Passive time-multiplexing super-resolved technique for axially moving targets

Zeev Zalevsky,^{1,2,*} Simone Gaffling,³ Jana Hutter,³ Lizhuo Chen,⁴ Wolfgang Iff,⁵ Alexander Tobisch,⁶ Javier Garcia,⁷ and Vicente Mico⁷

¹Faculty of Engineering, Bar-Ilan University, Ramat Gan 52900, Israel

²School of Advanced Optical Technologies (SAOT), Friedrich-Alexander-Universität Erlangen-Nürnberg, Erlangen 91052, Germany

³Pattern Recognition Lab, Department of Computer Science, Friedrich-Alexander-Universität Erlangen-Nürnberg, Martensstraße 3, Erlangen 91058, Germany

⁴Chair of Sensor Technology, Friedrich-Alexander-University Erlangen-Nürnberg, Martensstraße 3, Erlangen 91058, Germany

⁵Chair of Optics, Friedrich-Alexander-Universität Erlangen-Nürnberg, Martensstraße 3, Erlangen 91058, Germany

⁶Fraunhofer Institute for Integrated Systems and Device Technology IISB, Erlangen 91058, Germany

⁷Departamentode Óptica, Universitat de Valencia, C/Doctor Moliner 50, Burjassot 46100, Spain

*Corresponding author: zalevsz@biu.ac.il

Received 12 October 2012; accepted 4 November 2012; posted 27 November 2012 (Doc. ID 177984); published 16 January 2013

In this paper we present a super-resolving approach for detecting an axially moving target that is based upon a time-multiplexing concept and that overcomes the diffraction limit set by the optics of an imaging camera by *a priori* knowledge of the high-resolution background in front of which the target is moving. As the movement trajectory is axial, the approach can be applied to targets that are approaching or moving away from the camera. By recording a set of low-resolution images at different target axial positions, the super-resolving algorithm weights each image by demultiplexing them using the high-resolution background image and provides a super-resolved image of the target. Theoretical analyses as well as simulations and preliminary experimental validation are presented to validate the proposed approach. © 2013 Optical Society of America

OCIS codes: 100.6640, 100.2980, 110.4850, 120.0280.

1. Introduction

Super resolution in imaging systems is a strategy aimed to provide high-quality imaging incoming from low-resolution images. For a fixed illumination wavelength, the resolving power of an imaging system is mainly restricted by either the *F*-number of the optics or the detector characteristics through the size and number of the pixels [1,2]. In that sense, the aim of super-resolution techniques is to produce an improvement in the resolving power without changing the physical properties of the imaging system.

Based on this concept, many approaches have been proposed to achieve super resolution in several disciplines, such as far- [1] and near-field [3] imaging, computational super resolution by digital algorithms [4], super-resolving pupils using apodization techniques [5], and imaging by scanning procedures [6]. Those disciplines are implemented in different application fields with microscopy being probably the most fruitful one [7–17]. Nevertheless, super-resolution

¹⁵⁵⁹⁻¹²⁸X/13/070C11-05\$15.00/0

^{© 2013} Optical Society of America

approaches also apply in synthetic aperture radar $[\underline{18},\underline{19}]$, astronomical imaging $[\underline{20}]$, medical imaging $[\underline{21}]$, and imaging through turbid media $[\underline{22}]$, just to cite a few.

In particular, spatial-resolution enhancement and super resolution are critical in remote sensing, especially in satellite imagery and far-field imaging, where the aim is to capture and recognize targets having a size approaching or below the spatial resolution limit provided by the imaging system. Some examples allowing super resolution in remotesensing imagery are found to succeed with image restoration [23], shifting the set of low-resolution images [24,25], compressive sensing [26], and using turbulences [27–29].

In previous publications [30,31], we have showed a new concept for remote super-resolved imaging in which a target is laterally moving. From a set of low-resolution images and a priori knowledge of the high-resolution background, we could super resolve the laterally moving target using the ground land [30] or environmental structural components such as fences [31] as background. This highresolution background acts as an encoding element of the high-spatial-frequency content of the target, and the super-resolved image is retrieved by using a decoding algorithm involving time integration of the low-resolution images after being multiplied by a high-resolution image of the background. This results in the contours of the remote moving target being seen with high resolution corresponding to the resolution of the background in the calibration process [32]. In any case, a high-resolution image of the background (without the target) is needed for the decoding algorithm.

Another strategy is to keep fixed the target while moving the encoding element. Thus, raining drops [<u>31</u>], periodic structures such as gratings [<u>33,34</u>], and varied-size particles [<u>35</u>] have been used as encoding elements for time-multiplexing super resolution of remote or far-field targets.

In this paper, we show how our previously presented approach [30] can be implemented not for lateral movement but for axial movement in which the target is not moving in respect to the high-resolution background but rather scales up or down (depending if it is approaching or moving away) in respect to the background. Mathematics, numerical simulations, and preliminary experimental results are presented, validating the concept involved in the proposed approach.

2. Mathematics

In order to prove the proposed concept with the axially moving target, we denote by b(x) the *a priori* known high-resolution background and by s(x) the moving target which we aim to super resolve. $s_1(x)$ is a binary function equals to 1 within the region defined by the contour of the target s(x) and zero outside it. The axially moving target in front of the background b(x) can be written as

$$g(x) = \left(1 - s_1\left(\frac{x}{\beta t}\right)\right)b(x) + s\left(\frac{x}{\beta t}\right),\tag{1}$$

where βt is the scaling factor with β being the unit translation factor and t the time axis. The images captured by the camera are in low resolution. The function g(x) when captured by our imaging system is blurred, with the point spread function (PSF) of p(x) determined by the optical and geometrical limitations of our imager:

$$I(x) = \int \left(\left(1 - s_1 \left(\frac{x'}{\beta t} \right) \right) b(x') + s \left(\frac{x'}{\beta t} \right) \right) p(x - x') dx'$$

= $\beta t \int ((1 - s_1(x'')) b(\beta t x'') + s(x'')) p(x - \beta t x'') dx'',$
(2)

wherein the second line of Eq. (2) we changed the variables as $x'' = x / \beta t$. The decoding is as follows: we take the set of low-resolution images I(x), scale them, multiply them by the *a priori* known high-resolution background (being also properly scaled), and then time integrate:

$$r(x) = \int I(\beta tx) b(\beta tx) dt, \qquad (3)$$

where r(x) is the obtained reconstruction. In our mathematical derivation we assume that the scaling was not very significant, as it is enough to scale the various functions only by a few pixels to generate the desired orthogonality property [which we will see in Eq. (<u>6</u>)]. Thus, the scaling factor of βt is approximately 1 and the scaling of the blurring PSF p(x)is negligible as PSF is anyhow a relatively sharp, point like function. Thus we can approximate

$$I(\beta tx) = \beta t \int ((1 - s_1(x''))b(\beta tx'') + s(x''))p(\beta tx - \beta tx'')dx''$$

$$\approx \int ((1 - s_1(x''))b(\beta tx'') + s(x''))p(x - x'')dx''.$$
(4)

The obtained reconstruction is

$$r(x) = \int \int ((1 - s_1(x''))b(\beta t x'') + s(x''))p(x - x'')b(\beta t x)dx''dt$$

=
$$\int (1 - s_1(x''))p(x - x'') \left(\int b(\beta t x'')b(\beta t x)dt\right)dx''$$

+
$$\int s(x'')p(x - x'')dx'' \int b(\beta t x)dt.$$
 (5)

Because the background b(x) is sufficiently randomly distributed, the orthogonality property can be assumed:

$$\int b(\beta t x'') b(\beta t x) dt \approx \delta(x'' - x).$$
(6)

We also know that

$$\int b(\beta tx) \mathrm{d}t \approx \Delta T b(x),\tag{7}$$

where ΔT is the temporal integration period. Because we can assume that

$$p(x''-x)\delta(x''-x) \approx p(0)\delta(x''-x), \tag{8}$$

we get the final reconstruction result of

$$r(x) = p(0) - p(0)s_1(x) + \Delta T b(x) \int s(x'')p(x - x'')dx''.$$
(9)

The second term in the expression of Eq. (9) is a super-resolved contour of the axially moving target.

Please note that in our mathematics we are considering linear systems in intensity (we are using spatially incoherent illumination). Thus, g(x) presented in Eq. (1) is the intensity transmittance of the axially moving target in front of the background while Eq. (2) represents the convolution operation of such g(x) intensity distribution with the intensity-impulse response of the imager, which is the square modulus of the amplitude-impulse response.

Also please note that in Eq. $(\underline{6})$ we assumed the orthogonality property of the background. In general



Fig. 1. (a) Best low-resolution image without background. (b) Integration of all low-resolution images (with background). (c) One low-resolution image out of the set of captured images (with background). (d) Super-resolved reconstruction.

the background is not completely orthogonal as it also has finite spatial resolution, and thus in the orthogonality property of Eq. (6) the right wing should not have been a delta function but rather a spatially narrow function (e.g., a Gaussian function) whose width corresponds to the resolution of the background. In this case the mathematical derivation is the same except that in our final result of Eq. (9) the reconstruction r(x) would not include the term of $s_1(x)$ but rather this term blurred by the narrow spatial function from the right wing of Eq. (6), that is, the function whose width is related to the resolution of the background. This is of course very logical as this means that we can restore resolution only up to the highest spatial frequency that exists in our encoding function, which is in our case is the background.

3. Simulations and Validation

In the simulations we took a resolution target and axially shifted it in front of a random *a priori* known high-resolution background. The reconstruction was performed according to the protocol described in Eq. (3). In the simulations a set of 50 images was taken. The result of the simulation can be seen in Fig. 1, where in Fig. 1(a) the best low-resolution image without background is presented. In Fig. 1(b) we show the integration of all low-resolution images with the background behind the target. In Fig. 1(c) we show one low-resolution image out of the set of captured images (with background), and in Fig. 1(d) we





Fig. 2. (Color online) Experimental results: (a) Background at high resolution. (b) Left: low-resolution image out of the captured set of images; Right: super-resolved reconstruction.

present the super-resolved reconstruction. As the movement is axial and not lateral, one may see the blurring of the random background appearing as radial lines in the super-resolved reconstruction of Fig. 1(d). This is in contrast to the lateral movement, where the averaged reconstruction includes horizontal, and not radial, blurring lines.

We further performed a preliminary experimental validation in which a car was moving in front of a background while the super-resolving reconstruction was applied on a set of low-resolution images. The driving trajectory of the car in respect to the background was such that it was slightly approaching the camera, and thus, as desired, small magnification (scaling) was generated in respect to the background. In Fig. 2(a) we present the background captured at high resolution. In Fig. 2(b) in the left part we show the low-resolution image out of the captured set of images while in the right we present the super-resolved reconstruction, in which it is clear to see the improvement in resolution in the contour of the moving car.

4. Conclusions

In this paper we have presented a novel superresolution approach to be applied for axially (rather than laterally) moving targets that are scaled in front of an *a priori* known high-resolution background. One possible application for this superresolving approach can be detection of approaching missiles, where improvement of the resolution beyond the diffraction limit can assist in their earlystage identification.

References

- 1. Z. Zalevsky and D. Mendlovic, *Optical Super Resolution* (Springer-Verlag, 2003).
- Z. Zalevsky, D. Mendlovic, and A. W. Lohmann, "Optical systems with improved resolving power," in *Progress in Optics*, E. Wolf, ed. (Elsevier, 2000), Vol. 40, pp. 271–341.
- 3. D. Courjon, Near-Field Microscopy and Near-Field Optics (Imperial College, 2003).
- M. Bertero and C. De Mol, "Super-resolution by data inversion," in *Progress in Optics*, E. Wolf, ed. (Elsevier North-Holland, 1996), Vol. **36**, Chap. 3, pp. 129–178.
- P. Jacquinot and B. Roizen-Dossier, "Apodization," in *Progress in Optics*, E. Wolf, ed. (North-Holland, 1964), Vol. 3, Chap. 2, pp. 29–186.
- 6. T. Wilson and C. J. Sheppard, *Theory and Practice of Scanning Optical Microscopy* (Academic, 1984).
- 7. E. Betzig, J. K. Trautman, T. D. Harris, J. S. Weiner, and R. L. Kostelak, "Breaking the diffraction barrier: optical microscopy on a nanometric scale," Science **251**, 1468–1470 (1991).
- S. W. Hell and J. Wichmann, "Breaking the diffraction resolution limit by stimulated emission: stimulated-emissiondepletion fluorescence microscopy," Opt. Lett. 19, 780–782 (1994).
- U. C. Fischer, J. Heimel, H.-J. Maas, H. Fuchs, J. C. Weeber, and A. Dereux, "Super-resolution scanning near-field optical microscopy," Opt. Nanotech. 88, 141–153 (2003).
- M. G. L. Gustafsson, "Nonlinear structured-illumination microscopy: wide-field fluorescence imaging with theoretically unlimited resolution," Proc. Natl. Acad. Sci. USA 102, 13081–13086 (2005).
- M. J. Rust, M. Bates, and X. Zhuang, "Sub-diffraction-limit imaging by stochastic optical reconstruction microscopy (STORM)," Nat. Methods 3, 793–796 (2006).

- V. Mico, Z. Zalevsky, C. Ferreira, and J. García, "Superresolution digital holographic microscopy for three-dimensional samples," Opt. Express 16, 19260–19270 (2008).
- B. Huang, M. Bates, and X. Zhuang, "Super resolution fluorescence microscopy," Annu. Rev. Biochem. 78, 993–1016 (2009).
- A. Gur, D. Fixler, V. Micó, J. Garcia, and Z. Zalevsky, "Linear optics based nanoscopy," Opt. Express 18, 22222–22231 (2010).
- B. Luk'yanchuk, A. Khan, Z. Liu, Z. Chen, and M. Hong, "Optical virtual imaging at 50 nm lateral resolution with a white-light nanoscope," Nat. Commun. 2, 218 (2011).
- Y.-H. Lin and D. P. Tsai, "Near-field scanning optical microscopy using a super-resolution cover glass slip," Opt. Express 20, 16205–16211 (2012).
- 17. J. Lindberg, "Mathematical concepts of optical super resolution," J. Opt. 14, 083001 (2012).
- J. C. Curlander and R. N. McDonough, Synthetic Aperture Radar: Systems and Signal Processing (Wiley-Interscience, 1991).
- C. C. Schmullius and D. L. Evans, "Review article synthetic aperture radar (SAR) frequency and polarization requirements for applications in ecology, geology, hydrology, and oceanography: a tabular status quo after SIR-C/X-SAR," Int. J. Remote Sens. 18, 2713–2722 (1997).
- K. Puschmann and F. Kneer, "On super-resolution in astronomical imaging." Astron. Astrophys. 436, 373–378 (2005).
- M. D. Robinson, S. J. Chiu, C. A. Toth, J. Izatt, J. Y. Lo, and S. Farsiu, "Novel applications of super-resolution in medical imaging," in *Super-Resolution Imaging*, P. Milanfar, ed. (CRC, 2010), pp. 383–412.
- 22. Y. Choi, T. D. Yang, C. Fang-Yen, P. Kang, K. J. Lee, R. R. Dasari, M. S. Feld, and W. Choi, "Overcoming the diffraction limit using multiple light scattering in a highly disordered medium," Phys. Rev. Lett. **107**, 023902 (2011).
- 23. M. Elad and A. Feuer, "Restoration of a single superresolution image from several blurred, noisy and undersampled

measured images," IEEE Trans. Image Process. 6, 1646–1658 (1997).

- M. T. Merino and J. Núñez, "Super-resolution of remotely sensed images with variable-pixel linearreconstruction," IEEE Trans. Geosci. Remote Sens. 45, 1446–1457 (2007).
- F. Ling, Y. Du, F. Xiao, H. Xue, and S. Wu, "Super-resolution land-cover mapping using multiple sub-pixel shifted remotely sensed images," Int. J. Remote Sens. 31, 5023–5040 (2010).
- Z. X. Pan, H. J. Huang, and W. D. Sun, "Super resolution of remote sensing image based on structure similarity in CS frame," Proc. SPIE 8002, 80020H (2011).
- D. G. Sheppard, B. R. Hunt, and M. W. Marcellin, "Iterative multiframe superresolution algorithms for atmosphericturbulence-degraded imagery," J. Opt. Soc. Am. A 15, 978–992 (1998).
- Z. Zalevsky, S. Rozental, and M. Meller, "Usage of turbulence for superresolved imaging," Opt. Lett. 32, 1072–1074 (2007).
- E. Grossman, R. Tzioni, A. Gur, E. Gur, and Z. Zalevsky, "Optical through-turbulence imaging configuration: experimental validation," Opt. Lett. 35, 453–455 (2010).
- Z. Zalevsky, J. Garcia, and C. Ferreira, "Super resolved imaging of remote moving targets," Opt. Lett. **31**, 586–588 (2006).
 Z. Zalevsky, E. Saat, S. Orbach, V. Mico, and J. Garcia,
- Z. Zalevsky, E. Saat, S. Orbach, V. Mico, and J. Garcia, "Exceeding the resolving imaging power using environmental conditions," Appl. Opt. 47, A1–A6 (2008).
- A. Ilovitsh, S. Zach, and Z. Zalevsky, "Contour superresolved imaging of static ground targets using satellite platform," Appl. Opt. 51, 5863–5868 (2012).
- Z. Zalevsky, J. García, and V. Micó, "Transversal superresolution with noncontact axial movement of periodic structures," J. Opt. Soc. Am. A 24, 3220–3225 (2007).
- 34. V. Mico, O. Limon, A. Gur, Z. Zalevsky, and J. García, "Transverse resolution improvement using rotating-grating time-multiplexing approach," J. Opt. Soc. Am. A 25, 1115–1129 (2008).
- Z. Zalevsky, E. Fish, N. Shachar, Y. Vexberg, V. Micó, and J. Garcia, "Super-resolved imaging with randomly distributed, time- and size-varied particles," J. Opt. A 11, 1–6 (2009).