# Deformable Model Based Shape Analysis Stone Tool Application

Kyoungju Park
Dept. of CIS
University of Pennsylvania
Philadelphia, PA, 19104
kypark@seas.upenn.edu

April Nowell
Dept. of Anthropology
University of Victoria
Victoria, BC, Canada
anowell@uvic.ca

Dimitris Metaxas
CBIM Center
Rutgers University
New Brnswick, NJ08854
dnm@cs.rutgers.edu

## Abstract

*This paper introduces a method to measure the average shape of handaxes, and characterize deviations from this average shape by taking into account both internal and external information. In the field of Paleolithic archaeology, standardization and symmetry can be two important concepts. For axially symmetrical shapes such as handaxes, it is possible to introduce a simple appropriate shape representation. We adapt a parameterized deformable model based approach to allow flexibility of shape coverage and analyze the similarity with a few compact parameters. Moreover a hierarchical fitting method ensures stability while measuring global and local shape features step-by-step. Our model incorporates a physics-based framework so as to deform due to forces exerted from boundary data sets.*

## 1. Introduction

This paper introduces a method to represent and measure the average shape of handaxes and characterizes deviations from this average shape by taking into account both internal and external information using inherent properties of stone tools.

One of the most interesting areas of research in Paleoanthropology focuses on questions concerning the evolution of human intelligence [see papers in 12]. There is an implicit assumption in archaeology that modern cognitive abilities are required to produce highly standardized stone tool assemblages and highly symmetrical artifacts (e.g. symmetrical both in plan view and in cross-section).

The exact nature of the relationship between standardization and symmetry and the evolving human mind has been questioned [e.g. 5] as there are a number of factors that influence stone tool morphology that have little or nothing to do with differences in cognitive abilities (e.g. the type of raw material used to make a tool, its specific function, the reuse/re-sharpening of a tool etc). Nonetheless, these variables can still be useful for archaeologist interested in this area of research [12,15]. Therefore, it may be that as researchers observe changes in standardization and symmetry over time that one is also documenting concomitant changes in hominid [1] capabilities over time. For this reason, it is crucial to be able to quantify these variables in as accurate a manner as possible.

A number of traditional measurements manually calculate by experts to quantify handaxe shape [2]. More recently, computer based approaches that allow for automatic and detailed analyses have been proposed [9], and it is this type of approach that we discuss here.

When studying standardization and symmetry study, we need to consider both internal and external information. While medial axis representation [10] focuses on internal skeletons, curve representation [17] focuses on external information. Active shape models [11] represent the shape as a PDM that has mean shape and set of linearly independent variation modes. Though this model can be applied to various cases, it is often difficult to characterize features and derive intuitive description. Terzoupolus et al. [13,14] use a symmetry property to constrain the deformation of the model. Since their symmetry-seeking model assumes the symmetry, it cannot measure the degree of symmetry.

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[1] The term hominid refers to modern humans and their ancient ancestors. In this paper this would include *Homo erectus* and/or *Homo sapiens neanderthalensis*.

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We employ a deformable model approach that has been applied in numerous contexts [3,8] because of its compact shape representation. A parameterized deformable model employed here is created to capture various shapes and to analyze shape similarity using a limited number of parameters. A hierarchical fitting method ensures stability while allowing for flexibility of covered shape ranges.

Our model incorporates a physics-based framework [4]. Here, the model deforms due to forces exerted from boundary data points in order to minimizing overall forces of Lagrangian dynamics equation of motion. Model parameters are estimated to minimize overall parameter forces computed from boundary forces. Before fitting commences, the axis of symmetry and secondary axis are computed and used for guidance of shape estimation. Therefore the resulting shape parameters are good for axial symmetric shape analysis. Moreover we classify test cases according to its shape parameters.

While our deformable model approach can be applied to various types of retouched and unretouched stone tools, here we apply this methodology to Acheulian handaxes from Tabun Cave, a well dated, highly stratified, Middle-Upper Paleolithic cave site in Israel(see discussion in [5]). We then compare our method of shape analysis to more traditional approaches of quantifying handaxe morphology.

## 2. Deformable Handaxe Shape Model

In this section we briefly review our deformable model geometry and shape parameters that are suitable for quantifying symmetry and standardization of handaxe morphology.

### 2.1. Deformable Model Geometry

We define a shape model $s(u) = c + \mathrm{Re}(u)$ where c and R are the global translation and rotation of the model, and e(u) is a generalization of the ellipsoid primitive. One of the simplest shape descriptors is a change in the length of the global components along the direction of coordinate axes. This produces an orthogonal scaling operation on ellipsoid-like primitive.

$$e(u) = e(u; sc, a1(u), a2(u)) = sc\begin{pmatrix} a1(u)\cos u \\ a2(u)\sin u \end{pmatrix}$$

where u = (-pi, pi) a1, a2>=0; sc is the scaling parameter for the model and a1 and a2 are the axial length parameter functions. The scaling parameter sc is used for size invariant shape feature extraction. The function a1 and a2 are parameters that are evaluated at positive and negative directions along axes from its origin.

The shape presented by *e* deforms depending on the deformation parameters. While we can apply many deformation operations, we found that parameterized tapering is suitable for capturing the "curvature" and "irregularities" of the shape. Given the above primitive *e*, parameterized tapering is defined along the model axis y. We define the function t(u) as a linear function of u as follows:

$$s(u) = T(e; t(u)) = sc\begin{pmatrix} (1 + t(u)a2(u)\sin u)a1(u)\cos u \\ a2(u)\sin u \end{pmatrix} \quad (1)$$

where $t(u) = tapering * u / pi$.

By putting all the parameters together, the vector $q$, which refers to the degrees of freedom of the model with respect to the model parameters are as follows:

$$q = (a1(u), a2(u), t(u))^T \quad (2)$$

Figure 1 shows how the initial deformable primitive is changed when model parameters increase and decrease. While a solid line represents the initial deformable model, a dotted line represents the model after deformation.

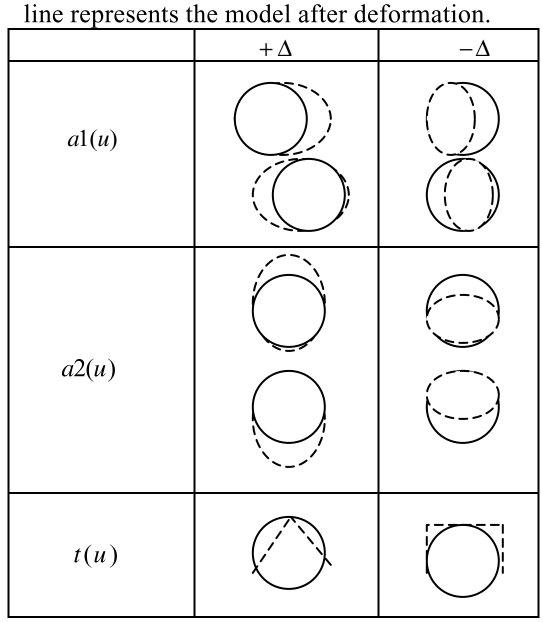


Figure1. Parameter Graph.

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The Jacobian of the shape primitive s can be computed in a way using a chain rule [4].

## 2.2 Shape Fitting

By incorporating the geometric definition of the models into the physics based framework, we create a dynamic model that deform due to forces exerted from datasets.

In shape estimation, the governing Lagrangian equations of motion can be simplified while preserving useful dynamics. We accomplish this by setting the mass density to zero so that the resulting equation yields a model that has no inertia and comes to rest as soon as overall forces equilibrate.

$$\dot{q} = f_q \qquad\qquad f_q = \int L^T f du$$

where q is the vector of the model parameters and $f_q$ is the associated generalized forces. Then generalized forces $f$ are computed from the boundary data forces. The Jacobian matrix L converts the data forces $f$ into forces that directly affect the parameters of the model. The data forces, taken from boundary points of the handaxe, are computed by distributing force weights to the closest line element on the model. The forces are exerted from data points to the nearest line element of the model.

By doing hierarchical fitting, we cannot only estimate global and local information but we can also ensure stable fitting. Furthermore, we can recover the shape for incomplete datasets because our parameter estimation is guided by parent parameters that are estimated at previous levels.

# 3. Global and Local Shape Measures

The resulting information can be used to measure the average of handaxe shape and characterize the deviations. In order to find the principal axis, the axis of symmetry, a model translates and rotates so that the longest bisecting line is the principal axis and the maximum width line, orthogonal to the principal axis, is the secondary axis. Then the model is scaled such that the maximum distance from the model center to the perimeter is set to 1.

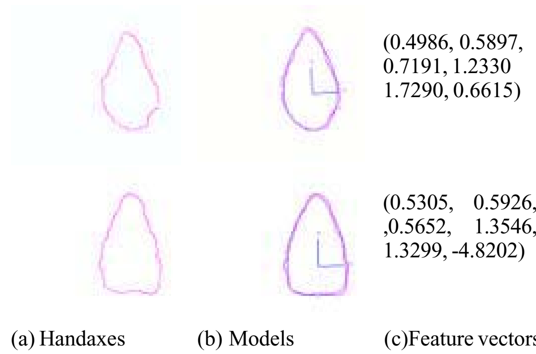


Figure 2. Global Shape Features. Given handaxes, the models approximate the shape and represent its features in six parameters. The feature vectors are (a1+, a1-, a2-, a2+, taper at tip, taper at base) and are explained in equation (2).

A model approximates the shape in a few numbers of parameters. The shape features of handaxes are measured with six variables of axial scaling parameters and tapering parameters. The axial scaling parameters, a1+, a1-, a2+ and a2- are positive/negative directional a1(u) and a2(u) parameters. The tapering at tip and base represent the curvature of the slope where tapering parameters range from –5 to 5. Figure 2 shows examples of handaxes, shape models and shape feature vectors.

While a1+,a1-,a2+,a2- and tapering at the tip and base are able to capture global features of handaxe morphology, the variations of a1, a2 and tapering at child-domain (parameters are continuously estimated at finite number of domains) capture the detailed information.

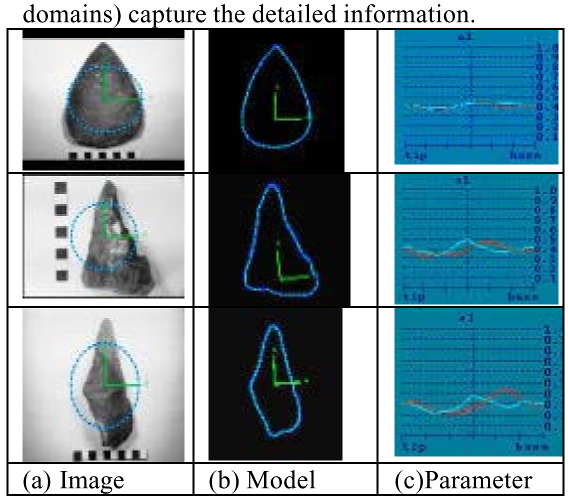


Figure 3. Local Shape Features

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Figure 3 depicts three examples of the methodology presented here. After measuring global shape feature vectors, the model estimates the variations of a1 and a2 parameters. The parameter graph shown in (c), draws the parameter a1+ in red and the parameter a1- in cyan. Hence, the difference of two lines visually represents the degree of symmetry.

Another important measure is the degree of symmetry in handaxes. In other applications for the symmetry study, they use the metric based calculation called SD(Symmetry Distance)[9]. Here, we use the parameter-based calculation that is a simpler and more intuitive abbreviation.

$$symmetry = \frac{1}{n}\sum_{n}\left|p_{a1} - q_{a1} + p_{a2} - q_{a2}\right| \qquad (3)$$

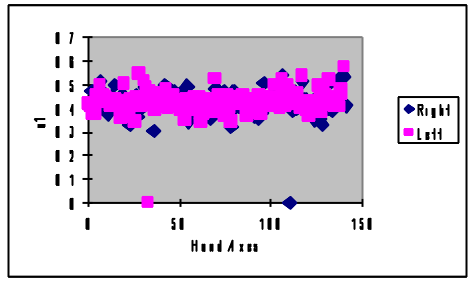
Symmetry is calculated using model parameters at each node $p$ and $q$. The degree of symmetry depends on the parametric differences of matching nodes w.r.t the axis of symmetry. The a1 and a2 parametric differences are summed up and divided by number of nodes, in our examples n=72. Model nodes are regularly spaced in $u$ coordinates where $-\pi <= u < \pi$. The node $p$ is a mirror node of the node $q$ according to the axis of symmetry. As a result, the degree of symmetry ranges from 0 to 1 where the smaller value means more bilateral symmetric.

## 4. Experimental Results

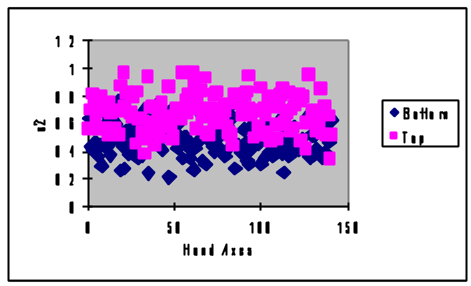
In Paleolithic archaeology following the work of François Bordes [2], traditional measurements of handaxe shape include width at midpoint, width at 1/3 points, width at 2/3 points, length and thickness.

While the traditional measurements such as width and length are defined in [1], we, here, do experiments how our model parameters can explain standardization and symmetry of handaxes' shape. Our study is conducted using Acheulian handaxes from Tabun Cave in Israel.

By testing a training set of 158 handaxes we obtain the following model parameters. Figure 4 shows a series of a1 parameters on the left and right sides and series of a2 parameter at top and bottom halves of the handaxes. Even from a cursory reading of the results it is obvious that three is greater left and right direction symmetry than top and bottom direction symmetry.



**(a) a1 parameter**



**(b) a2 parameter**

Figure 4 Model Parameters: Axial scaling parameters along the x and y-axis where the y-axis is the axis of symmetry.

We are able to characterize the shape of handaxes by conducting the statistical analysis of global feature vectors. The mean values, standard deviations and ranges of parameters are shown in Table 1. In order to demonstrate the effect of each feature, we performed a principal component analysis of all handaxes. The first two components with eigenvalues, 3.023 and

| | MEAN | STD | RANGE | PRINCIPAL COMPONENTS | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| a1+ | 0.696 | 0.104 | 0.434 - 0.943 | -0.016 | -0.010 | -0.083 | -0.731 | 0.674 | -0.056 |
| a1- | 0.701 | 0.095 | 0.465 - 0.973 | -0.014 | -0.003 | -0.040 | -0.672 | -0.737 | -0.031 |
| a2+ | 0.768 | 0.188 | 0.247 - 1.152 | 0.028 | 0.002 | -0.724 | 0.107 | -0.029 | -0.680 |
| a2- | 1.155 | 0.179 | 0.767 - 1.564 | -0.031 | 0.004 | 0.682 | -0.015 | 0.007 | -0.730 |
| t(tip) | 0.662 | 0.925 | -1.81 - 3.414 | 0.194 | 0.981 | 0.006 | -0.014 | 0.005 | 0.002 |
| t(base) | -0.606 | 1.712 | -5.0 - 3.662 | -0.979 | 0.194 | -0.039 | 0.022 | -0.001 | 0.006 |

**Table** 1.Shape Feature Vectors: The mean values, standard deviations and ranges of samples generally approximate the average shape of handaxes. The six principal components have the eigenvalues 3.0231, 0.7705, 0.0617, 0.0161, 0.0020 and 0.0005 respectively.

0.7705, account for 78.0 and 19.8 percentage of the total variance in observations. In Table 1, we clearly see that, the first component is a measure of tapering at base while the secondary component is related to tapering at tip. The axial parameters are relatively insignificant.

In terms of our analysis, we then build a hypothesis that most handaxes are symmetrical along the axis of symmetry; the descriptive analysis of a1+ and a1- parameters is nearly the same. The mean values of a2+ and a2- parameters inform us that maximum width point is located around 2/3(.6803) from top along the principal axis. Therefore, center of mass is usually located at the horizontal midpoint and vertically two-thirds from top.

We, then, focus on axial symmetry analysis by taking a look at symmetry in equation (3). Figure 5 is the clustered examples of handaxe artifacts in terms of the degree of symmetry. Figure 6 is the distribution of symmetry values, of the 158 handaxe artifacts.

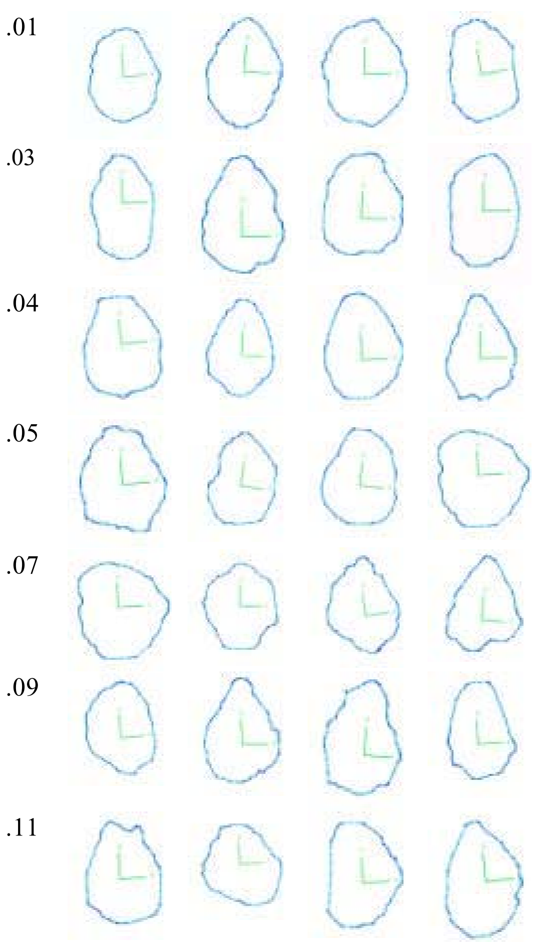



Figure 5. The degree of symmetry and handaxes examples.

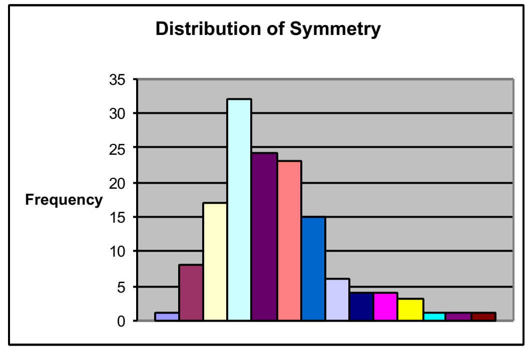



Figure 6. Distribution of symmetry values, of the sampled handaxes. The x-axis is the degree of symmetry ranging from 0.01 – 0.16 while the y-axis is the frequency.

## 4. Comparison

It is useful at this point to compare our approach with that of earlier computer-based attempts to study handaxe morphology. Specifically, the approach of Saragusti and her colleagues [9] quantifies the degree of symmetry in a handaxe while our method goes a step further by characterizing handaxe shape in terms of shape feature vectors. Secondly, in certain handaxes, the two approaches will produce different results in terms of the degree of symmetry observable in the artifact. The reason is usually because our method measures the symmetry according to the common reference frame, i.e. the axis of symmetry is the maximum length while Saragusti et al approach is looking for the axis of symmetry that minimizes its measurements.

More traditional methods of studying handaxes include the approach of Wynn and Tierson [16]. Their method cannot standardize the average shape of handaxes because they have many variables and cannot compactly describe the shape in a few numbers. Therefore, their method does not truly describe shape but rather highlights significant differences between groups of handaxes across specific variables. This means that their method is useful for classifying handaxes into different groups but it cannot be used to study symmetry or standardization. In contrast, our method can describe average handaxe shape (and deviations from this shape) using only six shape feature vectors and as noted above it is ideal for quantifying symmetry.

## 5. Discussion

Our deformable model-based approach successfully describes the average shape of handaxes so as to give compact standardization and symmetry parameters. Compared to other methods [9,16] being used by archaeologists, our method adapts parameter-based calculations for quantifying the degree of symmetry. One advantage of the parameter-based method is that the results are comparable between cases and therefore inter-assemblage comparisons are possible. Moreover, our method describes and analyzes the average shape that can be used for recovery while other approaches do not [9,16]. In a future, we are going to extend our method to 3-D measurements of stone tools.

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