Image Fusion with Spatial Frequency*

Lily R. Liang, Carl G. Looney
Computer Science Department/171
University of Nevada, Reno
Reno, NV USA
<looney,liang>@cs.unr.edu

Abstract. *A process is designed to fuse multiple images of the same scene to produce an image that contains less noise and more information. First, the speckle noise is removed. Second, histogram equalization is applied to expose details and maximize the information content of the image. Third, images are registered to prepare for fusion. In the fourth step, we apply our new pointwise spatial frequency methodology by computing it at each pixel in each image. The images are then fused at each output pixel location by comparing the pointwise spatial frequency values at that location in all images and selecting the pixel with the highest such value. The fifth step enlarges this image with fuzzy interpolation for more detail.*

Keywords. spatial frequency, image fusion, interpolation

1. Introduction

The ongoing research in image fusion is fueled by the emergence of shorter wavelength radars and better infrared (IR) and optical sensors. Rather than relying only on the modulation and other characteristics of returned radar signals, these new sensors capture images of scenes from synthetic array (aperture) radar (SAR), high range resolution (HRR) radar, infrared sensors, optical and hyperspectral sensors [8]. For example, the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) can capture pixel values in more than 200 bands [7].

Given a set of images of the same ground scene captured from the air, the problem is one of detecting and recognizing objects in clutter, noise, camouflage, inclement weather, with partial occlusion and from various angles of incidence and aspect. The use of multiple images can provide more information to the user. Here we design a methodology of five steps whereby multiple small images can be quickly processed to provide a clearer and larger one with more information. Each of the five steps adds to the achievement of this goal. The next section covers these steps in detail. A different fusion approach is given in [9].

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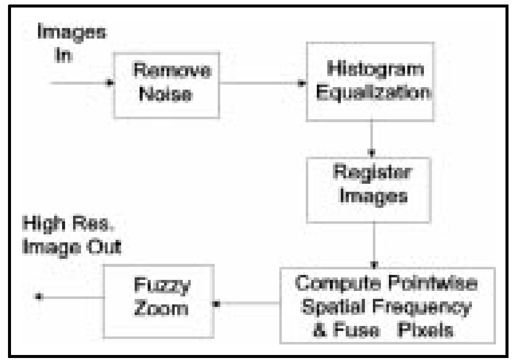

Fig. 1. The overall image fusion process.

2. Methodology

Noise Removal. For speckle noise removal we use a 3x3 neighborhood (nbhd) of each pixel and apply our modification of the alpha-trimmed mean [1] with $\alpha = 3$. We take the 9 pixel values in the nbhd, adjoin the center pixel value again so that there are now 10 pixel values, throw away the highest three pixel values and also the lowest three and average the remaining 4 grayscale values. This average is the new center pixel value that is written to the output image. This counts the center pixel twice as often as any other pixel, but if it is an outlier then it will not be in the averaged value for the new output pixel. Figure 2 shows our *3-trimmed mean process*.

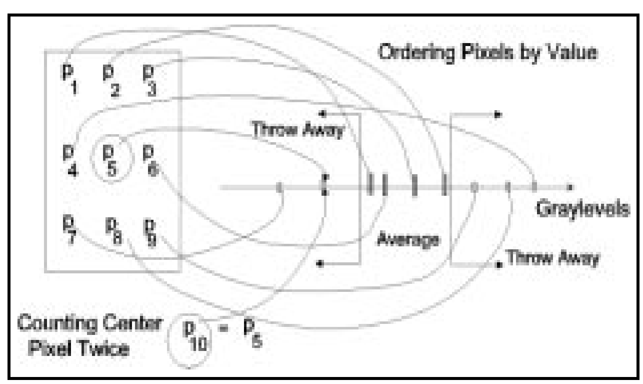

Fig. 2. Our modified 3-trimmed mean process.

Histogram Equalization. A normal histogram equalization is used here, but multi-level histogram equalization can be applied to manipulate the histogram to maximize the information content of the image and to expose more details [3,4].

Registration of Two Images. Before the pixels in different images can be fused together, they need to be registered with each other. Many different methods can be used to register image pixels [2] and *Matlab Image Processing Toolbox©* can be also be used. The input images used for the next steps were obtained from a single image by blurring different parts of it. Thus no registration process is needed here.

Fusion with Pointwise Spatial Frequency. Although [5] defined spatial frequency on a block by computing the adjacent difference magnitudes in the horizontal and vertical directions, the results of combining images with different parts out of focus to obtain a clearly focused image were good. For finer granularity we define the *pointwise spatial frequency* (psf) at a pixel by summing the magnitudes of differences from the center pixel and each other pixel in a 3x3 neighborhood (nbhd).

$$\mathrm{psf}(p_5) = \sum_{k \geq 5} |p_k - p_5| \tag{1}$$

Thus our psf includes all directions and is defined for each pixel rather than for a block in which all pixels are treated the same.

We fuse the R images at each pixel location by comparing the psf values of the R corresponding pixels. For all R pixels p_r at the same location we put $p_{out} = p_{r*}$ where r* is determined by

$$\mathrm{psf}(p_{r*}) = \max_r \{\mathrm{psf}(p_r): r = 1,...,R\} \tag{2}$$

Increasing the Resolution. The resolution of the fused output image is the same as the original images at this point. To expand the MxN image $\{p_F(i,j)\}$ to the (2M)x(2N) image $\{p(m,n)\}$, we use the well-known backward expansion method (for example, see [6]). We create an array $\{p_X(i,j)\}$ for the expanded image, but the pixels are blank. The respective forward and backward mappings of pixels are

$$T(i,j) = (2i, 2j), \quad T^{-1}(m,n) = (m/2, n/2) \tag{3a, b}$$

The task here is to find graylevel values for each of the (2M)x(2N) pixel locations in the enlarged image via the usual backward mapping method. For each pixel location (m,n) in the enlarged image, we map it back to the point (m/2, n/2) by the function $T^{-1}(m,n)$ defined above. The graylevel is to be interpolated from the four graylevel values of the original image given by

$$a = p(\lfloor m/2 \rfloor, \lfloor n/2 \rfloor), \quad b = p(\lfloor m/2 \rfloor, \lfloor n/2 + 1 \rfloor) \tag{4a,b}$$

$$c = p(\lfloor m/2+1 \rfloor, \lfloor n/2 \rfloor), \; d = p(\lfloor m/2 + 1 \rfloor, \lfloor n/2 + 1 \rfloor) \tag{5a,b}$$

where $\lfloor x \rfloor$ is the greatest integer less than or equal to x. Figure 3 shows the backward mapping of (m,n) into the point (m/2,n/2 that is not a pixel location. It is thus interpolated from the grayscales of the four nearest valid pixel locations.

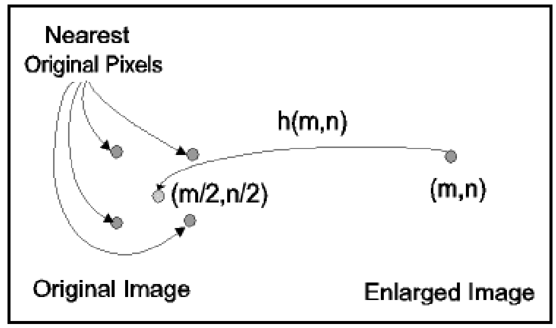

Figure 3. Fuzzy interpolation of graylevel.

The interpolation is a weighting of these four gray values where the weights are determined by the distance from the actual backward mapped location to the four corner points that are actual pixel locations in the original image. Thus

$$p(m/2, n/2) = W_1 a + W_2 b + W_3 c + W_4 d \tag{6}$$

The preliminary weights are computed via

$$w_1 = 1 / (\|(\lfloor m/2 \rfloor, \lfloor n/2 \rfloor) - (m/2,n/2)\|^2 + 1) \tag{7}$$

$$w_2 = 1 / (\|(\lfloor m/2 + 1 \rfloor, \lfloor n/2 \rfloor) - (m/2,n/2)\|^2 + 1) \tag{8}$$

$$w_3 = 1 / (\|(\lfloor m/2 \rfloor, \lfloor n/2 + 1 \rfloor) - (m/2,n/2)\|^2 + 1) \tag{9}$$

$$w_4 = 1 / (\|(\lfloor m/2 + 1 \rfloor, \lfloor n/2 + 1 \rfloor) - (m/2,n/2)\|^2 + 1) \tag{10}$$

where $\|z\|$ is the Euclidean (distance) length of z. The standardized weights that sum to unity are computed from the preliminary ones by

$$W_s = w_s / \Sigma_{q=1,4} w_q \tag{11}$$

The fuzzy weighted average of Equation (6) is the fuzzy interpolated value of a pixel at (m/2,n/2) if there were such a pixel in the original image that maps to (m,n). Thus we use the interpolated graylevel p(m/2,n/2) as the graylevel for the pixel at location (m,n) in the enlarged image. This fills in the graylevels for all pixels in the new enlarged image and lightly smooths it as well, which takes out the blockiness associated with nearest neighbor interpolation. It appears to be an improvement over the usual bilinear interpolation.

3. Experiments

Fig. 4 shows the original image *building.tif*. We convert this to *building.pgm* for easy manipulation of the pixels by our programs in C. Heavy random noise is added in Fig.5, but it is mostly removed in Fig. 6 with our modified 3-trimmed mean.

In Fig. 7 and 8 the respective rightmost tree and leftmost tree were blurred. Then Figures 7 and 8 were histogram equalized, shown in Figures 9 and 10 in enlarged form for better viewing. These were then fused image and the result is shown in enlarged form in Fig. 11.

Fig. 4. Original image.

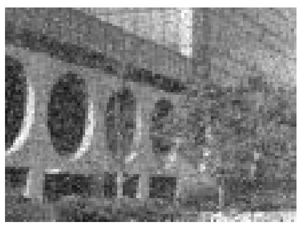

Fig 5. Random noise added.

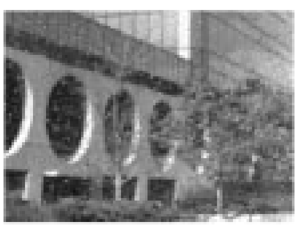

Fig. 6. 3-trimmed mean result.

Fig. 7. Input image 1.

Fig. 8. Input image 2.

Fig. 9. Enlarged hist. eq. of Fig 7.

Fig 10. Enlarged hist. eq. of Fig 8.

Fig. 11. Enlarged fusion of blurry figures.

4. Conclusions

We take R images of the same scene where $R \geq 2$, remove the speckle noise, equalize the histograms, register them if need be and compute the pointwise spatial frequency at each pixel in all R images. Then we fuse the images by considering all R pixels at the same location at one time. We compare the R psf's and find the r* for the largest psf. The pixel from image r* is put into the output image at this location.

It is clear from comparisons of Figure 11 with Figures 9 and 10, where each had a section that was blurry, that the fused image in Figure 11 was clear everywhere. Thus the fusion was very successful in this case where the blurry parts do not overlap. Also the removal of noise using the 3-trimmed mean was successful as shown in Fig. 6. We are considering ways to improve it. General fuzzy interpolation can be found in [6]. We are currently exploring techniques for improving fusion of pixels where all input pixels at the same location are degraded.

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