Information Fusion 36 (2017) 284–295

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

Full Length Article

Surface area-based focus criterion for multi-focus image fusion

Mansour Nejati[a], Shadrokh Samavi[a,b,*], Nader Karimi[a], S.M. Reza Soroushmehr[c], Shahram Shirani[b], Iman Roosta[a], Kayvan Najarian[c,d]

[a] Department of Electrical and Computer Engineering, Isfahan University of Technology, 84156-83111, Iran
[b] Department of Electrical and Computer Engineering, McMaster University, Hamilton L8S 4L8, Canada
[c] Department of Computational Medicine and Bioinformatics, University of Michigan, Ann Arbor 48109, USA
[d] University of Michigan Center for Integrative Research in Critical Care, Ann Arbor 48109, USA

ARTICLE INFO

Article history:
Received 26 September 2015
Revised 2 December 2016
Accepted 27 December 2016
Available online 28 December 2016

Keywords:
Multi-focus image fusion
Surface area
Focus criterion
Fusion metrics

ABSTRACT

Nowadays image processing and machine vision fields have become important research topics due to numerous applications in almost every field of science. Performance in these fields is critically dependent to the quality of input images. In most of the imaging devices, optical lenses are used to capture images from a particular scene. But due to the limited depth of field of optical lenses, objects in different distances from focal point will be captured with different sharpness and details. Thus, important details of the scene might be lost in some regions. Multi-focus image fusion is an effective technique to cope with this problem. The main challenge in multi-focus fusion is the selection of an appropriate focus measure. In this paper, we propose a novel focus measure based on the surface area of regions surrounded by intersection points of input source images. The potential of this measure to distinguish focused regions from the blurred ones is proved. In our fusion algorithm, intersection points of input images are calculated and then input images are segmented using these intersection points. After that, the surface area of each segment is considered as a measure to determine focused regions. Using this measure we obtain an initial selection map of fusion which is then refined by morphological modifications. To demonstrate the performance of the proposed method, we compare its results with several competing methods. The results show the effectiveness of our proposed method.

1. Introduction

Multi-focus image fusion has become an important field of research due to its efficiency and applications in image processing and computer vision. As the optical lenses used by most of imaging devices suffer from the limited depth of field, images being captured by these lenses are not homogeneously focused. This means that objects with particular depth will be in focus while other objects are blurred that leads to a view of scene which is undesirable for human visual perception [1]. This out-of-focus blurring effect is typically modeled as the convolution of a blur point spread function (PSF) with a sharp input image [2]. Due to the loss of details in the blurred parts of an image, some image processing tasks could fail and produce imperfect results [1,3]. Multi-focus image fusion is an effective technique to solve this problem by combining multiple images with complementary information to make an image with better visual perception and quality [1,3]. The image fusion has also been applied in various applications such as remote sensing, and multispectral image fusion [4,5].

Existing multi-focus image fusion algorithms can be generally divided into spatial and transform domain methods [6]. The basic problem in multi-focus image fusion is to properly distinguish focused pixels from the blurred ones. Spatial domain methods deal with pixels and operators based on pixel intensities. These methods consider sections with greater energy or larger changes of pixel intensities as in focus sections. This is due to the fact that focused parts have more details and edges than the blurred ones [6]. The main focus criteria employed in pixel-based spatial domain methods are spatial frequency (SF) [7,8], energy of gradient (EOG) [9–12], energy of Laplacian (EOL) [13] and other novel focus criteria [14–16] to evaluate the variation of pixel intensities around each pixel location to choose the focused pixels. Segmentation-based spatial domain methods [17–19] make use of a common segmentation method to produce homogenous segments of source images. Subsequently, they evaluate the variation of pixel intensities belonging to each segment for selecting the focused ones.

On the other hand, the transform domain methods evaluate coefficients of the transformed input images and employ the

* Corresponding author.
E-mail address: samavi@mcmaster.ca (S. Samavi).

http://dx.doi.org/10.1016/j.inffus.2016.12.009
1566-2535/

focus criteria based on these coefficients. In these methods, sections with greater coefficients of high frequency are accepted as the focused parts of an input image. This type of fusion is popular and many methods have been developed in the transform domain. Some examples of transforms used in multi-focus fusion algorithms are discrete wavelet transform (DWT) [20–22], dual-tree complex wavelet transform (DTCWT) [23,24], discrete cosine harmonic wavelet transform (DCHWT) [25], cross bilateral filter (CBF) [26], discrete cosine transform (DCT) [27,28], curvelet and contourlet transforms (CT) [29–31], guided filtering [32], empirical mode decomposition [33], non-subsampled contourlet transform (NSCT) [34,35], and pulse coupled neural network (PCNN) [36,37]. Moreover, learning-based methods that use support vector machine (SVM) [38,39] and sparse representations [40–42] are the other techniques exploited for multi-focus image fusion.

The CBF multi-focus image fusion algorithm proposed in [26] is based on the weighted average of source images where the weights are computed by applying cross bilateral filters on the source images. DCHWT [25] uses coefficients of the discrete cosine harmonic wavelet transform to compute these weights. Haghighat et al. [27], introduced a fusion method based on the variation of DCT coefficients of the source images where DCT coefficients with higher variation are chosen and the fused image is produced by applying inverse DCT transform on the selected coefficients. Authors in [32] employs guided filter to decompose source images into base and detail layers and weighted average of them is combined into the fused image. Matting-based spatial segmentation is employed in [6] to obtain the accurate focused regions of the source images. In [12], selection of focused pixels is performed based on local gradient energy. This selection consists of two stages. In the first stage, the overall focus detection is performed by calculating the gradient energy of a big area around each pixel. In the second stage, the gradient energy of a small area on the boundary of the overall detection is calculated for accurate focus pixels detection. The fusion algorithm of [21] employs the spreading of the wavelet coefficients distribution as sharpness measure.

In transform domain methods, coefficients of a transform are usually modified without considering the spatial consistency. Therefore, these methods may introduce visual artifacts, spurious data, and/or brightness/contrast distortions into the final result. In spatial domain methods on the other hand, since the level of blurriness of the image pixels might vary due to their distances from the camera's focal point, an adaptive window in terms of size and shape could better exploit local information for the analysis. Nevertheless, in many spatial domain methods the size/shape of the window is fixed. In order to overcome the mentioned shortcomings, in this paper we propose a new criterion for choosing the focused parts of an image and prove its correctness through a mathematical model. Based on this criterion, we develop a new multi-focus image fusion algorithm. In this algorithm, the two input source images are considered as two surfaces where the surface area of regions enclosed by intersection points is employed as focus measure for distinguishing the focused pixels from the blurred ones.

In this paper, we first show a characteristic of one-dimensional signals and then use this characteristic in images as focus criterion. For one-dimensional signals, when considering a part of a focused signal and its low-pass filtered version, bounded by two consecutive intersection points, we will prove that the focused signal has longer path. We will extend this idea to two dimensions and propose our focus criterion based on surface areas. The two input images will be considered as two surfaces. When these two surfaces are plotted on the same coordinate system they intersect in some regions. The areas of the surfaces surrounded by intersection points will be used as a criterion for identifying focused regions. Based on the proposed focus criterion, we develop a new spatial domain multi-focus fusion method that contains four main steps. In the first step, we find the intersection points of pre-registered input images. In the second step, most of the false intersection points mainly caused by noise and/or compression artifacts are removed. Thirdly, for each pixel in input images, the surface area of the enclosed region around that pixel, surrounded by intersection points, is computed. Subsequently, focused pixels are selected using a specific selection rule based on the size of the computed surface area. Accordingly, an initial selection map is produced to specify the source image of each pixel. In the fourth step, the initial selection map is refined and the fusion is accomplished by applying the refined selection map to the input images.

The rest of the paper is organized as follows: in Section 2 we introduce our proposed focus criterion and its mathematical proof. In Section 3, our multi-focus image fusion method based on the proposed focus criterion is presented. Experimental results and comparison to other methods are given in Section 4. Finally Section 5 concludes this paper.

2. Proposed focus criterion

One of the problems in multi-focus image fusion is the lack of reliable focus criteria to distinguish focused pixels from the blurred ones. Thus, we intend to introduce a novel focus measure which is independent to degree of blurriness of the input images. For ease of computation, we assume that there are two input images with different focused areas. However, results in this case can be easily extended to cases with more than two input images.

2.1. Basic idea

In common case of multi-focus image fusion, we have two input images where each one has focused and blurred parts. To explain our focus measure, we assume that we have two input images with the same size denoted by I_F and I_B where I_F is an all-in-focus image, and its blurred version I_B is obtained by convolving I_F with a low-pass filter using the convolution as

$$I_B = I_F * H \tag{1}$$

where H is a low-pass filter convolved with the image I_F. Depending on the order of the low-pass filter, similar patterns can be observed in their corresponding pixel intensities with the expectation that deviation of pixel intensities in I_B is less than I_F. Now, for ease of analysis, we consider one specific row/column of each input image as an input signal and look at the fusion problem from different aspect which allows us to select the best path between two adjacent intersections of the signals. In this regard, we want to show that the path length of these signals between two consecutive intersections can be used for distinguishing focused signal from the blurred one. More precisely, if we consider the discrete focused and blurred signals as discrete curves, the focused curve between any two consecutive intersections with the blurred curve has larger length than the blurred curve. A mathematical proof to this premise is presented in the following Section. Fig. 1 shows a simple example for comparing two corresponding rows from the focused and blurred regions of two multi-focus images. The line segments inside the two dotted boxes are plotted in Fig. 1(c) and intersection points between these two signals are shown.

2.2. Theorem 1

Let γ_B is a blurred version of a discrete signal γ_F as the result of convolving γ_F with an averaging filter H, i.e. $\gamma_B = \gamma_F * H$. Assume that these signals intersect each other at the initial and final sample points only. The length of the path between two intersections points in the focused signal is larger than that of the blurred