3-D Imaging Correlography and Coherent Image Reconstruction

J.R. Fienup,[†*] R.G. Paxman,[†*] M.F. Reiley,[*◊] and B.J. Thelen[†]

† ERIM International
P.O. Box 134008
Ann Arbor, MI 48113-4008

* Advanced Modular Power Systems Inc.
4370 Varsity Drive
Ann Arbor, MI 48108

(734) 994-1200, ext. 2500
email: fienup@erim-int.com

ABSTRACT

By illuminating an object with a laser and collecting far-field speckle intensity patterns, at a regularly spaced sequence of wavelengths, one obtains the squared magnitude of the 3-D Fourier transform of the object. Performing 3-D phase retrieval to reconstruct a 3-D image (consisting of complex-valued voxels) is relatively difficult unless one has a tight support constraint. An alternative is to perform averaging of the autocovariance of the far-field speckle intensities, over an ensemble of speckle realizations, to estimate the squared magnitude of the Fourier transform of the underlying (incoherent) reflectivity of the object, by the correlography method. This also gives us an incoherent-image-autocorrelation estimate, from which we can derive an initial support constraint. Since the image, being incoherent, is real-valued and nonnegative, performing phase retrieval on this data is easier and more robust. Unfortunately the resolution for correlography is only moderate since the SNR is low at the higher spatial frequencies. However, one can then use a thresholded version of that reconstructed incoherent image as a tight support constraint for performing phase retrieval on the original speckle intensity patterns to reconstruct a fine-resolution, coherent image. The fact that the objects are opaque plays an important role in the robustness of this approach. We will show successful reconstruction results from real data collected in the laboratory as part of the PROCLAIM (Phase Retrieval with an Opacity Constraint for LAser IMaging) effort.

Keywords: Phase retrieval, 3-D imaging, correlography, support constraint, opacity, laser imaging

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[◊] Current address: Textron Systems, 535 Lipoa Parkway, Suite 149, Kihei, HI 96753

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By illuminating an object with a laser and collecting far-field speckle intensity patterns, at a regularly spaced sequence of wavelengths, one obtains the squared magnitude of the 3-D Fourier transform of the object. Performing 3-D phase retrieval to reconstruct a 3-D image (consisting of complex-valued voxels) is relatively difficult unless one has a tight support constraint. An alternative is to perform averaging of the autocovariance of the far-field speckle intensities, over an ensemble of speckle realizations, to estimate the squared magnitude of the Fourier transform of the underlying (incoherent) reflectivity of the object, by the correlography method. This also gives us an incoherent-image-autocorrelation estimate, from which we can derive an initial support constraint. Since the image, being incoherent, is real-valued and nonnegative, performing phase retrieval on this data is easier and more robust. Unfortunately the resolution for correlography is only moderate since the SNR is low at the higher spatial frequencies. However, one can then use a thresholded version of that reconstructed incoherent image as a tight support constraint for performing phase retrieval on the original speckle intensity patterns to reconstruct a fine-resolution, coherent image. The fact that the objects are opaque plays an important role in the robustness of this approach. We will show successful reconstruction results from real data collected in the laboratory as part of the PROCLAIM (Phase Retrieval with an Opacity Constraint for LAser IMaging) effort.

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1 INTRODUCTION

A novel imaging modality employs frequency-tunable laser illumination and Fourier intensity measurements to arrive at a fine-resolution, 3-D coherent image without the need for imaging optics (lenses) or heterodyne detection.[1-4] By illuminating an object with a laser and collecting far-field speckle intensity patterns, at a regularly spaced sequence of wavelengths, one obtains the squared magnitude of the 3-D Fourier transform of the object. One can attempt to perform 3-D phase retrieval to reconstruct a 3-D image (consisting of complex-valued voxels) of the object. Although phase retrieval for complex-valued objects is ordinarily difficult[5], it is easier in this case because most objects are opaque. That is, only the front surface of the object reflects light back to the receiver, making the effective object a 2-D surface embedded in 3-D space, and this makes the phase retrieval problem less difficult. We call this imaging modality Phase Retrieval with an Opacity Constraint for LAser IMaging (PROCLAIM).[1-4] However,

Email: fienup@erim-int.com; Telephone: (734)994-1200 ext. 2500; Fax: (734)994-5704
◊ Current address: Textron Systems, 535 Lipoa Parkway, Suite 149, Kihei, HI 96753

phase retrieval under these circumstances is still not sufficiently easy and reliable unless one has a tight support constraint, that is, unless we know fairly well on which 2-D surface the object reflectivity resides.

One can use the principles of imaging correlography[6-7] to more reliably reconstruct an image from the laser intensity data. By computing the autocovariance of the laser speckle intensities, for an ensemble of speckle realizations, one can estimate the squared magnitude of the Fourier transform of the underlying (incoherent) reflectivity of the object. Fourier transforming this yields an incoherent-image-autocorrelation estimate, from which one can derive an initial support constraint. To perform phase retrieval on this data is easier, since the image, being incoherent, is real-valued and nonnegative. The combination of a nonnegativity constraint and a loose support constraint is sufficient to make the phase retrieval algorithm more robust. A disadvantage of this approach is that the SNR is low at the higher spatial frequencies, and so only a moderate-resolution incoherent image can be reconstructed. However, this moderate-resolution image can be used to help obtain fine-resolution coherent images. A thresholded version of the incoherent image can be used as a tight support constraint for performing coherent phase retrieval on the original speckle intensity patterns to reconstruct a coherent image. The coherent image can be of finer resolution than the incoherent image. Thus we have a boot-strap method of using the incoherent image from imaging correlography to obtain a fine-resolution coherent image from far-field laser speckle patterns. The fact that the objects are opaque plays an important role in the robustness of this approach. We will show successful reconstruction results from real data collected in the laboratory as part of the PROCLAIM (Phase Retrieval with an Opacity Constraint for LAser IMaging) effort.

Section 2 describes the processing steps necessary to compute a 3-D image from the measured data; Section 3 describes how imaging correlography improves this process and shows experimental results; Section 4 shows experimental results of fine-resolution coherent imaging which were made practical by the correlography results.

2 REVIEW OF PROCLAIM PROCESSING STEPS

Figure 1 shows the baseline overall data flow for PROCLAIM image formation. A review of the processing steps is as follows.[1-4] The data, $D_k(u, v, w)$, for the k^{th} speckle realization, are noisy 3-D Fourier intensity measurements of the coherent optical fields. The coordinates (u, v) are in angle-angle (Fourier-plane CCD detector pixels) space and w is laser frequency. Inverse 3-D Fourier transformation of the Fourier intensity gives the 3-D complex autocorrelation of the image, $r_{dk}(x, y, z)$. This has a large impulse response term at the origin, which we subtract off. We accomplish this by subtracting the mean of $D_k(u, v, w)$ before the Fourier transformation. The complex autocorrelations suffer from two effects that make it difficult to estimate their support and therefore require refinement algorithms: sidelobes outside the support of $r_{dk}(x, y, z)$ and speckle nulls within the support of $r_{dk}(x, y, z)$. We attack the sidelobes by using Spatially Variant Apodization,[8] which eliminates most sidelobes without degrading resolution. We must do this on the complex autocorrelation. We attack the speckle drop-outs in a variety of ways. If we have multiple speckle realizations, we average their intensities to further reduce the effects of speckle. We then threshold the result to arrive at an estimate of the autocorrelation support. We can fill in the remaining speckle nulls with a closing (dilation followed by erosion) operation.[9] From the autocorrelation support we use intersection rules[10,11,4] to compute locator sets. In some problems, such as target classification, the locator set may be tight enough to successfully perform the task, and so it can be considered the desired output. Alternatively, we can use the locator set as a support constraint, along with an individual Fourier intensity data set to reconstruct a complex-valued, speckled image, for each speckle realization, using a phase retrieval algorithm. The intensities of the reconstructed images from all the speckle realizations can then be averaged to arrive at a speckle-reduced 3-D image.

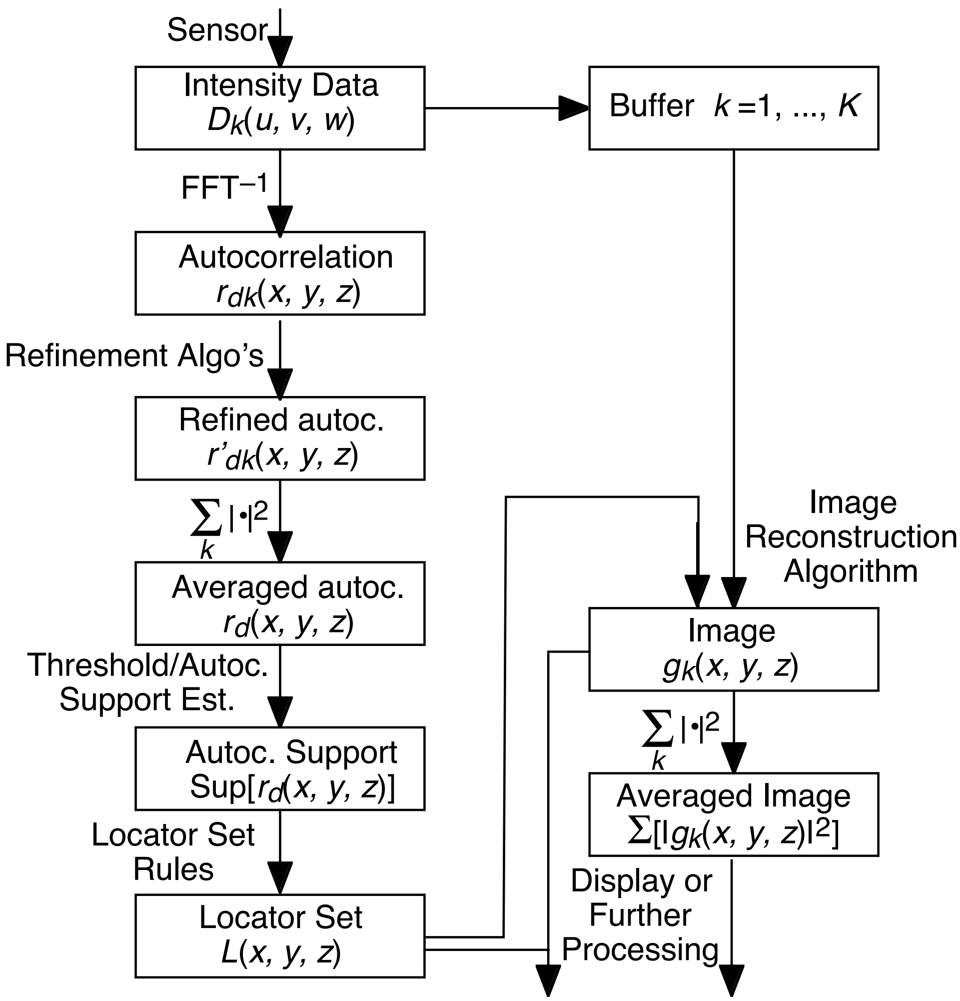

Figure 1. Data Processing Steps for PROCLAIM.

One problem with this baseline approach is that, depending on the geometrical shape of the object, the locator set might be considerably larger than the true object, since it is only an upper bound on the object support. In particular, it will often be thick in the z (height) dimension, even though the object itself, being opaque, is thin in the z dimension. This imperfection in the support constraint makes it difficult for the phase retrieval algorithm to reconstruct a coherent image from the measured Fourier magnitude data.

3 IMAGING CORRELOGRAPHY

An alternative to this baseline approach is to use Imaging Correlography[6,7] to help with the process. In imaging correlography, we use the averaged squared magnitude of the image autocorrelations to estimate $|F_I(u, v)|$, the magnitude of the Fourier Transform of the incoherent object reflectivity. The correlography process allows us to obtain information about the incoherent object even though we illuminate the object with a coherent laser. The Fourier transform of $|F_I(u, v)|^2$ is the averaged squared magnitude autocorrelation, $r_d(x, y, z)$ (see Fig. 1). Just like in baseline PROCLAIM, for imaging correlography we must retrieve the phase of $F_I(u, v)$; however, a big advantage of imaging correlography is that, since we are reconstructing an incoherent image, which is real-valued and nonnegative, we can impose a nonnegativity constraint during the iterative reconstruction. For the results shown in this paper, we used the iterative transform algorithm (ITA)[12] as the phase retrieval algorithm.

We applied the correlography method to real data collected in the laboratory. The object, a photograph of which is shown in Fig. 2, consisted of a flat arrowhead-shaped object (which resembles the Star Trek insignia, hence the name "STI"), which had glued to it three disks, of progressively smaller diameters, one on top of the other, forming a disk-like pyramid. In addition there was a small piece glued to one of the two legs, which was removed after the experiment was performed. The basic arrow shape was approximately parallel to the (x, y) plane, and so the pyramid of disks extended into the z, or height, direction. All parts of the object were made from ScotchLite tape, so it reflected back to the CCD array with ample intensity. The object was pasted onto a piece of clear glass. The total z extent of the object is three times the thickness of the tape, or approximately 15 mils.

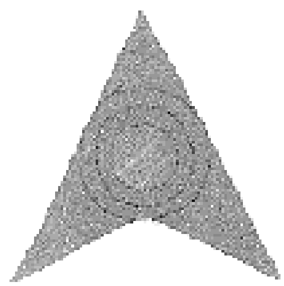

Figure 2. STI Object. The three concentric circles can be seen as dark circles at their edges. The small piece on one of the two lower legs was removed before this photograph was taken.

The collected data consisted of 1024x1024 (u, v) CCD pixels at 64 different laser frequencies, or a "data cube" of 1024x1024x64. Flat fielding in both spatial dimensions and the wavelength dimension of the data were performed. The averaged-autocorrelation estimate and the support constraint were computed by the steps illustrated in Fig. 1. For correlography we divided the data cube into 64x64x64 data sub-cubes, and treated each of these as an independent speckle realization. To avoid aliasing, these were embedded into arrays of zeros of size 128x128x128 prior to performing FFT's.

We computed the image-autocorrelation estimate by correlography in two different ways: one with sidelobe reduction and the other without. We used the former for support estimation and the latter for estimating the incoherent Fourier magnitude. Figure 3 shows a thresholded version of the incoherent image autocorrelation, our estimate of the support of the autocorrelation. Figure 4 shows the triple-

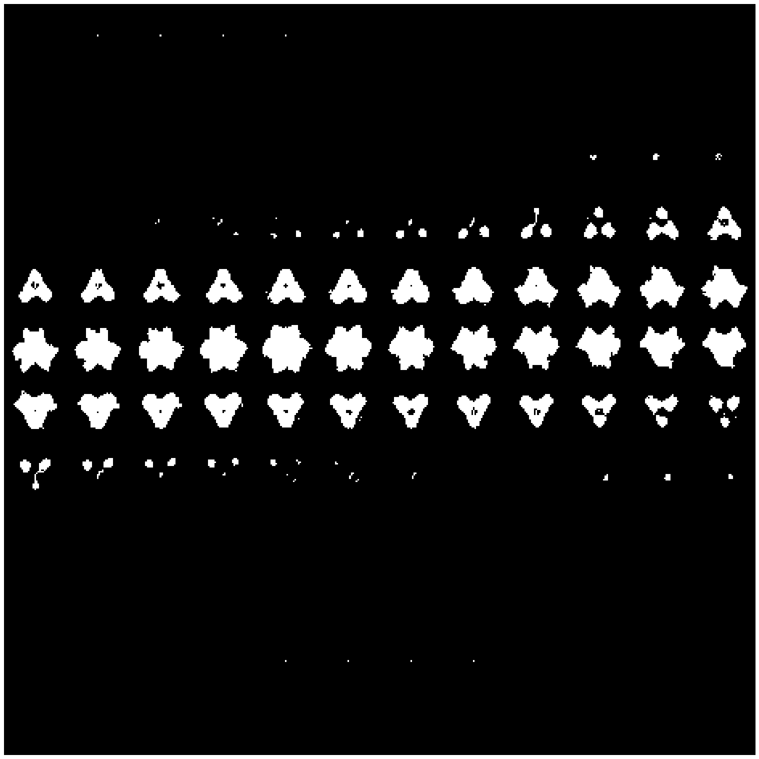

Figure 3. Thresholded Incoherent Image Autocorrelation Estimate (x-y Slices). The threshold value chosen was 0.009 times the peak value.

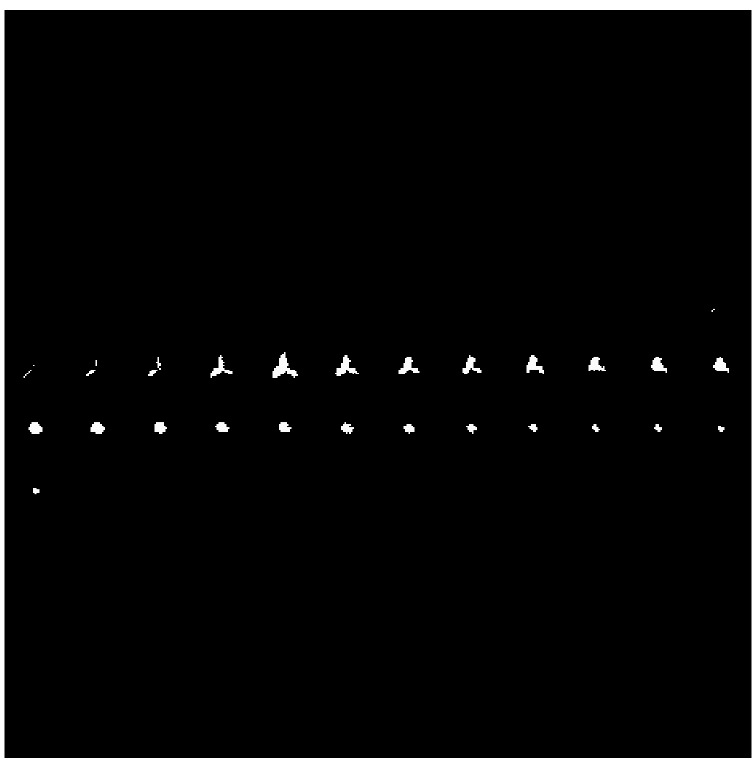

Figure 4. Locator Set Formed by Triple Intersection.

intersection locator set formed from the autocorrelation support. The two points employed by the triple intersection were those at the upper tips of the six-pointed figure in the x-y (z=0) slice of the autocorrelation support. The z=0 slice is the 65th slice, which is the fifth slice in the sixth row of slices shown in the figure. Because of the uncertainties (speckle noise, choice of threshold value) in estimating the autocorrelation support, there are uncertainties in the locator set computed from the autocorrelation support. Furthermore, it is relatively more harmful to the phase retrieval process to have a support constraint that is too small than to have one that is too large. For this reason, we enlarged the locator set by dilating it by one pixel, five times, to arrive at the support constraint shown in Fig. 5 (but showing just slices 50 to 98 so that they are enlarged and more easily seen). We used this as the support constraint for our phase-retrieval algorithm.

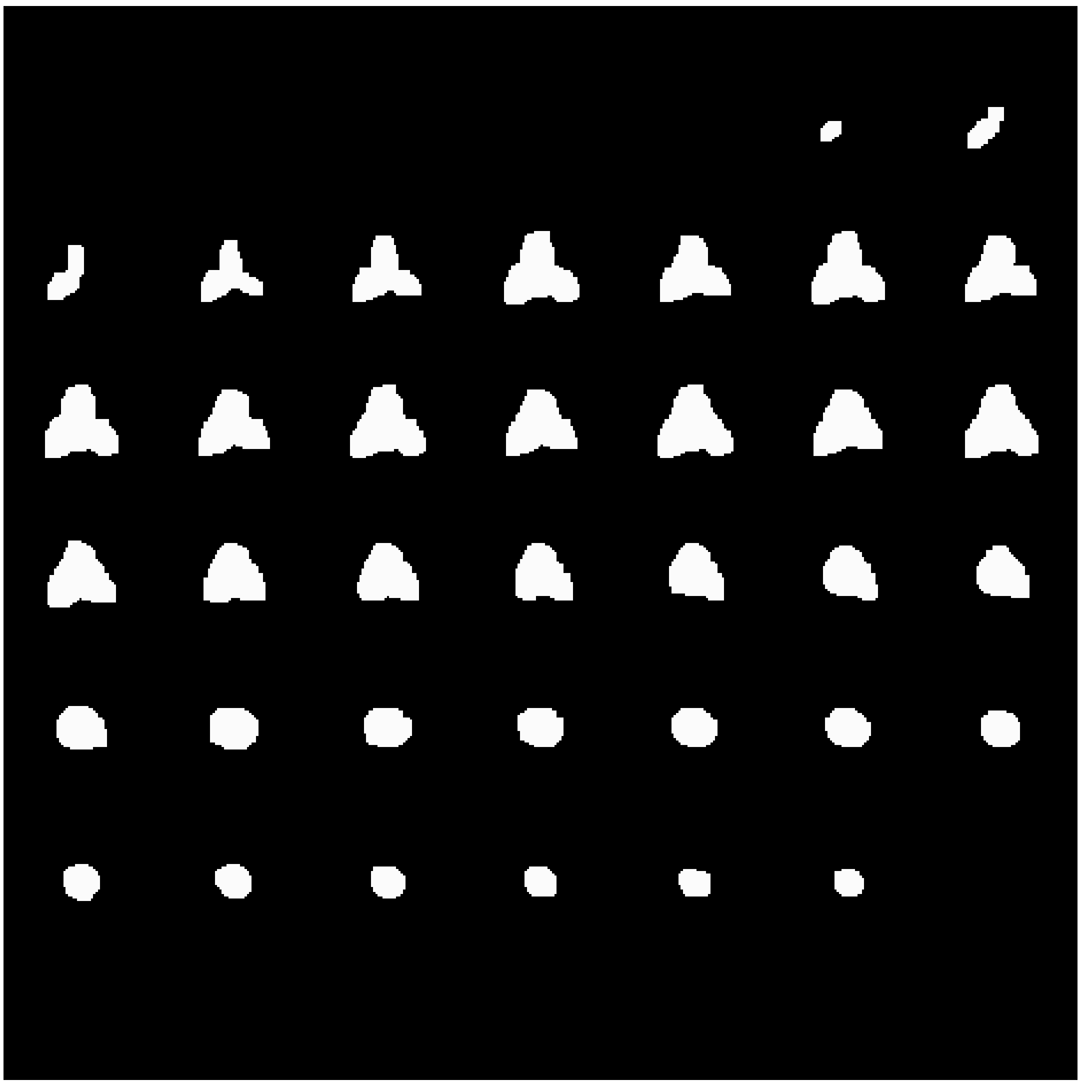

Figure 5. Support Constraint Formed by Dilating Locator Set (Slices 50-98).

To combat noise in the Fourier magnitude estimate, we multiplied the Fourier magnitude by a filter consisting of the autocorrelation of a sphere having a diameter of 40 pixels.

As an initial guess for the object, we filled the support constraint with real-valued random numbers. Using the support constraint, a nonnegativity constraint, and the filtered Fourier magnitude data, we performed the iterative transform algorithm. The result was the image shown in Fig. 6. In this image we see all the major features expected from this object.

To our knowledge, the image shown in Figure 6 is the first-ever 3-D image reconstructed from real laser correlography data. It constitutes a major advance in the state of the art.

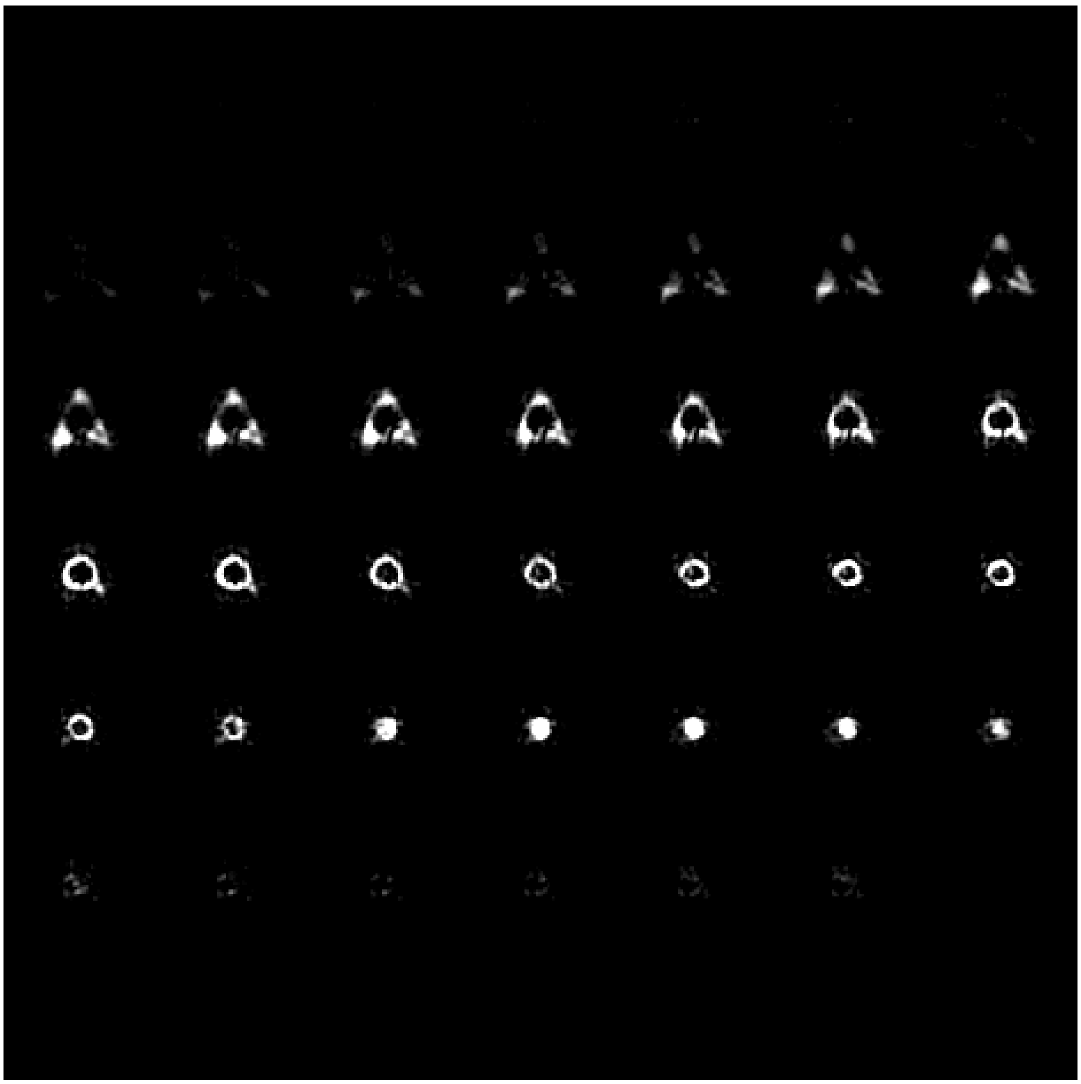

Figure 6. Incoherent Image Reconstructed by Iterative Transform Algorithm using Correlography Data.

4 FINE-RESOLUTION COHERENT IMAGE RECONSTRUCTON

The image shown in Figure 6 could be the final image product from the system. A disadvantage of this images is that, because of the statistical (speckle) noise associated with imaging correlography with a finite number of speckle realizations, it is of lower resolution than the collected data are capable of supporting. An alternative is to reconstruct a finer-resolution coherent image. This would ordinarily be difficult, given a loose support constraint. However, we could compute a very good support constraint by thresholding the incoherent image reconstructed from the correlography data. We then used one 128x128x64 sub-cube of measured laser intensity data and embedded the square root (amplitude) of it in an array of zeros in the z dimension to make it a 128x128x128 array. To control image sidelobes, we weighted that array of data by a weighting function of diameter 80 pixels that was computed by autocorrelating a filled sphere of diameter 40 pixels. For our initial estimate of the object, we filled the support constraint computed from the correlography image with circular-complex Gaussian random numbers. We then performed 130 iterations of the ITA, dilating the support constraint along the way. The resulting image is shown in Figure 7. Being a coherent image, it is speckled, as compared with the smoother incoherent image from imaging correlography. Using a greater extent of Fourier-magnitude data, it is of finer resolution than the correlography image. We could also use larger data sub-cubes (say, 256x256x64) to get even finer resolution coherent images.

The image shown in Figure 7 is, to our knowledge, the first 3-D image reconstructed from coherent 3-D Fourier magnitude data using the ITA, and it represents a significant advance in the state of the art. As before, prior knowledge of opacity has not been used here. This suggests that phase retrieval with opaque, complex-valued objects is considerably easier to achieve than for general complex-valued objects. Furthermore, this result could be used as an initial estimate in our algorithm that explicitly uses opacity,[1] but with this improved initial estimate we would expect to avoid local minima in the search and achieve an improved result.

5 CONCLUSIONS

We have demonstrated a new way to use 3-D Fourier intensity data to reconstruct a moderate-resolution 3-D incoherent image, and to use that image to obtain a better support constraint that allows us to reconstruct a fine-resolution 3-D coherent image. Repeating this for several different speckle realizations and incoherently averaging the resulting coherent images would yield a fine-resolution incoherent image.

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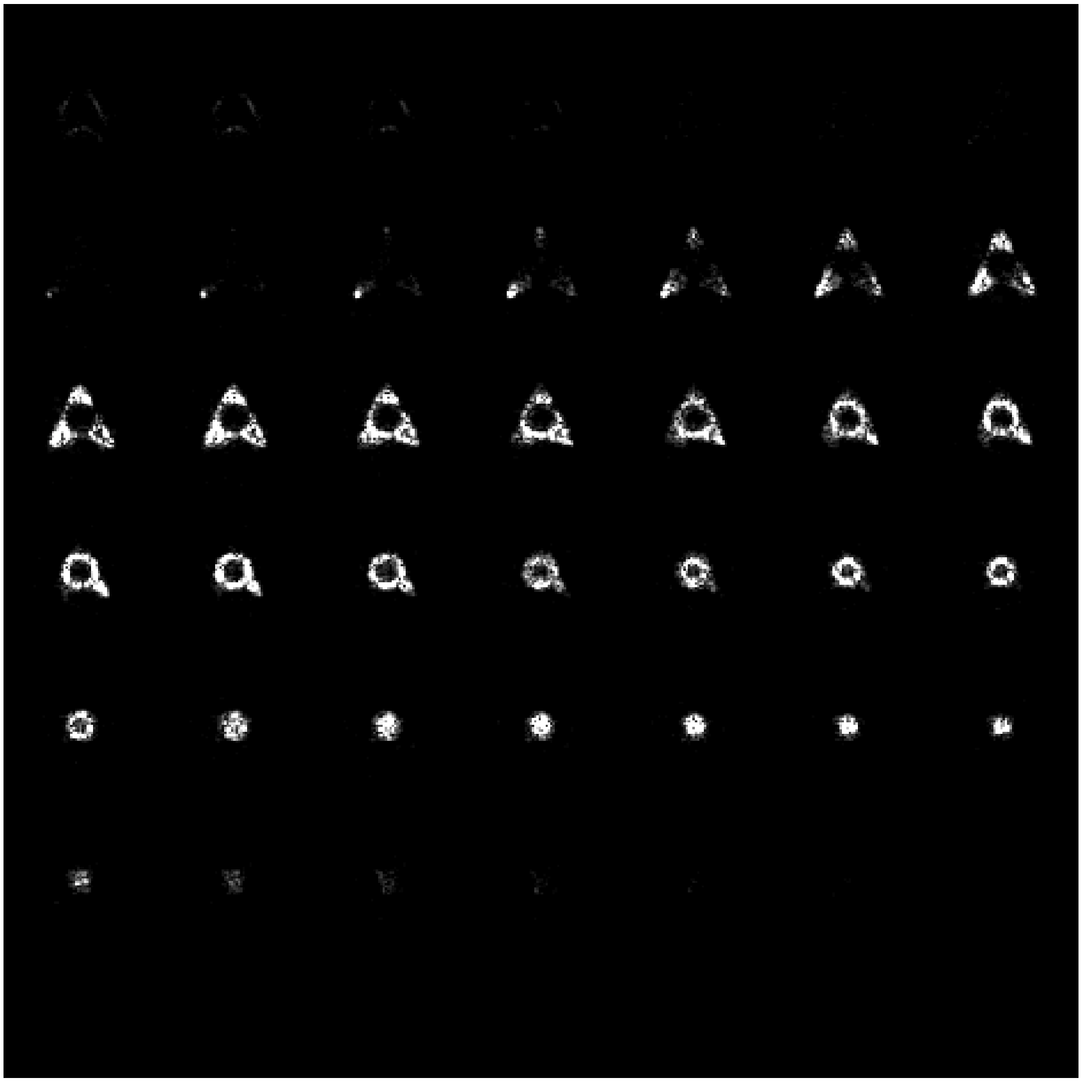

Figure 7. Coherent Image Reconstructed from One 128x128x64 Sub-Cube of PROCLAIM Data by Iterative Transform Algorithm.

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