Stone tools from the inside out: radial point distribution

Andrew T. R. Riddle and Michael Chazan

Abstract

The concept of shape is central to the classification of material culture. In the case of lithic technology, archaeologists have attempted to characterize shape quantitatively and qualitatively using diverse methods ranging from manual caliper measurements and metric ratios to digital artifact scans and statistical analyses. Three-dimensional modeling has opened up new avenues for shape analysis that permit a more holistic perspective on how objects occupy space. As a result, researchers are able to explore new qualities of artifacts that were previously inaccessible through more traditional shape analyses. This paper outlines a new method for quantifying distribution of mass in lithic specimens from three-dimensional point-cloud data. Radial point distributions (RPDs) are calculated from point-filled models based on the distances of each point to the model centroid. The resulting distribution data provide a means of quantifying three-dimensional shape that is readily compared through statistical analyses. RPD calculation requires no manual specimen alignment or landmark identification, thereby removing major sources of subjectivity. It is argued that RPDs provide a means of quantifying the 'balance' of lithic specimens, such as handaxes, allowing researchers to explore this tactile aspect of stone tools in conjunction with more traditional visual aspects of shape.

Keywords

Morphometrics; lithic technology; 3D modeling.

When Louis Agassiz had a new student at the Museum of Comparative Zoology, his practice was to present them with a fish and to leave them with this specimen to examine for days on end (Winsor 1991). This peculiar rite of initiation will not seem terribly foreign to many archaeologists, who spent their early years with collections of artifacts and little in the way of formal guidance. With lithic analysis, it is difficult to teach the skills of observation until a student has had a chance to immerse themselves in stone tools and get 'a feel' for these objects. There is, however, a rupture between the ways in which we as analysts experience stone tools as *tactile* objects and the methods of analysis we employ that are largely confined to the *visual* aspect of the tools. The development of typological analysis was built on the visible qualities of tools that could be represented in drawings, and quantitative analysis has maintained this focus through measurements that characterize plan view and section.

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The emergence of the *chaîne opératoire* approach to lithic analysis has emphasized 'invisible' aspects of lithic technology, particularly the conceptual models that guide core reduction and the shaping of tools (Chazan 2009). Part of this approach is the explicit recognition of the sensory aspects of technological process as experienced by the individual. Aside from guiding isolated technical actions, tactile feedback is essential for assessing quality of form and guiding the selection of technical strategies throughout the stone-working process. The appearance of an object is arguably the most present sensory cue for a flintknapper, as well for those observing the object's manufacture. In contrast, weight and balance are less easily conveyed yet are highly significant influences on decision-making. That being said, lithic analysts rarely explore variability in the 'feel' of specimens because of the subjectivity and lack of comparability inherent in traditional approaches.

In recent years, pioneering studies that apply 3D imaging in lithic analysis have focused on increasing rigor in the collection of metric data and improving the precision of archaeological systematics. In their test of the use of a cross beam co-ordinate caliper, Lycett, von Cramon-Taubadel, and Foley (2006) emphasize the need to develop methods that allow for evaluation of intra- and inter-observer error. Through an innovative application of 3D scanning to the analysis of handaxe morphology, Grosman, Smikt, and Smilansky (2008) point to the value of their method for avoiding errors inherent in manual measurement of complex shapes. A number of studies have explored the use of landmarks and semi-landmarks for 3D shape analysis. Archer and Braun (2010) use a 3D digitizer to record semi-landmarks on large cutting tools from the site of Elandsfontein, South Africa. These data are used for a statistical analysis of morphological variation in relation to raw material type. In a similar approach, Shott and Trail (2010) carry out a landmark analysis of Paleo-Indian points based on models generated by a 3D scanner (see also Thulman 2012). Bretzke and Conard (2012) took a step forward in using 3D models to gain access to data on convexity, twist and scar patterns – all difficult to quantify using traditional analog methods – to analyze Upper Paleolithic blade production at the site of Yabrud II, Syria. These studies demonstrate that 3D imaging technology offers an opportunity to increase analytical precision (Grosman, Goldsmith, and Smilansky 2010; Lin et al. 2010) and facilitate estimation (Clarkson and Hiscock 2011) in lithic analysis; however, these are but two uses of this relatively new technology and a focus solely on either risks underestimation of its potential.

Geometric morphometric (GM) analyses, including landmark-based and landmark-free approaches, have largely been applied to two-dimensional lithic data, particularly artifact plan-view outline (e.g. Costa 2010; Iovita 2010, 2011; Thulman 2012). While some three-dimensional GM studies have been undertaken on lithic specimens (Archer and Braun 2010; Lycett, von Cramon-Taubadel, and Gowlett 2010; Lycett and von Cramon-Taubadel 2013), they utilize low-resolution data collected by manual means that are suitable for the geometric analyses being conducted. Biological studies have demonstrated that high-resolution three-dimensional datasets can be utilized in more comprehensive comparative morphological analyses, such as 3D elliptical Fourier analysis (Chung et al. 2007). Unfortunately, such approaches have yet to be applied to archaeological lithic specimens. GM analyses are promising for lithic analysis because of their ability to characterize shape independent of size while simultaneously relating multiple reference points in a fashion that is not possible with traditional distance and ratio-based metrics.

The present work introduces a new data structure called the radial point distribution (or RPD) as a novel means of characterizing and comparing shape through three-dimensional model data.

RPDs describe the distribution of mass within a given object, providing an 'inside-out' perspective on form rather than traditional 'outward-in' visual representations (Riddle and Chazan 2010). Put simply, the frequency of vertices spaced at various distances from the model centroid are used to describe the arrangement of 'mass' within an object. These distributions can then be used to compare the shape of digital models and, by extension, the form of the objects the models represent. Although not a GM approach strictly speaking, RPDs have several advantageous qualities in common with geometric morphometric methods that make the approach uniquely suited to the characterization of three-dimensional artifact form where it intersects with tactile experience.

Method

Radial point distributions are constructed by calculating the number of vertices in a model that are positioned within a given distance range from the model centroid. The model centroid is here defined as the mean vertex position, calculated by averaging the X-, Y- and Z-axis values for all vertices in the model (cf. Zelditch, Swiderski, and Sheets 2012, 79). Note that this may be different from the centroid of a bounding box or sphere encompassing the same object (Fig. 1). In the case of simple objects of uniform density, centroid position is synonymous with centre-of-

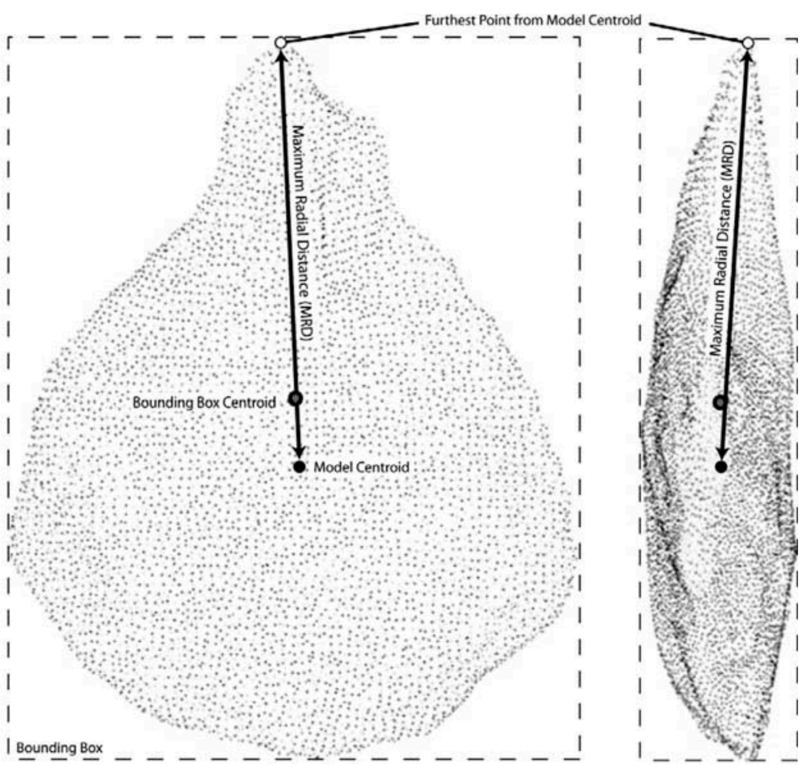


Figure 1 Plan and profile views of SPL097 cluster-decimated point cloud showing differing model centroid and bounding box centroid.

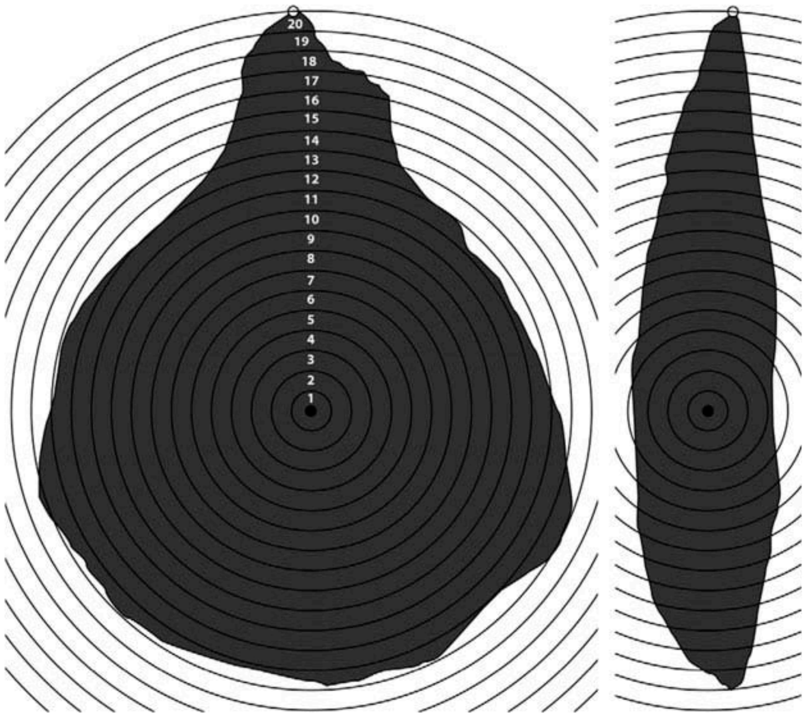


Figure 2 Plan and profile views of SPL097 illustrating 5 per cent volume shells emanating from the centroid.

mass. Centroid-vertex distances are calculated radially, which is to say that all points that fall within a range, regardless of their rotational position relative to the centroid, are included in the calculation. As such, RPD generation is objective insofar as that the process is orientation-independent and requires no subjective landmark selection to define common points of reference.

Distance intervals of identical range length, here termed volume shells, are used to subdivide the vertex population (Fig. 2). These shells can be conceptualized as nested spheres with progressively increasing radii corresponding to the distance ranges described above. The first, or innermost, shell has a radius equaling 5 per cent of the maximum radial distance (MRD). MRD is the distance from the centroid to the most distant vertex in the model and is, therefore, the minimum radius of a sphere centered on the centroid that encompasses all vertices (see Fig. 1). All vertices that fall within the first 5 per cent of the MRD, the first distance interval, are contained within the first shell. All vertices positioned within 5–10 per cent of the MRD, the second distance interval, are contained within the second shell, and so on. When this structure is used to parse point-cloud model data, the result is a frequency distribution that describes how the basic elements of the model – its points – are distributed throughout the spherical space that the object occupies. Such distributions can be quantitatively compared to determine the relative similarity in the form of an object as represented by point-cloud model data. Objects with similar forms, that is objects whose mass is similarly distributed within the spherical space they occupy, produce similar RPDs.

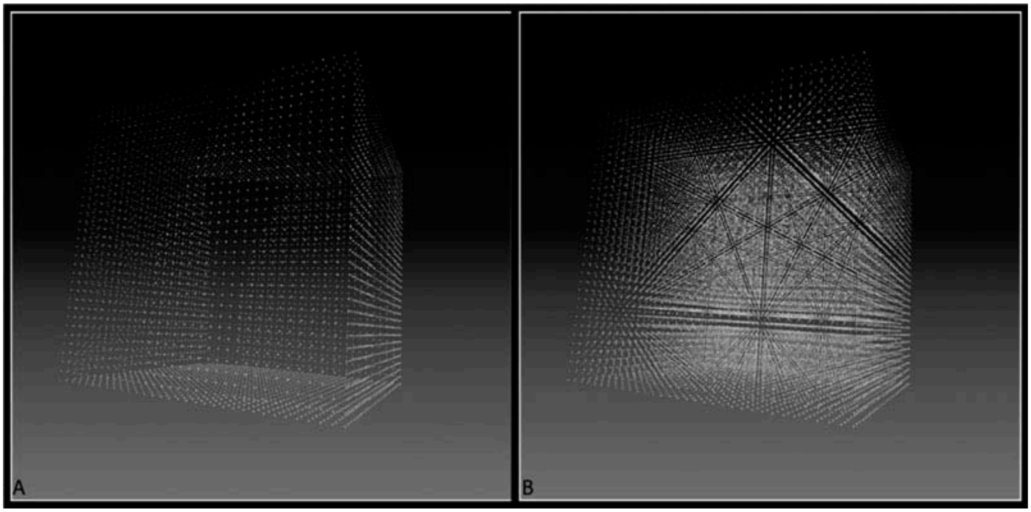


Figure 3 A – hollow cube model (2 per cent spacing; 6,146 vertices); B – filled cube model (2 per cent spacing; 24,389 vertices).

Digital point-cloud models typically comprise a hollow ‘skin’ representing the exterior surface of the object modeled (Fig. 3a). Therefore, an RPD generated from such a model describes the distribution of the object’s *surface* in reference to its centroid. In order to ensure that a given model’s data can be compared with those of other models, some pre-processing is required. Specifically, the spacing of points along the model’s surface must be regularized to remove any distributional bias. Optimization of surface meshes tends to result in high densities of points near curved segments where changes in shape need to be reflected, whereas redundant points in flat segments are minimized to reduce point counts. The result is an uneven point distribution that is not immediately compatible with RPD generation. A model with uneven point distribution can be made compatible through cluster decimation, a process by which points in proximity to each other are merged, resulting in an effectively even point distribution. Depending on the model’s post-decimation resolution, fine surface detail may be lost during this process, but the overall model shape is retained. The authors found a resolution of 1/100th of the maximum model length to be ideal as it adequately preserved object shape while keeping the total point count manageable, although higher resolutions are desirable if initial scanning resolution and computational capacity permits. Once regularized and checked to ensure that the decimated mesh has retained its vertex normals – the data indicating what direction is the ‘outside’ of the object – the model is suitable for analysis.

An RPD created with a common ‘hollow’ model only describes the distribution of the outer skin, not what is within it. While trails using such models have successfully grouped similarly shaped objects, such as cones, cylinders and pyramids, the results do not speak to the tactile qualities of such objects. In order to describe the entirety of the object modeled and thereby examine the distribution of volume, and thus mass, a model must be ‘filled’ with points (Fig. 3b). This can be achieved by infilling a model with a cloud of uniformly spaced points. Such a cloud should be constructed using a suitably small inter-vertex distance. In the authors’ experience, a value equal to 1/50th of the smallest axial dimension, typically a specimen’s

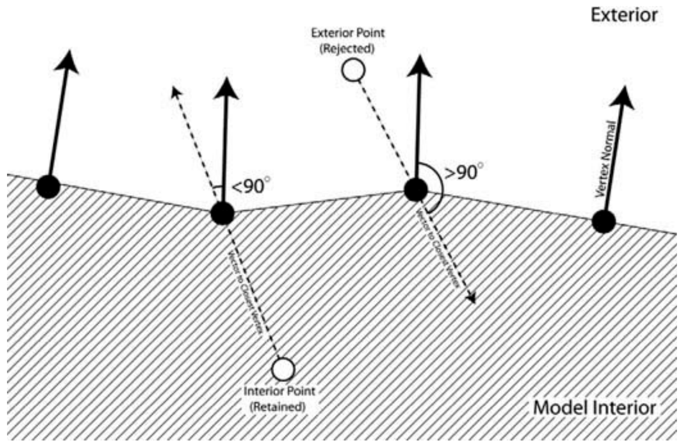


Figure 4 Point culling method – points exterior to the model will yield vector-normal angles greater than 90 degrees and can be rejected. Points within the model will yield angles less than 90 degrees and can are retained.

thickness metric, yielded sufficiently high resolution. Low resolution yields misleading distribution values that may not sufficiently reflect the density of certain parts of a model, particularly those parts that are as narrow or narrower than the inter-vertex distance. Again, higher resolutions are recommended where feasible.

The process used to fill surface models with a point cloud consists of three steps. A box-shaped cloud of equally spaced points is first generated around the surface model using the spacing distance defined above. The dimensions of this box should equal the maximum dimensions of the model in each coordinate plane such that the entire model is encompassed. Optimization of bounding box size to be as small as possible decreases computation time but does not otherwise influence the resulting dataset. Second, cycling through each of the cloud points in turn (Vertex A), determine the closest vertex on the surface of the model (Vertex B). Using these points, calculate the normalized vector from Vertex A to Vertex B. The angle between this vector and Vertex B's normal indicates whether Vertex A is contained within the model or not. Calculation of the inter-vector angle is accomplished by taking the scalar (dot) product of the two normalized vectors. If the angle is less than or equal to 90 degrees, Vertex A is within the model and is retained. If the angle is greater than 90 degrees, Vertex A is outside the model and can be discarded (Fig. 4). As the final step, the surface points of the original model are removed, leaving only the cloud points contained within the model.

It is noteworthy that infilling of this kind will, depending on the spacing of points within the model, remove surface detail from the artifact to varying degrees, akin to what one would expect on a water-rolled specimen (Grosman et al. 2010). As this technique is intended to generate data regarding the distribution of mass throughout an object, the loss of fine arris detail is inconsequential. Nevertheless, care should be taken to select a spacing value that will preserve as much of the overall form as possible without unnecessarily increasing computational requirements. The authors found that processing a filled model using the aforementioned resolution on a mid-range desktop computer (Quad Core, 3 GHz, 8 GB RAM) required between five and ten minutes per specimen. Processing time increases exponentially with resolution refinement, although more powerful computing systems could reduce these times considerably.

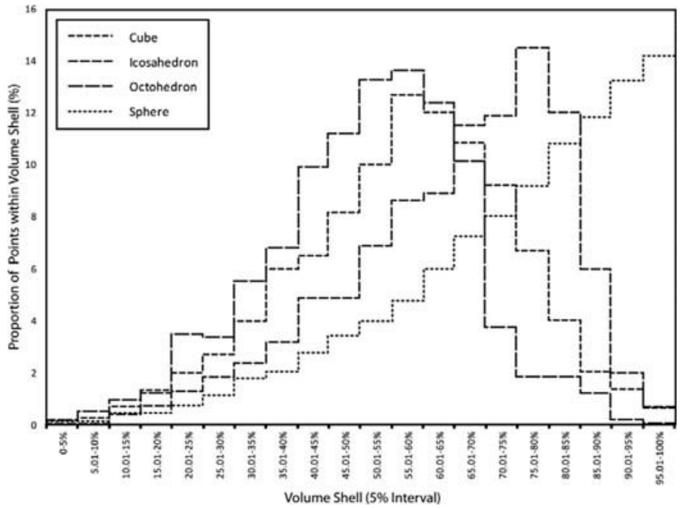


Figure 5 Example radial point distribution histogram for four simple geometric objects.

Radial point distributions using filled-model data describe the organization of mass for an object within the spherical space the object occupies. The centroid of such a model corresponds closely to the actual centre-of-mass for the object represented. As an RPD is calculated using the centroid as a reference point, the resulting vertex distributions can be used to compare the 'balance' or 'feel' of two or more objects assuming equal size and material density (but see below for how relative size can be incorporated into distribution comparison). Figure 5 depicts overlapping mass distributions of four simple geometric objects, and Figure 6 shows the results of cluster analysis on basic geometric forms using RPDs.

The RPD approach to shape comparison has several notable advantages. For instance, range calculation and the resulting vertex catchments do not rely on a particular model alignment. Centroid position and interval ranges are precisely the same for a given model regardless of the orientation of the model, and therefore the method is *orientation-independent*. Also, like many geometric morphometric approaches, the method is *scale-independent*; the resulting distribution uses normalized frequencies of vertices for each interval, each in turn defined as a proportion of the maximum radial distance. The size of the model has no effect on the generation of the distribution curve. For example, two models that are identical in every respect save for one being twice as large as the other in all dimensions would generate identical RPD curves. While one is clearly larger than the other, the distribution of 'stuff' within the space the object occupies is the same.

In addition, the shape of an object can be *quantitatively* compared using RPD datasets. Various metrics, including mean sum error and median error, can be used to evaluate the relative difference between forms as expressed by differences in distribution interval frequencies. Squared Euclidean distance works well for this purpose. These values can in turn be employed for hierarchal clustering and other relational expressions of distributional differences. For instance, Fig. 7 shows the result of a hierarchal cluster analysis of RPDs for Acheulean bifaces from Stratum 9, Excavation 1, Wonderwerk Cave, South Africa (for information on Wonderwerk Cave, see Chazan et al. 2008, 2012). The RPD is objective in its generation so that

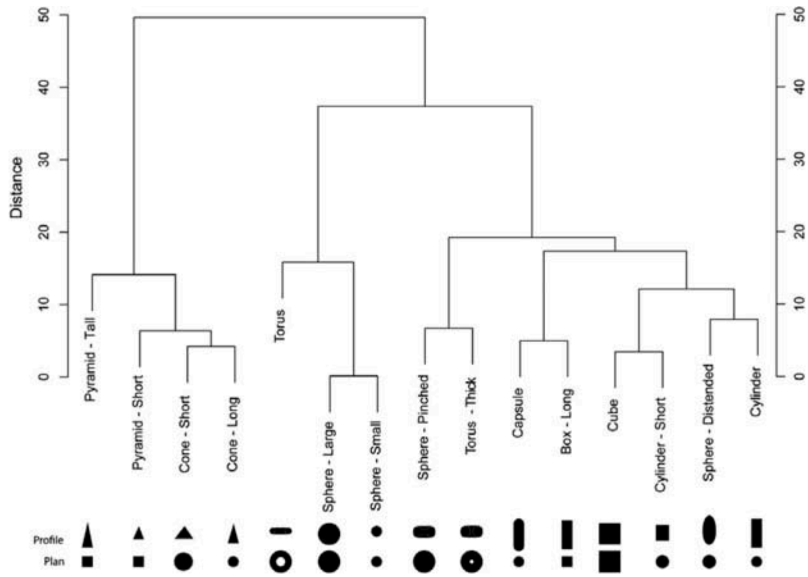
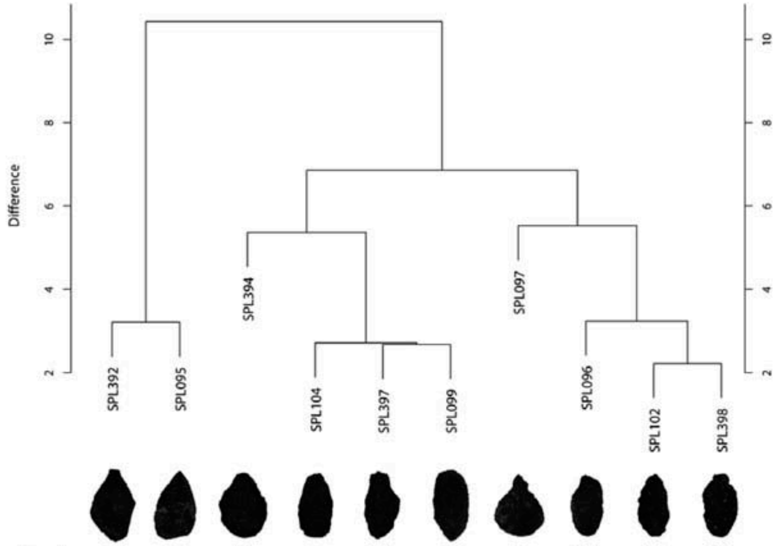


Figure 6 Clustering dendrogram of simple geometric models depicting three main clusters. Note that the spheres yield a difference of 0, as they have identical mass distributions.

subjective bias introduced by comparative sample selection according to a given typology or size grading is largely avoided, but see below for potential restrictions.

The resolution of RPDs is also noteworthy. Using 5 per cent radial intervals and assuming non-decimal frequency values, the RPD has a theoretical resolution of 4.9 × 1021 unique distributions. Although the actual range of distributions likely to be encountered is much lower, the effective resolution would be, at minimum, on the order of several hundred million unique signatures. Such resolution is more than sufficient for differentiating minute variations in specimen form even assuming a relatively high degree of morphological similarity.

Several methodological restrictions are equally worthy of note. First, the required *pre-processing investment* is not trivial. In order to create a RPD, the model to be analyzed must be subjected to a series of pre-processing routines, as detailed above. While these operations are not excessively time- or effort-intensive, they are necessary and add to the complexity and duration of the RPD calculation process, increasing the potential for procedural error. Second, although touted as an advantage, *scale independence* can also be a detriment in certain studies. Since the RPD calculation process detailed above ignores differences in object size by normalizing all metrics relative to the object's maximum dimension, the resulting shape curves do not reflect variation in scale, only the relative distribution of vertices within a particular model. Studies seeking to explore differences in form including size would necessitate specifying a uniform vertex spacing for all models included in the study. This value should be set by the smallest model in the sample, thereby ensuring a minimum resolution for all subsequent model analyses. Use of non-normalized vertex counts in the RPD will then yield results that take into account object size and can be used to compare object scale and form together. Note, however, that inter-model differences measured in this way do not distinguish between scale and form,



Length (mm)	141	120	105	97	121	136	97	155	109	155
Thickness (mm)	36	46	27	35	37	37	20	32	22	32
L/T Ratio	3.91	2.60	3.88	2.77	3.27	3.67	4.85	4.84	4.95	4.84
B1/B2 Ratio	1.38	1.96	1.48	1.17	0.77	0.85	3.00	1.10	1.25	0.99

Figure 7 Clustering dendrogram of Wonderwerk Stratum 9 biface sample showing three clusters. Note that clusters do not correlate with the metrics and outlines provided below each specimen. B1: Breadth 1/5th length from base; B2: Breadth 1/5th length from tip. All measurements were taken with digital calipers on the physical artifact except for SPL 95, which was measured digitally from the 3D model.

and therefore a large discrepancy in distribution interval values could equally reflect a significant difference in size or in shape. In these cases, normalized RPD values can be used to ascertain the contribution of form variation to the perceived distribution differences.

Orientation independence, likewise, has its disadvantages. The absence of orientation data in the RPD means that it is not possible to infer the specific morphology of an object from its distribution alone. While the RPD reflects the distribution of mass between volume shells, it cannot differentiate between mass distributions within volume shells. One can infer that the object has one or more extensions from a central mass, but it is impossible to determine with certainty the proximity of these extensions to each other.

Equifinality presents its own unique difficulties. Given the orientation-independent nature of RPD calculation, it is possible for objects with very different morphologies to generate similar vertex distributions. Most commonly, objects with complex morphologies, especially those with extensions (e.g. four-legged table) or recurving surfaces (e.g. radiator), produce distribution profiles that can be near-identical to those of more simple objects of radically different shape (e.g. handaxe). Consequently, RPD distributions are not ideal for analyzing shape similarities in a model sample where the specimens include a combination of simple and complex forms. The authors do not consider this to be a significant weakness of the RPD as it is expected that most analyses will be aimed at comparing the shape of specimens that have already been identified as comparable, such as a sample of flaked stone bifaces. Nevertheless, equifinal results must be recognized as a potentially misleading artifact of the proposed methodology.

Lastly, *differential magnitude* between specimens, for example as calculated by squared Euclidean distance, is interpretively neutral. To illustrate, one can imagine three specimens whose RPDs differ by a value of 100 for specimens A and B and by a value of 1,000 for specimens A and C. The difference between these values carries no essential interpretive significance beyond that specimens A and B are more similar to each other in form than specimens A and C. How this observation is interpreted depends entirely on the context of the analysis.

Discussion

As evidenced by our initial trials with basic geometric forms, the RPD meets intuitive similarity matches. Interestingly, RPDs do *not* replicate typological groupings within the Wonderwerk biface sample based on traditional metrical analyses. As shown in Figure 7, the pairings and overall cluster organization do not correlate with length, thickness, length/thickness ratio or breadth 1/breadth 2 ratio. Consequently, we assert that RPDs, rather than being a means of evaluating or refining existing typological systems, are a means of investigating an aspect of tool design and variability that has been inaccessible to rigorous empirical research. RPDs expand the range of inquiry into the dynamics of tool use and manufacture by providing access to an aspect of the tactile experience (as opposed to visual experience) of these tools.

The question remains, however, of how this method can contribute to our understanding of tool manufacture and use. The literature on the cognitive science of tool use points to a need to integrate the tactile reality of tools into existing research frameworks. Although there have been cross-cultural studies of visual perception of three-dimensional objects (Biederman, Yue, and Davidoff 2009), studies that account for the tactile properties of objects are limited. There is strong evidence that tool use draws on widely distributed cognitive processes and combines both the perception of 3D form and the functional properties of the tool as an object distinct from the human body (Frey 2007, 2008; Randerath, Martin, and Frey 2012; Welchman et al. 2005). There is thus justification for developing a multiplicity of perspectives on tools that includes their tactile properties.

The distribution of mass described by RPDs is a means of describing the distribution of weight in an object as experienced by a person holding said object. Put another way, objects with similar mass distributions and, importantly, the same density, have similar ‘balance’ when held in the hand. Of course, this depends entirely on how the object is held and manipulated, but the kinds of balance that can be experienced wielding objects with similar RPDs are likewise similar. This is also not to say that the objects will feel the same in all respects, given that surface texture, material type and other factors contribute to the overall tactile experience. Rather, how the balance of an object is sensed as it is manipulated – swung, thrown, lifted, etc. – will be shared by objects with very similar RPDs. In cases where balance is central to the function of a tool, as has been asserted for handaxes (Chazan 2011), RPDs provide a window into the functional affinities of these objects and, as such, have great potential for exploring how this proxy measure of tactile phenomena maps onto existing typologies, morphological variability and functional interpretations of handaxes and similar classes of artifacts.

RPDs are more intuitively useful for analysis of tools that were not hafted because distribution of mass would be more relevant to the prehension of the tool in such cases. In a hafted context, the entire ensemble of parts would be judged for appropriate balance and thus analysis of one component would be insufficient. In this sense, handaxes are an ideal subject for RPD-based studies being large, manual tools where distribution of mass is integral to its function, albeit depending on the prehension technique employed. That being said, there are instances where distribution of mass may play an important role in the design and function of elements within a composite tool. Attempts have been made, for instance, to distinguish atl-atl dart points from arrow points on the basis of traditional morphometrics and statistical inquiry (cf. Corliss 1972, 1980; Shott 1993, 1997; Thomas 1978). If dart and arrow points exhibit significant differences in mass distribution, perhaps as a result of or related to aerodynamic constraints, an RPD analysis would reveal distinct signatures for each type that could be compared quantitatively.

Conclusion

Radial point distributions provide a method for quantitative analysis of mass distribution in any three-dimensional form, and here it is argued that lithic studies in particular can benefit from its use. This approach is not intended to replace more traditional methods of shape analysis, and indeed some newer geometric morphometric approaches, such as elliptical Fourier analysis, are compatible with both two- and three-dimensional datasets and are better suited to represent and compare subtleties of surficial form. Instead, RPDs stand out as a means of providing access to the tactile qualities of artifact shape, an aspect of stone tools that was previously accessible to qualitative research. RPDs thus exemplify how 3D analysis approaches provide opportunities to do what we have always done and with greater precision, but also a means of exploring aspects of the archaeological record that have thus far eluded researchers.

We suggest that RPDs have the potential to help incorporate an objective perspective on tactile experience into research on tool design. In the context of Wonderwerk Cave, we anticipate that RPDs will provide additional perspective on the emergence of bifacial technology that will complement traditional morphological analysis, use wear and technological analysis. However, we also see a pressing need for experimental studies to understand the limits of human perception of weight distribution to provide a point of reference for interpreting the archaeological data.

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Andrew T. R. Riddle
Archaeological Services Inc.

Michael Chazan
University of Toronto
mchazan@chass.utoronto.ca

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Andrew Riddle is a Senior Archaeologist at Archaeological Services Inc. His PhD research was on lithic technological change in the Canadian Arctic and he has published on digital morphometrics for lithic analysis.

Michael Chazan is Professor in the Department of Anthropology at the University of Toronto and Director of the Archaeology Centre. He co-directs the Wonderwerk Cave Research Project with Liora Kolska Horwitz and is currently engaged in renewed excavations at the site with Dr Horwitz and Francesco Berna.