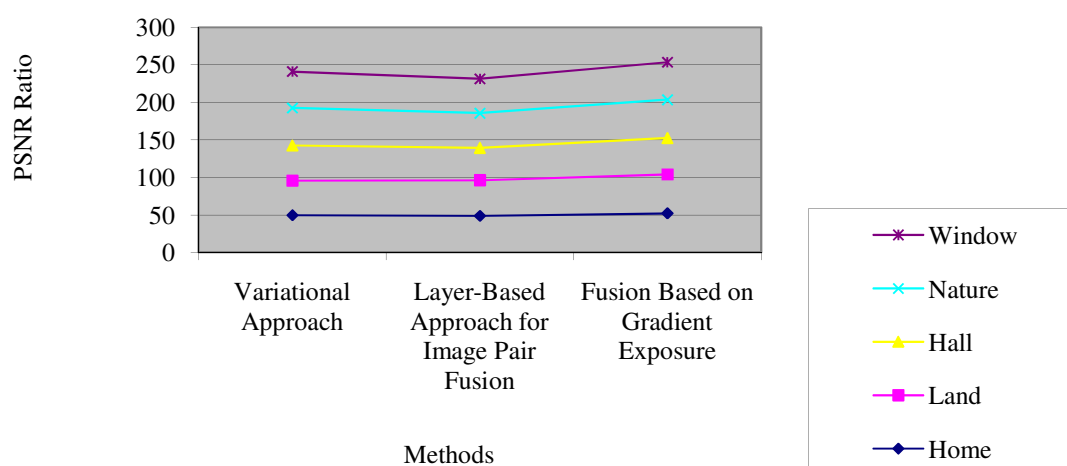


Fig 2. Comparison of Peak Signal Noise Ratio for Different Methods

The structural fidelity measure is a full-reference assessment based on the Structural Similarity (SSIM) Index, and the naturalness measure is a non-reference assessment based on statistics of good-quality natural images. SSIM is calculated for five images in this research work and the SSIM values are tabulated.

Images	Variational Approach	Layer-Based Approach for Image Pair Fusion	Fusion Based on Gradient Exposure
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Table 3. Structural Similarity Ratio Comparison for Different Methods

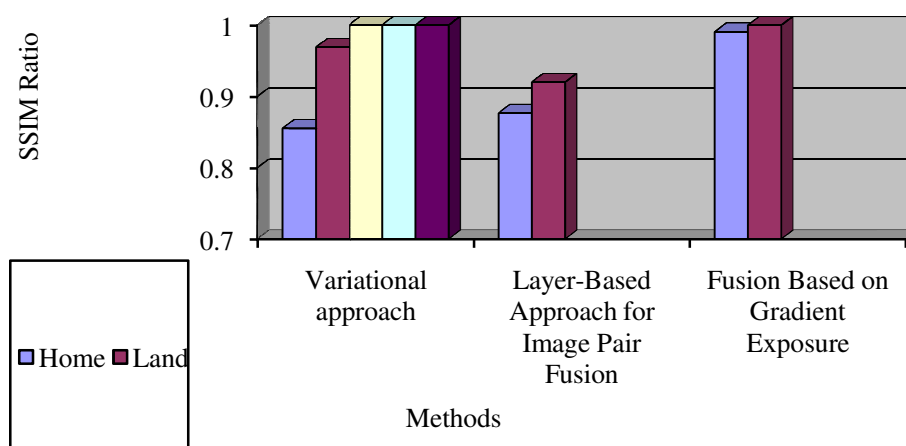


Fig 3. Comparison of Structural Similarity for Different Methods

Demonstrate the effectiveness of the scheme with a number of experiments. Experimental results

showed the image fusion results are experimented with the existing performance values. Some of the

existing systems are Navie Fusion, Denoising, BM3D, WLS, GDC and GIF, The table 8.1 and figure 8.1 shows the comparative study of the proposed scheme with existing schemes.

7 Conclusion

A new fusion scheme is achieved in the proposed system by considering local variation and gradient reversal suppression. The visible scene contrasts and the scene gradient can be captured adaptively by utilizing the different exposures. A gradient model is proposed to carry out the scene reproduction by preserving both the visible contrasts and the gradient consistency. The proposed system maintains visible contrasts and the gradient consistency effectively. MRI Fusion based on Gradient Exposure technique blends images in a multi-exposure sequence, showed by simple quality measures like saturation and contrast. In order to preserve the brightness variation in sequence the multi resolution fashion can be accepted. The proposed system uses JPEG images and it supports well for two-dimensional (2-D) images. A special concentration will be carried out in future for three-Dimensional (3-D) images which will be widely useful for medical field for controlling plasma and monitoring plasma issues.

8 References

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