Contents lists available at ScienceDirect

Journal of Archaeological Science

Morphometrics of Second Iron Age ceramics – strengths, weaknesses, and comparison with traditional typology

J. Wilczek [a, b, *], F. Monna [a], P. Barral [c], L. Burlet [a], C. Chateau [d], N. Navarro [e]

[a] ARTéHIS, UMR 6298 CNRS-Université de Bourgogne, ARTéHIS, Bat. Gabriel, F-21000 Dijon, France
[b] Ústav archeologie a muzeologie, Masarykova univerzita, Arna Nováka 1, 602 00 Brno, Czech Republic
[c] Laboratoire Chrono-Environnement, UMR 6249 CNRS, Université de Franche-Comté, UFR Sciences et Techniques, 16 route de Gray, F-25030 Besançon Cedex, France
[d] Université de Bourgogne, UFR SVTE, 6 bd Gabriel, F-21000 Dijon, France
[e] Laboratoire PALEVO, Ecole Pratique des Hautes Etudes, UMR uB/CNRS 6282-Biogéosciences, Université de Bourgogne, 6 Boulevard Gabriel, F-21000 Dijon, France

ARTICLE INFO

ABSTRACT

Although the potential of geometric morphometrics for the study of archaeological artefacts is recognised, quantitative evaluations of the concordance between such methods and traditional typology are rare. The present work seeks to fill this gap, using as a case study a corpus of 154 complete ceramic vessels from the Bibracte *oppidum* (France), the capital of the Celtic tribe Aedui from the Second Iron Age. Two outline-based approaches were selected: the Elliptic Fourier Analysis and the Discrete Cosine Transform. They were combined with numerous methods of standardisation/normalisation. Although standardisations may use either perimeter or surface, the resulting morphospaces remain comparable, and, interestingly, are also comparable with the morphospace built from traditional typology. Geometric morphometrics also present the advantage of being easily implemented and automated for large sets of artefacts. The method is reproducible and provides quantitative estimates, such as mean shape, and shape diversity of ceramic assemblages, allowing objective inferences to be statistically tested. The approach can easily be generalised and adopted for other kinds of artefacts, to study the level of production standardisation and the evolution of shape over space and time, and to provide information about material and cultural exchanges.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

Ceramics are the most abundant and well-documented archaeological artefacts from the Second Iron Age. Traditionally, ceramics are used to study a wide range of issues: from establishing chronological sequences and cultural entities, through the definition of social, economic and cultural relationships and organisation, to the understanding of how archaeological complexes were formed. Archaeologists seek to answer these questions through the creation and application of ceramic typologies (e.g. Orton et al., 1992; Shepard, 1985).

Typology aims at assigning ceramic fragments to predefined types. Classification uses one or several discriminant criteria, such as the overall form, the shape of a particular ceramic part (body, rim, foot…), the decoration, or the clay used. Although the method has been proved to be effective for treating huge ceramic assemblages, it may be affected by operator subjectivity, ensuing from specialisation, personal skills and professional experience. This has been demonstrated by the pioneer work of Hodson et al. (1966) on Iron Age brooches. To improve objectivity, at least in data treatment, over the past few decades, archaeologists have introduced statistical techniques, such as the popular seriation (Kendal, 1969, 1971) and cluster analysis (Hodson, 1970), occasionally supplemented by other methods, such as non-metric multidimensional scaling (Drennan, 1976), correspondence analysis (Duff, 1996), principal component analysis (Hodson, 1969) or principal coordinate analysis (Camiz et al., 2003). However, these approaches cannot overcome drawbacks related to the choice of relevant descriptors, and also to difficulties which may arise in coding the state of categorical variables without any ambiguity.

Recent developments in image, video and audio processing have led to remarkable advances in geometric morphometrics, used

nowadays to study shapes in a broad range of fields. Many studies by anthropologists and evolutionary biologists are now based on these techniques (e.g. Slice, 2005; Zelditch et al., 2004), while their application in archaeology, except for biological remains (physical anthropology, archaeozoology, archaeobotany, and palynology; e.g. Ottoni et al., 2013; Terral et al., 2010; Vigne et al., 2007) is rarer and more recent (e.g. Karasik and Smilansky, 2008, 2011; Saragusti et al., 2005). Nonetheless, their potential for expressing forms unambiguously has been successfully exploited to study lithic artefacts (Brande and Saragusti, 1996; Buchanan, 2006; Buchanan and Collard, 2007, 2010; Lycett, 2009 and citations therein), sculptures (Buxeda i Garrigós and Gordaliza, 2011; Urbanová et al., 2011) and Bronze Age axes (Forel et al., 2009; Monna et al., 2013). Up to now, morphometric applications for ceramic taxonomy are scarce, but very promising: Gilboa et al. (2004) used computational typology to classify ceramics, while other authors have examined the potential of morphometrics for predicting the complete form from shards that include the rim or the bottom of the vessel (Karasik and Smilansky, 2011; Martínez-Carrillo et al., 2009, 2010). In practice, several parameters of geometric morphometrics can be fine-tuned, from sampling resolution and size normalisation (i.e. the acquisition process and shape definition), to the computation of shape variables.

The corpus used here was discovered at the *oppidum* of Bibracte, Burgundy, France. During the late Second Iron Age, Bibracte was the capital of a Celtic tribe, the *Aedui*. Archaeological excavations, undertaken each year over several decades, have unearthed a wide variety of ceramics, from plates to bottles (Barral et al., 1995; Paunier and Luginbühl, 2004; Paunier et al., 1994). If properly applied, computer-intensive techniques can do far more than merely categorise objects that can be readily differentiated by the naked eye. The present work provides an assessment of various operational combinations, considering either open contours treated by Discrete Cosine Transform (DCT) or closed contours treated by Elliptic Fourier Analysis (EFA), where the effects of size and orientation have been removed with different normalisation techniques. These approaches correspond to different ways of apprehending the ceramic shape. All these combinations produce morphospaces, which were all compared with each other and with the morphospace produced by more traditional descriptive methods (Vaginay and Guichard, 1988). Thus, it is possible to evaluate *i*) the pertinence of the traditional typology using several different quantitative estimates of shapes, and *ii*) the strengths and weaknesses of these various definitions of ceramic shapes in an operational context.

Morphometrics allows the calculation of an average shape, an idealised centroid shape, which takes into account all the individuals in the group, and not merely a single element, supposed to be the best representation, as often used in typology. Another parameter of interest is the diversity of shape within a group, which is at least as important as the mean shape, and may reveal the level of product standardisation of a given ceramic type. These two parameters are also explored here.

2. Material and methods

2.1. Corpus

Data were acquired from a corpus composed of ceramics discovered at Bibracte, all dating from the 2nd century B.C. to the beginning of the 1st century A.D. Only items presenting a complete, well-preserved cross-section, for which drawings are available in the literature, were retained for the present study (literature details are available in Supplementary materials S1). Although the "complete, well-preserved cross-section" constraint considerably

downsizes the number of analysable individuals, drawings of 154 ceramics were processed. Some may not be entirely reliable because of the errors inherent in any manual representation (lack of precision, possible interpretation in the drawing process, etc.). However, the disparity of the corpus is large enough to render such uncertainties negligible.

Using the well-established typological system of Bibracte (Barral et al., 1995), the 154 ceramics studied were attributed to 8 main functions on the basis of their shape: 35 plates, 20 dishes, 24 bowls, 18 cups, 14 goblets, 27 pots, 9 vases and 7 bottles.

2.2. Numerical analysis of classical typology

2.2.1. Character coding

Structured descriptive typology elaborated by Vaginay and Guichard (1988) for a contemporary site (Feurs, Rhône-Alpes, France) has been selected to describe our ceramics. Such a system allows the shape similarity between items to be quantified using a combination of several observed features, categorised metric indexes and angles. Only descriptors directly related to the morphology of vessels were taken into account. For some descriptors, additional levels were added to allow a full description of items from Bibracte (see Supplementary materials S2 for details). The final descriptive system consists of 15 categorical descriptors, each with between 2 and 10 levels.

2.2.2. Similarity computation between ceramics

The degree of resemblance between objects was achieved by computing Gower's coefficient (Gower, 1971; Legendre and Legendre, 1998) from the 15 categorical descriptors mentioned above. This similarity coefficient, $S_{i,j}$, between two individuals (*i* and *j*) for *p* variables, was computed following:

$$S_{i,j} = \frac{\sum_{k=1}^{p} w_{i,j,k} g_{i,j,k}}{\sum_{k=1}^{p} w_{i,j,k}}, \tag{1}$$

where all variables were treated as qualitative. Therefore $g_{i,j,k} = 1$ when both character states agree, and 0 otherwise. Kronecker's delta $w_{i,j,k}$ is a weight equal to 0 when the information is missing, and which evolves between 0 and 1 otherwise, allowing more weight to be ascribed to the most important descriptors for typological distinction. An arbitrary triple weight was attributed to certain descriptors characterising the whole form, because they are fundamental in traditional typology to identify the main types (see Supplementary materials S2 for details). The absence of certain signs for two items, for example the absence of a foot, was considered as an indicator of similarity, so that $g_{i,j,k} = 1$ in such cases. A Principal Coordinate Analysis (PCoA), also called metric multidimensional scaling, was computed to visualise the level of similarity of items. In practice, this analysis used a dissimilarity matrix D. The transformation $D = \sqrt{1-S}$ was preferred for computation because it is less likely to generate negative eigenvalues, synonymous with non-Euclidean dimensions (Legendre and Legendre, 1998).

2.3. Morphometrics

2.3.1. Sampling outlines

Drawings were scanned in greyscale at a resolution of 1200 dpi and stored in TIF format. All images were oriented on the natural axis on which the artefacts originally stood. After possible noise had been eliminated from the scans, the half cross-section was extracted, in the R environment (R Core Team, 2012), using a modified version of the function "conte" (Claude, 2008). Sampling was at

equally spaced points, providing a dataset of 154 (number of individuals) × n (number of points per individual) × 2 (planar x-y-coordinates).

The optimal number of points, n, to be sampled to produce a good representation of the original contour was investigated using a representation error percentage, $E\%$, computed on the basis of the original perimeter, P (Sheets et al., 2006):

$$E\% = 100 \times \left(1 - \frac{\sum d_{i,j}}{P} \right), \qquad (2)$$

where $d_{i,j}$, is the distance between two consecutive points on the reconstructed outline. By varying n, the optimum was chosen when $E\%$ stabilised around low values. This choice will be exposed in the "Results and Discussion" section. Symmetric contours were obtained by mirroring the coordinates of the external half-section drawings (Fig. 1).

2.3.2. Shape variables

Computation of shape variables is known to be very sensitive to the orientation and size of individuals, as well as to the position of the starting point (Tatsuta et al., 2004). Different approaches normalising size and orientation were therefore tested: several types of baseline registration (Bookstein, 1991), and normalisation to perimeter (Schmittbuhl et al., 2003) or surface (Navarro et al., 2004), which are currently and frequently used in the literature (see Fig. 2 for a visual summary of the different methods of normalisation). They refer to different views of the object size. It is

noteworthy that orientation and size are frequently normalised with the major axis of the first ellipse (Kuhl and Giardina, 1982). This procedure was not followed here, as it is not adapted to the present corpus: the major axis does not always correspond to the plane on which artefacts originally stood (imagine a bottle and a plate), affecting the homology between objects, in terms of orientation.

Shape variables characterising ceramics were obtained by Discrete Cosine Transform (DCT) for open outlines, and by Elliptic Fourier Analysis (EFA) for closed ones. In both these Fourier-type methods, the outlines are decomposed into an infinite series of repeating trigonometric functions called harmonics. Each harmonic is expressed by two Fourier coefficients, in the case of DCT (Dommergues et al., 2007; see also the appendix of Forel et al., 2009), and four for EFA (Kuhl and Giardina, 1982; Lestrel, 1989; Lestrel et al., 2010; Rohlf and Archie, 1984). The contribution of harmonics is additive for the reconstruction quality of the outlines, meaning that more harmonics reflect more precisely the form studied. The DCT was computed using an adaptation for R of the MATLAB toolkit CDFT (Dommergues et al., 2007). The EFA was processed using a modified version of the "efourier" function, as reported in Claude (2008).

It is noteworthy that techniques mixing landmarks and sliding semilandmarks on outlines (Bookstein, 1997) were not explored. The interest of the semi-landmark approach to describe outline, with respect to Fourier methods, resides in its potential to segment the whole shape into smaller pieces, comparable among individuals, using precisely defined landmarks. Although extremely
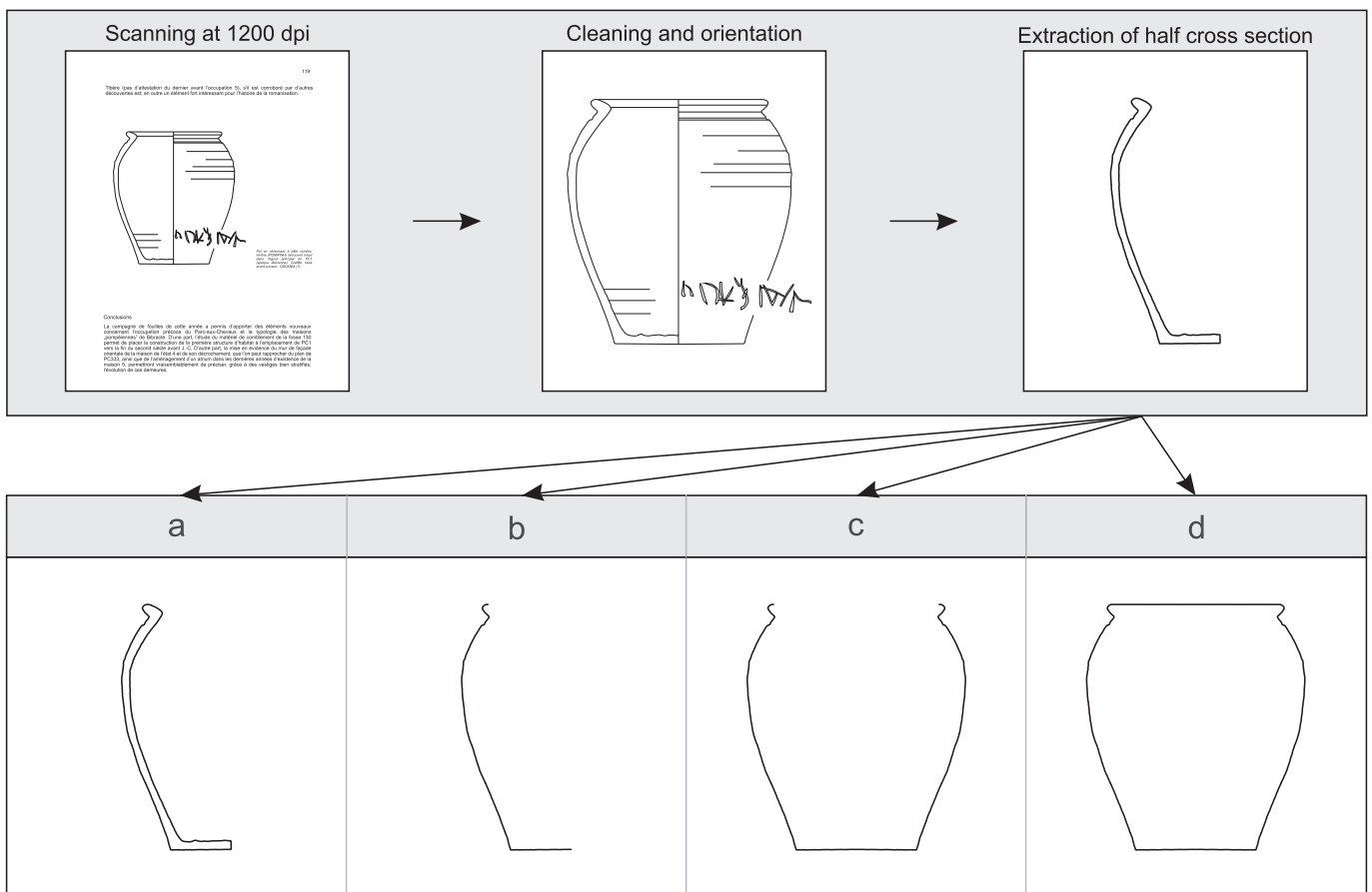

Fig. 1. Data processing and contour representations of the ceramic vessels. a) closed and b) open contour representing half of the complete cross-section; c) open contour of the outer shape of the ceramic vessel without the rim, and d) closed contour of the outer shape of the complete ceramic vessel.
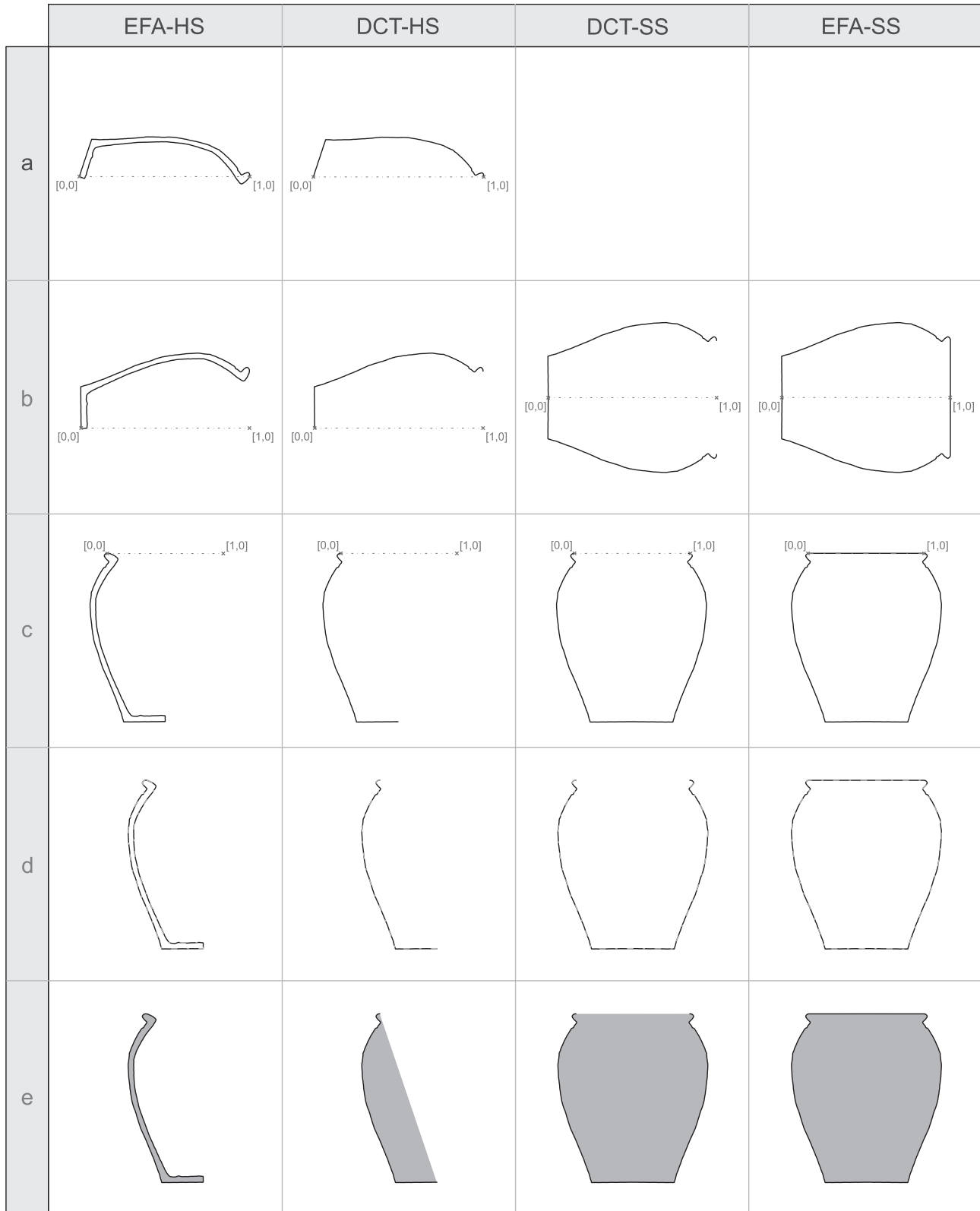
Fig. 2. Normalisation of size and orientation. EFA and DCT: Elliptic Fourier Analysis and Discrete Cosine Transform for closed and open contours, respectively. HS and SS for half section and symmetrised section. a–c) Baseline registration (Bookstein, 1991) sends two specific points to the respective coordinates (0,0) and (1,0), rotating, translating and scaling all contours; the coordinates are no longer dependent on size, position or orientation; d) size normalisation relative to the perimeter (Schmittbuhl et al., 2003) and e) size normalisation relative to the square root of the area bounded by the polygon contour (Sundberg, 1996; Hurth et al., 2003; Navarro et al., 2004); in cases d and e, the orientation was standardised to the natural axis on which the ceramic vessels originally stood.
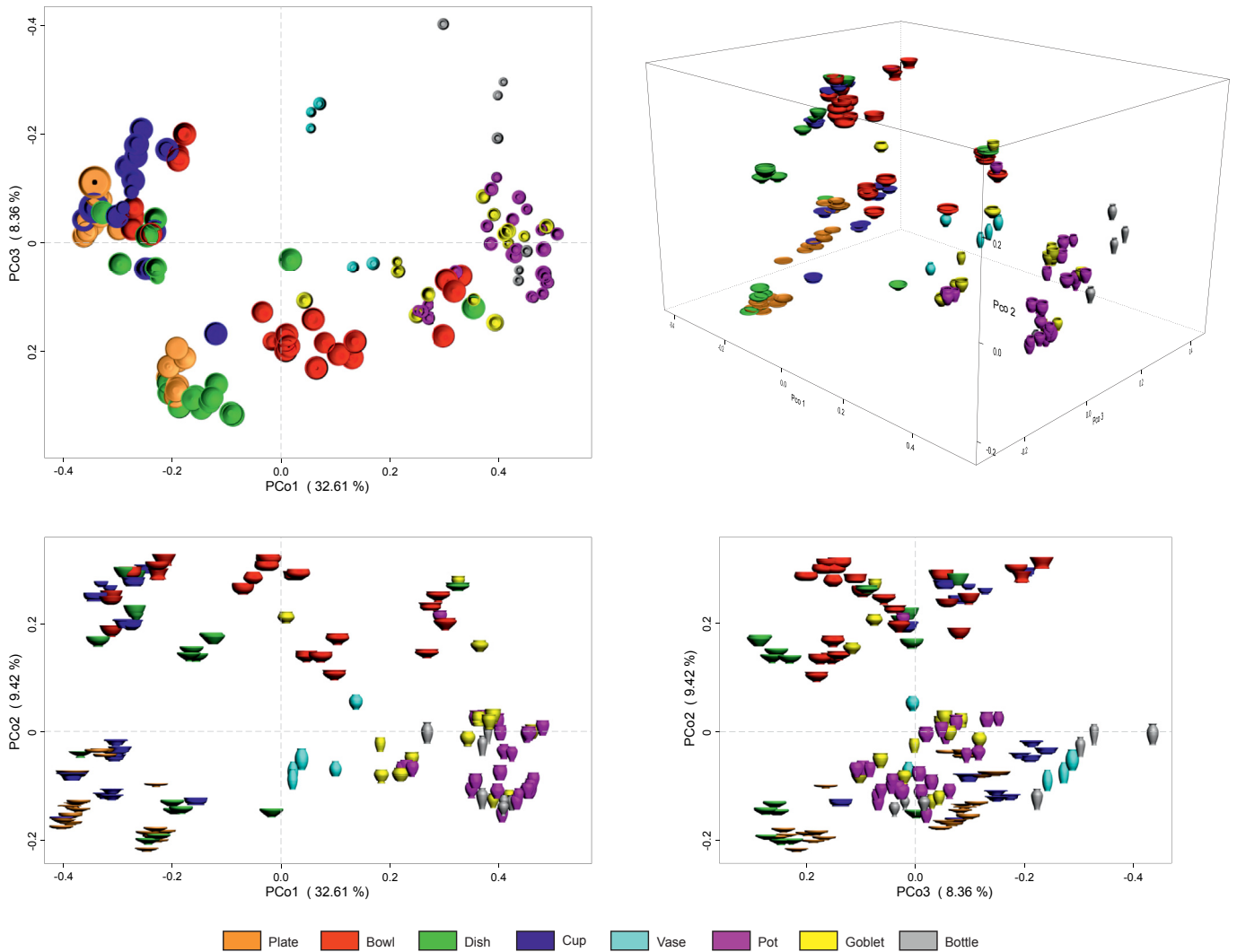
Fig. 3. Principal Coordinate Analysis. Projection of the 154 items in a PCo3 *vs* PCo2 *vs* PCo1 morphospace. These three axes (out of a total 154 axes − number of items) account for more than 50% of the total variance (see Supplementary materials S3 for an animation depicting the projection of items in a 3D morphospace). Items were attributed to ceramic types following the typological system of Barral et al. (1995). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

powerful, they were not applied here because a sufficient set of true landmarks could not be straightforwardly identified across our heterogeneous corpus.

Principal component analyses (PCA) were then performed on the covariance matrices of the obtained Fourier coefficients, producing a series of morphospaces. All individuals can be plotted in each morphospace, to allow comparison in a visually friendly form.

2.4. Concordance between morphospaces

The agreement between the typological-based morphospace (PCoA) and each geometric morphometric-based morphospace (PCA) was checked using PROTEST, a Procrustean randomisation Test, which appears to be more powerful than the traditional Mantel test (Jackson, 1995; Peres-Neto and Jackson, 2001). Basically, the PROTEST approach compares multivariate datasets: the first matrix is translated, reflected, rotated and dilated to minimise the sum of the squared residual deviations between the elements of the first (original) and the second (target) matrices (Jackson, 1995). A PCoA space can be constructed, allowing a visual inspection of morphospace similarities, while the statistical significance can be

obtained by permuting elements (here $n = 9999$) within the matrices under comparison (Jackson, 1995; Peres-Neto and Jackson, 2001).

2.5. Unsupervised model-based clustering

Multivariate Gaussian mixture models were used for unsupervised classification (Fraley and Raftery, 2007) of ceramics using the R package mclust (Fraley et al., 2012). The number of clusters was explored from 2 to 12 groups for different modelling of the variance-covariance matrices. The optimal model for classification (number of clusters and matrix modelling) was determined from the Bayesian Information Criterion, BIC (Fraley and Raftery, 1998; Schwarz, 1978), according to the value of the Δ-BIC (i.e., the gain in information when an additional cluster is envisaged).

2.6. Mean shapes and morphological diversities

The mean shape for each ceramic group was reconstructed by inverse Fourier functions. Palaeontologists have long developed various metrics to analyse diversity of shape (disparity), where
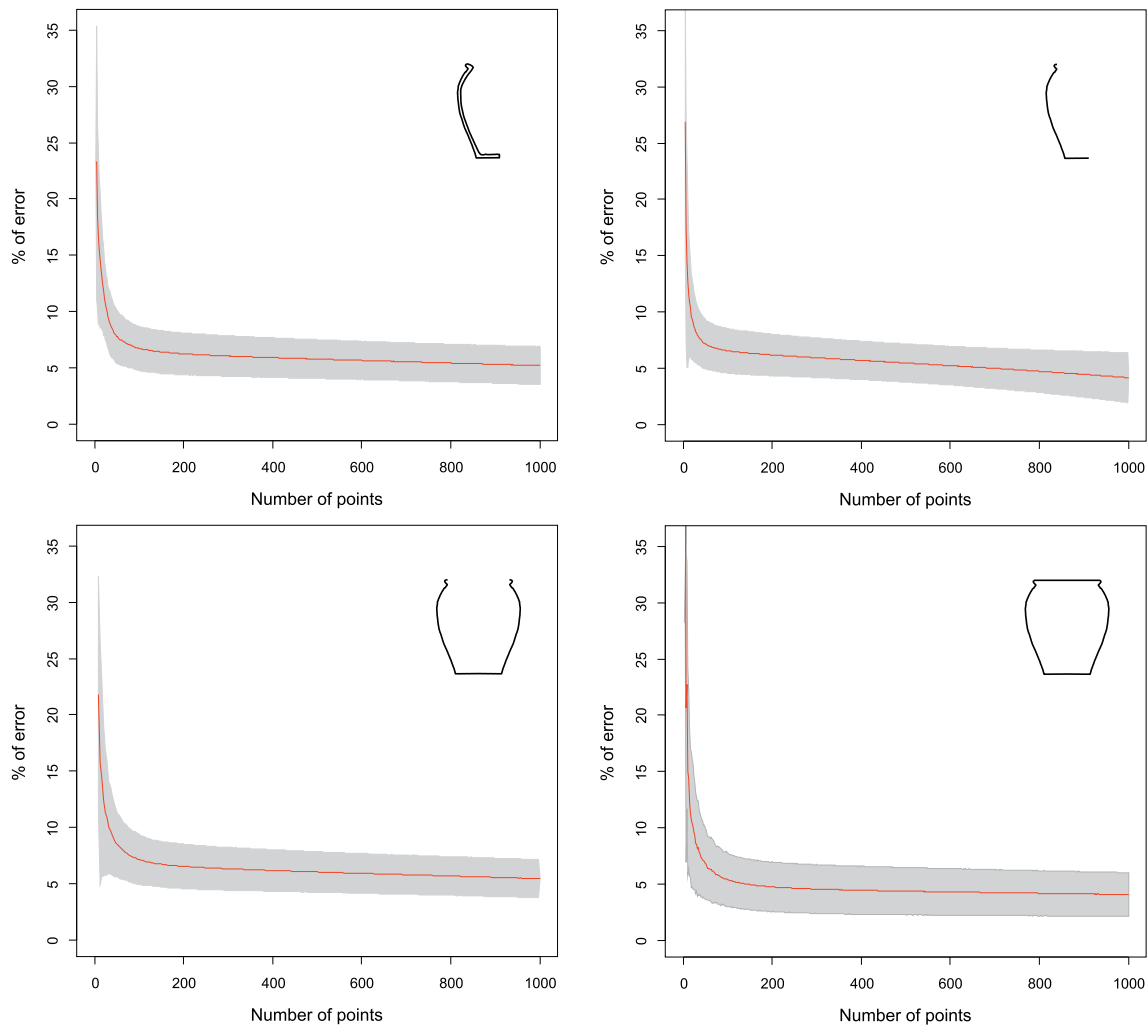
Fig. 4. Effect of the number of points sampled along the outline on contour quality for each of the four representations. The red line represents the mean value of root-mean-square deviation, and the grey surface the 95% confidence region. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

emphasis is laid on dissimilarity (e.g. total variance) or spatial distribution within the morphospace (e.g. convex hull, clustering *vs* scattering; Navarro, 2003). Among all possible metrics, the area of the convex hull on the first two principal components was privileged as a surrogate of morphological diversity within each ceramic group.

3. Results and discussion

3.1. Typological-based morphospace

Computation of PCoA using the dissimilarity matrix does not produce any negative eigenvalues, so the space is Euclidian and the distances between items are meaningful. The first three principal coordinate axes account for more than 50% of the variation. Fig. 3 illustrates the shape variation of ceramics in the PCoA-based morphospace, although the underlying parameters are categorical (see Supplementary materials S3 for an interactive projection of items in a 3D morphospace). Note that in some cases, certain individuals (e.g. vases), which slightly differ in terms of morphology, occupy exactly the same position in the graph. Even a typology based on a large number of categorical descriptors cannot produce a morphospace able to express the entire shape variability of ceramics. Despite this disadvantage,

the Bibracte types are reasonably well clustered: negative values of both PCo1 and PCo2 characterise flat forms, such as *plates*, while *bottles* and *pots* are clustered in the bottom right-hand corner. Other types are more broadly scattered (i.e. *bowls* and *cups*), illustrating the great variation in shape that exists within these functional groups.

3.2. Morphometric-based morphospaces

In Fig. 4, the evolution of the error percentage according to the number of points sampled exhibits a stabilisation around 100 points, with a steady representation error at about 5–7%. Nevertheless, as a precaution, 200 points were sampled, regularly spaced along the outlines.

The effect of the number of harmonics on the quality of representation was also studied. The original form was first obtained by a 200-point sampling, and then compared to the shapes reconstructed by increasing the harmonic number from 1 to 100; the second value corresponding to the Nyquist frequency (Lestrel, 1989; Lestrel et al., 2004a,b, 2005, 2010). The reconstruction quality criterion is the root-mean-square deviation, RMSD, between the 200 points composing the original outline, and their equivalent on the reconstructed outline. Although the representation becomes steady with a low number of harmonics (ca. 10),
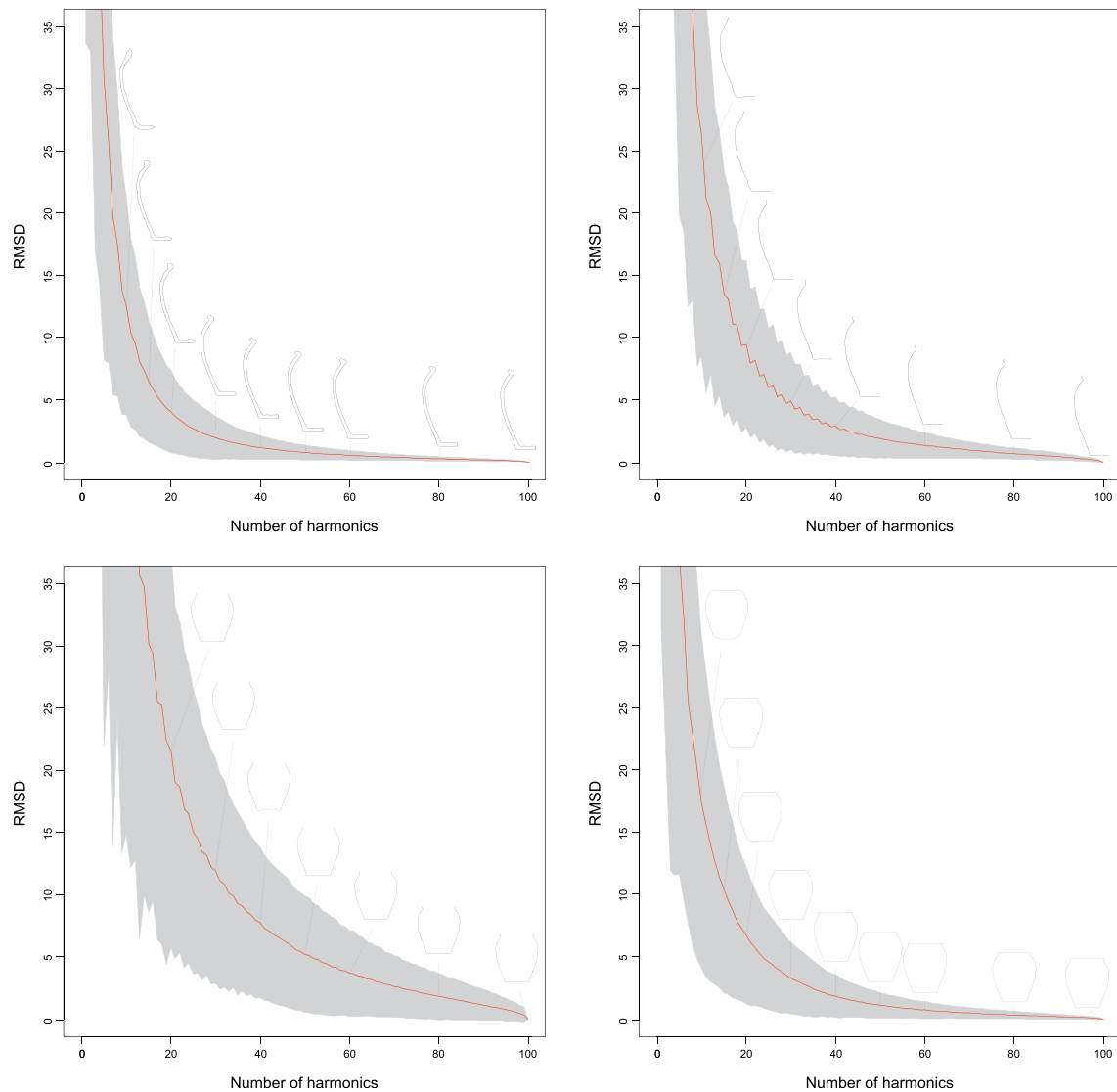
Fig. 5. Effect of the number of harmonics on the contour quality for each of the four representations. The red line represents the mean value of root-mean-square deviation, and the grey surface the 95% confidence region. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

additional details are recovered with more coefficients (Fig. 5). That is why, for the following analyses, 20 harmonics were retained in both DCT and EFA.

Principal components were computed for each of the 18 approaches depicted in Fig. 2 (four of them are depicted in Fig. 6). In all cases, the total variance explained by the two first principal components ranges between 80% and 99%, depending on the method used. The elongation of the artefacts is mainly carried by PC1. This feature clearly dominates the analyses as, similarly to the PCoA-based morphospace, the *bottles* and *plates* are located at opposite sides of PC1, while the other items are found in a more central position.

3.3. Evaluating the similarities between the different approaches

A total of 18 distance matrices based on the different morphometric approaches and normalisation (Fig. 2) and one distance matrix based on typology were processed. The agreement between all pairs of matrices appears to be significant using PROTEST (Table 1). However, despite this overall resemblance, the degree of similarity varies for each pair considered (Fig. 7). The procedures

based on perimeter (d) and surface (e) normalisations occupy the same position in Fig. 7, while the others appear as separate clusters (a, b, c). It is not really surprising to find the perimeter (d) and surface (e) normalisations clustered in a central position, between the normalisations based on height (b) and width (c), because the former are somehow a combination of the latter. In any case, normalisation to the surface or perimeter should be preferred because they are closely related to volume, which is as fundamental as shape in the purpose of ceramics. The morphospace using standardisation by chord (a) lies very close to the traditional typology. Nevertheless, because of the nature of this Bookstein registration using chord, two half cross-sections cannot be merged to reconstruct the original shape, as information about opening is lost. If the aim of the study is related to the overall aspect of artefacts, then losing a feature, such as the opening angle, is prohibitive. The chord is thus no better adapted for standardisation than the major axis of the first ellipse. It may sometimes be preferable to emphasise local features of the outline, containing relevant information about the artefact, such as its symbolic or social role, and the know-how of craftsmen, which could have been masked by treating only the overall aspect.
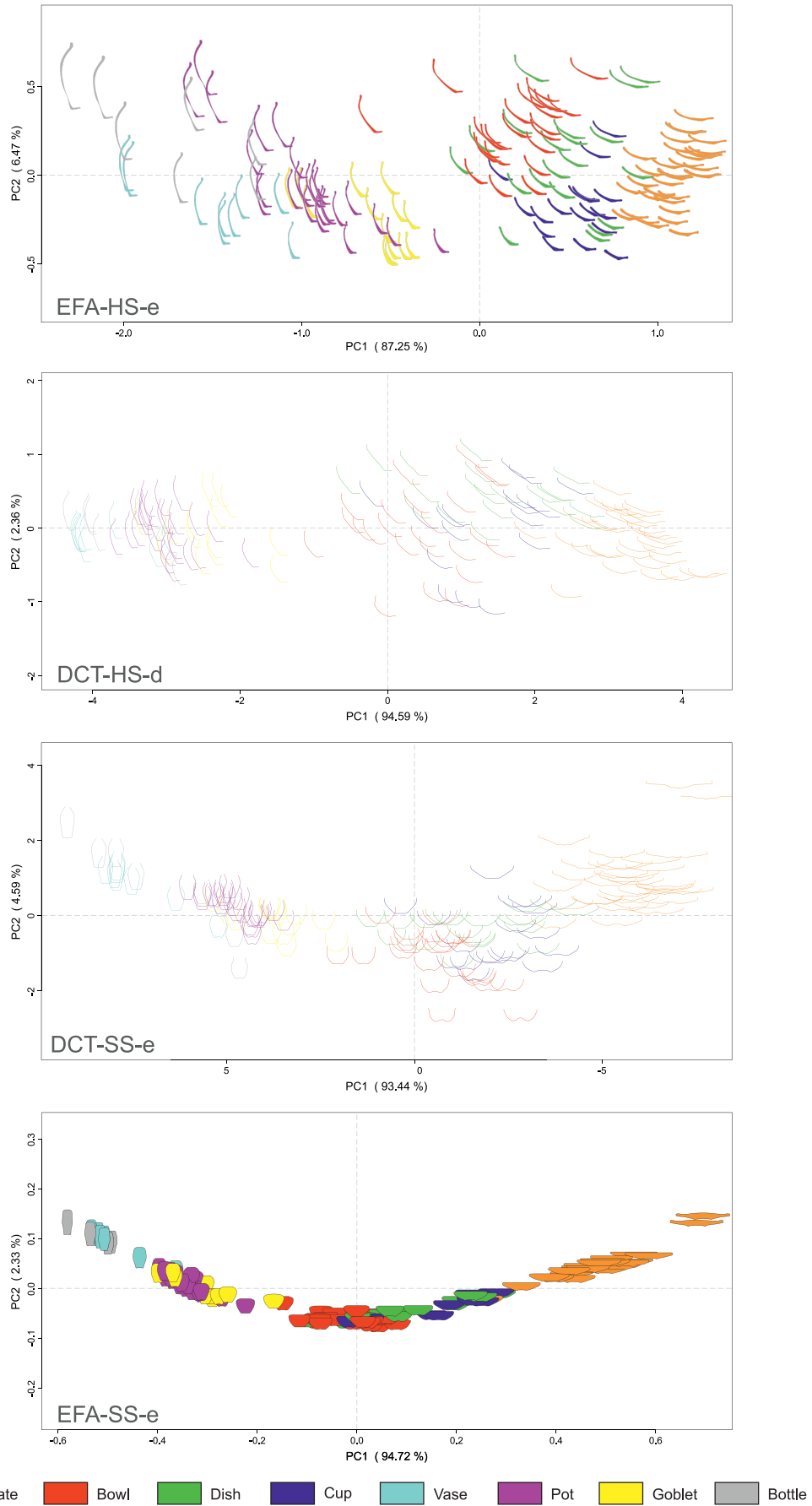
Fig. 6. Principal Component Analysis. Projection of the 154 items in a PC2 *vs* PC1 morphospace. The two axes always account for more than 93% of the total variance. The figure code helps to find the corresponding approach in Fig. 2. Items were attributed to ceramic types following the typological system of Barral et al. (1995). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Similarity matrix for the different approaches. Lower half matrix: PROTEST statistic. *p* < 0.05 in all cases. See Fig. 2 caption for acronym definition.

		TYPO	EFA-HS a	b	c	d	e	DCT-HS a	b	c	d	e	DCT-SS b	c	d	e	EFA-SS b	c	d	e
TYPO		1.00																		
EFA-HS	a	0.59	1.00																	
	b	0.53	0.64	1.00																
	c	0.47	0.49	0.68	1.00															
	d	0.62	0.71	0.91	0.84	1.00														
	e	0.59	0.67	0.85	0.88	0.95	1.00													
DCT-HS	a	0.55	0.84	0.67	0.49	0.68	0.62	1.00												
	b	0.50	0.57	0.99	0.68	0.89	0.83	0.65	1.00											
	c	0.44	0.43	0.67	0.99	0.82	0.85	0.47	0.68	1.00										
	d	0.58	0.61	0.89	0.84	0.98	0.93	0.63	0.89	0.83	1.00									
	e	0.58	0.66	0.91	0.80	0.95	0.91	0.71	0.90	0.79	0.96	1.00								
DCT-SS	b	0.50	0.57	0.99	0.68	0.89	0.83	0.65	1.00	0.68	0.89	0.90	1.00							
	c	0.44	0.43	0.67	0.99	0.82	0.85	0.07	0.68	1.00	0.83	0.79	0.68	1.00						
	d	0.59	0.62	0.88	0.86	0.98	0.94	0.62	0.87	0.84	0.98	0.94	0.87	0.84	1.00					
	e	0.57	0.62	0.92	0.86	0.97	0.94	0.66	0.92	0.85	0.97	0.96	0.92	0.85	0.97	1.00				
EFA-SS	b	0.50	0.56	0.99	0.67	0.88	0.82	0.63	1.00	0.67	0.88	0.90	1.00	0.67	0.87	0.91	1.00			
	c	0.47	0.45	0.68	0.99	0.83	0.86	0.48	0.68	1.00	0.84	0.80	0.68	1.00	0.86	0.86	0.68	1.00		
	d	0.61	0.64	0.88	0.87	0.98	0.94	0.65	0.87	0.86	0.98	0.95	0.87	0.86	0.98	0.97	0.87	0.88	1.00	
	e	0.59	0.63	0.95	0.81	0.97	0.92	0.68	0.95	0.81	0.96	0.97	0.95	0.81	0.95	0.98	0.95	0.82	0.97	1.00

Classical typology can be viewed in essence as a degeneration of morphometrics, because it takes into account only some shape criteria, while morphometrics contains all shape information. Although typology does not exactly match any of the morphometric morphospaces (Fig. 7), there is good statistical agreement between the two approaches (Table 1). This concordance clearly demonstrates the value of the classification proposed by Vaginay and Guichard (1988). Morphometrics, however, has greater potential, more particularly in terms of quantitative evaluation, which is not readily accessible with the traditional descriptive approach.

Constraining the outline approach by landmarks may improve point correspondence because the homology between elements on the outline is increased (e.g. McCane, 2013). Here ceramics were constrained with only two landmarks (see Fig. 2), because it was
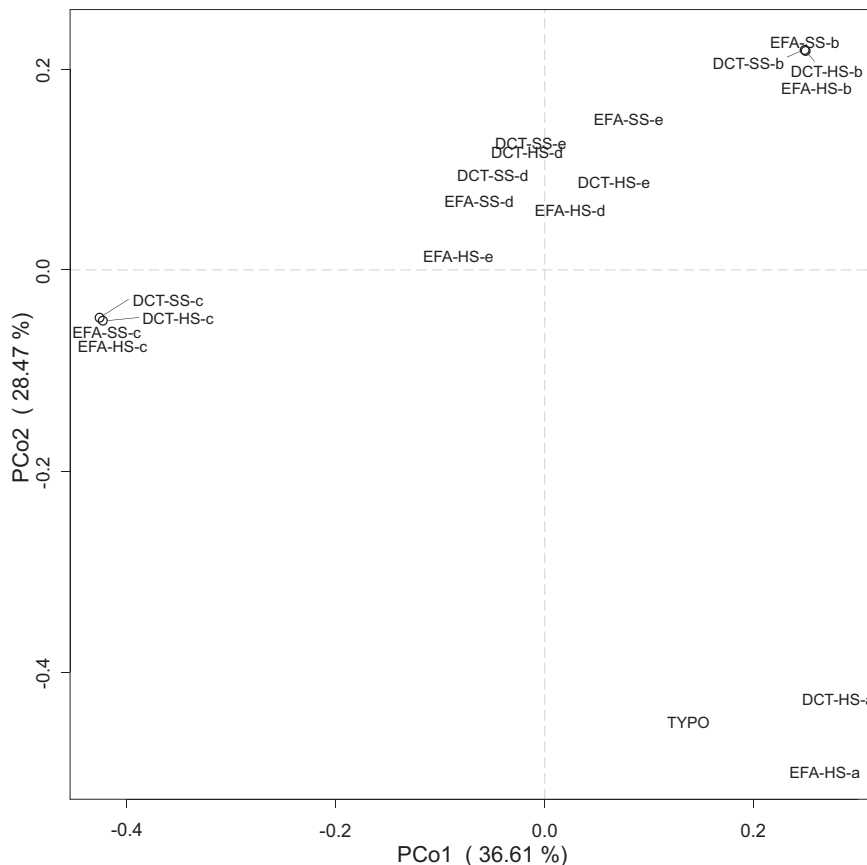

Fig. 7. Principal Coordinate Analysis. Projection of the typological morphospace (TYPO) and the 18 different morphospaces of shape variables in a PCo2 *vs* PCo1 space based on PROTEST statistics. The two axes account for more than 65% of total variance. See Fig. 2 for acronym definition.

Table 2
Concordance between the traditional typological classification of Barral et al. (1995) and unsupervised model-based clustering based on the EFA-SS-e morphospace.

		Model-based groups						
		1	2	3	4	5	6	7
Traditional typology	Plates	29			6			
	Dishes	6	13		1			
	Bowls		6	15	2	1		
	Cups	1	2		15			
	Goblets					9	5	
	Pots					11	16	
	Vases						2	7
	Bottles				1		2	4

Fig. 9. Shape diversity of the eight ceramic groups using the "EFA-SS-e" morphospace (Fig. 6), computed as the surface of the convex hull of PC2 vs PC1 (the two axes account for more than 97% of the total variance).

not possible to define additional landmarks easily and unambiguously across the corpus. As a consequence, pairwise point matching is probably not fully optimal and could be improved. That would be problematic if precise description of curve inflexion, such as that at the neck, was required. Here, losing such precision is not as important, given the disparity of ceramic shapes and the embedding of broad homology within the complete outline.

3.4. Unsupervised model-based clustering

Unsupervised model-based clustering was performed from the "EFA-SS-e" harmonic coefficients. An optimal model with seven clusters and a VEI modelling (i.e. diagonal, varying volume, equal shape) of the variance-covariance matrices was chosen in the light of the Δ-BIC evolution with an increasing number of groups (see Supplementary materials S4). These seven clusters match well the traditional typology of Barral et al. (1995), with each cluster corresponding mainly to one single type (Table 2 and Supplementary materials S5), except when the size drives the difference (e.g., goblets and pots). This is additional evidence that the traditional typology is still compatible with a more recent quantitative expression of shape. Morphological typology built over years, although funded on empirical observations, may therefore produce very reliable systems. Modern morphometrics followed by
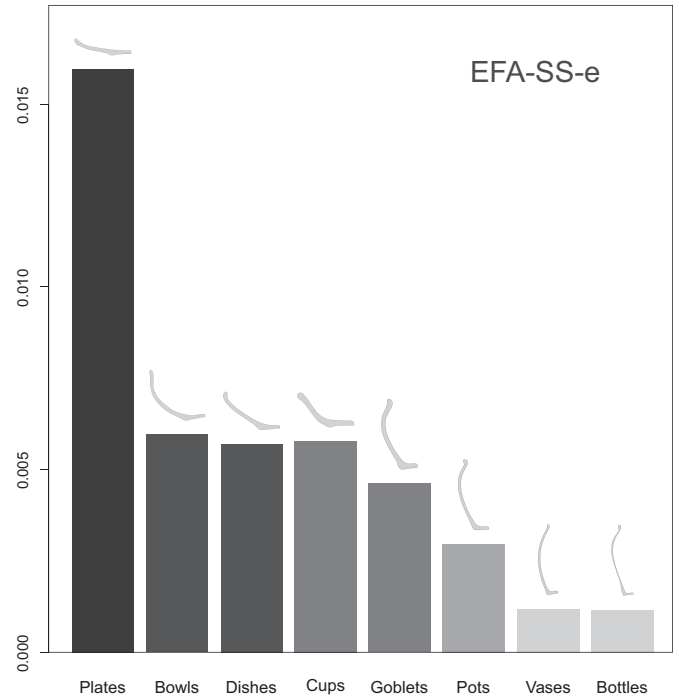
unsupervised classification nevertheless provides a quantitative tool to build these typologies numerically, independently of the operator.

3.5. Reference shape and diversity estimation

The mean shapes of the 8 known ceramic types from Bibracte are displayed in Fig. 8. Dispersion of each ceramic group was computed as the area of its convex hull in the "EFA-SS-e"
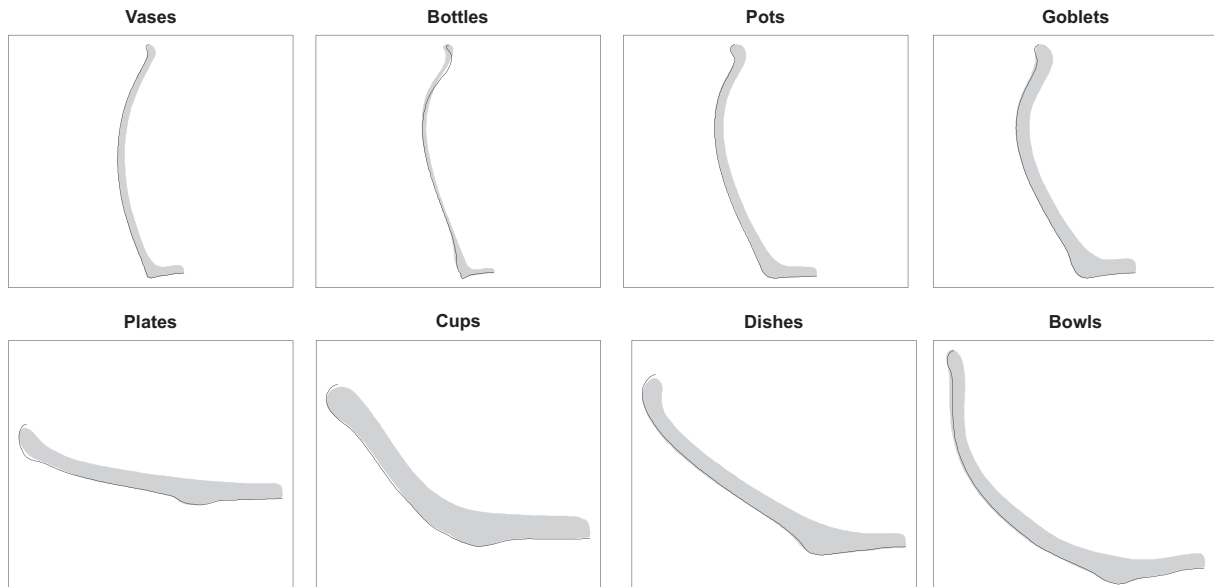

Fig. 8. Mean shapes of main ceramic groups from Bibracte following the typological system of Barral et al. (1995). Grey polygons represent inverse transform for EFA-HS-e, while solid black lines are the inverse transform for DCT-HS-d.

morphospace, using PC1—PC2 (Fig. 9). The diversity of ceramics used for presenting food (*plates*) is twice that of the other functional groups. Ceramics used for consuming food (*bowls, dishes*) and liquids (*cups, goblets*) show similar dispersion, followed by the vessels for cooking and storage (*pots*). The most homogenous groups were related to ceramic types dedicated to storing and presenting liquids (*vases* and *bottles*). Interestingly, group disparity may be related to functional and technical constraints, but also to the ostentatious nature of the vessels (Barral, 2002, 2005; Barral and Huet, 2006; Paunier and Luginbühl, 2004; Paunier et al., 1994).

4. Conclusion

Shape corresponds to the variation that remains, once position, size and orientation are removed. The definition of size (e.g. volume, height, etc.) may be governed by functional considerations. It has profound implications for the resulting shape, so that this choice must be made by the archaeologist in relation to the intended goal. Here, both approaches, DCT and EFA, combined with perimeter or surface standardisation can be efficiently used. As a very heterogeneous and diversified assemblage, consisting of specimens with low and high shapes (e.g. *plates and barrels*) has been taken into account, morphospaces are mainly driven by elongation. This is probably why morphometrics matches traditional ceramic typology so well. This finding could be perceived as trivial, but in fact the same approach can be applied to a group of individuals presenting far more resemblance. Shape diversity is expressed in simple, readable graphics, allowing comparisons and intuitive understanding of the entire assemblage. Within a given type, the amount of shape variation quantifies the structural constraints together with the level of standardisation of the products. Morphospaces are continuous by nature and can accept forms that have not yet been discovered. Mean shape can easily be reconstructed and is a better reference form than an isolated individual, supposed to reflect some typical standard.

The entire morphometrics pipeline (acquisition, standardisation, and computation of shape variables) can be fully automated, ensuring rapid processing and reproducibility.

Acknowledgements

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jas.2014.05.033.

References

Barral, P., 2002. Quelques traits remarquables de la composition et de l'évolution du vaisselier céramique à La Tène finale en pays éduen. In: Méniel, P., Lambot, B. (Eds.), Repas des vivants et nourriture pour les morts en Gaule - Découvertes récentes de l'Âge du Fer dans le massif des Ardennes et ses marges Repas des vivants/nourriture pour les morts en Gaule. Actes du XXVème colloque de l'Association Française pour l'Etude de l'Age du Fer (Charleville-Mézières, 25—27 mai 2001). Mém. 16 de la Soc. Arch. Champenoise, supplément au bull. n° 1, pp. 157—165.

Barral, P., 2005. L'habitat rural de La Tène finale dans les plaines de Saône et du Doubs: données socio-économiques et culturelles. In: Hiérarchie de l'habitat rural dans le nord-est de la Gaule à La Tène moyenne et finale. Publication des journées d'étude de Nancy, (22—23 novembre 2002). Archéologia Mosellana, vol. 6, pp. 239—274.

Barral, P., Huet, N., 2006. La céramique peinte gauloise dans la Vallée de la Saône: Groupes techno-typologiques, économie de la production et modes de diffusion. In: Baray, L. (Ed.), Artisanat, sociétés et civilisations: hommage à Jean-Paul Thevenot. Revue Archéologique de l'Est, supplément 24, pp. 473—491.

Barral, P., Luginbühl, T., Huet, N., Oberli, D., Reymond, S., Reymondin, S., Wagner, C., 1995. Typologie des formes de céramique régionale de Bibracte. Centre archéologique euroéen du Mont Beuvray, Glux-en-Glenne, 78 pp.

Bookstein, F.L., 1991. Morphometric Tools for Landmark Data: Geometry and Biology. Cambridge University Press, 435 pp.

Bookstein, F.L., 1997. Landmark methods for forms without landmarks: morphometrics of group differences in outline shape. Med. Image Anal. 1 (3), 225—243.

Brande, S., Saragusti, I., 1996. A morphometric model and landmark analysis of acheulian hand axes from Norhern Israel. In: Marcus, L.F., Corti, M., Loy, A., Naylor, G.J.P., Slice, D.E. (Eds.), Advances in Morphometrics. Plenum Press, New York, pp. 423—435.

Buchanan, B., 2006. An analysis of Foslom projectile point resharpening using quantitative comparisons of form and allometry. J. Archaeol. Sci. 3, 185—199.

Buchanan, B., Collard, M., 2007. Investigating the peopling of North America through cladistics analyses of Early Paleoindian projectile points. J. Anthropol. Archaeol. 26, 366—393.

Buchanan, B., Collard, M., 2010. A geometric morphometrics-based assessment of blade shape differences among Paleoindian projectile point types from western North America. J. Archaeol. Sci. 37, 350—359.

Buxeda i Garrigós, J., Gordaliza, A.V., 2011. Morphometrics and compositional classes. The study of anthropomorphic sculptures from Teotihuacan (México). In: Villalonga, G., Annabel, E., Juan, J., Tolosana-Delgado, R., Ortego, M.I. (Eds.), Proceedings of the 4th International Workshop on Compositional Data Analysis. Barcelona, pp. 1—21.

Camiz, Z., Rova, E., Tulli, V., 2003. Quantitative study of images in Archaeology: II. Symbolic Coding. In: Shader, M., Gaul, W., Vichi, M. (Eds.), Between Data Science and Applied Data Analysis. Springer Berlin, Heidelberg, pp. 633—642.

Claude, J., 2008. Morphometrics with R. Springer, 318 pp.

Dommergues, C.H., Dommergues, J.-L., Verrecchia, E.P., 2007. The Discrete Cosine Transform, a Fourier-related method for morphometric analysis of open contours. Math. Geol. 39, 749—763.

Drennan, R.D., 1976. A refinement of chronological seriation using nonmetric multidimensional scaling. Am. Antiq. 41 (3), 290—302.

Duff, A.I., 1996. Ceramic micro-seriation: types or attributes? Am. Antiq. 61 (1), 89—101.

Forel, B., Gabillot, M., Monna, F., Forel, S., Dommergues, C.H., Gerber, S., Petit, C., Mordant, C., Chateau, C., 2009. Morphometry of Middle Bronze Age palstaves by discrete cosine transform. J. Archaeol. Sci. 36, 721—729.

Fraley, C., Raftery, A.E., 1998. How many clusters? which clustering method? Answers via model-based cluster analysis. Comput. J. 41 (8), 578—588.

Fraley, C., Raftery, A.E., 2007. Model-based methods of classification: using the mclust software in chemometrics, 18 (6), 1—13.

Fraley, C., Raftery, A.E., Murphy, T.B., Scrucca, L., 2012. mclust Version 4 for R: Normal Mixture Modelling for Model-Based Clustering, Classification, and Density Estimation. Technical Report no. 597. Department of Statistics, University of Washington.

Gilboa, A., Karasik, A., Sharon, I., Smilansky, U., 2004. Towards computerized typology and classification of ceramics. J. Archaeol. Sci. 31, 681—694.

Gower, J.C., 1971. A general coefficient of similarity and some of its properties. Biometrics 27 (4), 857—871.

Hodson, F.R., 1969. Searching for structure within multivariate archaeological data. World Archaeol. 1 (1), 90—105.

Hodson, F.R., 1970. Cluster analysis and archaeology: some new developments and applications. World Archaeol. 1 (3), 299—320.

Hodson, F.R., Sheath, P.H.A., Doran, J.E., 1966. Some experiments in the numerical analysis of archaeological data. Biometrika 53 (3—4), 311—324.

Hurth, E., Montoire, S., Schmittbuhl, M., Le Minor, J.-M., Schaaf, A., Viriot, L., Chaline, J., 2003. Examination of the tooth morphospace of three Mimomys lineages (Arvicolinae, Rodentia) by elliptical Fourier methods. Coloq. Paleontol. 1, 325—334.

Jackson, D.A., 1995. PROTEST: a PROcrustean Randomization TEST of community environment concordance. Écoscience 2 (3), 297—303.

Karasik, A., Smilansky, U., 2008. 3D scanning technology as a standard archaeological tool for pottery analysis: practice and theory. J. Archaeol. Sci. 35, 1148—1168.

Karasik, A., Smilansky, U., 2011. Computerized morphological classification of ceramics. J. Archaeol. Sci. 38, 2644—2657.

Kendal, D.G., 1969. Some problems and methods in statistical archaeology. World Archaeol. 1 (1), 68—76.

Kendal, D.G., 1971. Seriation from abundance matrices. In: Hodson, F.R., Kendall, D.G., Tautu, P.T. (Eds.), Mathematics in the Archaeological and Historical Sciences, pp. 215—252. Edinburgh.

Kuhl, F.P., Giardina, G.R., 1982. Elliptic Fourier features of a closed contour. Comput. Graph. Image Process. 18, 236—258.

Legendre, P., Legendre, L., 1998. Numerical Ecology. Elsevier, Amsterdam, 853pp.

Lestrel, P.E., 1989. Method for analyzing complex two-dimensional forms: elliptical Fourier Functions. Am. J. Hum. Biol. 1, 149—164.

Lestrel, P.E., Caesar, R.M., Takahashi, O., Kanazawa, E., 2004a. A Fourier-wavelet representation of 2-D shapes: sexual dimorphism in the Japanese cranial base. Anthropol. Sci. 112, 3—28.

Lestrel, P.E., Cesar, R.M., Takahashi, O., Kanazawa, E., 2005. Sexual dimorphism in the Japanese cranial base: a Fourier-wavelet representation. Am. J. Phys. Anthropol. 128 (3), 608–622.

Lestrel, P.E., Ohtsuki, F., Wolfe, C.A., 2010. Cranial vault shape in fossil hominids: Fourier descriptors in norma lateralis. HOMO – J. Comp. Hum. Biol. 61, 287–313.

Lestrel, P.E., Takahashi, O., Kanazawa, E., 2004b. A quantitative approach for measuring crowding in the dental arch: Fourier descriptors. Am. J. Orthod. Dentofac. Orthop. 125 (6), 716–725.

Lycett, S.J., 2009. Quantifying transitions: morphometric approaches to Palaeolithic variability and technological change. In: Camps, M., Chauhan, P. (Eds.), Sourcebook of Paleoithic Transitions: Methods, Theories, and Interpreations. Springer, New York, pp. 79–92.

Martínez-Carrillo, A.L., Lucena, M., Fuertes, J.M., Ruiz, A., 2010. Morphometric analysis applied to the archaeological pottery of the valley of Guadalquivir. In: Elwa, A.M.T. (Ed.), Morphometrics for Nonmorphometricians. Springer, pp. 307–323.

Martínez-Carrillo, A.L., Ruiz-Rodriguez, A., Lucena, M., Fuertes, J.M., 2009. A proposal of ceramic typology based on the image comparison of the profile. Comput. Appl. Archaeol., 1–7.

McCane, B., 2013. Shape variation in outline shapes. Syst. Biol. 62 (1), 134–146.

Monna, F., Jebrane, A., Gabillot, M., Laffont, R., Specht, M., Bohard, B., Camizuli, E., Petit, C., Chateau, C., Alibert, P., 2013. Morphometry of Middle Bronze Age palstaves. Part II – spatial distribution of shapes in two typological groups, implications for production and exportation. J. Archaeol. Sci. 40, 507–516.

Navarro, N., 2003. MDA: a MATLAB-based program for morphospace-disparity analysis. Comput. Geosci. 29 (5), 655–664.

Navarro, N., Zatarain, X., Montuire, S., 2004. Effects of morphometric descriptor changes on statistical classification and morphospaces. Biol. J. Linn. Soc. 83 (2), 243–260.

Orton, C., Tyers, P., Vince, A.G., 1992. Pottery in Archaeology. Cambridge. 269 pp..

Ottoni, C., Flink, L.G., Evin, A., Geörg, Ch, De Cupere, B., Van Neer, W., Bartosiewicz, L., Linderholm, A., Barnett, R., Peters, J., Decorte, R., Waelkens, M., Vanderheyden, N., Ricaut, F.-X., Hoelzel, A.R., Mashkour, M., Karimlu, A.F.M., Seno, S.S., Daujat, J., Brock, F., Pinhasi, R., Hongo, H., Perez-Enciso, M., Rasmussen, M., Frantz, L., Megens, H.-J., Crooijimans, R., Groenen, M., Arbuckle, B., Benecke, N., Vidarsdottir, U.S., Burger, J., Cucchi, T., Dobney, K., Larson, G., 2013. Pig domestication and human-mediated dispersal in western Eurasia revealed through ancient DNA and geometric morphometrics. Mol. Biol. Evol. 30 (4), 824–832.

Paunier, D., Barral, P., Luginbühl, T., Parrate, C.-A., 1994. Système de description et de gestion du mobilier céramique. Glux-en-Glenne, Lausanne. 63 pp..

Paunier, D., Luginbühl, T., 2004. Bibracte, le site de la maison 1 du Parc aux Chevaux (PC1). Des origines de l'oppidum au règne deTibère. Glux-en-Glenne. 472 pp..

Peres-Neto, P.R., Jackson, D.A., 2001. How well do multivariate data sets match? The advantages of a Procrustean superimposition approach over the Mantel test. Oecologia 129 (2), 169–178.

R Core Team, 2012. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0. http://www.R-project.org/.

Rohlf, F.J., Archie, J.W., 1984. A comparaison of Fourier methods for the description of wing shape in mosquitoes (Diptera: Culicidae). Syst. Zool. 33 (3), 302–317.

Saragusti, I., Karasik, A., Sharon, I., Smilansky, U., 2005. Quantitative analysis of shape attributes based on contours and section profiles in artifacts analysis. J. Archaeol. Sci. 32, 841–853.

Schmittbuhl, M., Allenbach, B., Le Minor, J.-M., Schaaf, A., 2003. Elliptical descriptors: some simplified morhpometric parameters for the quantification of complex outlines. Math. Geol. 35 (7), 853–871.

Schwarz, G., 1978. Estimating the dimension of a model. Ann. Stat. 6 (2), 461–464.

Sheets, H.D., Covino, K.M., Panasiewicz, J.M., Morris, S.R., 2006. Comparison of geometric morphometric outline methods in the discrimination of age-related differences in feather shape. Front. Zool. 3, 15.

Shepard, A.O., 1985. Ceramics for the Archaeologist. Washington. 414 pp..

Slice, D., 2005. Modern Morphometrics in Physical Anthropology. Springer, 383 pp.

Sundberg, F.A., 1996. Morphological diversification of Ptychopariida (Trilobita) from the Marjumiid biomere (Middle and Upper Cambrian). Paleobiology 22 (1), 49–65.

Tatsuta, H., Mizota, K., Akimoto, S.-I., 2004. Relationship between size and shape in the sexually dimorphic beetle *Prosopocoilus inclinatus* (Coleoptera: Lucanidae). Biol. J. Linn. Soc. 81 (2), 219–233.

Terral, J.-F., Tabard, E., Bouby, L., Ivorra, S., Pastor, T., Figueiral, I., Picq, S., Chevance, J.-B., Jung, C., Fabre, L., Tardy, Ch, Compan, M., Bacilieri, R., Lacombe, T., This, P., 2010. Evolution and history of grapevine (*Vitis vinifera*) under domestication: new morphometric perspectives to understand seed domestication syndrome and reveal origins of ancient European cultivars. Ann. Bot. 105 (3), 443–455.

Urbanová, P., Vachút, P., Měchurová, Z., 2011. Analýza podobnosti drobné středověké plastiky pomocí trojrozměrných modelů. In: Sborník prací Filozofické fakulty Brněnské University - řada archeologická (M), vol. 14–15, pp. 219–232.

Vaginay, M., Guichard, V., 1988. L'habitat gaulois de Feurs (Loire). Fouilles récentes (1978–1981). Documents d'archéologie française, 14. Paris, Éd. de la Maison des Sciences de l'Homme. 200 pp..

Vigne, J.D., Bignon, O., Callou, C., Cucchi, T., Mashkour, M., Auffray, J.C., Baylac, M., 2007. Geometrics morphometrics and fragmented archaeological skeleton remains: examples, limits and perspectives. J. Morphol. 268 (12), 1145.

Zelditch, M., Swiderski, D.L., Sheets, H.D., 2004. Geometric Morphometrics for Biologists. Elsevier Academic Press, 478 pp.