Superresolved imaging of remote moving targets

Javier García

Departamento de Óptica, Universitat de Valencia, c/Dr. Moliner, 50, 46100 Burjassot, Spain

Zeev Zalevsky

School of Engineering, Bar-Ilan University, Ramat-Gan 52900, Israel

Carlos Ferreira

Departamento de Óptica, Universitat de Valencia, c/Dr. Moliner, 50, 46100 Burjassot, Spain

Received October 4, 2005; revised December 4, 2005; accepted December 4, 2005; posted December 7, 2005 (Doc. ID 65164)

We present a superresolving approach that allows one to exceed the diffraction limit and recover highly resolved contours of moving targets from a sequence of low-resolution images. The presented approach is suitable for remote sensing applications. The resolution decoding algorithm that is used to recover the high-resolution features of the target can be run partially via optical means and that way can be used to reduce the required computational complexity.

OCIS codes: 100.6640, 100.3020.

There is a large set of approaches used to detect moving targets by use of statistical and image-processing algorithms.[1–7] Although this Letter also deals with detection of moving targets, its focus is not on the development of new algorithms with a low false alarm rate and a high probability of detection but is rather on exceeding the diffraction-limiting resolving capabilities of the imaging sensor (the diffraction limit and not a geometrical limitation).

Superresolution is one of the most fascinating and applicable fields in optical data processing. The existing superresolving approaches are based on the basic understanding that a high-resolution spatial distribution can be obtained if *a priori* information on the object exists, which allows one to compromise appropriately on other dimensions in exchange for a gain in spatial degrees of freedom.[8–10] The sacrificed axes that are used to multiplex the additional spatial resolution that is to be gained can be, for instance, time,[11] wavelength,[12] or polarization.[13] Time multiplexing is perhaps the most common approach to superresolution that overcomes the limitations of diffraction. In this technique, which may be performed in an all-optical manner, an encoding periodic grating should be projected and shifted on top of the inspected object, while an identical decoding grating should be positioned and shifted in front of the detector. The time-averaging results in a high-resolution image.[12,14] In real remote imaging applications it is not possible to project the grating, and thus such a configuration is not practical.

In this Letter we suggest an approach that may be easily used for remote imaging applications and produces highly resolved information on a moving target. Prior to the detection process, the algorithm requires mapping of the background by imaging it with high resolution. This calibration process is done only once. Then, a low-resolution imaging system can be permanently put in place and used for high-resolution imaging of moving targets. The moving target passes in front of the background while images are captured by the low-resolution sensor. Then, a decoding algorithm is applied in which the high-resolution reference background is used as the decoding function. The images are integrated in time, and eventually the low-pass component of the decoded and integrated image is digitally removed (for instance, by using morphological image processing operations). The result is that the contours of the remote moving target are seen with high resolution corresponding to the resolution of the background in the calibration process. The improvement in resolution can be significant and may be the difference in determining whether the target is to be identified and (or) recognized. Special digital detection algorithms for moving targets can be used in addition to superresolved imaging. Note that a high-resolution reference image can be captured using a different sensor than the one used for low-resolution imaging (e.g., a sensor positioned on a satellite can be used to capture the high-resolution reference image while the camera of a cellular phone can be used for the low-resolution imaging). Also, although the straightforward application of superresolution is imaging with visible and infrared sensors, this technique can be applied to other spectral sensing bands as well.

We denote the background scenery as $b(x)$, the target as $s(x)$, and the blurring point spread function (generated due to blurring of the optics and diffraction) as $p(x)$. We denote by $s_1(x)$ a binary function with the shape of the target but with a gray level of one:

$$s_1(x) = \begin{Bmatrix} 1 & s(x) > 0 \\ 0 & s(x) = 0 \end{Bmatrix}. \tag{1}$$

Note that all variables are optical intensities and the imaging system is operating under incoherent illumination.

The intensity of the target moving in front of the scenery can be expressed mathematically as

$$t(x,t) = [1 - s_1(x - vt)]b(x) + s(x - vt), \tag{2}$$

where v is the target's velocity. The blurred intensity $I(x,t)$ captured by the imaging camera equals

$$I(x,t) = \int t(x',t)p(x - x')\mathrm{d}x'. \tag{3}$$

Substituting Eq. (2) into Eq. (3) yields

$$I(x,t) = \int b(x')p(x - x')\mathrm{d}x' - \int s_1(x' - vt)b(x')p(x - x')\mathrm{d}x' + \int s(x' - vt)p(x - x')\mathrm{d}x'. \tag{4}$$

The decoding process involves multiplication of $I(x,t)$ by the high-resolution *a priori* known background $b(x)$, shifting the product back a distance of vt (to obtain the reconstructed target in the same spatial position) and summing all the images captured along the observation period (the sequence of images that we use for superresolution). Thus

$$R(x) = \int I(x + vt,t)b(x + vt)\mathrm{d}t, \tag{5}$$

where $R(x)$ is the reconstructed image. The relative shift of two images in the sequence (related to vt) can easily be found by correlating them with each other (although V is unknown). This is done as part of the decoding processing step.

By substituting Eq. (4) into (5) and changing the integration variables from x' and t into $x''=x'-vt$ and t, one obtains

$$R(x) = \int b(x+vt)\left[\int b(x''+vt)p(x-x'')\mathrm{d}x''\right]\mathrm{d}t - \int b(x+vt)\left[\int s_1(x'')b(x''+vt)p(x-x'')\mathrm{d}x''\right]\mathrm{d}t + \int b(x+vt)\left[\int s(x'')p(x-x'')\mathrm{d}x''\right]\mathrm{d}t. \tag{6}$$

Since the scenery (the background) is not correlated with itself one may assume that

$$\int b(x+vt)b(x''+vt)\mathrm{d}t = \delta(x-x'') + k_1, \tag{7}$$

where k_1 is a constant. The meaning of k_1 is that the background is not completely uncorrelated and there is a bias. Using this relation in Eq. (6) yields

$$R(x) = k_3 - s_1(x)p(0) - k_1\int s_1(x'')p(x-x'')\mathrm{d}x'' + k_2\int s(x'')p(x-x'')\mathrm{d}x'', \tag{8}$$

where k_2 and k_3 are constants:

$$k_2 = \int b(x+vt)\mathrm{d}t, \qquad k_3 = p(0) + k_1\int p(x-x'')\mathrm{d}x''. \tag{9}$$

Since due to the definition of s_1 one may write that

$$k_2 s(x) - k_1 s_1(x) = k_4 s(x), \tag{10}$$

where k_4 is a constant as well, one has the relation

$$R(x) = k_3 + k_4\int s(x'')p(x-x'')\mathrm{d}x'' - s_1(x)p(0), \tag{11}$$

which means that the reconstructed image is equal to a constant plus the low-resolution target image (i.e., the target blurred by the blurring point spread function) minus the high-resolution contour of the target (i.e., s_1). Thus, the suggested approach recovers the high-resolution contour of the target, and to extract it one should subtract from $R(x)$ the low-resolution (i.e., blurred) target and background (appearing within constant k_2 and thus also in constant k_3).

In the experiments we used an image of scenery taken from an aircraft. The target was an aircraft moving across the scenery. The velocity of the moving target was approximately 10 pixels between sequential video frames. In Fig. 1, one can see a sample from the captured temporal sequence. In the bottom part we present the high-resolution image with the target, and in the top part we present the low-resolution image seen through the low-resolution sensor (including the target). The arrows indicate the position of the target airplane. In the temporal sequence the target moves all along the full field of view (across the background). After we apply a summation over all the low-resolution images, the low-resolution moving target can be extracted, as seen in Fig. 2a. Then, we apply a decoding algorithm involving multiplication of each of the low-resolution images of the temporal sequence by the high-resolution image of the reference background and then summation. The low-resolution background and the target were subtracted from the accumulated reconstruction. Alternatively, it is possible to apply desharpening masking or perform morphological operations such as top-hat transformations to remove the low-frequency component.[15] The result is seen in Fig. 2b. One can see the improvement between the blurred image in Fig. 2a and the

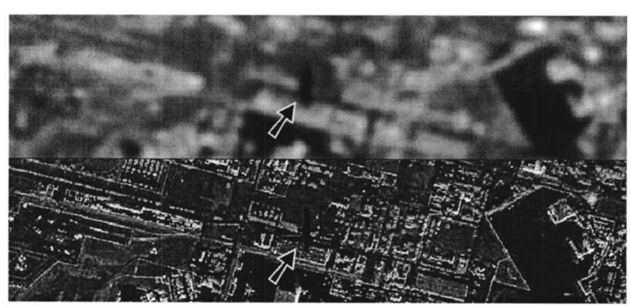

Fig. 1. Bottom, sample of the high-resolution image. Top, sample of the low-resolution image. The arrows signal the target position.

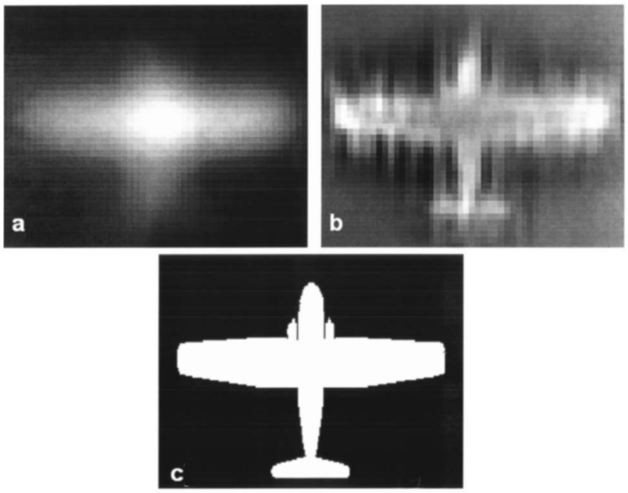

Fig. 2. a, Summation of all the blurred images. b, Result of high-pass filtering of the raw reconstructed image. c, High-resolution reference target.

reconstruction in Fig. 2b. Indeed, the contour is highly resolved. For comparison, the original high-resolution target is presented in Fig. 2c. The resemblance between Figs. 2b and Fig. 2c is visible.

In the simulation we used a binary object, but this fact is not important for the approach presented here, since the superresolved outcome is obtained for only the contour of the target. Thus, it is not important what happens inside the target region. In any case, superresolved detection of the contour may allow identification and recognition of the observed object (in our case it allows us to verify that an airplane is involved).

Note that the decoding procedure, in which the time sequence of low-resolution images that are multiplied by the decoding high-resolution reference background image, can be done in an all-optical manner as well. For this purpose, the decoding mask (i.e., the high-resolution reference background) should be displayed on top of a spatial light modulator placed in front of the camera. The summation operation performed in the time domain is obtained anyhow due to the integration time of the detection array.

Also, please note that we did not assume that the motion of the target is known in advance. The relative motion is obtained by registration via correlation of sequential video frames (i.e., finding the relative shift between images).

To conclude, in this Letter we have demonstrated an approach that makes it possible to recognize and (or) identify high-resolution moving targets with remote sensing systems while using a low-resolution imaging equipment. The approach involves a numerical algorithm, the computational complexity of which can be reduced with optical processing done by placing a spatial light modulator in front of the imaging sensor.

This work was supported by Fondo Europeo de Desarrollo Regional funds and Spanish Ministerio de Educación y Ciencia project FIS2004-06947-C02-01, and by Valencian Government projects GRUPOS03/117 and IIARC0/2004/217. Z. Zalevsky's e-mail address is zalevsz@eng.biu.ac.il.

References

1. P. M. Narenda, ed., in Proc. SPIE **0302**, (1981).
2. Y. Gao, J. Li, and Z. Shen, in Proc. SPIE **5640**, 341 (2005).
3. J. L. Dale, D. J. Dwyer, and J. Thornton, in Proc. SPIE **5612**, 94 (2004).
4. A. A. Kostrzewski, G. D. Savant, P. I. Shnitser, M. A. Piliavin, S. Sandomirsky, A. A. Vasiliev, and D. P. Casasent, in Proc. SPIE **5129**, 129 (2003).
5. Z. Lu and T. Zhang, in Proc. SPIE **5102**, 338 (2003).
6. H. Lange, in Proc. SPIE **3720**, 202 (1999).
7. P. Russo, V. Markandev, T. H. Bui, and D. Shrode, Proc. SPIE **1383**, 60 (1991).
8. Z. Zalevsky, D. Mendlovic, and A. W. Lohmann, in *Progress in Optics* (Elsevier, 1999), Vol. XL, Chap. 4.
9. Z. Zalevsky and D. Mendlovic, *Optical Super Resolution* (Springer, 2002).
10. D. Mendlovic and A. W. Lohmann, J. Opt. Soc. Am. A **14**, 558 (1997).
11. W. Lukosz, J. Opt. Soc. Am. **56**, 1463 (1966).
12. A. I. Kartashev, Opt. Spektrosk. (USSR) **9**, 204 (1960).
13. W. Gartner and A. W. Lohmann, Z. Phys. **174**, 18 (1963).
14. A. Shemer, Z. Zalevsky, D. Mendlovic, N. Konforti, and E. Marom, Appl. Opt. **41**, 7397 (2002).
15. T. Szoplik, J. García, and C. Ferreira, Appl. Opt. **34**, 267 (1995).