

IMAGE FUSION BASED ON NON-NEGATIVE MATRIX FACTORIZATION*

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ABSTRACT

Non-negative Matrix Factorization technique (NMF) has been shown to have various applications to image processing, because of its power of local or part-based representation of objects and/or images. In this paper, we present an image fusion method based on NMF, not by the part-based representation feature of NMF, but by its wholly representation of the images needed to be fused: the images are fused by NMF with the parameter r of the NMF to be set to 1. Our experimental results show that the proposed method is efficient and effective for image fusion compared with many other image fusion methods.

1. INTRODUCTION

The multi-sensor image fusion is referred to as the iterated processing of images obtained from different sensors by an algorithm, so that a new image is obtained to meet the needs. The fused image possesses high reliability, clear definition, and easy intelligibility. As a key research field of the multi-sensor information fusion and a potent information fusion technique, multi-sensor image fusion has already been found wide applications in many fields such as machine vision, iatric diagnosis, military affairs and remote sensing.

One of the most representative fusion algorithms is Wavelet Transform method. Wavelet transform method has good locality in space and frequency domain, thereby it can retain high frequency information of an image in an effective way. It, however, often loses some feature information of the original images to some degree, such as edge information.

Recently Lee and Seung [2] proposed a new technique called Non-negative Matrix Factorization

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(NMF), to obtain a reduced representation of data. NMF differs from other methods by its use of non-negativity constraints. They demonstrated with a set of face images [3] that NMF can be used to obtain a basis of localized features in an unsupervised way. Many of those localized features correspond to the intuitive notion of face parts such as eyes and mouths. The amount of features depends on the parameter r in the NMF Algorithm. This paper presents a study on the application of NMF to image fusion area. The main goal is to present and test NMF as a convenient and efficient technique that can be used for fusion. The motivation of introducing NMF to image fusion is that our data is positively defined and NMF is based on positive restrictions, meaning that NMF can be a suitable technique for such a problem. Furthermore we presents that when we configure the NMF with parameter r to be one, i.e., we obtain only one feature from the input images by NMF, this feature is characterized to be the image fused from the original images. We analyze NMF techniques in many fusion problem and show that NMF really works, and has better fusion results in some problems compared with the wavelet transform method.

2. IMAGE FUSION BASED ON NMF

NMF is a method to obtain a representation of data using non-negativity constraints. These constraints lead to a part-based representation because they allow only additive, not subtractive, combinations of the original data [2]. Given an initial database expressed by a $n \times m$ matrix V , where each column is an n -dimensional non-negative vector of the original database (m vectors), it is possible to find two new factor matrices W and H to approximate the original matrix $V_{iu} \approx (WH)_{iu} = \sum_{a=1}^r W_{ia} H_{au}$ according to some cost function. The dimensions of the factor matrices W and H are $n \times r$ and $r \times m$ respectively. Usually, r is chosen such that $(n + m)r < nm$. Each column of the matrix W represents a basis vector in the data space, while each column in H corresponds to the weights needed to

approximate the corresponding column in V using the basis from W . This means that if we consider the observed images from different sensors as the observation data V , performing NMF on data with parameter r means to find r basis vectors (images) such that the observed images are the positive and linear combination of these r basis images.

In order to estimate the factor matrices, an objective function has to be defined. A reasonable objective function is given by $F = \sum_{i=1}^n \sum_{u=1}^m [V_{iu} - (WH)_{iu}]^2$. This

objective function can be related to the likelihood of generating the images in V from the basis matrix W and weight matrix H . An iterative approach to reach a local maximum of this objective function is given by the following algorithm[2]:

$$\begin{aligned} W_{ia} &\leftarrow W_{ia} \sum_{\mu} \frac{V_{i\mu}}{(WH)_{i\mu}} H_{a\mu} \\ W_{ia} &\leftarrow \frac{W_{ia}}{\sum_j W_{ja}} \end{aligned} \quad \begin{aligned} H_{a\mu} &\leftarrow H_{a\mu} \sum_i W_{ia} \frac{V_{i\mu}}{(WH)_{i\mu}} \end{aligned}$$

Initialization is performed by using random initialization of the matrices W and H under the constraints of non-negativity on their elements. The convergence of the algorithm has been proved. See [2] and [3] for more information.

For image fusion, the observed images can be viewed as the non-negative weighted of some substantial image. Our novel idea for image fusion is to find this substantial image as the fused image by application of NMF technique. NMF is a technique for finding a part-based representation of input data, i.e., if the parameter of NMF is set to be r (generally $r > 1$), the input data are linear and non-negative combinations of the r parts derived from NMF on the input data. Similarly, if the parameter r of NMF is set to be only one, the input data are linear and non-negative combinations of the only one part derived from NMF on the input data, i.e., the non-negative weighted of that part. Therefore, the only part derived from NMF with $r = 1$ on the input data is the substantial feature (global feature) of the input data. Hence, the NMF technique is applied to image fusion in this paper.

Visual Example Using NMF

David Guillaumet[4] tested the availability of NMF in obtaining the multi-basis which spans the training data. Their results show that applying the NMF method with different configurations of the parameter r can obtain different multi-basis. Similarly in this paper, we study the possibility of applying NMF to synthetic vectors to obtain the global feature vector of the synthetic vectors, herein the synthetic vectors are viewed as the images from different sensors, while the global feature vector is viewed

as the image obtained from the fusion process. In this example, the synthetic vectors, which are shown in Fig.1(b) and Fig.1(c) respectively, were generated from a same Gaussian vector, shown in Fig.1(a), with separate but positive-random weights(factors). Then, the NMF was applied to vectors in Fig.1(b) and Fig.1(c) with the configuration of the parameter r to be 1. The resultant base extracted by NMF is shown in Fig.1(d), which is exactly the same as the original vector in Fig.1(a). This means that the NMF can extract global feature of a set of data when it is applied to this set of data with r to be 1. In addition, for image fusion application, the images obtained from different sensors can be regarded as the ones from a same fused image with separate weightings. Therefore we can use the NMF technique to image fusion.

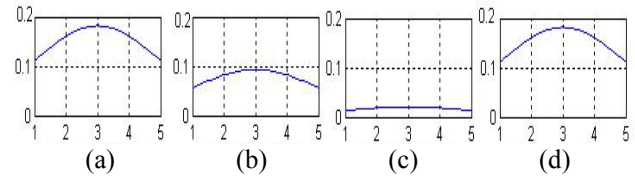


Fig.1 visual example of applying NMF to finding global feature vector from its many weightings

Notice that our novel idea on image fusion is to find, from the observed images, a substantial image as the resultant fused image, while the NMF with $r=1$ makes this available in that it presents a technique to find a base from observations: it finds a substantial image, which we also call the base image from the observed images such that each observed image can be expressed by this base image with minimum recovery errors (reconstructed errors). It should be noticed that the observed images should be registered and made to be in same size such that the fusion can be conducted.

3. EXPERIMENTS

We applied our proposed method to many image fusion tasks. In this section, we only show some image fusion results with the proposed NMF method and experimental comparisons with some other typical methods such as simple mean method and wavelet transform method. In our following three examples, the observed images include the images which are generated from a same original image but with different focuses (example 1), highly blurred images from a same original image (example 2), and the images from different image sensors (example 3). The fusion performances for the first two examples can be easily evaluated by just a comparison of the original image and the fused one, while that of the last example can only be evaluated by visualization since it is a real world problem where the original image is unknown.

The wavelet transform method we used in our experiments is first to transform the observed image and

get the wavelet coefficients, fuse the wavelet coefficients obtained from all the observed images and inversely transform the fused wavelet coefficients into an image. This image is considered to be an image fusion result. In our experiment, the order of the wavelet transform is selected to be 3, and the fused coefficient is calculated by $[F^{LH}, F^{HL}, F^{HH}] = [A_i^{LH}, A_i^{HL}, A_i^{HH}]$ if $E(A_i) > E(A_j)$ for all $j \neq i$, where

$$E(A_i) = |A_i^{LH}| + |A_i^{HL}| + |A_i^{HH}|,$$

and $A_k^{LH}, A_k^{HL}, A_k^{HH}$ are the wavelet coefficients of the observed image A_k in corresponding frequency channels described in superscript.

3.1 Fusion of Different Focus Images

In this example, from an unblurred image shown in Fig.2(a), four images Fig.2(a)-(d) were achieved with each having a blurred corner, through Gaussian noises added to the four corners of the unblurred image by Photoshop respectively. The image fusion was performed on these four images with wavelet transform method, Laplacian method and our NMF based methods. Fig.3(b)-(d) show the fused image from these methods respectively.

PSNR, mean square error, entropy and root cross entropy are four typical measures for performance evaluation of fused image. Table 1 shows our experimental results for comparison. It can be seen that the method in this paper is minimum in mean square error and root cross entropy, maximum in entropy value and the peak-to-peak signal-to-noise ratio. Therefore, the NMF based method presented in this paper is advantageous in retaining the more useful information of each image needed to be fused.

Table 1 comparison of the three algorithms on image fusion performance

	PSNR	Mean Square Error	Entropy	Root Cross Entropy
NMF based method	31.7073	43.8881	7.5445	0.0826
WT method	26.3332	151.2714	7.4564	0.1935
Laplacian method	30.2523	61.3552	7.4584	0.2084

Notice that there is a strip overlap of the blurred areas in the left-bottom blurred and the left-up blurred images shown in Fig.2(a) and Fig.2(b). By comparison of the fused images in Fig.3(b), (c) and (d) via visualization, there is a gray strip in this overlapped area in the fused images Fig.3(c) and Fig.3(d) from the wavelet transform method and Laplacian method respectively, while this gray strip is too light to visualize from the fused image

shown in Fig.3(b) which is obtained via NMF based method, showing the effectiveness of the NMF based method proposed.

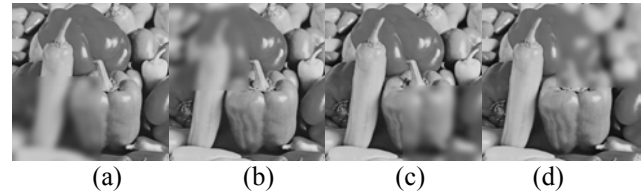


Fig.2 images obtained by blurring the (a) left-bottom, (b) left-up, (c) right-bottom and (d) right-up of the image shown in Fig.3(a)

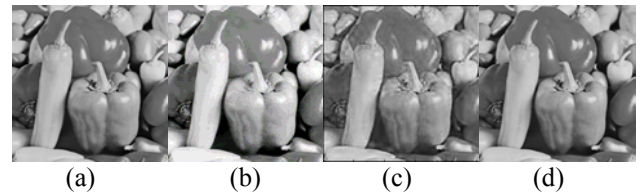


Fig.3 (a) original image and the fused image from (b) NMF, (c) wavelet transform method, and (d) the Laplacian fusion method

3.2 Fusion of Highly Blurred Images

We performed experiments on the clock image shown in Fig.4, the image commonly used in image fusion for evaluation of image fusion performance. We first partially

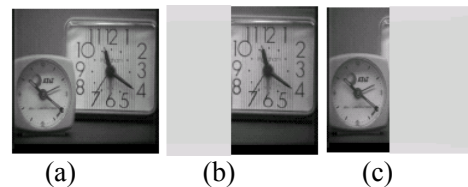


Fig.4 (a) original clock image and (b) the image derived from approximately total coverage of its left half, and (c) that derived from approximately total coverage of its right half

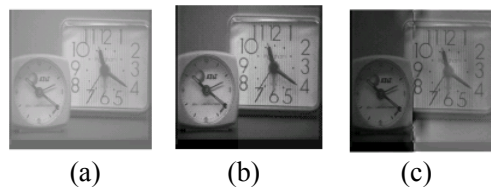


Fig.5 the fused images from (a) simple mean method, (b) NMF based method, and (c) wavelet transform method respectively

blurred the vivid original image to get the images as the multi-sensory observations: the left and the right half of the image is nearly absolutely covered, shown in Fig.3(b) and Fig.3(c) respectively. The fused images by applying

three methods respectively are shown in Fig. 5 and the evaluation marks in Table 2.

From visualization, the proposed method is evidently better than wavelet transform method and simple mean method, whereas, clear square effect in the fusion result from the wavelet transform fusion method can be seen, which corresponds to the boundary area between the blurred and vivid parts of the images needed to be fused.

Table 2 comparison of the three algorithms on image fusion performance for blurred clock images

	MSE	PSNR
NMF based method	88.5	28.6626
Simple mean method	4139.3	11.9615
Wavelet transform method	2594.2	13.9907

3.3 Fusion of Two Real Images

The proposed method was also conducted to the fusion of a forward infrared image in Fig.6(a) and a micro-light image in Fig.6(b) which were obtained from two separate corresponding sensors. The images were strictly registered before the fusion was conducted. Three fusion methods mentioned above were applied, and the fusion results were obtained and shown in Fig.7.



Fig.6 two images of a same region from (a) forward infrared and (b) micro-light sensors respectively



Fig.7 fused images from (a) simple mean method, (b) NMF based method, and (c) wavelet transform method

4 CONCLUSIONS

This paper presents a new idea of image fusion. The idea is that the fused image should be a substantial image of all the observed images which are obtained from separate sensors, and Non-negative Matrix Factorization (NMF) technique is firstly applied for finding such a substantial image. In this analysis, NMF can extract such a substantial image from the observed images by setting the parameter

r to 1. Our experiments shows that a better image fusion performance can be obtained when NMF based method is used compared with simple mean method and wavelet transform method. Our further study will be in image fusion when each image is obtained with different observation precision.

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