Multi-focus Image Fusion using Average Filter-based Relative Focus Measure

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Abstract—In an image taken by typical digital sensors, only those objects within the depth of field are in focus while the others are out of focus. Fusing multi-focused images is particularly useful for resolving this problem. This paper proposes a pixel-based multi-focus image fusion method. While most previous methods use the focus measure calculated independently for each source image, the proposed method calculates the relative focus measure between a pair of source images. This paper notes that a well-focused region in an image shows better contrast, sharpness, and details than the corresponding region that is defocused in another image. Based on the observation that the average filtered version of a well-focused region in an image shows a higher correlation to the corresponding defocused region in another image than the original well-focused version, a new and fast multi-focus image fusion method is proposed. Experimental results of various sample image sequences show the superiority of the proposed method in terms of subjective evaluation.

Keywords—multi-focus; image fusion; image enhancement; average filter;

I. INTRODUCTION

Digital sensors such as cameras usually have a finite depth of field. Therefore, in an image taken by typical digital sensors, only those objects within the depth of field are in focus while the others appear out of focus. This problem may be resolved by fusing multi-focused images. A variety of multi-focus image fusion methods have been developed [1]. These methods typically employ their own focus measure for the fusion.

This paper proposes a pixel-based multi-focus image fusion method fast enough to be implemented directly into state-of-the-art digital sensors. To the authors’ knowledge, all focus measures proposed to-date calculate the measure for each source image independently. They are designed without a consideration for differences between multi-focused images. Experiments, as outlined in this paper, improve the performance of focus measure by using the relative difference signal for calculating the proposed measure.

II. PROPOSED FOCUS MEASURE AND FUSION METHOD

It has been observed that a well-focused region in an image contains better contrast, sharpness, and details than the corresponding region that is defocused in another image. Therefore, the average filtered version of a well-focused region in an image begins to show a higher correlation to the corresponding region that is defocused in another image than the original well-focused version. Accordingly, the average filtered version of a defocused region in an image will likely show a lower correlation to the corresponding region that is well-focused in another image than the original defocused version. Based on this observation, a new simple and effective focus measure is proposed.

In this paper, an image is denoted by $X = \{x(m,n); 1 \leq m \leq M, 1 \leq n \leq N\}$, where $M$ and $N$ are the vertical and the horizontal image size, respectively. The average filtered version of $X$ is denoted by $\bar{X} = \{\bar{x}(m,n)\}$ and calculated as follows:

$$\bar{x}(m,n) = \frac{1}{N_{A}} \sum_{(i,j) \in A} x(i,j),$$

where $A_{m,n}$ is the averaging window centered at $(m,n)$ and $N_{A}$ is the number of pixels in $A_{m,n}$. When two images, 1 and 2, denoted by $X^{(1)} = \{x^{(1)}(m,n)\}$ and $X^{(2)} = \{x^{(2)}(m,n)\}$, respectively, are used, the proposed focus measure of image 1 to image 2 at $(m,n)$, denoted by $f_{2:1}(m,n)$, is calculated as follows:

$$f_{2:1}(m,n) = \sum_{(i,j) \in B_{m,n}} \left| x^{(1)}(i,j) - \bar{x}^{(2)}(i,j) \right|,$$

where $B_{m,n}$ is the block centered at $(m,n)$. If $f_{2:1}(m,n)$ is greater than $f_{2:2}(m,n)$, $x^{(1)}(m,n)$ is determined to be the better focused pixel than $x^{(2)}(m,n)$. Almost all previously proposed focus measures calculate the focus measure of image 1 only based on image 1 itself. However, the proposed focus measure utilizes the relative information of image 2 to calculate the focus measure of image 1; this new approach improves the measuring performance, as highlighted in section III.

Literature on the subject highlights two types of fusion rules that are used once a focus measure has been selected. The
first rule is to select the pixel showing optimal focus and the second rule is to calculate the weighted sum based on the focus measure. The selection-based rule is known to be highly sensitive to noise and to show discontinuities in the transition regions between focused and defocused regions. The weighted sum-based rule is known to lose details in homogeneous regions. This paper adopts the combined form of these two fusion rules. Denoting the fused image of $X^{(1)}$ and $X^{(2)}$ by $X^{(1\&2)} = \{x^{(1\&2)}(m,n)\}$, the proposed fusion rule is as follows:

$$x^{(1\&2)}(m,n) = \begin{cases} x^{(1)}(m,n), & f_{x^{(1)}}(m,n) > \lambda, \\ x^{(2)}(m,n), & f_{x^{(2)}}(m,n) > \lambda, \\ \frac{f_{x^{(1)}}(m,n) + f_{x^{(2)}}(m,n)}{2}, & \text{otherwise,} \end{cases}$$

where $\lambda$ is a threshold value. When the number of source images is greater than two, this fusion rule is applied recursively, as follows:

1) Given multi-focus images $X^{(k)} = \{x^{(k)}(m,n)\}$, $k = 1, 2, \ldots, K$, set $s = 1$.
2) Using fusion rule (3), obtain $X^{(s\&s+1)}$ and save the result as $X^{(s+1)}$.
3) Repeat step 2) by increasing $s$ for $s = 2, \ldots, (K-1)$.
4) Declare $X^{(K)}$ as the final fusion result.

III. EXPERIMENTAL RESULTS

In the experiments discussed in this paper, the size of window $A_{m,n}$ and block $B_{m,n}$ is set to be 11×11 and 9×9, respectively. The larger size may be considered a preferable choice, but better results are achieved at the expense of increased complexity. Experiments on various test images have shown that improvements in and subjective tests resulting in the use of the larger size are almost negligible for the performance. The threshold value $\lambda$ is experimentally decided as 1.4 based on the subjective test results.

A multi-focus sample image sequence was obtained for performance tests, as illustrated in Fig. 1. This sequence was created by taking photographs with different focuses, compensating camera motion, and cropping the area most effectively showing the range of focus. In the image sequence, focuses remain fixed on one of six resistors in the image. In the experiment described in this paper, image fusion is performed by selecting two, four, and six images from each image sequence (Table I).

<table>
<thead>
<tr>
<th>Name</th>
<th>Number of Images</th>
<th>Selected images</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resister2</td>
<td>2</td>
<td>Resister-1,-6</td>
</tr>
<tr>
<td>Resister4</td>
<td>4</td>
<td>Resister-1,-2,-5,-6</td>
</tr>
<tr>
<td>Resister6</td>
<td>6</td>
<td>Resister-1,-2,-3,-4,-5,-6</td>
</tr>
</tbody>
</table>

Fig. 1. Sample image sequence: Resister (size 1288×1384).

Fig. 2. Experimental results for sample image sequence: Resister.
Based on a thorough review of the literature on the subject, five other methods are selected for performance comparisons: “Z” [2], “H” [3], “SML” [4], “BGS” [4], and “Li” [5]. Unfortunately, “BGS” and “Li” have shown unstable results for the image sequences used in this paper’s experiment when the number of source images is greater than two. Therefore, they are only used in this paper for fusing two source images.

For the subjective comparison, the resulting fused images for the sample image sequence are shown in Fig. 2. The well-focused regions gradually expand as the number of source images increases. For detailed comparisons, a portion of Fig. 2 showing critical comparisons of methods was selected, enlarged, and incorporated in Fig. 3. Comparisons may be summarized as follows:

1) When the background area in Fig. 3 is closely observed, it may be noted that “Z” relatively loses texture details.
2) For both object and background, the result of “SML” is smoother than that of other methods.
3) For the sharp edges on the boundary of the resister, “BGS” shows discontinuities.
4) For two lines of red and blue, “Li” has blurred results.
5) On two lines of red and blue and “40” on the right side of Resister6 in Fig. 3, “Z” shows unexpected blobs.
6) When compared to other methods, noticeable distortion cannot be found in the images of “H” and the proposed method.

IV. CONCLUSIONS

This paper proposes a pixel-based multi-focus image fusion method. While most previous methods use focus measures calculated independently for each source image, the proposed method calculates the relative focus measure between a pair of source images. The proposed method allows for a simple calculation of the focus difference between two images and provides a fast recursive formula for fusing multi-focused images. Experimental results using a critical image sequences, including images in which focus is placed on one of multiple objects, were performed. The results were compared to five other promising methods selected thorough a review of the literature. In subjective tests, the proposed method is superior.

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