

Multifocus Image Fusion Using Spatial Features and Support Vector Machine

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Abstract. This paper describes an application of support vector machine to pixel-level multifocus image fusion problem based on the use of spatial features of image blocks. The algorithm first decomposes the source images into blocks. Given two of these blocks (one from each source image), a SVM is trained to determine which one is clearer. Fusion then proceeds by selecting the clearer block in constructing the final image. Experimental results show that the proposed method outperforms the discrete wavelet transform based approach, particularly when there is movement in the objects or misregistration of the source images.

1 Introduction

Optical lenses often suffer from the problem of limited depth of field. Consequently, the image obtained will not be in focus everywhere. A possible way to alleviate this problem is by image fusion [1], in which several pictures with different focus parts are combined to form a single image. This fused image will then hopefully contain all relevant objects in focus.

In recent years, various methods based on multiscale transforms have been proposed, including the Laplacian pyramid [2], the gradient pyramid [1], the ratio of Low pass pyramid [3] and the morphological pyramid [4]. More recently, the discrete wavelet transform (DWT) [5], [6] has also been used. In general, DWT is superior to the previous pyramid based methods [6]. While these methods often perform satisfactorily, their multiresolution decompositions and consequently the fusion results are not shift invariant because of an underlying down sampling process. When there is slight camera/object movement or when there is misregistration of the source images, their performance will thus quickly deteriorate.

In this paper, we propose a pixel level multifocus image fusion method based on the use of spatial features of image blocks and support vector machines (SVM). The implementation is computationally simple and is robust to shift problem. Experimental results show that it outperforms the DWT based method. The rest of this paper is organized as follows. The proposed fusion scheme will be described in Section 2. Experiments will be presented in Section 3, and the last section gives some concluding remarks.

2 SVM Based Multifocus Image Fusion

2.1 Feature Extraction

In this paper, we extract two measures from each image block to represent its clarity. These are described in detail as follows.

2.1.1 Spatial Frequency (SF)

Spatial frequency is used to measure the overall activity level of an image [7]. For an $M \times N$ image F , with the gray value at pixel position (m, n) denoted by $F(m, n)$, its spatial frequency is defined as

$$SF = \sqrt{RF^2 + CF^2} . \quad (1)$$

where RF and CF are the row frequency

$$RF = \sqrt{\frac{1}{MN} \sum_{m=1}^M \sum_{n=2}^N (F(m, n) - F(m, n-1))^2} ,$$

and column frequency

$$CF = \sqrt{\frac{1}{MN} \sum_{n=1}^N \sum_{m=2}^M (F(m, n) - F(m-1, n))^2} ,$$

respectively.

2.1.2 Absolute Central Moment (ACM) [8]

$$ACM = \sum_{i=0}^{I-1} |i - \mu| p(i) . \quad (2)$$

where μ is the mean intensity value of the image, and i is the gray level.

2.1.3 Demonstration of the Effectiveness of the Measures

In this section, we experimentally demonstrate the effectiveness of the two focus features. An image block of size 64×64 (Fig. 2(a)) is extracted from the ‘‘Lena’’ image. Fig. 2(b) to Fig. 2(e) show the degraded versions by blurring with a Gaussian filter of radius 0.5, 0.8, 1.0 and 1.5 respectively. As can be seen from Table 1, when the image becomes more blurred, the two features are monotonic accordingly. These results suggest that both two features can be used to reflect image clarity.

2.2 The Fusion Algorithm

Fig.2 shows a schematic diagram of the proposed multifocus image fusion method. Here, we consider the processing of just two source images, though the algorithm can be extended straightforwardly to handle more than two.