# Fusion of Multifocus Images to Maximize Image Information

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## ABSTRACT

When an image of a 3-D scene is captured, only scene parts at the focus plane appear sharp. Scene parts in front of or behind the focus plane appear blurred. In order to create an image where all scene parts appear sharp, it is necessary to capture images of the scene at different focus levels and fuse the images. In this paper, first registration of multifocus images is discussed and then an algorithm to fuse the registered images is described. The algorithm divides the image domain into uniform blocks and for each block identifies the image with the highest contrast. The images selected in this manner are then locally blended to create an image that has overall maximum contrast. Examples demonstrating registration and fusion of multifocus images are given and discussed.

**Keywords:** Image registration, image fusion, image blending, image contrast, image gradient

## 1. INTRODUCTION

Image fusion is the process of combining information in two or more images of a scene into a highly informative image. An image contains different types of information. The objective in image fusion is to increase information that is relevant to a particular application. If the objective in image fusion is to increase overall image contrast, relevant information will be image contrast. Given two or more images of a scene captured at different focus levels, to increase image contrast, we will first register the images and then fuse them. If the images are captured by a stationary camera, the images will be already registered and the fusion process can begin immediately. However, if the images are captured by a handheld or mobile camera, fusion of the images requires registration of the images prior to fusion.

Image registration is the process of spatially aligning two or more images of a scene. The process brings into correspondence individual pixels in the images. Therefore, given a point in one image, the registration process will determine the positions of the same point in all the images. The warping model chosen to align the images should be a true representation of the geometric difference between images. When the scene is relatively flat and the distance of the camera to the scene is much larger than variation in scene depth, captured images will be related by the affine transformation. Under the affine transformation, parallel lines in the scene appear parallel in the images. If variation in scene depth is small but distances of scene points to the camera vary greatly, images of the scene will be related by the projective transformation. Under the projective transformation, straight lines in the scene appear straight in the images. In this paper, a scene and camera setup where captured images are related by the projective transformation is considered.

Given a set of images of a scene taken by a camera from slightly different viewpoints and/or view directions, we first register the images and then fuse the registered images in such a way as to maximize overall image contrast. This operation is useful in close-range imagery in order to increase overall image details. A camera can focus on a plane in a scene. As a result, only scene parts falling in the focus plane appear sharp. Scene parts in front of or behind the focus plane appear blurred. Often critical information needed to analyze a scene could be missing due to image blurring. To create an image that is sharp everywhere, it is suggested to capture images of the scene at different focus levels and fuse the images.

In the following sections, after reviewing relevant literature on image registration and image fusion, image registration using the projective geometry is described. Then, image fusion by cutting high-contrast regions in the images and smoothly stitching them together is outlined. Next, experimental results are presented and analyzed. Finally, the results are summarized and lessons learned are mentioned.

## 2. BACKGROUND AND PROBLEM DESCRIPTION

### 2.1. Image Registration

Image registration has been an active area of research for nearly four decades. Initial methods had only two parameters, which allowed translational differences between images [1]. With the development of invariant moments [10,18] and point landmarks [14], the methods were extended to handle translational and rotational differences between images. Nonlinear methods were later introduced to enable registration of images with local geometric differences by optimization methods [2] and through approximation [6] and piecewise [4] means. Comprehensive reviews of image registration methods are given in [3,9].

Image registration accuracy is controlled by: 1) the accuracy correspondence is established between a number of point landmarks in the images and 2) the accuracy of the transformation function modeling the geometric difference between the images. If geometries of two images are related by a nonlinear transformation, a linear model cannot register the images accurately no matter how accurate the landmark correspondences are. On the other hand, if the geometries of two images are related by a linear transformation, use of a nonlinear transformation may not improve the registration accuracy and it may actually worsen the registration accuracy compared to the linear transformation. The key in achieving a highly accurate registration is to accurately locate corresponding landmarks in the images and use a transformation function that truly represents the geometric difference between the images.

In this paper the projective transformation will be used to relate the geometries of two images. We assume the scene is rather flat and the images are obtained by a camera with small changes in viewpoint and view angle. Distances of scene points to the camera are allowed to vary considerably though, enabling the camera to view nearby as well as distant scene points. Although a large percentage of remote sensing and surveillance images fall into this category, to the author's knowledge no published work has used projective transformation to register images. This paper explores use of projective transformation in image registration.

### 2.2. Image Fusion

Although image analysis systems can benefit greatly from image fusion, image fusion is rarely used as a tool to analyze images. A great deal of effort has gone into combining information in registered images. The images used in image fusion are, therefore, limited to those captured by stationary cameras or cameras capturing registered images. In order to take full advantage of image fusion techniques, in this paper the fusion process is coupled with image registration, allowing information in images taken by handheld and mobile cameras to be fused.

Image fusion techniques either work in the spatial domain or in the frequency domain. Methods that work in the spatial domain work directly with image intensities. Methods that work in the frequency domain transform the images and work with the image frequencies. Jones and Nikolov [13] describe an image fusion method that works in the spatial domain. They find the intensity at a point in the output from a weighted sum of intensities of corresponding pixels in the input. Petrović and Xydeas [16] use image gradients to fuse images. A multiresolution approach is taken where at each resolution, input images are represented by gradient maps and the gradient maps are combined to a new gradient map. Then, a reconstruction process similar to the wavelet approach is taken to create the output from the combined gradient map. Wang et al. [17] find the wavelet transform of the images and fuse the transform coefficients. The largest coefficients or a weighted sum of the coefficients of the transformed images are combined to create the fused transform image. The inverse transform of the fused transform image is then computed to find the fused image.

The method proposed here works in the spatial domain. An image is split into small blocks and in each block the image containing the highest contrast is selected and the selected images are smoothly blended together to produce an image that is highly informative everywhere. Image contrast is used as the relevant information to fuse multifocus images. Multifocus images have been previously fused using artificial neural networks [15].

## 2.3. Problem Description

Two or more images of a rather flat scene captured by a camera at different focus levels, view-points, and view angles are available. The images can be considered those captured by a handheld camera focusing on different parts of a scene. It is assumed that changes in scene depth compared to distances of scene points to the camera are negligible. We would like to 1) register the images and 2) fuse the registered images in such a way to maximize overall image contrast.

# 3. PROJECTIVE REGISTRATION

The first task in multifocus image fusion is to register the images so that a scene point will have the same coordinates in all the images. Image registration is achieved by locating a set of unique landmarks in one of the images and finding the corresponding landmarks in the remaining images. From the correspondences, the best four satisfying the projective constraint are identified and used to calculate the projective parameters. Registration is carried out two images at a time. One of the images will be used as the *reference* and the remaining images will be one by one registered to it. An image that is registered to the reference image will be called the *target* image.

## 3.1. Landmark Selection

Landmarks are considered unique points in an image. Uniqueness is required in order that the same landmarks can be reliably located in the target images. Points where lines or edge intersect are unique. Such points can be located in an image by finding image regions where the sum of gradients in the directions normal to each other is locally maximum. The *inertia matrix* defined by

$$\mathbf{C}(x,y) = \begin{bmatrix} \overline{I_x(x,y)I_x(x,y)} & \overline{I_x(x,y)I_y(x,y)} \\ \overline{I_y(x,y)I_x(x,y)} & \overline{I_y(x,y)I_y(x,y)} \end{bmatrix}$$

measures image gradients normal to each other in a neighborhood. In the above formula, $I(x,y)$ denotes the intensity at $(x,y)$, $I_x$ and $I_y$ denote intensity gradients in $x$ and $y$ directions, and the overbar implies sum over a small circular neighborhood centered at $(x,y)$. The inertia matrix has two eigenvectors and two eigenvalues. The eigenvector corresponding to the larger eigenvalue represents the direction where the sum of gradient magnitudes is maximum within the circular region under consideration. The second eigenvector shows the direction normal to the first. If a local neighborhood contains a well-defined corner, it contains considerable gradients in directions normal to each other and will produce two large eigenvalues. Therefore, if both eigenvalues of an inertia matrix are relatively large, the center of the neighborhood is taken as a point landmark.

Because calculation of eigenvalues at all image pixels is wasteful, and also because corners do not exist in homogeneous areas, search for the landmarks is carried out among the image edges. An edge point where its eigenvalues are larger than those at edge points adjacent to it is taken as a landmark. To avoid selection of weak landmarks, an edge point is taken as a landmark if both of its eigenvalues are larger than a prespecified threshold value. To avoid selection of landmarks that are very close to each other, once a landmark is selected, landmarks closer than a prespecified distance to it are not selected. This process will produce landmarks that are well spread over the image domain. The process to select landmarks in an image can be summarized as follows:

1. Find edges in the image.
2. At each edge point:
    a. Calculate the inertia matrix and find its eignvalues.
    b. If both eigenvalues are larger than those at adjacent edges, add the edge point to the list of landmarks.
3. Sort the list in the descending order of the smaller eigenvalue of the landmarks. Then do the following:
    a. Remove the top landmark in the list and report it.
    b. Remove from the list all landmarks that are within a prespecified distance of the reported landmark.
    c. If the desired number of landmarks is already reported or no more landmarks exist in the list, exit. Otherwise go to Step 3a.

## 3.2. Landmark Correspondence

Corresponding landmarks in two images of a scene can be determined in two ways. They can be determined by selecting landmarks in the reference and target images separately and finding the correspondence between them. This process is known as *point pattern matching* [12]. Alternatively, the correspondences can be determined by selecting templates centered at the landmarks in the reference image and searching for the templates in the target image. In this paper, the latter method is chosen for two reasons. First, the method uses information in larger neighborhoods to find the correspondences, thus, the obtained correspondences are more reliable. Second, since the images to be registered have only small translational and rotational differences, template matching can efficiently find the correspondences. We will select a circular template centered at landmark $(x,y)$ in the reference image and search for it in the target image in a small circular search area centered at $(x,y)$ using correlation coefficient as the similarity measure. This process is known as *correlation template matching* and is described elsewhere in detail [11].

### 3.3. Projective Transformation

Image acquisition is a projective process. Under the projective transformation, straight lines in the scene are mapped to straight lines in an image of the scene. This, of course, requires that lens distortions do not exist, or if they exist, they are removed by a decalibration process [7]. Two images of a flat scene are also related by a projective transformation because straight lines in the scene are mapped to straight lines in both images and so straight lines in one image appear straight in the other. Denoting coordinates of corresponding points in the reference and target images by $(x,y)$ and $(X,Y)$, respectively, the relation between two images of a rather flat scene can be written as

$$x = \frac{AX + BY + C}{DX + EY + 1}$$
$$y = \frac{FX + GY + H}{DX + EY + 1}.$$

This projective transformation has eight unknown parameters, which can be determined if the coordinates of 4 corresponding point landmarks in the images are known. We first determine about ten strong and well dispersed landmarks in the reference image and find the correspondences in the target image by template matching. Some landmarks selected in the reference image may not exist in the target image. Therefore, fewer than ten correspondences may be found. The coordinates of corresponding landmarks may then be used to determine parameters *A* through *H* of the transformation by the least-squares method. A better accuracy can be achieved if instead of using all the correspondences the best four are used. Some correspondences may contain positional errors due to the digital nature of images and inaccuracies in template matching. The four correspondences best satisfying the projective constraint will be used to determine the transformation parameters.

Suppose from one set of four correspondences parameters *A–H* are computed. Then, given a landmark with coordinates $(X_i,Y_i)$ in the target image, the coordinates of the corresponding landmark in the reference image $(x'_i,y'_i)$ can be determined using the above relations. We take the best set of four correspondences to be the one that minimizes

$$E = \sum_{i=1}^{n} \left\{ (x_i - x'_i)^2 + (y_i - y'_i)^2 \right\}^{1/2}.$$

$n$ shows the number of available correspondences. The sum of distances rather than the sum of squared distances is used to reduce the effect of possible wrong or inaccurate correspondences in selecting the best four correspondences. Note that the process uses the coordinates of four correspondences to find the projective parameters and finds the four that most closely match the correspondences under the projective constraint.

## 4. IMAGE FUSION BY IMAGE BLENDING

We would like to cut pieces of each image that are well-focused and smoothly stitch them together to create an image that appears well-focused everywhere. To achieve this, the image domain is partitioned into uniform blocks and within each block the image that is best focused is selected. Therefore, each block will have an associating image and an image could be associated with 0, 1, or more blocks depending on how well-focused it is. The simplest method will cut the well-focused blocks from the images and stitch them together to create the fused image. This, however, will produce an image where the boundary between two adjacent blocks may appear very different in contrast. To smooth out the boundary between adjacent blocks, instead of cutting and stitching the image blocks, the entire images are blended with weights that monotonically decrease from the block centers. Monotonically decreasing weight functions that approach zero rapidly will be used to ensure that the effect of a selected image remains mostly within the block it belongs to.

The proposed image fusion method has a number of parameters. One parameter is the block size. As the size of image blocks decreases more blocks are obtained, so the process becomes slower. As the size of blocks increases, the process becomes faster, but it may miss small but high-contrast regions in the images. In the following, we will find the optimal block size to maximize overall image contrast while achieving a required speed. A second free parameter shows the rate with which the weight functions approach zero. This is the width of the radial functions defining the weight functions. We let this parameter be proportional to the width of the blocks. Therefore, when smaller blocks are selected, narrower weight functions will be used and when larger blocks are selected proportionately wider weight functions will be used.

Contrast will be measured using intensity gradient magnitude. Since corresponding blocks in registered images show the same scene parts, the image containing the largest number of high gradient pixels within a block will be the image with the highest contrast within that block. Therefore, assuming $N$ images are given and each image has been subdivided into an array of $n_r \times n_c$ blocks, assuming $k$ and $l$ denote the row and column indices of a block, and letting $\boldsymbol{I}_{kl}$ denote the image that contains the highest contrast among the $N$ images within block $kl$, we compute the fused image $\boldsymbol{O}(x,y)$ from

$$\boldsymbol{O}_{xy} = \sum_{k=1}^{n_r} \sum_{l=1}^{n_c} W_{kl}(x,y) \boldsymbol{I}_{kl}(x,y), \tag{1}$$

where $W_{kl}(x,y)$ is the value of the weight function centered at the $kl$th block at location $(x,y)$, and $\boldsymbol{I}_{kl}(x,y)$ represents the intensity or color of the image representing block $kl$ at location $(x,y)$. Once the “best” image for each block is selected, its actual intensity or color values are used in the above formula. Note that the value at $(x,y)$ in the output is determined from the weighted sum of the input values at $(x,y)$. The contribution or weight of the image selected for a block is much larger than the contribution of other images. The intensity or color at a pixel within a block in the output, therefore, is very close to the intensity or color of the pixel in the image selected to represent the block. In the following, rational Gaussian (RaG) functions [8] will be used to blend the image intensities or colors. RaG blending functions are defined by

$$W_{kl}(x,y) = \frac{G_{kl}(x,y)}{\sum_{m=1}^{n_r} \sum_{n=1}^{n_c} G_{mn}(x,y)},$$

where $n_r$ and $n_c$ denote the number of image blocks vertically and horizontally, and $G_{kl}(x,y)$ represents the value of a Gaussian of height 1 centered at the $kl$th block at $(x,y)$:

$$G_{kl}(x,y) = \exp\left( -\frac{(x - x_{kl})^2 + (y - y_{kl})^2}{2\sigma^2} \right).$$

$(x_{kl}, y_{kl})$ are the coordinates of the center of the $kl$th block, and $\sigma$ is the standard deviation of the Gaussians. In the following, we will refer to $\sigma$ as the *width* of the blending functions and let it be equal to half the width of the image blocks ($w$) and determine the optimal width as follows:

1. Set $w$ to some initial values determined experimentally and let $\Delta$ represent the increment or decrement in block size.
2. Determine the sum of gradient magnitudes within block $kl$ in each image for $k = 1,\ldots,n_r$ and $l = 1,\ldots,n_c$ and let the image having the highest sum within block $kl$ be $\boldsymbol{I}_{kl}$.
3. Find the sum of gradient magnitudes of the image obtained by fusing the images.
4. Increment or decrement $w$ by $\Delta$ in the gradient-ascent direction of the gradient sum and repeat Steps 2 and 3 until either $w$ becomes equal to the smallest allowed block size or the image with the highest gradient sum is reached. Denote the obtained $w$ by $w_{max}$.
5. Find the image best focused within each block in the image domain according to Step 2 when letting $w = w_{max}$. Then, create a new image by blending the selected images with weight functions of width $\sigma_{max} = w_{max}/2$ centered at the corresponding blocks.

Parameter $\Delta$ determines the speed of computation. A smaller $\Delta$ will produce more blocks, increasing the computation time. On the other hand, a larger $\Delta$ may produce very large blocks, missing small but high contrast regions. A smaller $\Delta$

will produce a more optimal solution at the cost of a slower speed. In our experiments, $\Delta$ was set to 16 pixels and the initial value for $w$ was set to 64 pixels. The width of Gaussians is set to half the width of the blocks. By using much narrower Gaussians the boundary between individual blocks becomes visible and by using much wider Gaussians the effect of a block may stretch beyond the adjacent blocks, reducing overall image contrast.

## 5. RESULTS AND DISCUSSION

In this section, examples of the proposed image registration and fusion are given and evaluated. Figure 1 shows five images of a scene containing a number of objects (bottles and cartons) obtained at five different focus levels by a handheld camera. The images were obtained by focusing the camera on individual objects from front to back. The distances of the camera to the objects are at least several times larger than the widths of the objects. The objects are lined up in a plane, therefore, the scene can be considered approximately planar, making it possible for the projective transformation to register the images.


(a) (b) (c)

(d) (e)

Figure 1. (a)–(e) Images of a 3-D scene obtained at different focus levels by a handheld camera.

To increase the similarity between image pairs and increase the correspondence accuracy, the third image was used as the reference and the remaining images were one by one registered to it. Figures 2(a)–(d) show the first, second, fourth, and fifth images when warped to the geometry of the third image. The fused image is shown in Figure 2(e). This is the final result. Figure 2(f) shows the largest rectangular area of Figure 2(e) covering the scene.

For the process to work well, the images should not contain occluded points. That is, a point in one image should not be hidden in other images. This necessitates that if a 3-D scene is imaged, viewpoint and view angle differences between the acquisitions be relatively small. Also, the scene being imaged should be relatively flat. That is, deviation of scene points from an approximating plane should be much smaller than the distances of the scene points to the camera. This ensures that the geometries of the images are related by projective transformations.

A second example is given in Figure 3. Figures 3(a)–(d) were captured by a handheld camera of a truck scene. Each image was obtained by focusing the camera on one of the trucks. Image 3(c) was used as the reference and the other images were registered to it. The registration results are shown in Figures 3(e)–(g). Fusing the registered images resulted in image 3(h). This is the final result. All four trucks now appear sharp. Some minor misregistration spots can be observed in the fused image due to the fact that the scene is not quite planar. However, since high-contrast points in an image belong to or fall near the focus plane, and the fusion process cuts high-contrast regions from the images and stitches them together, misregistration errors do not appear in the fused image if a sufficiently small block size is used.

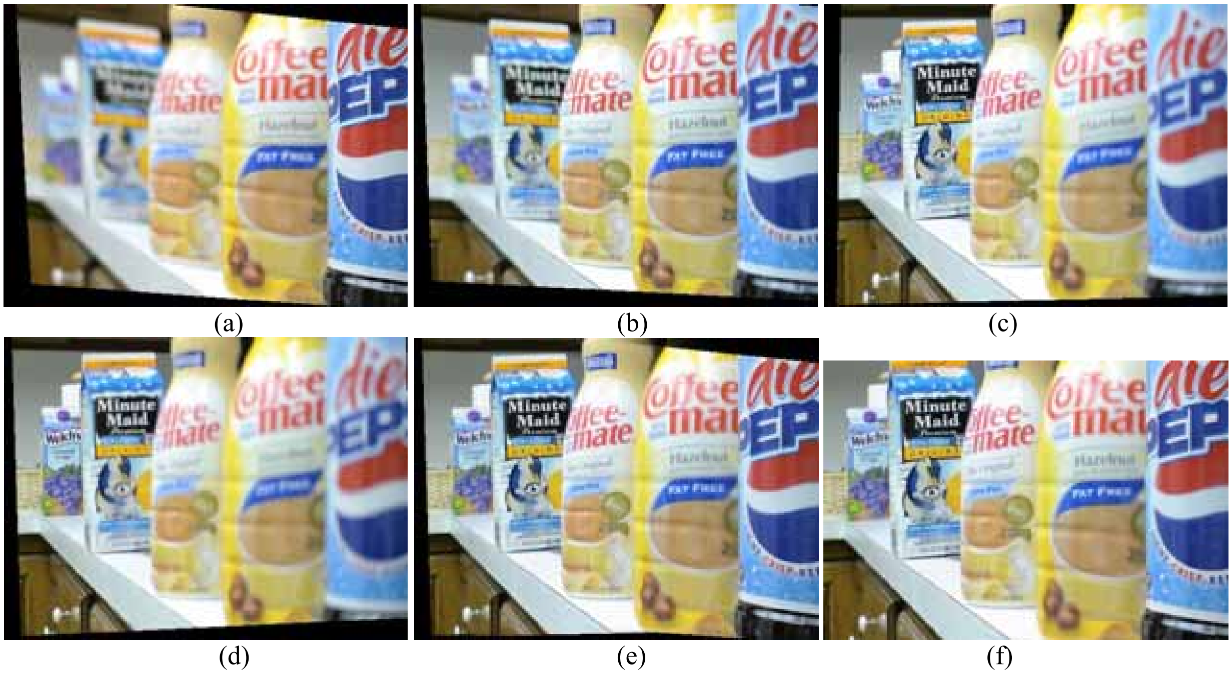



Figure 2. (a)–(d) Registration of images 1(a), 1(b), 1(d), and 1(e) to image 1(c). (e) Fusion of images (a)–(d). (f) The largest rectangular area in (e) covering the scene.

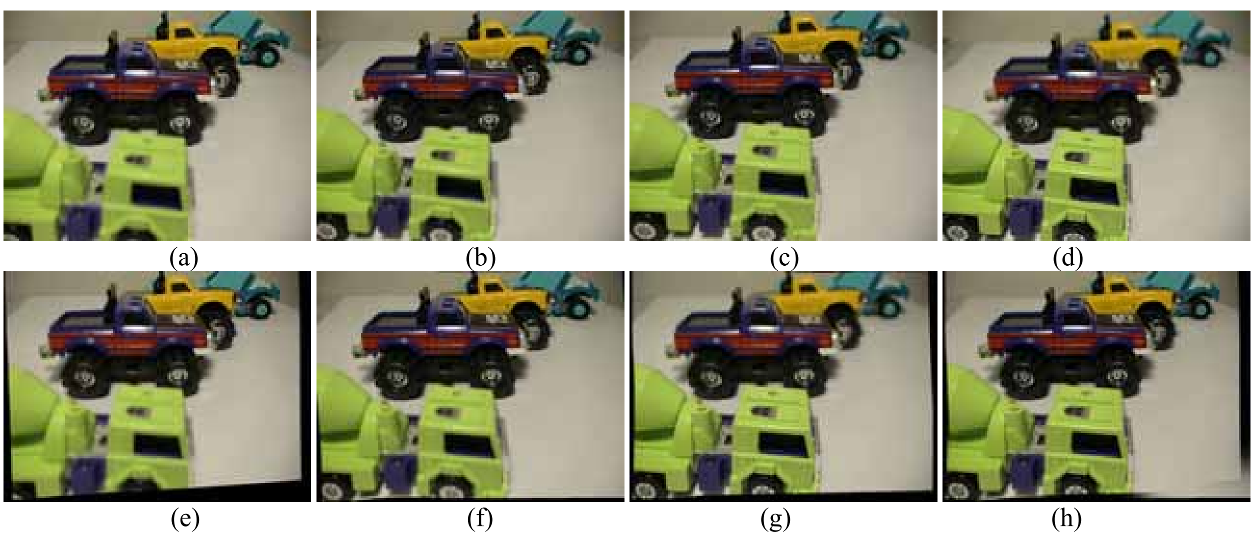
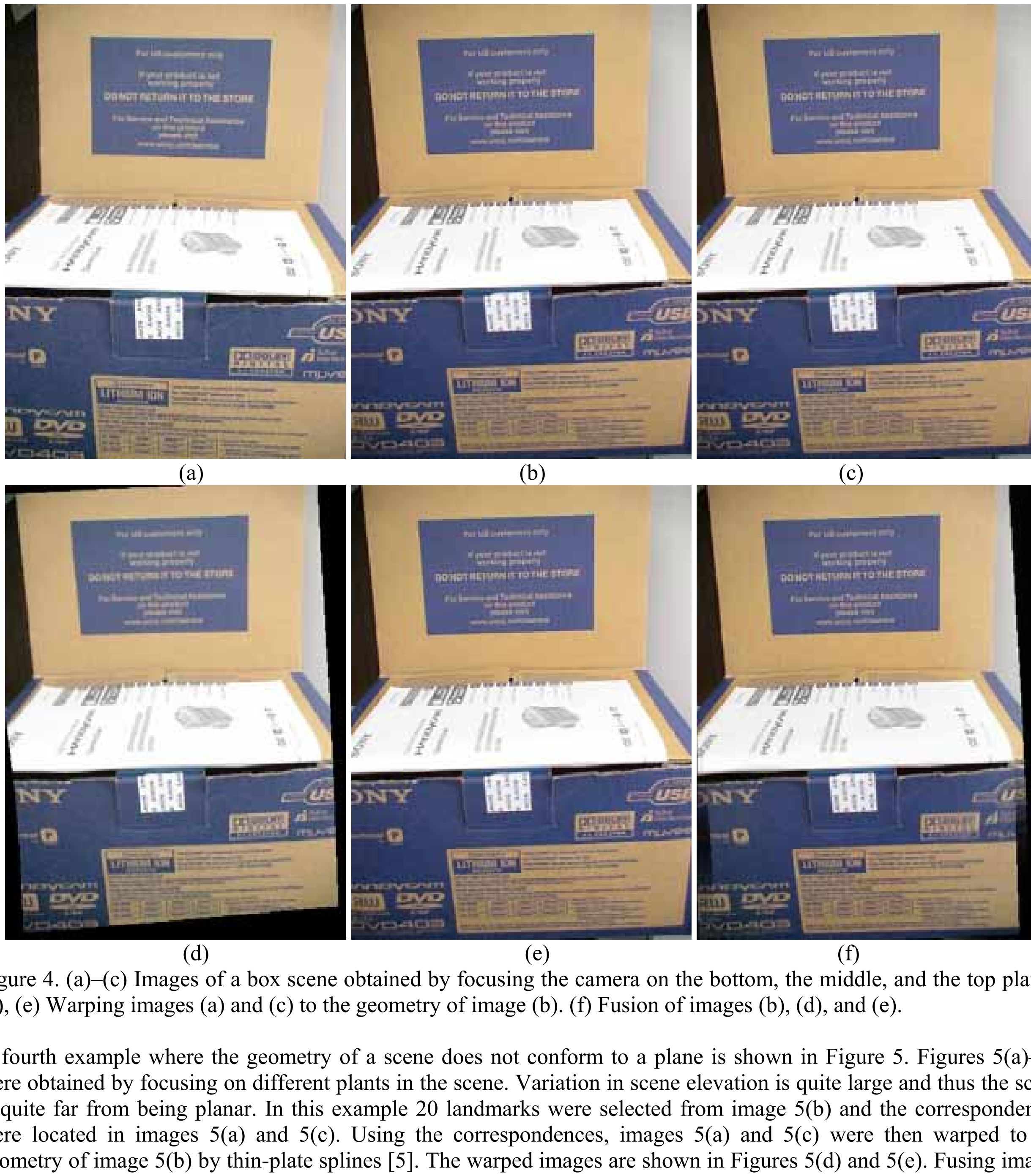



Figure 3. (a)–(d) Multifocus images of a scene containing four trucks. (e)–(g) Images (a), (b), and (d) warped to register to image (c). (h) Fusion of images (c), (e), (f), and (g).

Considering that the proposed fusion algorithm follows a local process, when scene parts fall on or near the focus plane, they appear sharp. Therefore, image regions appearing sharp in an image can be considered scene parts approximately falling in the focus plane. This means, images of a complex scene can be registered and fused by a combination of projective transformations. To demonstrate this, an example is given in Figure 4. The scene contains a box with its top cover open. Three planar faces can be observed. The top and the bottom planes are vertical and approximately parallel to the image plane. The middle plane is horizontal. Three images were obtained, one focusing on the top plane, one focusing on the bottom plane, and one focusing midway between the two to capture details in the horizontal plane. Four corresponding points were selected in each plane and a projective transformation was determined from each set of four correspondences. The transformations were then blended with weight functions inversely proportional to their distances to the centers of the three planes. Warping images 4(a) and 4(c) to the geometry of image 4(b) resulted in images 4(d) and 4(e). By fusing images 4(b), 4(d), and 4(e), image 4(f) was obtained. This is the result of registering and fusing images 4(a)–(c).




(a) (b) (c)

(d) (e) (f)

Figure 4. (a)–(c) Images of a box scene obtained by focusing the camera on the bottom, the middle, and the top planes. (d), (e) Warping images (a) and (c) to the geometry of image (b). (f) Fusion of images (b), (d), and (e).

A fourth example where the geometry of a scene does not conform to a plane is shown in Figure 5. Figures 5(a)–(c) were obtained by focusing on different plants in the scene. Variation in scene elevation is quite large and thus the scene is quite far from being planar. In this example 20 landmarks were selected from image 5(b) and the correspondences were located in images 5(a) and 5(c). Using the correspondences, images 5(a) and 5(c) were then warped to the geometry of image 5(b) by thin-plate splines [5]. The warped images are shown in Figures 5(d) and 5(e). Fusing images 5(b), 5(d), and 5(e), image 5(f) was obtained. This is the result of registering and fusing images 5(a)–(c). If the scene cannot be approximated by a plane, a proper nonlinear transformation should be used to register the images. Once the images are registered, the proposed fusion algorithm can be used to combine the images into one that appears well-focused everywhere.

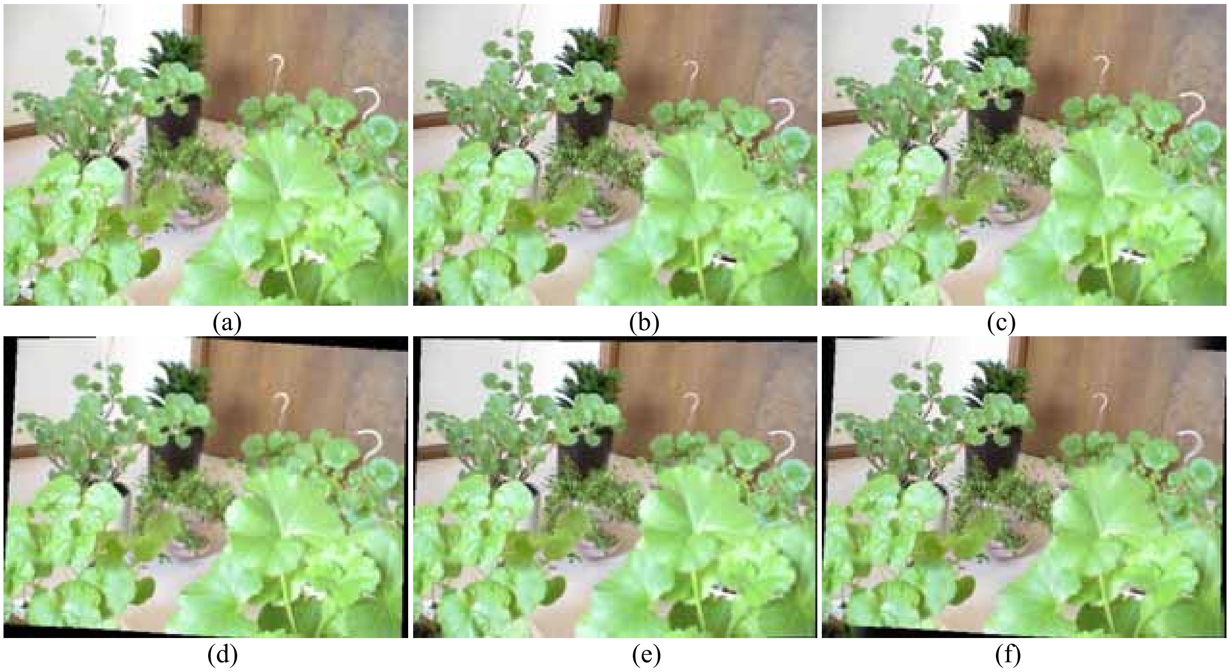



Figure 5. (a)–(c) Images at different focus levels of a plant scene. (d), (e) Warping images (a) and (c) to the geometry of image (b) by thin-plate splines. (f) Fusion of images (b), (d), and (e).

## 6. SUMMARY AND CONCLUSIONS

When an image of a 3-D scene is taken, only scene parts at the focus plane appear sharp. Other scene parts appear blurred, missing critical information that may be needed to understand the scene. If images at different focus levels of the scene can be captured, the images can be fused to produce an image that appears sharp everywhere. When a handheld camera is used or when the camera is in motion while capturing the images, the images will not be spatially aligned, making fusion of the images impossible. To enable fusion of multifocus images, a method to register the images is needed. When the camera is relatively far from the scene, the scene can be considered planar and projective transformation can be used to register the images. For more complex scenes, instead of projective transformation, thin-plate splines, multiquadrics, rational Gaussian, and other nonlinear transformation functions may be needed to register the images [19]. Once the images are registered, the proposed fusion method may be used to combine the images to maximize image contrast.

The registration method described in this paper is based on the projective imaging geometry, which is the most natural model for registering images of a relatively flat scene. Projective transformation may be used when distances of the scene points to the camera are much larger than the distances of scene points to the plane approximating them. The proposed fusion algorithm uses intensity gradient (contrast) as the relevant information to maximize overall image information in the fused image.

By combining image registration with image fusion, partially blurred images can converted into a highly detailed image, facilitating automated processes that rely on image details to understand a scene. The combined registration and fusion method is especially effective when analyzing close-range imagery containing unavoidable blurring due to image defocus.

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