Image Enhancement Using Histogram Filling with Pattern Selective Image Fusion for Multi Focus Image Reconstruction

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***Abstract*—This paper presents a method for removing focal blur in images using fusion algorithm. Different focal images can be combined to give a single fused image with all focused information. Pattern selective image fusion provides a mechanism for combining multiple images through identifying salient features in the source images and combining those features in to a single fused image. However one of the typical drawbacks of the image fusion algorithm is the reduction in contrast which is undesirable. Loss of contrast in images can be typically attributed to loss of pixel information. The post processed image from fusion algorithm can be further processed using histogram filling algorithm which will lead to better sharper images. Therefore the contribution of this paper is twofold (a) removal of focal blur with the help of effective fusion algorithm, (b) recycling of pixel information to improve contrast and produce better results. Experimental results show the performance of the depth of focus extension using consumer video camera outputs.**

***Keywords*—auto focusing, contrast enhancement, histogram filling, focal blur, image fusion.**

I. Introduction

Recently, image fusion has become an important research topic in image analysis and computer vision [1, 2, and 3]. Image fusion refers to the image processing techniques that produce a new, enhanced image by combining images from one or more sensors. The fused image is then made more suitable for human/machine perception, and for further image processing tasks such as segmentation, feature extraction and object recognition. In this paper we propose a new pattern selective image fusion method that extends the depth of field of the sensor through the manipulation of multiple images at the same scene. An interesting observation motivating this approach is that, even though any single image may not have the entire scene in focus, the settings of the sensor and sensor optics can usually be adjusted so that at least some portion of the scene has the desired visual quality. The challenge, therefore, is to generate a set of images with varying apertures and focus settings, then to combine these images in to a single result where each scene feature has maximal focus.

Prior work on the image fusion process has focused on operating on multiple intensity images based on wavelet and discrete cosine transformations [4, 5, 6] or use of a known camera point spread function (PSF) [5]. Other methods use pyramid based representation to decompose the source image in to different spatial scales and orientations [7]. Similar results, although with more artifacts and less visual stability can be achieved with the use of other basis functions [8]. Another technique similar to pyramid representation, have been based on wavelet transform as a means to decompose the image in to various sub bands [5, 6]. From the decomposed sub- bands the output is generated through selecting the sub bands that have maximum energy and reconstructing the fused sub-band. This representation, however, has an inherent limitation due to the sensitivity of the wavelet transform to translation and rotation and therefore is not particularly suitable for the fusion of images where, even after registration, residual motion is present. Pattern selective image fusion method proposed in this paper is mainly composed of four step process: *pyramid construction, feature saliency computation,* *blending function, and reconstruction of the fused images*. The basic crux of the problem is deciding which portions of each image are in better focus than their respective counterparts in the associated frames and combining these regions to form the synthesized extended depth of focus image. In short, due to low pass filtering nature of the modified Bessel function present in the defocused images, the discrimination method of choice invariably involves quantification of high frequency content [1, 3]. Scenes containing large local changes in illumination and objects at greatly varying distances are impossible to image with high image quality throughout the scene [2, 4]. Known methods for adjusting a sensors integration time and aperture, including methods such as automatic gain control and automatic iris selection, are commonly used to adjust for overall illumination in a scene, but cannot compensate for large local variations in the scene brightness. Likewise, physical limitation in standard sensor optics result in finite depth of field, which enables features within the depth of field to be in focus while scene contents outside the depth of field suffer from progressively increased blurring as the features are further and further from the depth of focus [9]. Thus it can be affirmed that the output fused image suffers from the following drawbacks: illumination variation, increased blurring, reduction in contrast. To overcome these drawbacks the second part of algorithm uses a histogram based approach which is a novel method that has not been worked upon till now. In this method the empty histogram bins that occur during contrast enhancement procedure are procured using a new histogram filling algorithm. Therefore the novelty of the proposed paper is twofold: (i) removal of focal blur in images using pattern selective color fusion, (ii) contrast enhancement of fused images using histogram filling algorithm. The rest of the paper is organized as follows: In Section II we will propose the image fusion algorithm followed by histogram filling algorithm in Section III. Experimental results are given in Section IV and Section V concludes the paper.

II. Pattern Selective Image Fusion

The fusion problem is solved as follows: Given N images of a static scene obtained at different depth of focus using a stationary camera, it is required to combine the images in to a single image that has the maximum information content without producing details that are non-existent in the given images. The proposed approach here selects the most informative image for each local area and blends the selected images to create a new image. The foundation for combining multiple images into a single, enhanced result is the pattern selective fusion process itself. To simplify this discussion, we assume the fusion process is to generate a composite image C from a pair of source images denoted with A and B.

A. Pyramid Construction for Image Fusion

The pyramid representation can be used both for assessing the salience of the source image features, and for the reconstruction of the final image result. The following definitions for the pyramid are used. The fusion method described within this paper use a Laplacian pyramid representation. Laplacian pyramids are constructed for each image using the *filter subtract decimate (FSD)* method [8]. Thus the k^{th} level of the FSD Laplacian pyramid, L_k, is constructed from the corresponding Gaussian pyramid level k based on the relationship.

$$L_k = G_k - wG_k = G_k(1-w), \qquad (1)$$

where w represents a standard binomial Gaussian filter, usually of 5×5 spatial pixels extent. When constructing the FSD Laplacian, due to the decimation process and the fact that w is not an ideal filter, a reconstruction of the original image based on the FSD Laplacian pyramid incurs some loss of information. To partially correct for this effect, an additional correction term is added to the Laplacian. This term is obtained by subtracting the filtered Laplacian from the original Laplacian, and results in the corrected FSD Laplacian given by,

$$\tilde{L}_k = L_k + (1-w)L_K = (2-w)(1-w)G_k. \qquad (2)$$

The addition of this term allows the reconstruction to restore some of the frequency information that would be otherwise lost. Throughout this paper, while referring to Laplacian representation of the image, the corrected FSD Laplacian defined above should be assumed.

B. Feature Saliency Computation

The feature saliency computation process, expresses a family of functions that operate on the pyramids of both images yielding saliency pyramids. In practice, these functions can operate on the individual pixels or on a local region of pixels within the given pyramid level. The saliency function captures the importance of what is to be fused. When combining images having different focus, for instance, a desirable saliency measure would provide a quantitative measure that increases when features are in better focus. Various such measures, including image variance, image gradients, have been employed and validated for related applications such as auto focusing [3, 4, 5]. The saliency function only selects the frequencies in the focused image that will be attenuated due to defocusing. Since defocusing is a low pass filtering process, its effects on the image are more pronounced and detectable if the image has strong high frequency content. One way to high pass filter an image is to determine its Laplacian or second derivative in our case.

$$\nabla^2 L_K = \frac{\partial^2 L_k}{\partial x^2} + \frac{\partial^2 L_k}{\partial y^2}, \qquad (3)$$

Also we know that in the case of Laplacian the second derivatives in the x and y directions can have opposite signs and tend to cancel each other. In the case of textured images, this phenomenon may occur frequently and the Laplacian at times may behave in an unstable manner. We overcome this problem by defining absolute Laplacian as

$$\nabla^2 L_K = \left|\frac{\partial^2 L_k}{\partial x^2}\right| + \left|\frac{\partial^2 L_k}{\partial y^2}\right|, \tag{4}$$

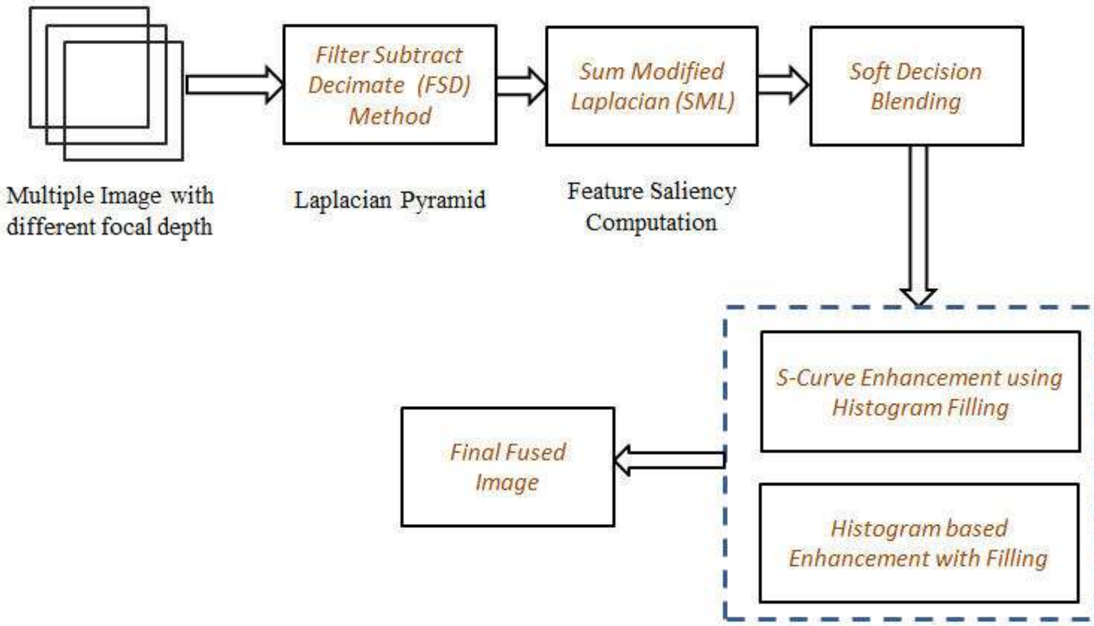


Fig 1. Block diagram of the proposed pattern selective image fusion along with histogram filling for removal of focal blur.

Note that the modified Laplacian is always greater or equal in magnitude to the Laplacian. In order to accommodate for possible variations in the size of texture elements, we computer the partial derivative by using a variable spacing between the pixels used to compute the derivatives. Hence a discrete approximation to the modified Laplacian is given by,

$$ML(i,j) = \left|2I(i,j) - I(i-1,j) - I(i+1,j)\right| + \left|2I(i,j) - I(i,j-1) - I(i,j+1)\right|, \tag{5}$$

Finally, the focus measure at a point (i, j) is computed as the sum of modified Laplacian values, in a small window around (i, j), that are greater than a threshold value.

$$F(i,j) = \sum_{x=i-N}^{i+N} \sum_{y=j-N}^{j+N} M_k(x,y) \, for M_k(x,y) \geq T_1. \tag{6}$$

The parameter determines the window size used to compute the focus measure. In contrast to auto focusing methods, we typically use a small window of size, i.e. $N = 1$. The above equation can be referred to as *sum modified Laplacian (SML)*.

C. *Soft Decision Blending and Reconstruction*

The reconstruction process, operates on each level of the pyramid of the original images in conjunction with sum modified Laplacian to generate the composite image C. The reconstruction process iteratively integrates information from the lowest to the highest level of the pyramid as follows:

$$L_{ck} = F_k . L_{Ak} + (1 - F_K) L_{Bk}, \tag{7}$$

$$C_k = L_{ck} + w[C_k + 1] \uparrow 2. \tag{8}$$

where C_k represents the reconstructed image from level N, the lowest level, to level k and $\uparrow 2$ refers to the expand process. The expansion process consists of doubling the width and height of the image by introducing columns and row in the original and then convolving the resulting image by the w filter. A typical problem that can occur with any type of image fusion is the appearance of unnatural borders between the decisions regions due to overlapping blur at focus boundaries. To combat this, *soft decision blending (SDF)* can be employed using smoothing or low pass filtering of the saliency parameter F_k. In this paper Gaussian smoothing has been used for obtaining the desired effect of blending. This creates weighted decision regions where a linear combination of pixels in the two images A and B are used to generate corresponding pixels in the fused image C. Then we have,

$$L_{ck} = \begin{cases} L_{Ak}, \tilde{F}_k < l, \\ L_{Bk}, \tilde{F}_k > h, \\ \tilde{F}_k . L_{Ak} + (1 - \tilde{F}_K) L_{Bk}, \text{otherwise}. \end{cases} \tag{9}$$

where $\tilde{F}_k$ is now a smoothed version of its former self.

III. Histogram Filling based Image Enhancement

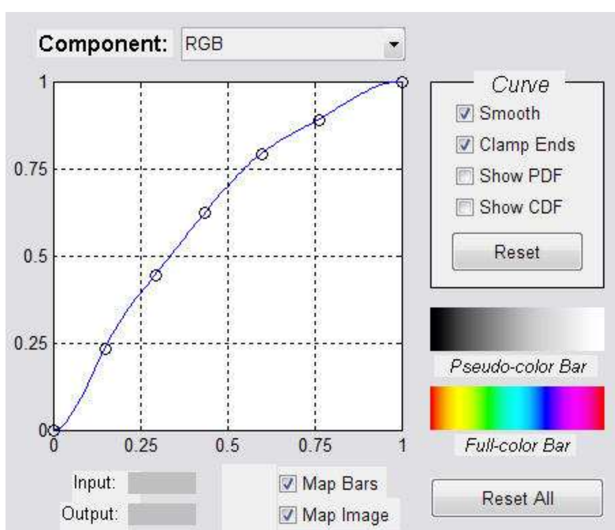
In this section we will elaborate on the second part of our algorithm. One of the main drawbacks of multi focal fusion is that the contrast of the final fused image is reduced. This can lead to poor visual quality. To improve the contrast details of the fused image we will be using a histogram filling based approach. Fig 2 (a) represents s-curve based image enhancement which is very common procedure and found in any common imaging software such as Photoshop, image viewer etc. The image after s-curve adjustment has lot of empty bins in its histogram as shown in Fig 2 (b). These bins if can be filled will further improve the visual quality of the image and thereby we have our new algorithm histogram filling method as shown in Fig 2(c). The illustrative flow chart given in Fig. 3 clearly indicates how the proposed algorithm makes use of the decimal values which would otherwise be truncated. First the decimal fraction is divided in to one of the four groups: 0-0.25, 0.25-0.5, 0.5-0.75, and 0.75-1.0. After which we should decide to which bin this fraction will be allotted to in the histogram. This depends on the number of empty bins in the histogram that follow contrast stretching example. Suppose after contrast stretching example we have 10 empty bins after pixel intensities 100. Now for all the pixels in image which have 100 as there integer part so for ex: 100.1, 100.2, 100.3, 100.4, 100.5, 100.6, 100.7, 100.8, 100.9, and 101. Now as per the existing method all the above pixel intensities will come under bin number 100 on the histogram. But with the proposed method instead of allotting all the pixels to bin number 100, we will allot them to bins 100-109 since we know that after bin number 100 there are 10 empty bins available for pixels to occupy. This procedure is applied to all the pixels which will eventually lead to well spread histogram with no empty bins and better quality.

In the flow chart the P(x, y) represent the pixel intensities, Dmin represent the contrast scaling average which used to estimate the contrast range and J will decide which group the fraction belongs to for histogram filling.

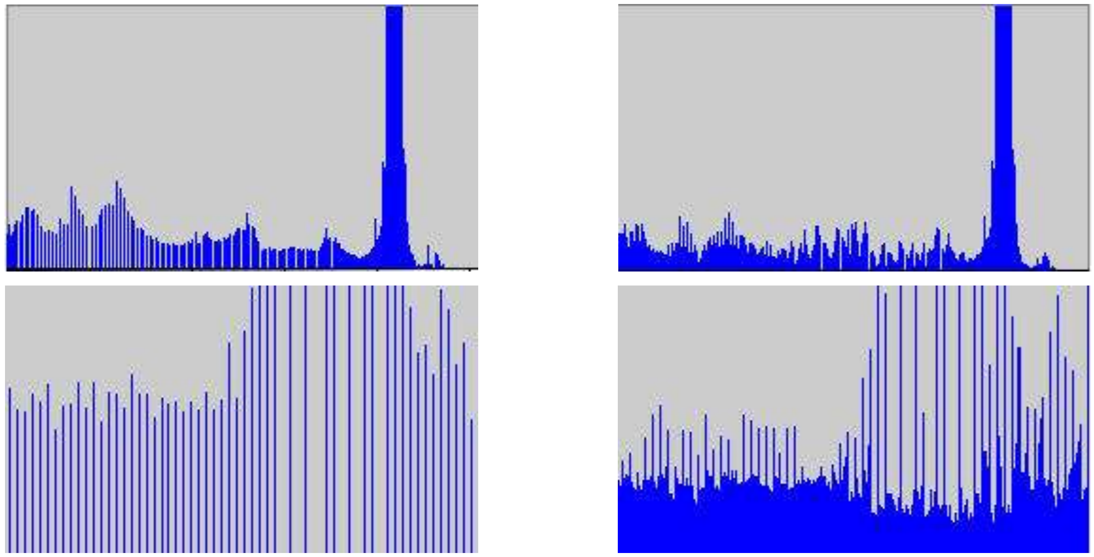
IV. Experimental Results

In this section we experimentally demonstrate the effectiveness of the pattern selective fusion algorithm along with histogram filling algorithm. Experiments were performed on a 24-bit RGB color image of size 256 x 256. Here, each image contains multiple objects at different distances from the camera. Thus one or more objects naturally become out of focus when the image is taken. For example, the focus is on the one object in Fig 4(a), while that in Fig 4(b) is on another object.

Fig 4(c) and (d) show the output of proposed fusion and enhancement method. The SML salient operator enhances the sharp edges and textures and makes them predominant for further selection and reconstruction. It can be seen the all objects are in focus in the final fused image and any undesired discontinuities at the region boundaries are prevented by soft decision blending function.



(a)



(b) (c)

Fig 2. Histogram filling method: (a) Typical s-curve based image stretching, (b) histograms with empty bins as a result of stretching operation, (c) the histograms that are filled with appropriate values to improve the quality of image.

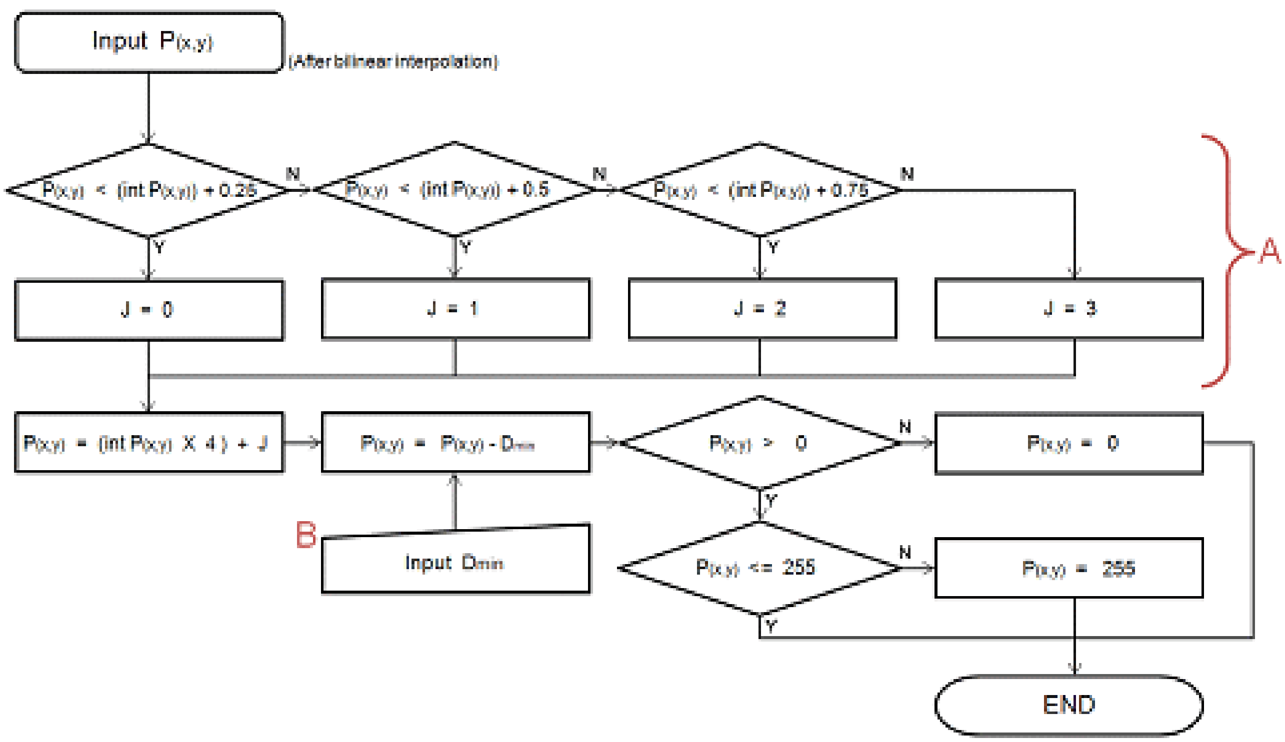
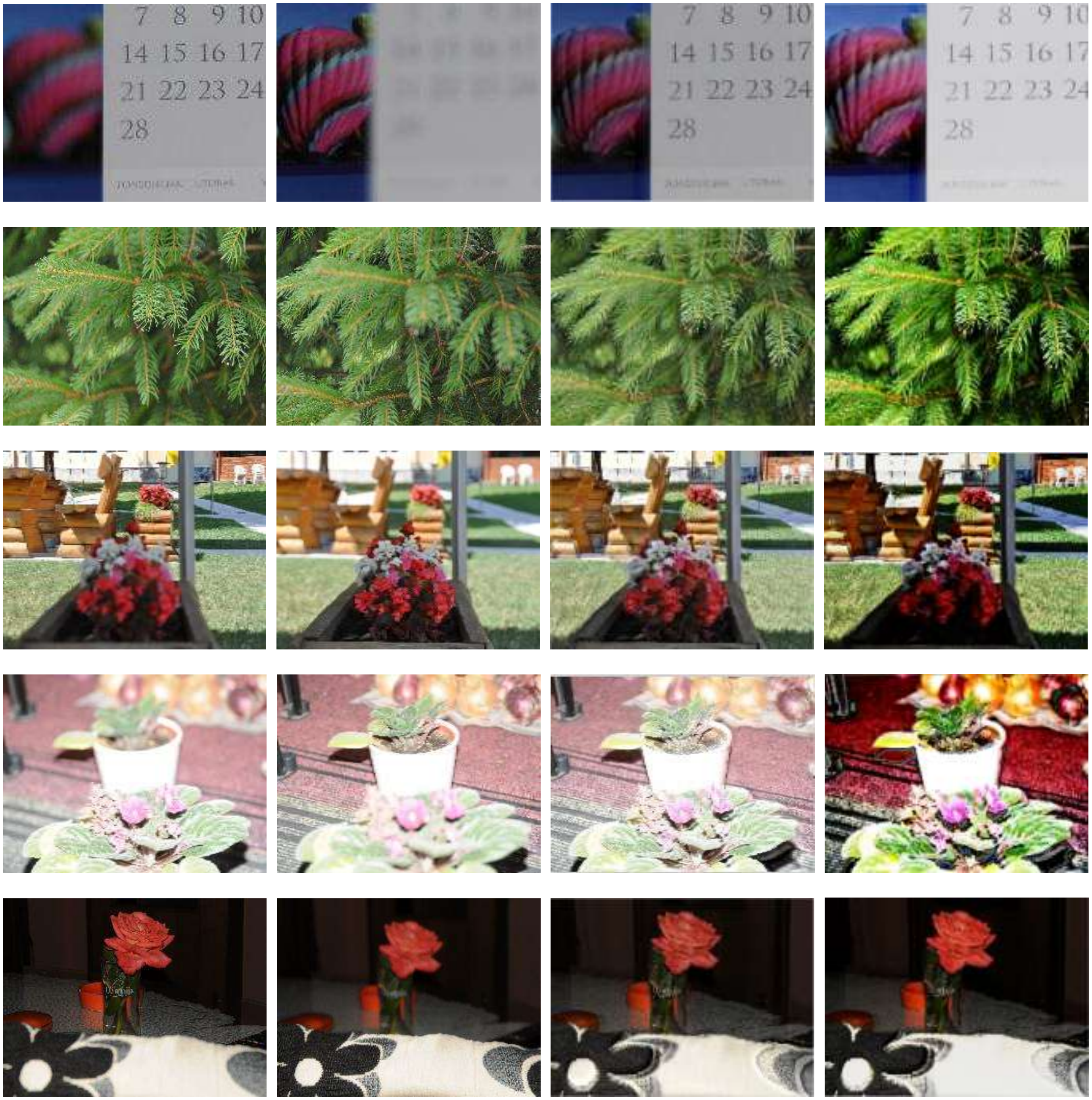


Fig 3. Illustrates the flow chart of the proposed algorithm. It represents how the empty bins in the enhanced histograms are calculated and histogram filling takes place.



(a) (b) (c) (d)

Fig 4. The experimental results are given above. The out of focus images are given in (a) and (b). The proposed pattern selective fusion algorithm is given in (c) and the results of contrast based histogram filling method are given in (d). It can be seen from (d) that the focal blur is completely eliminated from the output image and contrast has been remarkably improved using histogram filling method.

V. Conclusion

In this paper we proposed a pattern selective fusion algorithm for the synthesis of extended depth of focus imagery. The pyramid structure followed by sum-modified-Laplacian and soft decision blending make the algorithm effective and easy to implement. Also, no particular characteristics of the imaging is need to be known a priori; the main requirements are that underlying assumptions governing the fusion process.

A natural extension to the work presented here will include the application of pattern selective fusion to image sequences and also for dynamic range enhancement. The second fold of the paper dealt with loss of large amounts of data during fusion process. Also the proposed histogram filling algorithm can extended to any method that involve truncation of decimal integers followed by creation of empty bins in their histogram. The experimental results have been carried out for commercial photography purpose but the same can be extended to areas of medical imaging. Future works in this topic include coming up with a mathematical model that could be proposed as an entirely new algorithm. Also we need to extend this method to other image adjustment procedure and see the effectiveness. More number of test images need to be captured and tested. Peak signal to noise ratio (PSNR) and Root mean square (RMS) values need to be plotted for analysis of the proposed. The MATLAB toolkit shown in Fig. 5 for image fusion and histogram filling also need to completed and released as public license.

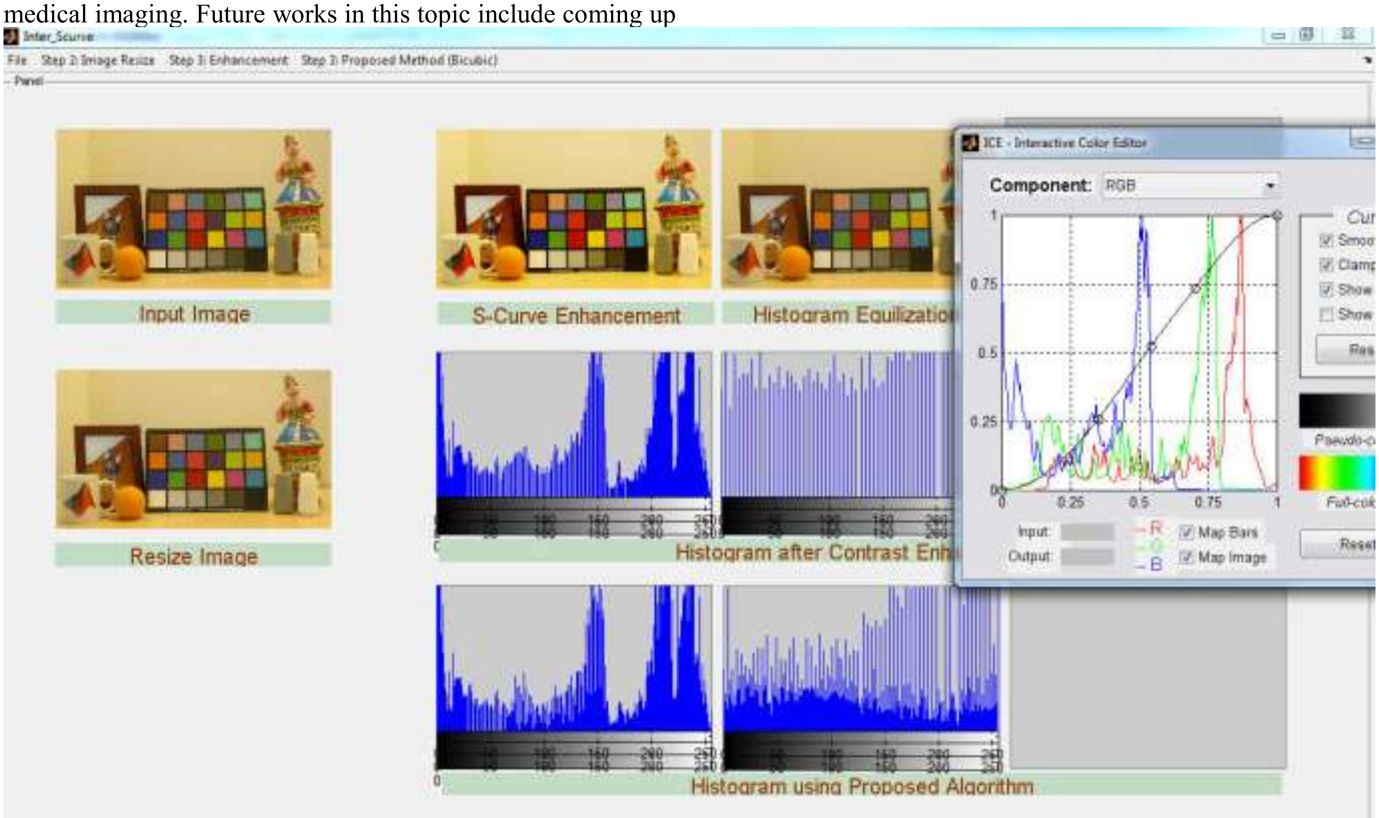


Fig 5. Matlab toolkit which is under development.

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