Improved Fusing Infrared and Electro-Optic Signals for High Resolution Night Images

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ABSTRACT

Electro-optic (EO) images exhibit the properties of high resolution and low noise level, while it is a challenge to distinguish objects with infrared (IR), especially for objects with similar temperatures. In earlier work, we proposed a novel framework for IR image enhancement based on the information (e.g., edge) from EO images. Our framework superimposed the detected edges of the EO image with the corresponding transformed IR image. Obviously, this framework resulted in better resolution IR images that help distinguish objects at night. For our IR image system, we used the theoretical point spread function (PSF) proposed by Russell C. Hardie *et al.*, which is composed of the modulation transfer function (MTF) of a uniform detector array and the incoherent optical transfer function (OTF) of diffraction-limited optics. In addition, we designed an inverse filter based on the proposed PSF to transform the IR image. In this paper, blending the detected edge of the EO image with the corresponding transformed IR image and the original IR image is the principal idea for improving the previous framework. This improved framework requires four main steps: (1) inverse filter-based IR image transformation, (2) image edge detection, (3) images registration, and (4) blending of the corresponding images. Simulation results show that blended IR images have better quality over the superimposed images that were generated under the previous framework. Based on the same steps, the simulation result shows a blended IR image of better quality when only the original IR image is available.

Keywords: Theoretical PSF, IR image transformation, EO image edge detection, image blending.

1. INTRODUCTION

Infrared (IR) imaging systems depend on thermal contrast between target and background to generate real-time images. These systems create images by utilizing the infrared energy emitted by the objects as a result of their temperature difference with background and emissivity. Unfortunately, the created IR images have low resolution and high noise level. Therefore, accurately distinguishing objects at night is a challenging topic that has perplexed scientists and engineers for a long time. Fusing IR and electro-optic (EO) images is an effective way to solve this challenge. It combines images from two different sources to obtain a single composite image with improved resolution, low noise, and ability to see clearly at night.. Up to now, scientists have developed many efficient image fusion algorithms, such as the expectation maximization (EM) fusing algorithm [1], the discrete wavelet transform (DWT) fusing algorithm [2], and the Laplacian pyramid fusing algorithm [3]. Additionally, much literature focuses on presenting techniques for

Infrared Imaging Systems: Design, Analysis, Modeling, and Testing XXIII, edited by Gerald C. Holst, Keith A. Krapels,
Proc. of SPIE Vol. 8355, 835517 · © 2012 SPIE · CCC code: 0277-786X/12/$18 · doi: 10.1117/12.950905

estimating a high-resolution IR image via the optimized IR image system [4-5], e.g., with reduced aliasing. However, based on the existing approaches, it is still impossible to accurately distinguish the edges of different objects at night when they have a similar temperature and background.

We have proposed a novel framework to solve this challenging problem in [6]. Since EO images exhibit properties of high resolution and low noise level, the principle idea of our proposed framework was to utilize the high resolution property of EO images to help us reconstruct the corresponding edges of different objects. Assuming we had a pair of EO and IR images, then four necessary steps were required to complete this framework: (1) transform the original IR image into an IR image via the established system point spread function (PSF) and designed inverse filter; (2) detect a clean edge map of the high resolution EO image; (3) register the transformed IR image and the detected clean edge map; and (4) superimpose the detected edge map of the EO image onto the transformed IR image. In that framework, we adopted a theoretical PSF for the IR image system, which consisted of the modulation transfer function (MTF) of a uniform detector array and the incoherent optical transfer function (OTF) of diffraction-limited optics. Final simulation results showed that, with the help of the superimposed edge map, we could distinguish between objects in the transformed IR image and even small parts of a single object. Moreover, the performance was independent of the object's temperature and background. Therefore, that proposed framework could be regarded as a breakthrough with regard to night-time distinguishing of objects.

In this paper, we propose improvement on our previous framework. This new approach blends the edge-detected EO image with the transformed IR image and the original IR image. The improved framework requires four main steps: (1) inverse filter-based IR image transformation, (2) EO image edge detection, (3) image registration, and (4) blending of the corresponding images. Here, step 3) is not required when only an IR image is available. Simulation results will show that images generated using our improved framework have edges that are clearly visible and seamlessly matched with the corresponding objects. In particular, we compare the results generated by the use of EO and IR images to those generated by the use of only an IR image. The following questions will be addressed in this paper:

(1) Are there some things we can see now that we could not see before?
(2) How do the results look if we use only IR images for processing? Can we derive the best image with only IR images?
(3) Are there things we can only see partially now?
(4) Are there "false alarms"—e.g., things that should not be seen that are now seen falsely? Could this include some extraneous patterns?
(5) In summary, what are the improvements in picture quality using our framework?

The remainder of this paper is organized as follows. Section 2 is the IR image transformation process based on the previously proposed theoretical PSF and designed inverse filter. Section 3 presents the edge detection of EO images and the related image registration process. The blended image results and discussion are provided in Section 4. Finally, some conclusions and future work are addressed in Section 5.

2. IR IMAGE TRANSFORMATION

2.1 Theoretical PSF

We adopt the Russell C. Hardie *et al.* proposed theoretical PSF [7] for IR image systems, which consists of the MTF of a uniform detector array and the incoherent OTF of diffraction-limited optics.

The primary contributor is the finite detector size, and this effect is spatially invariant for a uniform detector array. We begin by considering an infrared system with this uniform detector array. We can model the effect of the integration of light intensity over the span of the detectors as a linear convolution operation with a PSF determined by the geometry of a single detector. The second contributor is the optics, and we assume an isoplanatic model for optics. Theoretical descriptions of this infrared imaging system can be found in [6-8].

We consider a particular IR imaging system as an example [7], the typical system considered is the forward looking infrared (FLIR) imager. Here, we adopt the same parameter settings as that in [7]. This systems has square detectors of size a=b=0.040mm, the imager is equipped with 100mm $f/3$ optics, the center wavelength =0.004mm and the cutoff frequency 83.3 cycles/mm are used for the OTF calculation. In Figure 1, Figure 1(a) shows the effective MTF of the detectors, |D (u, v)|, and figure 1(b) shows the diffraction-limited OTF for the optics, H (u, v). The overall system MTF is shown in Figure 1(c), and the continuous system PSF is shown in Figure 1(d).

2.2 Inverse filtering and IR image transformation

Usually direct inverse filtering is the simplest approach we can take to restoring a degraded image, which ignores the noise term in the model and forms an estimator in the form of [9]

$$\hat{F}\,(u,v) = \frac{G\,(u,v)}{H\,(u,v)} \tag{1}$$

where G (u, v) is the degraded image and H (u, v) is the system PSF. Then, we obtain the corresponding estimate of the image by taking the inverse Fourier transform of $\hat{F}\,(u,v)$.

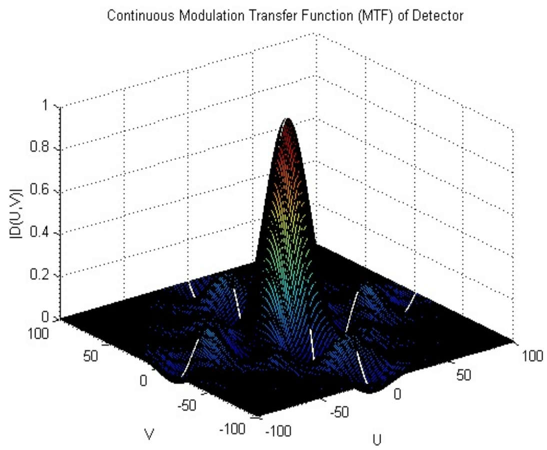
In this paper, we assume the proposed theoretical PSF to be H (u, v) in the designed inverse filter. If we let the original IR image pass through the designed inverse filter, then we can obtain a transformed IR image with temperature information of the objects. Figure 2 shows two examples of the IR image transformation based on the designed inverse filter.

3. IMAGE EDGE DECTION AND REGISTRATION

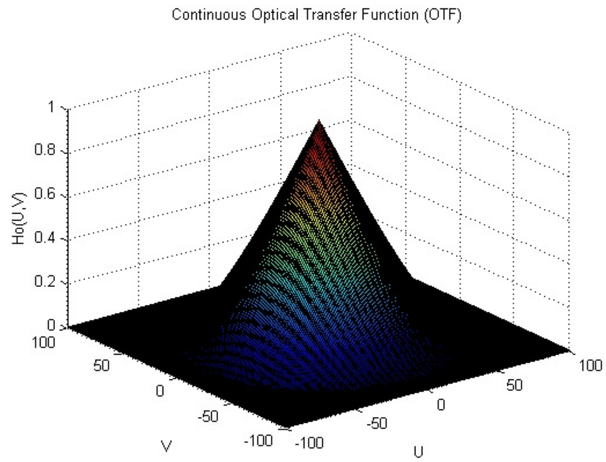
3.1 Image edge detection

Image edge detection refers to the process of identifying and locating sharp two-dimensional discontinuities in an image. The discontinuities are abrupt changes in pixel intensity that characterize boundaries of objects in a scene. By far, edge detection is the most common approach for detecting meaningful discontinuities in intensity values. There are many edge operators to perform edge detection, e.g., Sobel, Prewitt, Roberts, Laplacian of a Gaussian (LoG), Zero crossings and Canny. So far the Canny edge detection algorithm [10] has been known as the optimal edge detector. The detailed description of the Canny edge detector can be found in [10], and the syntax for the Canny edge detector in Matlab is

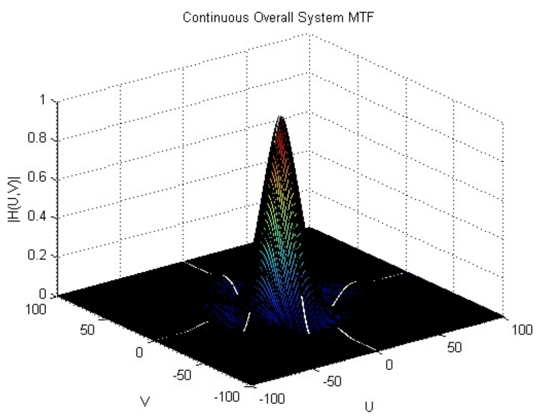
[g, t] = edge (f, 'canny', T, sigma) (2)



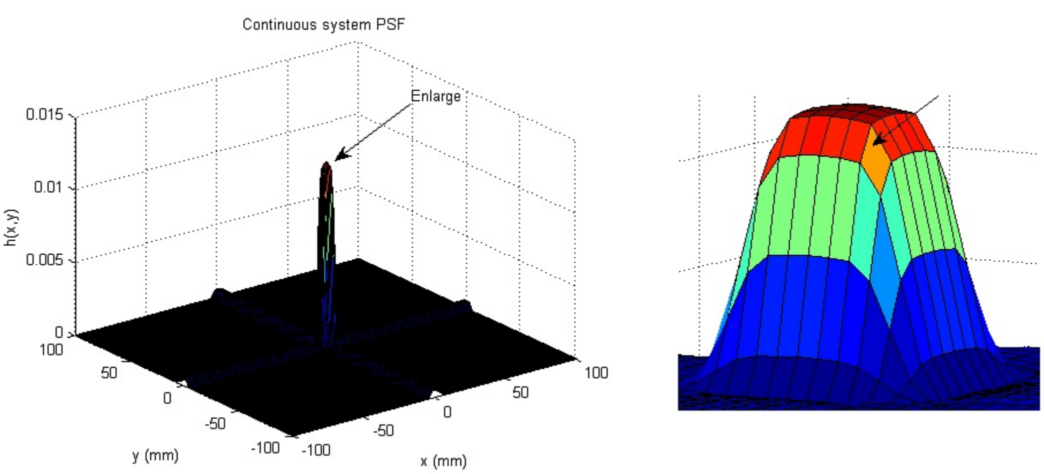
(a) Effective MTF of the detectors in the FLIR imagers



(b) Diffraction-limited OTF of the optics

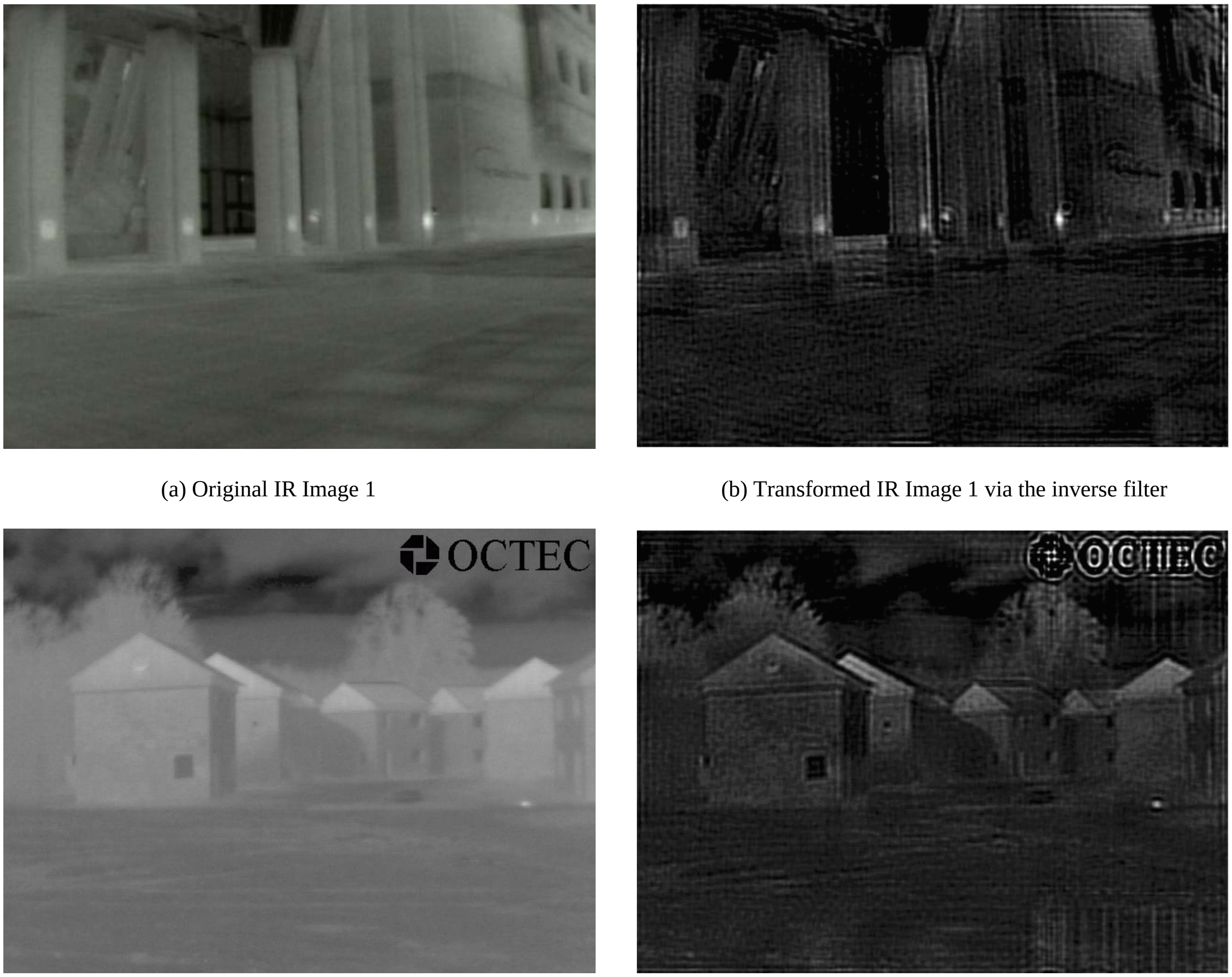


(c) Overall system MTF



(d) Overall continuous system PSF (right side figure is the enlarged PSF)

Figure 1. FLIR system parameters.



(a) Original IR Image 1

(b) Transformed IR Image 1 via the inverse filter

(c) Original IR Image 2 (public image)

(d) Transformed IR Image 2 via the inverse filter

Figure 2. Examples of the IR image based on the designed inverse filter.

where f is the original EO image, T is a vector, T = [T1, T2], containing the two thresholds of the preceding procedure, and sigma is the standard deviation of the smoothing filter. We can change these parameters so as to produce clean edge maps. Here T1=0.04 and T2=0.09.

Figure 3 shows two edge detection results of EO images via the Canny edge operator, where sigma is chosen to be the default value 1. Seen from the obtained results, we can find out that the edge-detected images are clean, and results cover all essential information in original EO images.

3.2 Image pair registration

Image registration methods, which seek to align two or more images of the same scene, generally consist of the following basic steps: 1) detect features, 2) match corresponding features, 3) infer geometric transformation, and 4) use the geometric transformation to align one image with the other. In this paper, we adopt the cp2tform function from the Matlab image processing toolbox to do the manual image pair registration. The more complicated image registration

(a) Original EO Image 1

(b) Detected edge of EO Image 1

(c) Original EO Image 2

(d) Detected edge of EO Image 2

(c) Detected edge of IR Image 2

Figure 3. Two edge detection results of EO images via the Canny edge operator, where sigma is the default value 1.

processes (e.g., image registration involves shift, rotation and transformation), are beyond the scope of our paper. In some particular cases, we could complete a partial image registration rather than the whole image registration. We could even adopt other methods to help obtain the exactly aligned images (e.g., image warping).

4. BLENDED IMAGE RESULTS

The last step of our framework is to blend the edge-detected EO image with the transformed IR image and the original IR image. On one hand, in order to make the blended edge seamlessly match with its corresponding object, we let the edge-detected image pass through a small size low pass filter (e.g., 2 by 2). On the other hand, in order to make sure the superimposed edge is not prominent in the blended image, we set the pixel value of the detected edge to be 0.4 rather than its default value 1.

In this paper, we adopt the alpha blending process [11] to achieve the fourth step. Two images before blending are read in the variable "a" and "b", respectively. Then, the two images are blended and stored in the variable "c" using the formula

$$c = (1 - \alpha) \times a + \alpha \times b \tag{3}$$

During this process, we first blend the transformed IR image with the original IR image, and then we blend the obtained result with the edge-detected image. Here, we fix the blending fraction's values to be 0.8 and 0.01, respectively. Figure 4 shows two blended images that are generated with both EO and IR images. Based on the same steps, Figure 5 shows a blended image that is generated when only original IR image is available. Seen from the obtained results, we can clearly see the seamless edge in the blended images and accurately distinguish objects at night via the superimposed edge, especially for objects with a similar temperature, and tiny parts of any object, which are extremely difficult or even impossible based on traditional object distinguishing approaches.

Now, we are able to answer the questions in Section 1 as follows:

1) We can clearly see the edge of each object, which will help distinguish objects at night. We also can see the edge of a tiny part of any object, which seems to be impossible using the previous methods. Moreover, we can see the edge of any color gas (e.g., smoke) or liquid and, in some particular cases, we can even see the edge of any colorless liquid or gas. Blending the transformed IR image (temperature information) with the original IR image makes the final IR image look "sharper" than that of the original IR image only.
2) Generally speaking, if only IR images are available, we can use the same parameter settings to complete the proposed three-step framework (without registration) and obtain similar blended results as those of available EO images. However, the detected edge of an object, such as the edge of its shadow area rather than the real object, is not accurate, and it is impossible to detect the shape of smoke (gas) only based on the original IR image only (see results of "OCTEC" image).
3) There is nothing we can see partially if both EO and IR images are available. However, if only IR images are available, we can only see partially gas/smoke—e.g., we can only see a light point from blended "OCTEC" IR image.
4) If we have both EO and IR images, there are no "false alarms." However, if only IR images are available, sometimes there are "false alarms"—e.g., we detected the edge of its shadow area rather than the house in

the "OCTEC" IR image, and we could only see the light point of a fire but could not see the edge of its smoke. We think the shadow area belongs to one kind of the extraneous pattern.

5) Comparing the results of both EO and IR images with that of only the IR image, our proposed framework can help accurately distinguish any object in the IR image. In addition, the improved framework can make the superimposed edge seamlessly match with the original objects, and the reduced edge's value can ensure that the superimposed edge is not prominent in the blended image.

5. CONCLUSIONS AND FUTURE WORK

It is a challenge to accurately distinguish objects with the IR image, especially objects with a similar temperature or tiny parts of any object. Therefore, in contrast to the traditional approaches used in image fusing, we blended the edge-detected EO image with the corresponding transformed IR image and the original IR image. This was achieved by the alpha blending process. Simulation results showed that we could clearly distinguish objects, and even small parts of a single object, regardless of their temperature. Generally speaking, if only IR images are available, our framework could achieve similar performances to those of available EO images, except for some special objects or objects that have some extraneous patterns. On the contrary, we will consider how to utilize merits of IR images to improve EO images in the future, e.g., include objects' temperature information in EO images.

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(a) Blended result of IR Image 1

(b) Blended result of IR Image 2

Figure 4. Blended images generated with both EO and IR images.

Figure 5. Blended result of IR image 2 when only original IR image is available.