AN AUTOMATED AND UNIVERSAL METHOD FOR MEASURING MEAN GRAIN SIZE FROM A DIGITAL IMAGE OF SEDIMENT

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Abstract Existing methods for estimating mean grain size of sediment in an image require either complicated sequences of image processing (filtering, edge detection, segmentation, etc.) or statistical procedures involving calibration. We present a new approach which uses Fourier methods to calculate grain size directly from the image without requiring calibration. Based on analysis of over 450 images, we found the accuracy to be within approximately 16% across the full range from silt to pebbles. Accuracy is comparable to, or better than, existing digital methods. The new method, in conjunction with recent advances in technology for taking appropriate images of sediment in a range of natural environments, promises to revolutionize the logistics and speed at which grain-size data may be obtained from the field.

INTRODUCTION

Using photographs to quantify grain size (and other properties) of sediment beds is of considerable utility because it offers unparalleled savings in cost and labor, and unrivalled rapidity compared to manual methods, especially if measurements can be made in a completely automated fashion. Photographic methods thus can provide much greater spatial coverage and resolution of grain-size measurements than methods such as sieving and laser diffraction (Rubin, 2004; Barnard and others, 2007). In addition, measurements are non-intrusive which, from a logistics point-of-view, means that bulky samples do not need to be transported and, from a science and monitoring point-of-view, means that only those grains that are exposed to the flow (and are thus subject to transport or winnowing) are sampled.

Applying this relatively simple concept has been hampered by two principal challenges; the first has been obtaining quality images of sediment, particularly of sands, and especially of sands under water. This issue has recently been addressed by a series of new instruments designed for a variety of fluvial and oceanic environments (Rubin and others, 2007; Barnard and others, 2007; Rubin and others, 2010; Buscombe and others, 2010). The second challenge has been the development of an analytical process that is fully automated, precise (to within a few percent), and fully transferable (or universal) across all of the non-cohesive sediment sizes (from silt to cobble) and mineralogy. To date, automated methods for grain size estimation from images have relied on calibration (Rubin, 2004; Carbonneau and others, 2004, 2005; Verdu and others, 2005; Buscombe and others, 2008), on complicated sequences of image processing that isolate and measure each individual grain (e.g., Graham and others, 2005), or on both. In this paper, we briefly describe a new method for estimating mean grain size that overcomes both of these disadvantages. For a more detailed presentation of the method, its range of applicability, and especially for the mathematical reasoning behind the approach, see Buscombe and others (2010).

Most automated grain-size methods start by identifying the outlines of each grain and then assign a measurement to it. In this way, a grain-size distribution can be determined, from which population statistics such as the mean are calculated. This approach relies on sophisticated sequences of image processing algorithms which mimic what a person may achieve by manually digitizing grain boundaries. Currently, the best algorithms work well on dry coarse-gravel riverbeds, usually, but not exclusively, supported in a sand or fine gravel matrix (e.g., Sime and Ferguson, 2003; Graham and others, 2005). However, previous application of this approach has used sediment population-specific coefficients and tunable parameters for filters and image processing operations (such as filter window size), because of the optical differences between different sets of grains in various environments. In addition, the methods are often sensitive to the specific sequence of operations. Therefore, these techniques have been neither transferable between different sediment populations nor applicable across the full range of non-cohesive sediment sizes (see reviews by Graham and others, 2005; Buscombe and Masselink, 2009; Warrick and others, 2009; Buscombe and others, 2010).

The new approach outlined in this paper is essentially statistical, quantifying pixel intensity variations in an image and relating these quantities to grain size. The approach is very different from most existing methods (e.g., physical methods such as sieving/calipers, and image analysis as described above), because the individual grains are not measured. Statistical methods developed to date (including the one outlined in this paper) produce measurements of mean grain size only, not the whole distribution of sizes. However, the statistical approach avoids the major difficulties inherent in detecting the boundaries of every grain in an image, a problem compounded by differences in sediment type and grain-size fraction. Further, a statistical approach can operate at finer scales than traditional image analysis methods (i.e., it can return robust estimates at coarser image resolutions: Carbonneau, 2005; Graham and others, 2005), and it offers the potential for grain size and other features to be expressed and modeled mathematically.

Statistical methods follow from Rubin (2004) who showed that, in images of natural sediments with different mean grain size, the spatial autocorrelation coefficient at a given lag is a function of the mean grain size. No tunable parameters are required, although calibration is needed for each sedimentary environment and/or camera-lighting system. Calibration is required to address optical effects unique to the camera system (lens, spatial distortions and lighting), and to address non-random aspects of the structure of the sediment bed (for example imbrication, and correlations of grain size with grain shape and color). Warrick and others (2009) successfully used a calibration catalogue obtained from photographs of sediment that had similar grain size ranges but were in very different environments, which suggests that calibration catalogues may be more important for the specifics of the lighting-camera system than for the properties of the sediment. Questions remain, however, regarding the sensitivity of results to how calibration is performed. Key questions include how many grain-size fractions the catalogue should contain, to what pixel lag, and what degree of overlap is acceptable in the calibration curves. Given these issues, a universal algorithm (i.e., one that does not need calibration) is highly desirable.

Here, we propose a method to estimate mean grain size from an image that requires neither calibration nor image segmentation procedures. The method is tested with over 450 images of natural sediment beds composed of mixed grain sizes, with mean grain sizes spanning 3 orders of magnitude, from photographs of various grains from silt to cobble, the samples from each sediment environment photographed with a different camera and lighting system. This method uses spatial autocorrelation profiles (autocorrelation coefficients at increasing pixel lag distance: hereafter, correlogram) from a set of calibration images (of known sediment size) to give highly accurate estimates of mean grain size in an image by solving a simple least-squares problem (Rubin 2004). This method – variously termed the autocorrelation (Barnard and others, 2007; Warrick and others, 2009) or the look-up catalogue (Buscombe 2008; Buscombe and Masselink 2009) approach - has been shown to be highly accurate for close-up photographs of sand and gravel (Rubin and others, 2007; Barnard and others, 2007; Buscombe and Masselink, 2009; Warrick and others, 2009), and similar techniques have been shown to work well for larger-scale, coarser-resolution imagery from aerial platforms (e.g. Carbonneau and others, 2004, 2005; Carbonneau, 2005).

IMAGE REQUIREMENTS

To be usable in our new method, an image should contain only non-cohesive unlithified/ uncemented clastic material, so that the entire image is composed of stationary grains touching each other (Figure 1). The lighting, provided by a natural or artificial source, should be such that the pixel values are higher (i.e., lighter) on the tops and flanks of individual grains, lower (i.e., darker) in the pores between grains, and that there is a noticeable gradient in pixel intensity with distance across the grain/pore. In photography terms, the optimum image for statistical grain sizing is one in which the features are well-resolved, and which has a high dynamic range. Note that although we define the dark regions between grains as pores for the purposes of this paper, this usage should not be confused with the more common definition of sediment porosity, even though these quantities may be related.

Figure 1 Examples of suitable images of sediment for the method outlined in this paper.

METHOD

Buscombe and Masselink (2009) showed that the spatial autocorrelation algorithm was one of several techniques which could be used within the calibration framework of Rubin (2004). Rubin's original development was in one dimension using stepwise (spatial) calculations of correlation. Here we follow the two-dimensional extension of Buscombe (2008), which uses the frequency domain rather than the spatial domain. Buscombe (2008) suggested the use of the two-dimensional autocorrelation function (here denoted R), because the transform normalizes magnitudes of spectral density, making different images comparable. The spectrum of an image maps its entire contents into frequency space, providing information that can be used to quantify the dominant wavelength of image features. The technique of Buscombe (2008) also allows estimates to be made of the major and minor grain diameters. Furthermore, it was suggested that the diameter of some contour between 0 and 1 of the two-dimensional surface of autocorrelation should be related to the mean grain size, which in turn suggested that mean grain size might be determined without calibration.

A brief summary of our approach is as follows: each pixel is multiplied by $-1^{(x+y)}$ to center it, and the mean subtracted from each pixel to eliminate harmonics. Then the fast Fourier transform is applied to this centered, de-meaned image. The absolute values of the Fourier transformed image are squared to give the variance spectrum. The inverse Fourier transform of the variance spectrum yields the autocovariance function, which is normalized by its total power (each value divided by the maximum value found at position x=0, y=0) to yield the two-dimensional autocorrelation function *R*. Fara and Scheidegger (1961) showed that it can also be found by the multiplication of the variance spectrum with the complex conjugate of the variance spectrum.

Expressed as such, intervals of lengths other than 2π can be handled by scale factors, and the wavelength of both the demeaned image and R is given by $\lambda = 2\pi/k$, where *k* is a vector of wavenumbers with units of length^{-1} (Fara and Scheidegger, 1961), or 1/pixels. The mean grain size will be represented by some value of *k*. Under basic Fourier theory, a waveform given by e^{-ikx} (where *e* is the base of the natural logarithm and x is…) will have wavelength (periodicity) $\lambda = 2\pi/k$, and the correlogram of such a function should be in anti-phase at $\lambda/2$ (half wavelength) lags; should equal 0 at $\lambda/4$ lags; and should equal 0.5 at $\lambda/2\pi = k$ lags. This suggests that the lag at which $R = 0.5$ is a suitable value for *k*. These relationships and their implications are discussed in detail in Buscombe and others, (2010).

To test this approach, we collected hundreds of images of sediment for which a measurement of the mean grain size was available. All images were of natural, non-cohesive, non-organic sediment, either taken *in situ* or in the laboratory. Over 450 images met the image criteria outlined above and were used to test the new technique. Sediment properties in images varied widely, with grain size ranging from 0.063 to 150 mm, and 10 different sedimentary “populations” were included (5 beaches, 3 rivers, and 2 continental shelves). All sediments were undisturbed, and photographs were taken both in air and water. Each sediment population was photographed using a different camera and lighting system.

These images were used to test the hypothesis that the optimum objective value of *k* is the lag at which the images autocorrelation surface (*R*) equals 0.5, as outlined above. This was achieved by computing the correlogram for each image to find lags associated with a range of coefficients of *R*, substituting these values for *k*, and correlating the resulting grain size estimates with the known mean grain size for each image. These analyses confirmed the lag at which $R = 0.5$ as the appropriate value for *k*, as this value yielded the highest correlation between observed and estimated mean grain size. Thus, scaling by image resolution *r* (units of length/pixel) provides a very simple yet universal measure which scales to near-unity with measured mean grain size, $z = 2\pi rk$. Wavenumber *k* may vary as a function of cross-section through *R*. In this case the value of *k* (in pixels) is found as the radius of an ellipse fitted to the coordinates of the contour $R = 0.5$. Software routines for performing the above analyses are available from the authors in various languages and tested on a number of operating systems.

VALIDATION AND RESULTS

“True” mean grain size was determined by manual point counts on images. Point counts are considered superior to sieving as the benchmark for testing statistical methods of image analysis, because it is the only method to compare different techniques using the exact same grains (Barnard and others, 2007; Rubin and others, 2004; Warrick and others, 2009). Point-counts were performed as follows. In each digital image, a grid composed of 100 intersections was drawn and the intermediate diameter of the grain (pore to pore) underneath each grid intersection was measured. The mean of all these manually measured values is therefore a grid-by-number estimate. It is important to note that it is the intermediate projected axis which is apparent in the image, not the true (or calipered) intermediate axis, but that both automated and manual techniques measure the projected axis. Counting grains at every grid intersection makes the grain selection free from operator bias. To avoid artificially reducing the calculated mean diameter by measuring grains that are not fully exposed (i.e., grains that are partially hidden by other grains), the person doing the counting has the option of moving from the grid intersection to the first complete grain in a specified direction. For further details and validation of this procedure, see Barnard and others (2007) and Buscombe and others (2010).

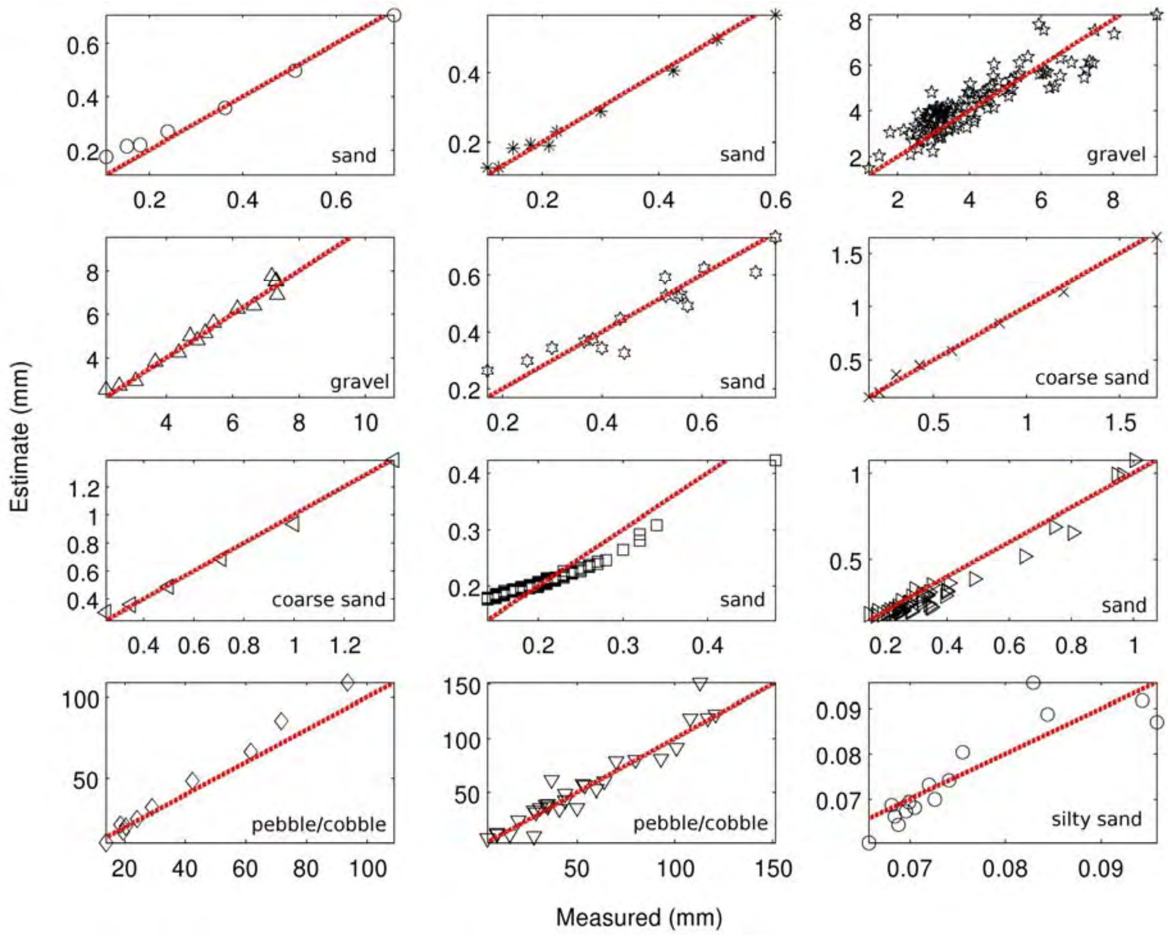

Figure 2 Estimated mean grain size in test images also analyzed using point counts ("measured" values), for 12 sediment populations photographed with different camera and lighting systems. Each symbol represents an individual photo. Solid lines show the 1:1 relationships. Compiled from data in Buscombe and others (2010).

Figure 2 shows estimated and "true" mean grain sizes for each of the 12 sediment populations tested. The histogram of these individual errors is approximately normal centered around zero, which supports our choice of 0.5 for the universal value of grain length scale *k*. Note that although the percentage-based errors appear to be linear, normalization makes these values non-dimensional and therefore non-linear and roughly equivalent to a phi-based measurements (cf., Warrick and others, 2009). The root mean squared (r.m.s, or irreducible) error (which includes both systematic or procedural bias, and random error/scatter) was calculated as 16%.

EXPERIMENTAL TRIALS

In order to explore the limits of the new technique and to inform its practical use, three physical experiments were carried out with photographic images of gravel-sized sediment. These experiments represented just three out of any number of physical situations which might conceivably degrade images and affect the accuracy of our technique. Others could include shadows cast by nearby objects, small areas of vegetation (e.g., algae or moss), and oblique viewing angles and resulting image distortions, all of which might benefit from tests to characterize the sensitivity of our results to real-life issues.

The first two experiments addressed practical aspects of implementation of our approach under water, specifically with coarse bed material where suspended sediment and refraction of light by the water/air interface will affect the photograph because the image must be taken at some distance above the bed. In contrast, imaging of sand under water is carried out in contact with the bed using a macro lens and a faceplate (e.g., Rubin and others, 2007). Because the faceplate is pressed onto the bed during imaging, the image is not affected by turbidity or random scattering of light.

In the first experiment, images were taken of well-rounded beach gravel through 50cm of water with an inexpensive waterproof camera. Point-counts of the grains were carried out to calculate the true mean grain size, and increasing concentrations of mud were mixed into the water and the bed was rephotographed. Differences between true and estimated grain-sizes with suspended-sediment concentrations of 3.31, 5.38, and 10.31 mg/L were 9, 26, and 30 %, respectively. There was thus a clear positive bias in estimated grain sizes with increased suspended sediment concentration.

The second experiment was conducted to test the effect of random ambient light on mean grain size estimates. One hundred images of well-rounded beach gravel were taken under water with agitation of the water surface sufficient to cause natural light to refract randomly on the gravel surface. Agitation did not induce motion of the grains. Again, point counts on 1 image were used as a benchmark to compare the results. Figure 3 shows the differences (in percent) between true and estimated mean grain size as a result of non-uniform “natural” scattering of light. Variability was within 10%, which is lower than the r.m.s. error of the method.

Figure 3 Error associated with randomly varying light, in 100 images of stationary gravel in water.

The third experiment was performed to examine the effect of variations in natural daylight, in air, on mean grain size estimates. Two images were taken of well-rounded stationary beach gravel at every hour through the day, from 1m above the bed. The first image of each pair was unshaded, and the second shaded by an umbrella. Errors in mean grain size estimates were once again evaluated against a point-count carried out on the grains in the image. Figure 4 shows the percent errors in estimated grain size as a function of sun angle, for both the shaded and unshaded photographs. Errors were on the order of 15 - 25 % when no measures were taken to shade the grains from direct sunlight, and were reduced to less than 5 % when images were shaded, which removed large directional shadows cast by grains on each other. These findings are consistent with the findings of Graham and others, (2005) and Warrick and others, (2009), who also found significant reductions in error when measures were taken to remove large shadows caused by oblique sun angles. We did not find a clear relationship between solar angle and error in this preliminary study. As significant improvements occurred in our experiments when lighting source was diffuse, we recommend shading from direct sunlight, because the discrepancies (in mean grain size) which may arise due to the unevenness of the surface (and possibly the intensity of sunlight) may outweigh those introduced by the angle of solar incidence.

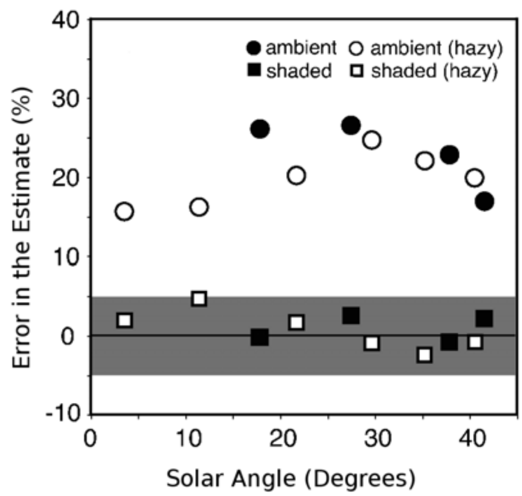

Figure 4 Error associated with different solar illumination angles, overall lighting (bright vs. hazy) and shading.

IMAGE CONSIDERATIONS

The minimum resolvable grain size in an image is a function of spatial resolution and of the distribution of grain sizes present (i.e., the sorting). While it is often possible to tell visually if grains in an image are adequately resolved, an automated and quantitative measure of resolution is highly desirable. Experiments were therefore conducted to find an objective measure of the point where grains become under-resolved. Randomly selected images were progressively down-sampled (i.e., interpolated over a smaller grid) and the standard deviation (contrast) computed for each downsample. We defined the point at which an image becomes under-resolved as the point where the greatest decrease in standard deviation per unit down-sample rate occurs. A more practical definition for an under-resolved image is one whose autocorrelation value at lag 1 is less than 0.7. The theoretical autocorrelation curve where $R(1) = 0.7$, therefore, may be taken as an approximation to the correlogram at the threshold between adequately and not adequately resolved. Correlograms at or below this threshold should not be used as it is highly likely that grains are under-resolved. One rule of thumb for optical image analysis is that the minimum grain radius be at least 2 - 3 pixels, which seems reasonable visually, and also agrees with the minimum workable grain scale of Warrick and others (2009).

The value $R = 0.5$ always corresponds to the steepest part of the correlogram of an image. Therefore, although ellipse-fitting on the 2D correlogram can return k at sub-pixel precision (i.e., decimal lags), the resulting mean grain size estimates are sensitive to small deviations away from *R* = 0.5 in this region (e.g., 0.49 or 0.51). This sensitivity could increase uncertainty in the estimated mean grain size. However, while it is beyond the scope of this paper to explore this in depth, we predict that this probably is only a significant concern when the image resolution is relatively poor, approaching the 2 - 3 pixel limit suggested above.

Autocorrelation should be calculated over sufficient lags to ensure *R* falls at least to below 0.5, but no farther than *R* = 0 as no new information is gained after that (Buscombe and others, 2010). Since there is a disproportionate amount of information in the first few lags, autocorrelation should be calculated for every 1 pixel shift. Lighting is crucial to the success of optical techniques, and the guidelines laid down by Rubin and others (2007); Warrick and others, (2009); and Buscombe and others, (2010) should be followed. Lighting should be optimized so that the contrast between pores and grains is maximized, but without overexposing either, and should avoid strong reflections from grain facets and crystal faces (see the grains in Figure 1 for examples). In general, lighting should be as diffuse as possible with no perceivable gradient, which means that lighting should be provided from at least two opposing sides of the image rather than from directly above (Rubin and others, 2007).

SUMMARY

We present a new method that determines mean grain size directly from an image using Fourier techniques. The resulting mean grain size is most closely related to the mean intermediate (b-axis) particle diameter. The measure may be thought of as more closely related to the mean of individual particle diameters rather than the moment-derived mean of a size-distribution evaluated over discrete grain-size classes. The method presented here is sensitive to the major axes of the projected areas of grains lying imperfectly in a semi-plane, which has been shown by Kellerhals and others, (1975) to, given sufficient sample size, satisfactorily approximate the true mean intermediate (b) axis. Thus the method presented here inherently accounts for the effects of overlapping grains. A correction factor would have to be applied to the results of the technique outlined here to provide estimates of the mean long (a) and short (c) axes of particles.

The measure of sediment size against which estimates have been compared is the mean of 100 particles, randomly sampled, on corresponding images, measured by eye from pore to pore across the intermediate (b) axis of the particle (here called point-counts). This measure has been found to be a linear function of the radius of an ellipse fitted to the *R* = 0.5 contour of the 2D correlogram. No averaging takes place in the estimate, over individual particles or sediment size classes. Therefore it is a measure which has very few degrees of freedom.

Physical experiments showed that turbid water can bias grain-size estimates (up to 40%), but that the random refraction of light by ripples resulted in small (less than 10%) random errors. The smallest errors (less than 5%) were found in shaded images of gravel beds that were illuminated by natural solar light and photographed in air. Shading was shown to be very important as it removes large directional shadows cast by grains on each other.

This new method should have a similar derivation for other similar statistical approaches, for example semivariance (e.g., Carbonneau and others, 2004, 2005; Verdu and others, 2005; Buscombe and Masselink, 2009). In addition, the insights obtained here may also be used to optimize the use of the spatial autocorrelation technique of Rubin (2004), which solves for mean grain size using a least-squares fit between the correlogram of a sample image (of unknown mean grain size) and a catalogue of correlograms associated with sediment of known mean grain size. For example, the theoretical forms of the correlogram as presented in this paper may be of use in the selection of grain-size fraction spacing, and other ways pertinent to calibration catalogue design.

There may be a unique value of *R* associated with several percentiles of the grain-size distribution, but this may be restricted to idealized cases of very well sorted sediment photographed at very high resolution. The highest level of precision will be achieved if the new method is partially calibrated. By this we mean that, if point-counts on (fine and coarse) end members of individual sediment populations reveal significant bias (in the form of an apparent slope in data away from the 1:1 line), maximum precision will be achieved by carrying out a regression and correcting for the slope of the bias. We predict that reliable estimates of the whole grain size distribution will always require some form of calibration, due to the multifarious nature of images of sediment.

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