A Novel Image Fusion Algorithm Based on Complexity Measurements for Multi-Focus Images

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Abstract

Image fusion extracts perceptibly clearer images from a set of distorted images of the same scene. Image fusion algorithms preserve complementary data and minimize noise. This paper presents a novel algorithm for image fusion that utilizes complexity measurements to form the new image. Original images are converted to binary images, divided into blocks, and then a fused image is acquired using one of five complexity measurements. The paper utilizes two quality measurements to evaluate the performance of the algorithms. The experiments were performed on one set of reference input images and four sets of non-reference input images. Experimental results show that the Length of Black and White Border outperformed all other complexity measurements. The proposed algorithm was compared against spatial frequency algorithm.

Keywords

Image Fusion, Multi-Focus images, Spatial Frequency, Complexity Measurement

1. Introduction

Due to limited lens capabilities, multi-focus images, containing objects lie in different depths, contain some objects focused on while the others are blurred. Therefore, many images for the same scene are taken in different depths and then fused to acquire an image contain all objects in focus [1]. The fused image has three main characteristics. First, it contains common features in all input images without redundancy. Second, it also keeps important information from input images, which is called pattern conservation. Third, it removes noise [2, 3].

Image registration is the process of applying geometrical transformations, such as translation, rotation or scaling, on input images for the same scene. Input images may be taken in different times, lighting conditions or by different sensors. Image registration is used to align one input image with another. Input images to fusion algorithms must be first aligned by image registration [4].

According to input images acquisition method, image fusion algorithms are divided into three classes [5]:

1. Pixel-based algorithms process input images pixel by pixel. This means that the pixels with the same coordinates from different input images are processed together. Although these algorithms enhance image contrast, they are time consuming and sensitive to the amount of noise in input images.
2. Region-based or object-based algorithms divide input images into blocks rather than pixels. Blocks with the same index from input images are processed together. Algorithms in this class overcome the problems of input images noise and defects of image registration process.
3. Hybrid algorithms combine the benefits of both Pixel-based algorithms and Region-based algorithms.

This paper presents a novel region-based image fusion algorithm based on complexity measurements. The main idea is to convert each n-bit input image to n binary images and then divide these binary images into a set of blocks. Then, using one complexity measurement, weights are given for each block in each binary image of each input image. Finally, the final fused image is acquired according to these weights. The proposed algorithm utilizes one of the following complexity measurements: Length of Black and White Border, Run-Length Irregularity, Border Noisiness, Transition Density and 4-Connectivity. The proposed algorithm is compared against the spatial frequency algorithm illustrated in reference [4].

The rest of this paper is organized as follows: Section II introduces the used complexity measurements and the proposed algorithm. Quality measurements and evaluation algorithms are presented in Section III. Finally, results, a conclusion and recommended future work are presented in sections IV, V and VI respectively.

2. Image Fusion Based On Complexity Measurements

Kawaguchi [6] viewed image complexity as an image threshold problem. According to that, binary images can be categorized as “informative” regions (simple patterns), less than threshold, and “noise-like” regions (complex patterns), greater than threshold. This categorization is done via segmentation based on a complexity measurement. The Human Visual System (HVS) is not affected by the replacement of noise-like regions with other noise-like regions [6, 7, 8]. There are several metrics to measure the image complexity, such as: the length of the Black and White border [7], run length irregularity [7], the border noisiness [7, 8], Transition Density [9] and 4-Connectivety [7].

A) Complexity Measurements

This section presents five complexity measurements used in the proposed algorithm:

1) <u>Length of Black and White Border:</u> It computes the complexity of a block through dividing the summation of color changes along rows and columns by the maximum number of color changes [8, 9]. This computation is done using the following equation [6]:

$$\alpha = \frac{Summation\ \ of\ color\ \ changes\ \ along\ \ rows\ \ and\ \ columns}{2\ x\ N\ x\ (N-1)} \tag{1}$$

Where α is the Length of Black and White Border, N is the block size. α values fall in [0, 1], with typical threshold of 0.3 [9].

2) <u>Run-Length Irregularity:</u> The complexity of a block is computed through the distribution of its black and white pixels. If the black and white pixels have uniform distribution, it is a simple block. Otherwise, it is a complex one [8].

Run-Length Irregularity values fall in [0, 1], with typical threshold of 0.2. Run-Length Irregularity can be computed through the following equations [8, 9]:

$$\beta = \mathrm{MIN}\ \{\overline{\widehat{H}_s\ (r)}, \overline{\widehat{H}_s\ (c)}\} \tag{2}$$

$$\overline{\widehat{H}_s\ (r)} = \mathrm{Average}\ \{\hat{h}_s(r_0), \hat{h}_s(r_1), \ldots, \hat{h}_s(r_{n-1})\} \tag{3}$$

$$\overline{\widehat{H}_s\ (c)} = \mathrm{Average}\ \{\hat{h}_s(c_0), \hat{h}_s(c_1), \ldots, \hat{h}_s(c_{n-1})\} \tag{4}$$

$$h_s\ =\ -\sum_{i=1}^{n} h[i]\ log_2\, p_i \tag{5}$$

$$p_i\ =\ \frac{h[i]}{\sum_{j=1}^{n} h[j]} \tag{6}$$

Where h_s is the histogram of the run-lengths along a row or a column, $\overline{\widehat{H}_s\ (r)}$ and $\overline{\widehat{H}_s\ (c)}$ are the average of the histograms of the run-lengths for rows and columns respectively, h[i] is the number of run-lengths of long equal to i, n is the block size and $\hat{h}_s$ is the normalized value of hs, as hs values are normalized to be in the range [0, 1]. The normalization factor is 6.8548 as it is the highest value that can be obtained [6].

3) <u>Border Noisiness:</u> This complexity measurement considers the blocks that lie on the boundary between informative blocks and noisy blocks. Any changes to these blocks will be noticed on the noisy blocks [7].

Border Noisiness takes values in the range [0, 1], with best threshold of 0.1 [9]. Border Noisiness, γ, can be computed through the following equations [8]:

$$\gamma\ =\ \frac{1}{n}\ MIN\ \{E_f\big(P_x(r)\big), E_f\big(P_x(c)\big)\} \tag{7}$$

$$E_f(X)\ =\ (1.0 - V(X)\ /\ MAXx\{V(X)\})\ \bar{X}. \tag{8}$$

$$X = \{x0, x1, \ldots, xm\text{-}1\} \tag{9}$$

$$P_x(r) = \{p(r_0 \oplus r_1), \dots, p(r_{n-2} \oplus r_{n-1})\} \quad (10)$$

$$P_x(c) = \{p(c_0 \oplus c_1), \dots, p(c_{n-2} \oplus c_{n-1})\} \quad (11)$$

Where V(x) is the variance of X, $\bar{X}$ is the average of X, $\oplus$ is the bitwise exclusive-or, p(x) is the number of ones in x, n is the block size and $MAX_x\{V(X)\}$ is equal to 15.6735, which is the maximum variance can be obtained [7].

4) Transition Density: The number of horizontal and vertical color changes in the block is used as a complexity measurement. It can be computed through the following equation [9]:

$$\eta = \sum_{i=1}^{n}\sum_{j=1}^{n-1}|x(i,j) - x(i,j+1)| + \sum_{i=1}^{n-1}\sum_{j=1}^{n}|x(i,j) - x(i+1,j)| \quad (12)$$

Where η is the Transition Density and n is the block size. A typical threshold will be 22 [9].

5) 4-Connectivity: This complexity measurement uses the number of connected areas. This is done using the following equation:

$$\omega = \frac{k}{N \ x \ N} \quad (13)$$

Where k is the number of 4-connected areas and N is the size of the block. ω falls in the range $[1/(2^N \ x \ 2^N), 1]$, with best threshold of 0.3 [7,9]. The number of connected areas is computed using the algorithm in List 1 [10].

B) The New Proposed Algorithm

This section presents the proposed algorithm, which is shown in List 2. The main idea is to convert each n-bit input image to n binary images and then divide these binary images into a set of blocks. Then, using one of the discussed complexity measurement, weights are given for blocks in binary images of each input image. Finally, the final fused image is acquired according to these weights.

3. Evaluation and Quality Measurements

The quality measurements used for evaluation will be different from one application to another. For fusion algorithms on multi-focus single sensor images, the quality measurements or criterion may be the blurriness, noise, contrast and the amount of information in the fused image.

Input images can be either reference or non-reference. Reference input images has an ideal image, which contains all objects focused on. This ideal image is used for evaluating the fused image. The non-reference input images have no ideal for evaluation. Therefore, evaluation of such images is performed by measuring the information or some criteria of the fused image or by comparing the fused image with the input images.

List 1: Binary Block Labelling.

Step 1: Construct a labelling block of the same size as the input block.
Step 2: Scan the input block from left to right, top to bottom.
Step 3: Set a label to the current pixel as follows:

- If only one of the upper and left neighbours is labelled, assign this label to the current pixel.
- If the upper and left neighbours have the same label, assign the current pixel the same label.
- If the upper and left neighbours have different labels, copy the upper neighbour label into the left neighbour label and assign it to the current pixel.
- If all neighbours are not labelled, assign a new label to the current pixel.

Step 4: Repeat step 3 until the end of blocks.

The quality measurements used for non-reference images in this paper are:

1. Standard Deviation (SD):

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{14}$$

$$\sigma 2 = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \mu)^2 \tag{15}$$

Where μ is the mean, σ is the standard deviation, N is number of pixel and x_i is the value or activity level of the i^{th} pixel. The more standard deviation values, the better image fusion results [11].

2. Mutual Information (MI):

$$MI = MI_{F,A} + MI_{F,B} \tag{16}$$

$$MI_{A,B} = \sum_{x=0}^{l-1}\sum_{y=0}^{l-1} P_{AB}(x,y)\log\frac{P_{AB}(x,y)}{P_A(x,y)P_B(x,y)} \tag{17}$$

Where MI is the mutual information, $MI_{F,A}$ is the mutual information between the fused image and the first input image and $MI_{F,B}$ is the mutual information between the fused image and the second input image. P_{AB} is the joint probability distribution between the two images A and B. $P_A(x, y)$ is the probability distribution for pixel (x, y) in image A and $P_B(x, y)$ is the probability distribution for pixel (x, y) in image B. l is the maximum pixel value (255 in gray scale). F is the fused image. The higher the mutual information value, the better the image fusion results [5].

Two evaluation measurements used for reference images are the Root Mean Square Error (RMSE) and the Peak Signal to Noise Ratio (PSNR), which is computed using the following equations:

$$RMSE = \sqrt{\frac{\sum\sum[R(i,j) - F(i,j)]^2}{MN}} \quad (18)$$

$$PSNR = 10 \log_{10} \frac{255^2}{RMSE^2} \quad (19)$$

Where R is the reference image, F is the fused image and M and N are the dimensions of the image. High PSNR and low RMSE indicate better fusion results [5].

List 2: Pseudo Code for the New Proposed Algorithm

Step 1: Convert each n-bit input image into n binary images (black and white) by bit plane slicing through Pure-Binary Coding system (PBC).
Step 2: Convert all PBC from the previous step to their equivalent Canonical Gray Coding system (CGC).
Step 3: Divide each bit plane in each input image into blocks of the size MxN.
Step 4: Scan the blocks of the input images from left to right, top to bottom.
Step 5: Compute the complexity of the corresponding blocks in the corresponding planes of all input images using one of the complexity measurements.
Step 6: Compute the weight of the corresponding block in the corresponding planes of all input image as follows:

- If it has the minimum complexity and higher than the threshold, its weight is plane number.
- If it has the maximum complexity and less than the threshold, its weight is the plane number.
- Otherwise, its weight is zero.

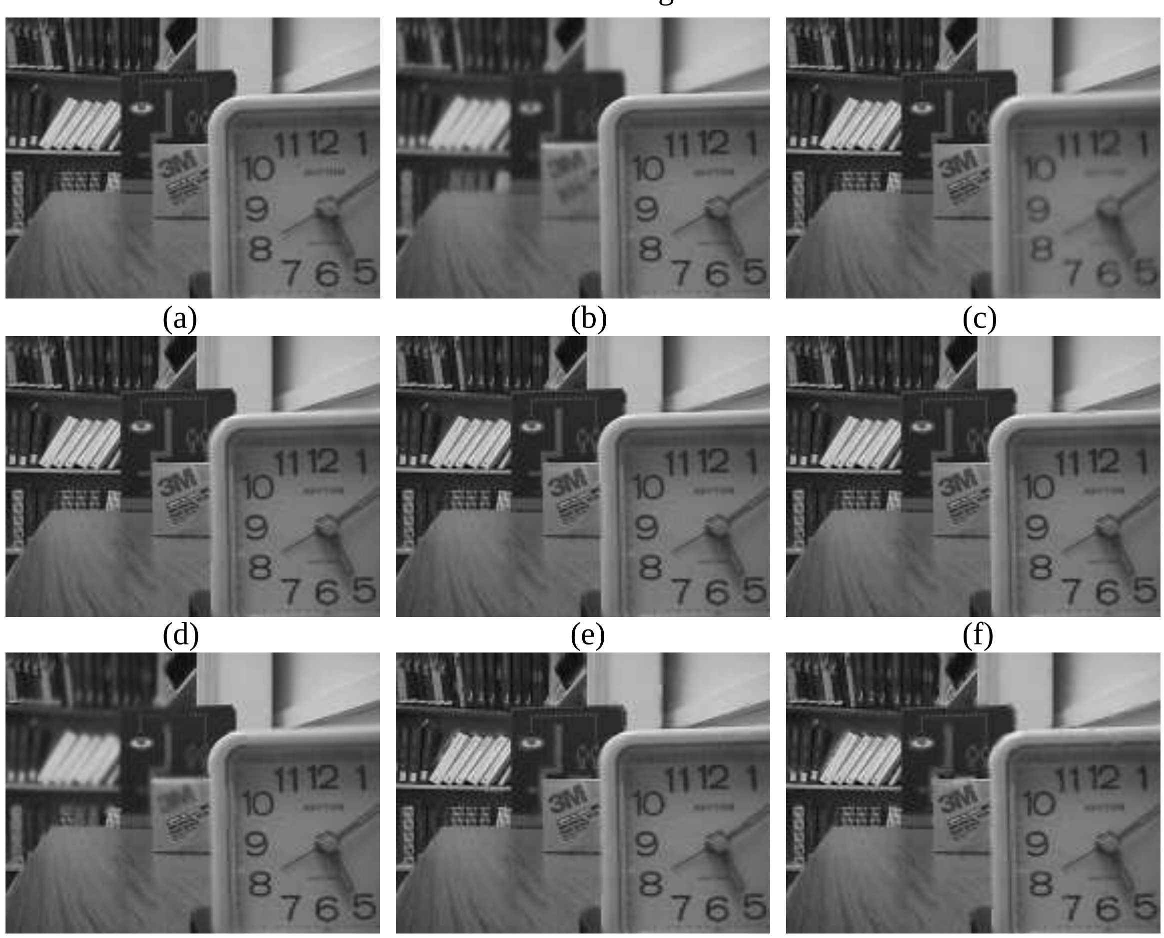
Step 7: Compute the weight of the corresponding blocks in each input image as the sum of all weights of the corresponding blocks in the bit planes of this input image.
Step 8: Select the block with maximum weight to be the fused block. If the blocks have equal weights, use the spatial frequency algorithm to select the fused block.
Step 9: Repeat Steps 5 through 8 until the end of blocks.
Step 10: Verify and correct fusion using a 3 x 3 window by computing the majority of the surrounding blocks:

1. If the majority of the surrounding blocks are from the first image, set the block from first image.
2. If the majority of the surrounding blocks are from the second image, set the block from the second image.
3. If the majority of the surrounding blocks are average, set the block as the average of the two input images.

4. Experimentation Results

The proposed algorithm is compared with the Spatial Frequency image fusion algorithm using C#.Net, .Net framework 3.5. The performance is evaluated using two experiments.

The first experiment compares the proposed algorithm using the five discussed complexity measurements against the spatial frequency algorithm using one reference input image, which is the disk image (640 x 480 PX). The results of the spatial frequency algorithms matches the results of reference [12], which uses a generic algorithm for selecting the best block size and then applying the spatial frequency algorithm. Fig. 1 (a) shows the reference image. Fig. 1 (b) shows the first input images with a focus on the clock. The library is focused on in the second input image shown in Fig. 1 (c). The results of applying the proposed algorithm using the five complexity measurement and the spatial frequency algorithm are shown in Fig. 1 (d) through Fig. 1 (i), respectively. Table 1 presents the evaluation of these results using the SD, MI, RMSE and PSNR. Higher SD, MI and PSNR and lower RMSE values indicate a better image fusion.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Fig.1: Disk image results. (a) Reference image. (b) First input image, focus on disk. (c) Second input image, focus on library. (d) Spatial Frequency Image Fusion results. (e) Length of Black and White Border Results. (f) 4-Connectivity Results. (g) Border Noisiness Results. (h) Transition Density Results. (i) Run Length Irregularity Results.

Table 1: Disk Image Fusion Results

Method	MI	SD	RMSE	PSNR
Spatial Frequency (25 x 43) TH = 0.5	6.6655	46.8863	3.8294	36.4681
Length of Black and White Border (23 x 23)	6.9797	46.8813	2.3377	40.7548
4-Connectivity (23 x 23)	6.9569	46.8950	2.6310	39.7283
Transition Density (5 x 5)	6.0458	46.4425	5.6504	33.0891
Run Length Irregularity (3 x 3)	5.4360	46.2623	7.7870	30.3033
Border Noisiness (23 x 23)	4.5579	44.5170	15.0490	24.5806

It could be noticed that the proposed algorithm using the Length of Black and White Border complexity measurement shows significant improvement in the MI, RMSE and PSNR about 0.02%, 0.3% and 1% more over the proposed algorithm using the 4-Connectivity complexity measurement, respectively. Also the proposed algorithm using the Length of Black and White Border complexity measurement shows significant improvement in the MI, RMSE and PSNR about 0.29%, 1.5% and 4.3% more over the Spatial Frequency algorithm, respectively. It also could be noticed that the proposed algorithm using this complexity measurement and the 4-Connectivity complexity measurement and the Spatial Frequency almost have almost the same SD value, which is the highest value. The Spatial Frequency and the proposed algorithm using the five complexity measurement can be ordered from best to worst as follows: Length of Black and White Border, 4-Connectivity, Spatial Frequency, Transition Density, Run Length Irregularity then Border Noisiness.

The second experiment compares the proposed algorithm using the five discussed complexity measurements and the spatial frequency algorithm using four image sets, which were acquired using Nikon D90 Digital SLR Camera with Nikon AF-S DX 18-105mm lens. Presented here two of these image sets.

The first image set is the Mouse image (268 x 178 PX). The first input image focuses on the wire shown in Fig. 2 (a), while the second input image focuses on the mouse shown in Fig. 2 (b). The results of applying the proposed algorithm using the five complexity measurements and the Spatial Frequency algorithm are shown in Fig. 2 (c) through Fig. 2 (h). Table 2 presents the values of the two used evaluation measurements, MI and SD, with higher values indicating better image fusion results.

Table 2: The Mouse Image Results.

Method	MI	SD
Spatial Frequency (6 x 32) TH = 1.0	6.5622	30.9163
Length of Black and White Border (48 x 48) TH = 0.3	6.5957	30.9144
4-Connectivity (48 x 48) TH = 0.3	6.5957	30.9144
Transition Density (6 x 6) TH = 22	6.4962	30.6337
Run Length Irregularity (4 x 4) TH = 0.2	6.4450	30.6163
Border Noisiness (18 x 18) TH = 0.1	6.5170	30.7124

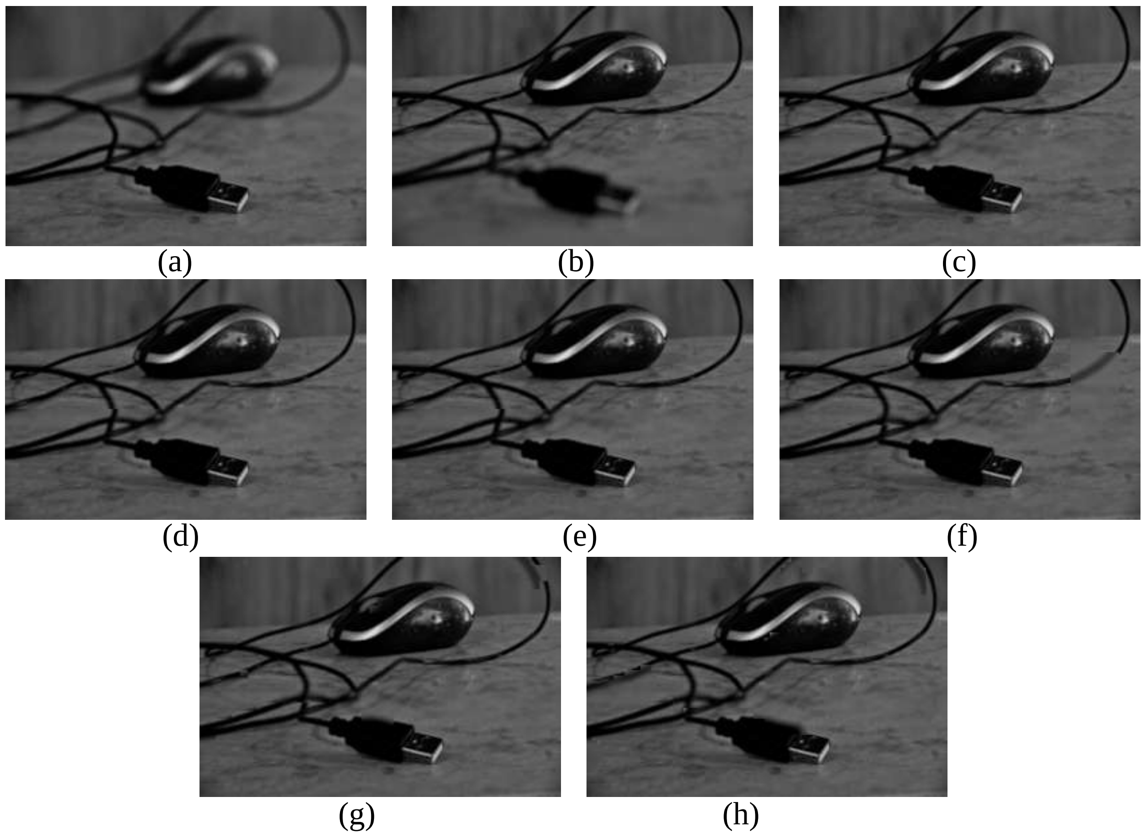


Fig.2: Mouse image results. (a) First input image, focus on wire. (b) Second input image, focus on Mouse. (c) Spatial Frequency Image Fusion results. (d) Length of Black and White Border Results. (e) 4-Connectivity Results. (f) Border Noisiness Results. (g) Transition Density Results. (h) Run Length Irregularity Results.

It could be noticed from the MI and SD values and from the subjective evaluation that the proposed algorithm using the Length of Black and White Border and the 4-connectivity are almost the same as the Spatial Frequency algorithm, which have improvement in the MI and SD about 0.05% and 0.2% more over the Transition Density, respectively. The compared algorithms are ordered from best to worst as follows: Length of Black and White Border, 4-connectivity, Spatial Frequency, Border Noisiness, Transition Density then Run Length Irregularity.

The second image is the Mickey image (268 x 178 PX). The first input image focuses on Mickey, shown in Fig.3 (a). The second input image focuses on the background, shown in Fig. 3 (b). Fig. 3 (c) through Fig. 3 (h) show the results of applying the proposed algorithm using the five complexity measurements and the Spatial Frequency algorithm, respectively. Table 3 presents the MI and SD values of these results.

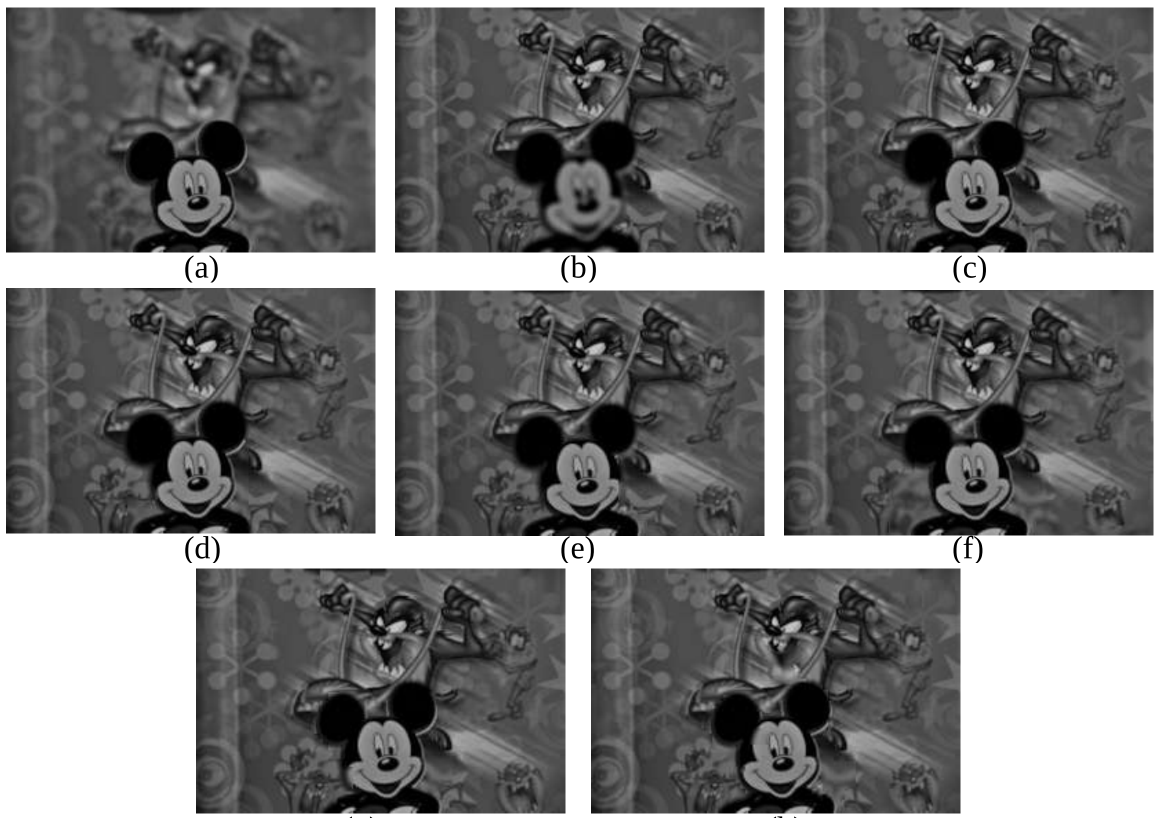


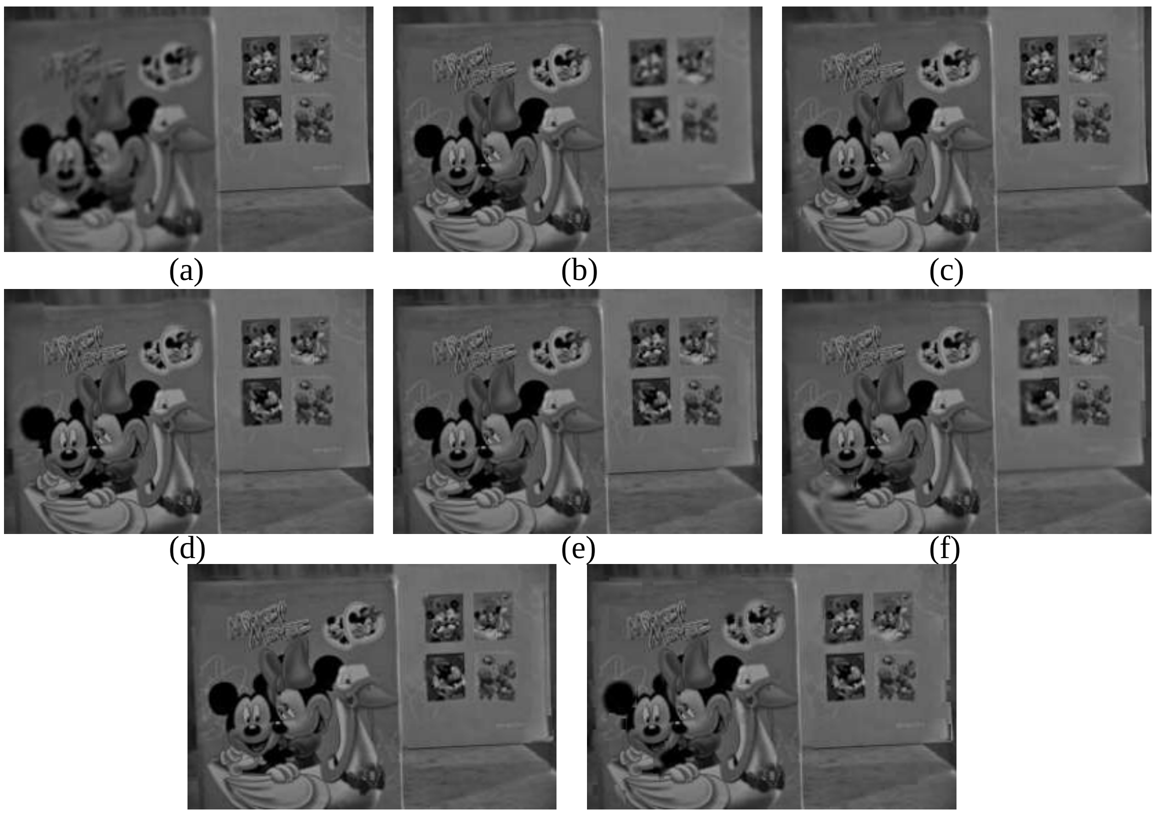
Fig.3: Mickey image results. (a) First input image, focus on Mickey. (b) Second input image, focus on background. (c) Spatial Frequency Image Fusion results. (d) Length of Black and White Border Results. (e) 4-Connectivity Results. (f) Border Noisiness Results. (g) Transition Density Results. (h) Run Length Irregularity Results.

Table 3: The Mickey Image Results.

Method	MI	SD
Spatial Frequency (12 x 20) TH = 0.0	7.6587	33.2493
Length of Black and White Border (22 x 22) TH = 0.3	7.5836	33.1811
4-Connectivity (27 x 27) TH = 0.3	7.6662	33.2054
Transition Density (6 x 6) TH = 22	7.4007	32.9458
Run Length Irregularity (4 x 4) TH = 0.2	7.1656	32.6836
Border Noisiness (19 x 19) TH = 0.1	6.9819	32.9761

It could be noticed that the proposed algorithm using the 4-Connectivity complexity measurements shows significant improvement in the MI about 0.1% more over the Spatial Frequency algorithm and has almost the same SD value. The order of compared algorithms from best to worst is as follows: 4-Connectivity, Spatial Frequency, Length of Black and White Border, Transition Density, Run Length Irregularity then Border Noisiness.

The third testing image is the Walt Disney2 image (268 x 178 PX). The first input image shown in Fig. 4 (a) focuses on left image, while the second input image shown in Fig. 4 (b) focuses on the right image. The results of applying the proposed algorithm using the five complexity measurements and the Spatial Frequency algorithm are shown in Fig. 4 (c) through Fig. 4 (h), respectively. Table 4 compares these algorithms using the MI and SD evaluation methods with higher values indicating better fused image.



(a) (b) (c) (d) (e) (f) (g) (h)

Fig.4: Walt Disney2 image results. (a) First input image, focus on the left image. (b) Second input image, focus on the right image. (c) Spatial Frequency Image Fusion results. (d) Length of Black and White Border Results. (e) 4-Connectivity Results. (f) Border Noisiness Results. (g) Transition Density Results. (h) Run Length Irregularity Results.

Table 4: The Walt Disney2 Image Results.

Method	MI	SD
Spatial Frequency (7 x 9) TH = 2.25	6.1380	28.1717
Length of Black and White Border (29 x 29) TH = 0.3	6.9130	28.1747
4-Connectivity (5 x 5) TH = 0.3	6.9593	28.2265
Transition Density (5 x 5) TH = 22	6.9734	28.2966
Run Length Irregularity (4 x 4) TH = 0.2	6.8224	28.1080
Border Noisiness (27 x 27) TH = 0.1	6.8627	27.8958

It could be noticed that the proposed algorithm using the Transition Density and the 4-Connectivity complexity measurements are very close to each other and they show significant improvement in the MI and SD values about 0.8% and 0.1% more over the Spatial Frequency algorithm, respectively. The compared algorithms are ordered from best to worst as follows: Transition Density, 4-Connectivity, Length of Black and White Border, Run Length Irregularity, Spatial Frequency then Border Noisiness.

The fourth image set is the Mouse-CD-R (268px X 178px). Fig. 5 (a) shows the first input image with focus on the CD-R. The second input image focused on the Mouse is shown in Fig. 5 (b). The results of applying the Spatial Frequency image fusion algorithm and the proposed algorithm are shown in Fig. 5 (c) through Fig.5 (h), respectively. Table 5 presents the evaluation of the results using the MI and SD evaluation methods with higher values indicating better image fusion results.

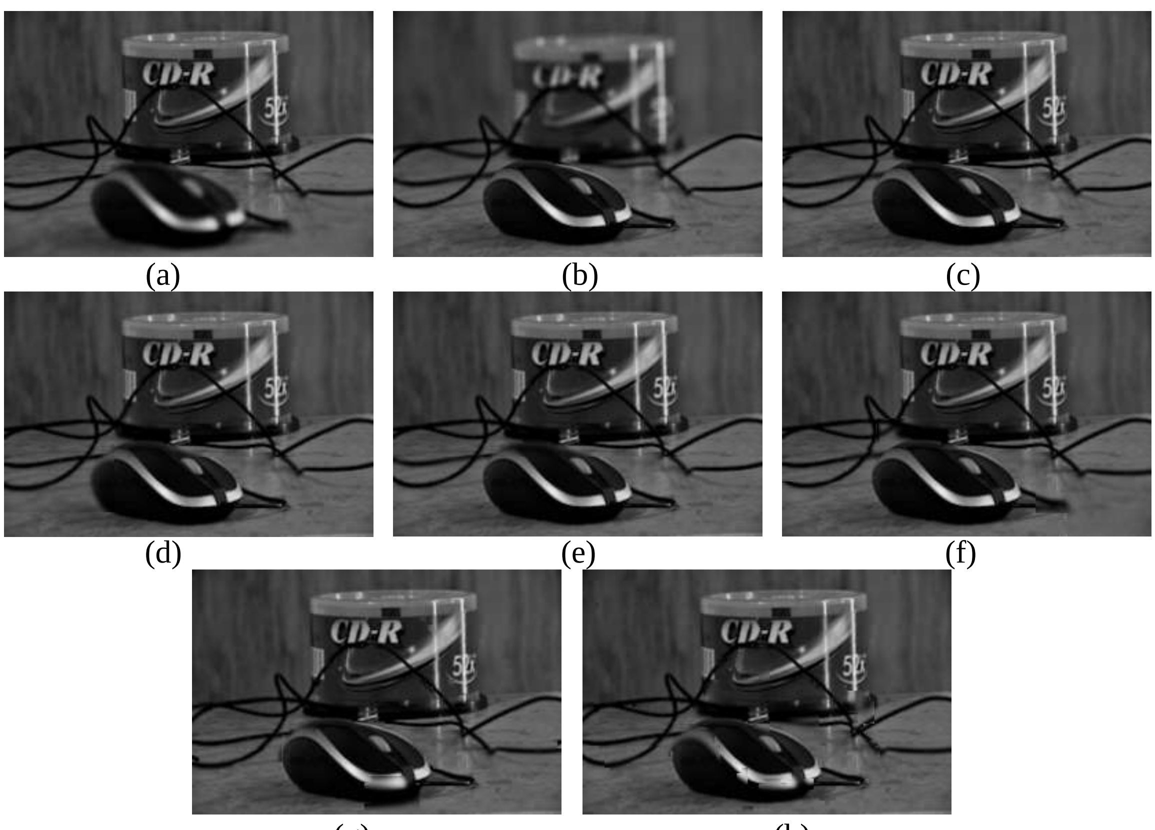


Fig.5: Mouse-CD-R image results. (a) First input image, focus on CD-R. (b) Second input image, focus on Mouse. (c) Spatial Frequency Image Fusion results. (d) Length of Black and White Border Results. (e) 4-Connectivity Results. (f) Border Noisiness Results. (g) Transition Density Results. (h) Run Length Irregularity Results.

Table 5: Mouse CD-R image results.

Method	MI	SD
Spatial Frequency (44 x 3) TH = 0.75	7.6994	36.2726
Length of Black and White Border (40 x 40) TH = 0.3	7.7524	36.1263
4-Connectivity (40 x 40) TH = 0.3	7.8459	36.1561
Transition Density (5 x 5) TH = 22	7.7243	35.9205
Run Length Irregularity (4 x 4) TH = 0.2	7.5969	35.6893
Border Noisiness (23 x 23) TH = 0.1	7.8026	35.7876

It could be noticed that the proposed algorithm using the 4-Connectivity complexity measurement shows significant improvement in the MI value about 0.2% more over the Spatial Frequency, although the Spatial Frequency shows improvement in the SD value about 0.15% more over it. The proposed algorithm using the five complexity Measurements and the Spatial Frequency algorithm can be ordered from best to worst as follows: 4-Connectivity, Spatial Frequency, Border Noisiness, Length of Black and White Border, Transition Density then Run Length Irregularity.

5 . Conclusion

Image fusion algorithms utilize spatial frequencies, transformation, or geometrical functions to extract perceptibly clearer images. A novel approach for image fusion is to utilize complexity measurements. This paper presented a novel Multi-Focus Single-Sensor image fusion algorithm. The algorithm utilizes five complexity measurements: Length of black and white boarder, Transition density, Run length regularity, Boarder noisiness and 4-Connectivity. The experimentation was performed over four distinct dataset. The results show that the five complexity measurements are ordered from best to worst as follows: Length of Black and White Border, 4-Connectivity, Border Noisiness, Transition Density then Run Length Irregularity. The proposed algorithm using the first two complexity measurements has the same or better MI values and produces the same or cleared images as the Spatial Frequency algorithm; although the Spatial Frequency algorithm may has better SD values.

6 . Recommended Future Work

A lot of enhancements are to be made to improve the proposed algorithm. These enhancements contain the replacement of the division to non-overlapping blocks of the same size by the division according to regions and edges. Also it contains improvement to the weights given to these blocks. The improvements applied to the Spatial Frequency, such as the two levels region based multi-focus image fusion method, can be applied to the proposed algorithm.

Future work also includes producing novel evaluation algorithm that uses complexity measurements for the evaluation of the other algorithms. It also includes using the proposed algorithm and the complexity measurements for the other categories of image fusion other than the multi-focus and for the multi-sensor image fusion.

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