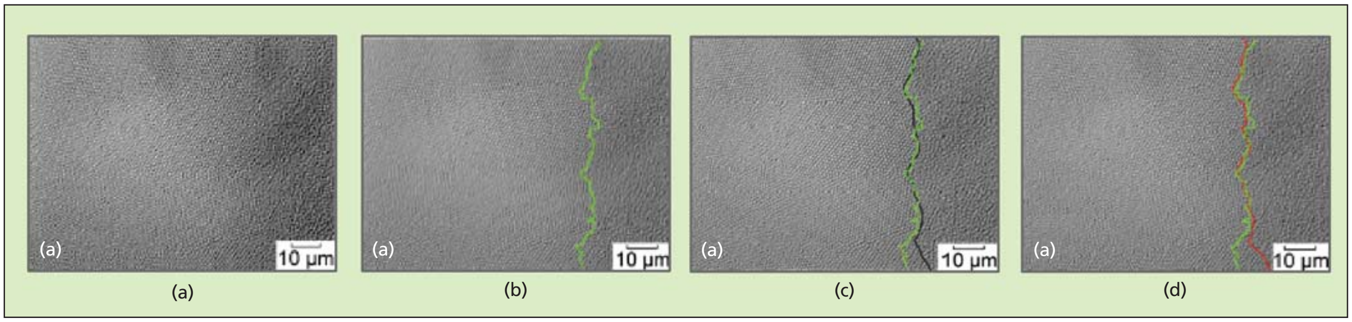

This **Image Sequence** illustrates the technique: (a) 1st image in the experiment sequence, (b) 1st automated interface technique (n=10) result superimposed on original image, (c) 1st automated interface technique (n=10) and authors' results superimposed on original image, and (d) 1st automated interface technique (n=10) and independent experts' results superimposed on original image.

sense that each sphere is "caged" by its neighbors and thus restricted to small movement about a lattice point. Between φ_f and φ_m is a regime of coexisting colloidal liquid and colloidal solid.

At the beginning of an experiment, a suspension is prepared at φ well below φ_f and placed in a cell. Then through slow evaporation or gravitational sedimentation, the spheres become concentrated toward one end of the cell, where crystallization starts when φ_f is reached. When the sphere size falls within a range accessible to optical microscopy, the disordered (liquid) phase and the ordered (solid) phase (and, hence, the boundary between them) are visible to, and clearly distinguishable by, a human observer. However, prior image-data-processing techniques do not enable automated distinction between regions of order and disorder in images of closely packed spheres.

In the present technique, automated distinction (see figure) is made possible by differences between the motions of the spheres in the liquid and solid regions. In particular, the technique exploits the fact that in the solid phase, the spheres are restricted to their small "cages," whereas in the liquid phase, the spheres are free to move. Consequently, when images are averaged over successive frame periods, the liquid region tends to become blurred or gray while the solid region retains a higher degree of contrast, showing the spheres as individual particles. Each frame-averaged image is subjected to a brightness-slicing, a cleaning (noise-suppression), and a particle-finding operation. These operations utilize the brightness and contrast differences between the solid and liquid regions. Then the image region showing particles is deemed to be the solid region and the phase boundary is located accordingly.

This work was done by Mark McDowell and Richard B. Rogers of Glenn Research Center and Elizabeth Gray of Scientific Consulting, Inc. Further information is contained in a TSP (see page 1).

Inquiries concerning rights for the commercial use of this invention should be addressed to NASA Glenn Research Center, Innovative Partnerships Office, Attn: Steve Fedor, Mail Stop 4–8, 21000 Brookpark Road, Cleveland, Ohio 44135. Refer to LEW-18157-1.

Low-Complexity Lossless and Near-Lossless Data Compression Technique for Multispectral Imagery

The technique allows substantially smaller compressed file sizes when a small amount of distortion can be tolerated.

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This work extends the lossless data compression technique described in "Fast Lossless Compression of Multispectral-Image Data," (NPO-42517) *NASA Tech Briefs*, Vol. 30, No. 8 (August 2006), page 26. The original technique was extended to include a near-lossless compression option, allowing substantially smaller compressed file sizes when a small amount of distortion can be tolerated. Near-lossless compression is obtained by including a quantization step prior to encoding of prediction residuals.

The original technique uses lossless predictive compression and is designed for use on multispectral imagery. A lossless predictive data compression algorithm compresses a digitized signal one sample at a time as follows: First, a sample value is predicted from previously encoded samples. The difference between the actual sample value and the prediction is called the prediction residual. The prediction residual is encoded into the compressed file. The decompressor can form the same predicted sample and can decode the prediction residual from the compressed file, and so can reconstruct the original sample.

A lossless predictive compression algorithm can generally be converted to a near-lossless compression algorithm by quantizing the prediction residuals prior to encoding them. In this case, since the reconstructed sample values will not be identical to the original sample values, the encoder must determine the values that will be reconstructed and use these values for predicting later sample values. The technique described here uses this method, starting with the original technique, to allow near-lossless compression.

The extension to allow near-lossless compression adds the ability to achieve much more compression when small amounts of distortion are tolerable, while retaining the low complexity and good overall compression effectiveness of the original algorithm.

This work was done by Hua Xie and Matthew A. Klimesh of Caltech for NASA's Jet Propulsion Laboratory. For more information, contact iaoffice@jpl.nasa.gov. NPO-46625