Product-based Multiresolution Image Fusion

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ABSTRACT

We combined images from different sensors that were enhanced by multiscale products of the wavelet coefficients. Using the wavelet transform, we used a multiresolution analysis to form products of coefficients across scales. Then, a fusion rule was applied to the product images to determine how the original images could be combined. Using this approach, we were able to decrease the sensitivity of the fusion process to noise.

Keywords: multiresolution image processing, sensor fusion, wavelet transform

1. INTRODUCTION

An accurate method for combining images from different sensors is the key to a successful image sensor fusion process. Fusion rules vary in complexity when it comes to number of source images and the number of input pixels per fused pixel. It will always be a debate on whether a low level general approach or a specialized high level approach will result in a viable sensor image fusion algorithm.[1,2]

Several approaches combine images based on visibility or contrast. Using visibility as a measure limits the analysis to the signal and feature level thus reducing the pre-assumptions needed for the fusion rules. One definition of visibility in an image is can be thought of as scaled contrast.[3] The contrast of an image is calculated to determine a contrast vector field. The first derivative in the horizontal direction and vertical directions of an image are found and recorded in separate contrast images. Using differential geometry, a two-dimensional vector field representing the absolute contrast and direction is found. Therefore, the maximum contrast at each point can be determined.

In an effort to localize the effect of contrast, a gradient map at multiple resolutions was used as the basis for the fusion decision process.[4] A gradient map was processed rather than the original image. A gradient map is formed from the difference between adjacent pixels as the Euclidian distance of the contrast components in the horizontal and vertical directions. The wavelet transform was used to process the gradient maps. The filters used in the transform were a function of a wavelet and the z-transform of the gradient operator. To get a high contrast fused image, the fusion rules favor high absolute contrast values, so the fusion rule simply followed the “choose max” approach.

Another multiresolution approach used an orthogonal representation of images based on the wavelet transfrom.[5] Although not developed specifically for the fusion of different sensor images, the orthogonal representation accumulates the results of images into a single representation. Using an eigenvector approach the maximum direction of the contrast can be found. We used a similar orthogonal representation to combine two images from different sensors, although ours is not downsampled. Since edges can be associated with regions of high

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contrast we contemplated a method that has been used to detect edges in noisy environments. We use the product of wavelet coefficients across two scales, and used the resulting product images to determine how the original images should be fused. In the next section, we briefly describe our approach, then described some experimental results.

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2. FUSION USING MULTISCALE PRODUCTS

Using the wavelet transform, an image *I(x,y)*, it may be decomposed into lower resolution approximation images at *j* different scales $A_{2^j}I$, and three detail images $D^1_{2^j}I$, $D^2_{2^j}I$, $D^3_{2^j}I$, at each scale where $-1 \le j \le -J; (n,m) \in Z^2$.

$$A_{2^j}I = I(x,y) \otimes \phi_{2^j}(-x)\phi_{2^j}(-y) \tag{1}$$

$$D^1_{2^j}I = I(x,y) \otimes \phi_{2^j}(-x)\psi_{2^j}(-y) \tag{2}$$

$$D^2_{2^j}I = I(x,y) \otimes \psi_{2^j}(-x)\phi_{2^j}(-y) \tag{3}$$

$$D^3_{2^j}I = I(x,y) \otimes \psi_{2^j}(-x)\psi_{2^j}(-y). \tag{4}$$

The product of noisy wavelet coefficients between different scales has been shown to detect intensity discontinuities better than traditional methods.[6] Therefore, considering the discontinuities as local variations in contrast, we used an orthogonal wavelet that detects changes in the first derivative. For example, using the first two scales of the wavelet transform (j = -1, -2), a product is formed between the image's nondownsampled wavelet transform coefficients of the two scales,

$$C^k I = \prod_{j=-1}^{-2} D^k_{2^j} I, \tag{5}$$

for k = 1, 2, 3 resulting in three product images. Then, the energy of each product image is rescaled so that it has the same energy as $D^k_{2^{-1}}I$ such that

$$\sum (C_1^k I)^2 = \sum (D_{2^{-1}}^k I)^2 . \tag{6}$$

The formation of products and rescaling of energy occurs for each subband independently. Then, the first level of the wavelet transform of the image is replaced with the rescaled product image. Therefore, an image was represented with Eqs. 1-4 with the $D_{2^{-1}}^k I$'s replaced with $C^k I$, and j = -1.

The fusion rule is applied to the images $C_1^k I$. In our examples, we used the maximum of corresponding coefficients in the two images to form one set of $C^k I$'s. For the approximation images, $A_{2^j} I$'s, we used their average between the two scales. In other words, the product images form two binary images described by

$$M1(x, y) = \begin{cases} 1 & C_1^k I_1 \rangle C_1^k I_2 \\ 0 & otherwise \end{cases} , \tag{7}$$

$$M2(x, y) = \begin{cases} 1 & C_1^k I_2 \rangle C_1^k I_1 \\ 0 & otherwise \end{cases} . \tag{8}$$

These images form a product with the original wavelet coefficients at the first scale as shown in Fig. 1. When the results of these products are formed, their sum is taken as the inverse wavelet transform of the fused image. In this way. images were fused based on multiscale products. Therefore, a complete representation of an image was formed, and the inverse wavelet transform was calculated to produce a final image.

4. EXPERIMENTS

We used two sets of images shown in Figs. 2 and 3 in our experiments. The images in Fig. 2 consisted of an aerial scene and a binary image consisting of a large ring. The result of fusion using multiscale products is shown in Fig. 4(a). It can be seen that visually, the images seemed to be combined while preserving the important information. The images in Fig. 3 show images of a person's face in the visible and infrared. Their fusion in Fig. 4(b) also shows the retention of important information. To examine the noise sensitivity of the method, the fusion process was repeated with noise added to each image. The mean-squared-error (MSE) is shown as a function of SNR (in each input image) in Fig. 5 for the images in Fig. 2, and Fig. 6 for the images in Fig. 3. In both Figs, the +'s indicate the results of the choose max fusion rule, and the o's indicate the results of forming the magnitude of both input images. Although not shown, the results here had a slightly lower MSE that using one scale in almost all cases.

4. CONCLUSION

Using multiscale products of the wavelet transform seems to form the basis of an effective method for the fusion of images from different sensors. Using this approach, we were able to decrease the sensitivity of the fusion process to noise.

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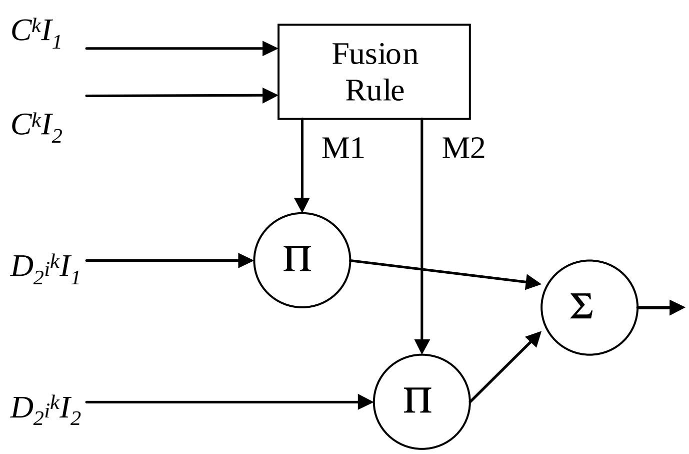
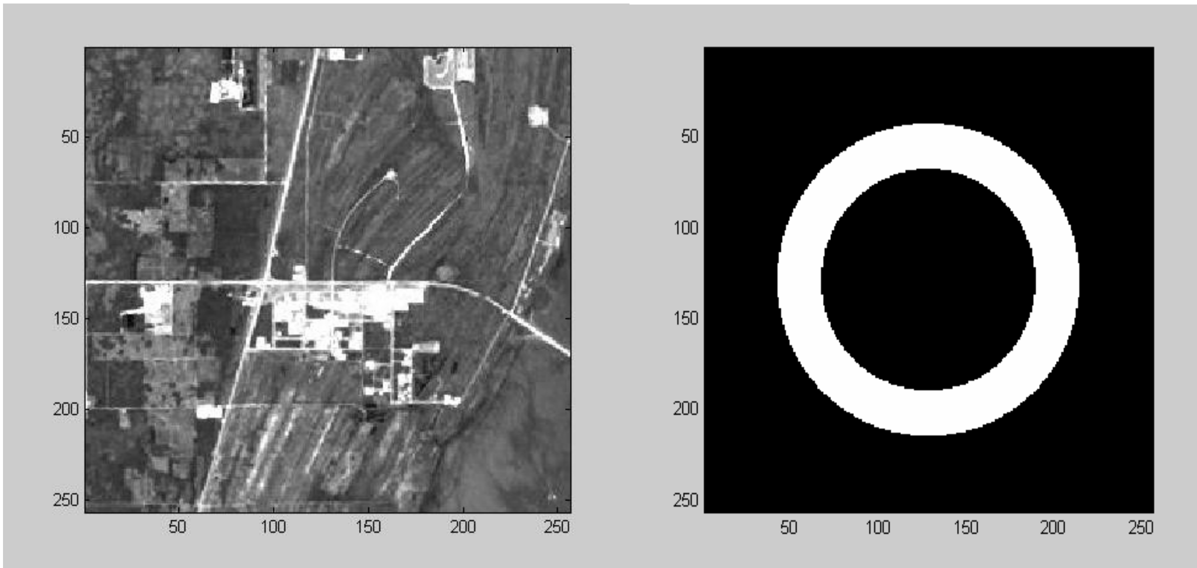


Figure 1 Block diagram of fusion process.



(a) (b)

Figure 2 Images used in experiments.

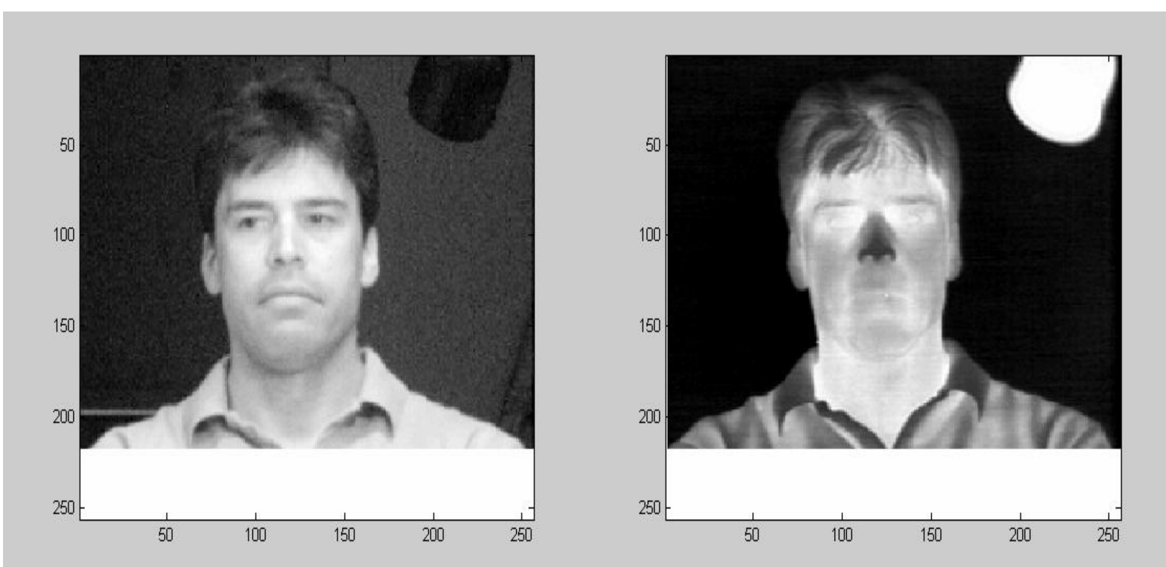
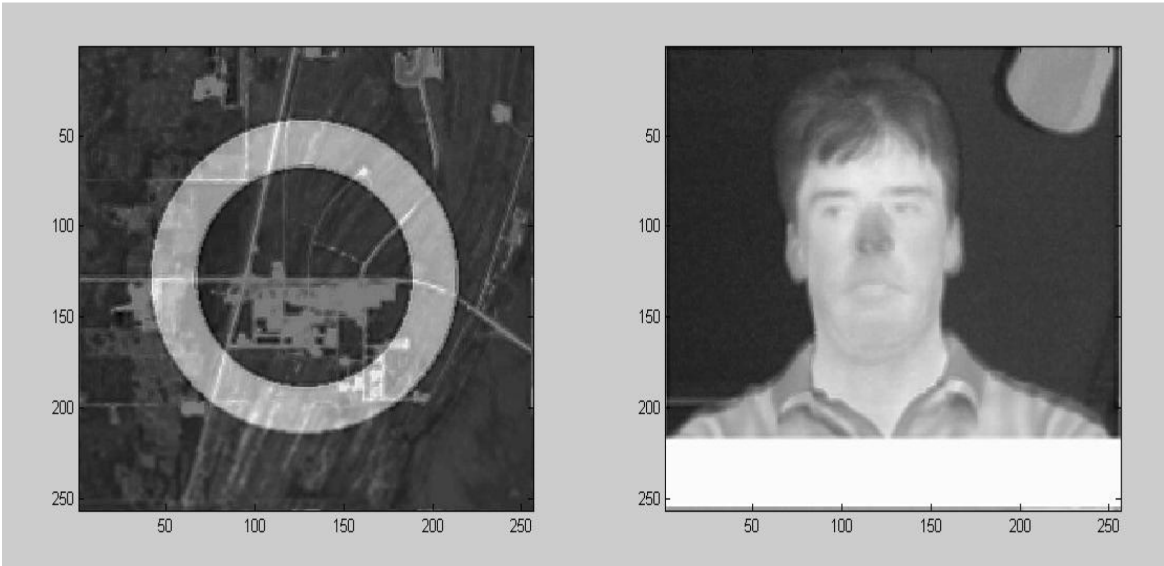


Figure 3 Visible and infrared images used in experiments.



(a) Figure 4 Results of fusion experiments. (b)

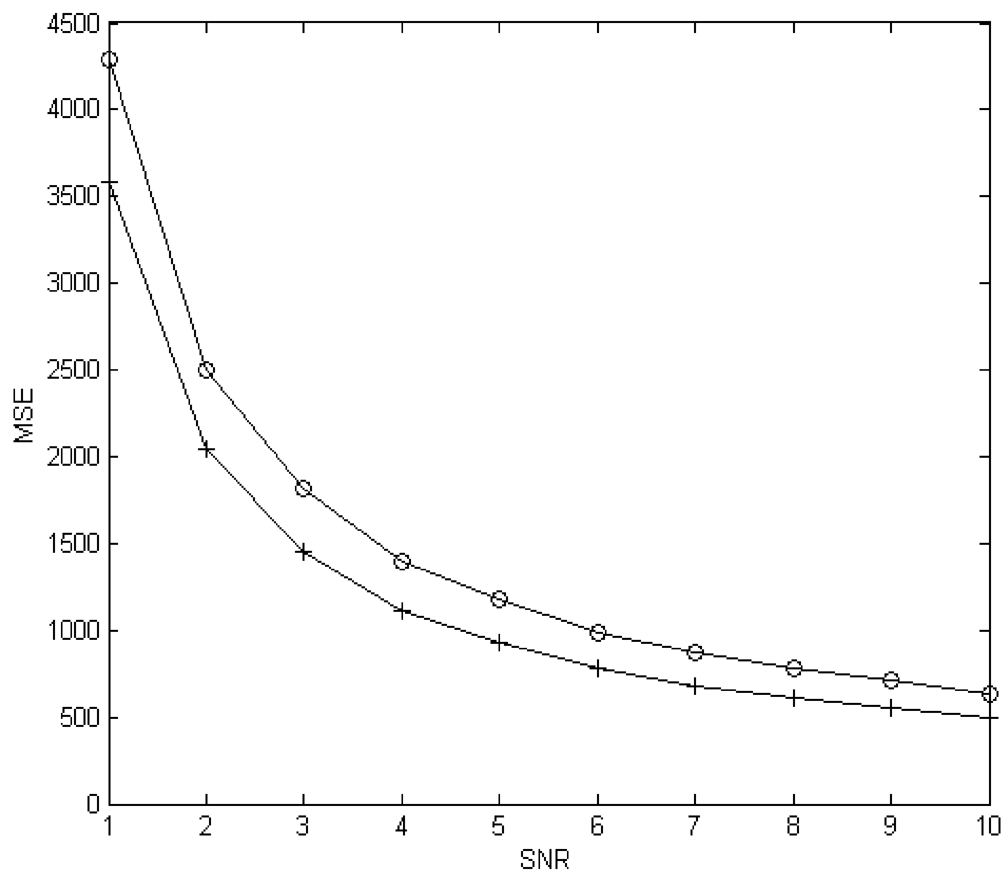


Figure 5 MSE of resultant image in Fig. 4(a) as a function of SNR of input images, o magnitude, + choose max.

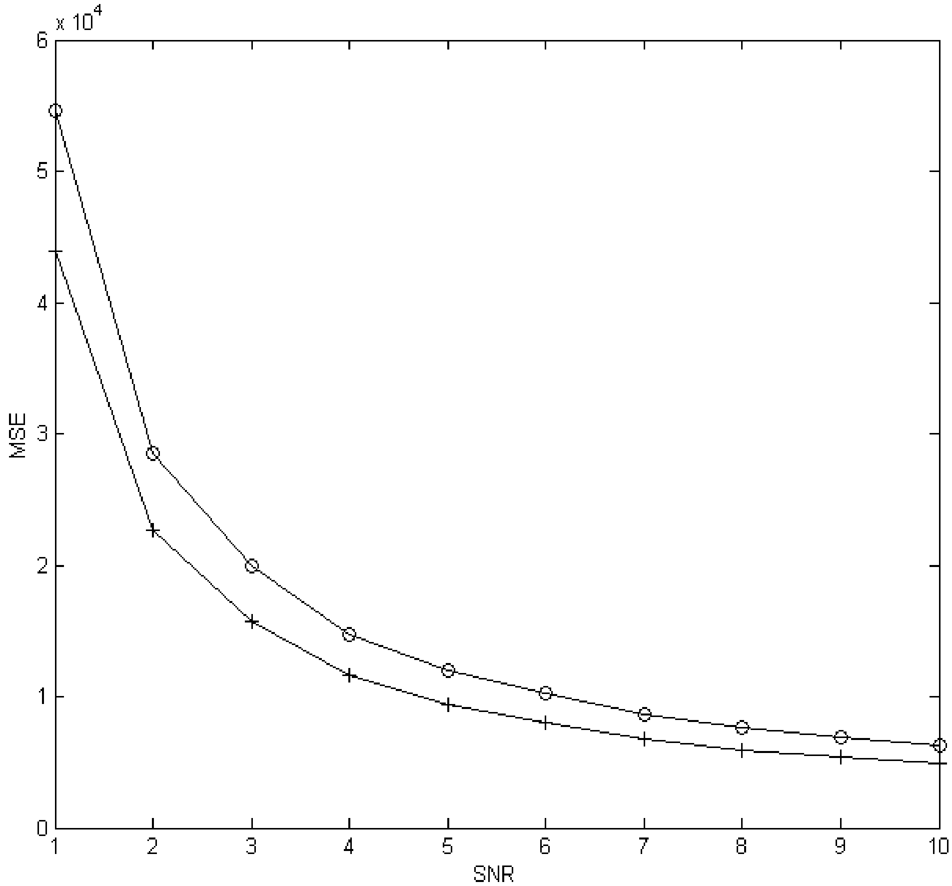


Figure 6 MSE of resultant image in Fig. 4(b) as a function of SNR of input images, o magnitude, + choose max.