Detection of Matching Fragments of Pottery

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Abstract. A major obstacle to the wider use of 3D object reconstruction and modeling is the extent of manual intervention needed to construct 3D models. Such interventions are currently massive and exist throughout every phase of a 3D reconstruction project: collection of images, image management, establishment of sensor position and image orientation, extracting the geometric detail describing an object, merging geometric, texture and semantic data. This work aims to develop a solution for automated documentation of archaeological pottery, which also leads to a more complete 3D model out of multiple fragments. Generally the 3D reconstruction of arbitrary objects from their fragments can be regarded as a 3D puzzle. In order to solve it we identified the following main tasks: 3D data acquisition, orientation of the object, classification of the object and reconstruction.

Keywords: Archaeological Ceramics, 3D Reconstruction, 3D Puzzle, 3D Acquisition

1. Introduction

Reassembly of fragmented objects from a collection of thousands randomly mixed fragments is a problem that arises in several applied disciplines, such as archaeology, failure analysis, paleontology, art conservation, and so on. Solving such jigsaw puzzles by hand may require years of tedious and delicate work, consequently the need for computer aided methods is obvious (Leitao and Stolfi 2002). The assembling of an object from pieces is called mosaicing (Langenscheidt 1989). It is similar to the automatic assembly of jigsaw puzzles (Burdea and Wolfson 1989). In archaeology, most of the finds are in form of fragments, especially in the area of ceramics. Therefore mosaicing is of great interest in this field, since it enables both, a real and a virtual reconstruction of the original object. Most of the ceramic is rotationally symmetric since it was produced on a potter's wheel. Using this fact, one can solve the mosaicing problem even if there are gaps between the fragments, just like a human would solve this problem. Figure 1a shows a box filled with archaeological fragments, which possibly could fit to each other. Figure 1b illustrates manually identified, matching fragments.

More generally mosaicing can be seen as a special case of object recognition by approximate outline matching: The specific problem of identifying adjacent ceramic fragments by matching the shapes of their outlines was considered by (Üçoluk and Toroslu 1999, Hori et. al. 1999, Kong et. al. 2001 and Kanoh et. al. 2001). (Marques et al. 2002) present a 2D object matching technique based on the comparison of a reference contour to the contours in the image partition.

Similarly, (Leitao and Stolfi 2002) demonstrate a multiscale matching method and (Papaioannou et. al. 2001) present a semi-automatic reconstruction of archaeological finds (Papaioannou et al. 2001). We observe a main focus on the analysis of the outline of the break curve: 2D outline matching is most common (Leitao and Stolfi 2002, Kanoh et. al. 2001, Kong et. al. 2001, Burdea and Wolfson 1989, Kosiba et al 1994), but work on 3D outline matching exist (Üçoluk and Toroslu 1999). Surface matching of fractured surfaces is proposed in Papaioannou et al. 2001. So far, no complete system from acquisition to reconstruction has been described. This paper focuses on the reconstruction of pottery out of many fragments based on the profile. With respect to our previous work (Sablatnig and Kampel 2002), the paper describes the finding and matching of candidate fragments as its main contribution. Our approach to pottery reconstruction is based on the following main tasks: After acquiring 3D data with the Minolta VIVID 900, we start with the estimation of the correct orientation of the fragment, which leads to the exact position of a fragment on the original vessel. Next, the classification of the fragment based on its profile section allows us to decide to which class an object belongs to, presented in Section 2. Since we know the orientation of the candidate fragments we defined a two-degrees-of-freedom search space for representing the alignment of two fragments. A matching algorithm based on the point-by-point distance between facing outlines is proposed in Section 3. Reconstruction results on synthetic and real data are given in Section 4, followed by conclusions and outlook on future work.

(a) (b)

Fig. 1. Archaeological objects: (a) Box with possibly, matching fragments, (b) Matching fragments.

2. Determination of Matching Candidates

Archaeological pottery is assumed to be rotationally symmetric since it was made on a rotation plate. With respect to this property the axis of rotation is calculated using a Hough inspired method (Sablatnig and Kampel 2002). In order to reconstruct complete pots out of fragments, profiles with similar attributes are to be found in an archive database. Classification of newly found fragments of unknown type is performed by comparing the description of the new fragment with the description of already classified fragments. The fragment structure is formed by its shape features (or geometric features like the profile) and its properties (or material like clay, color and surface). The description of the fragment is structured in a description language consisting of primitives and relations. Primitives are a representation of shape features, relations represent the properties.
The description language, which was originally designed to solve 2D automatic visual inspection problems (Sablatnig 1997), is applied and extended in order to solve the classification problems. The actual profile contains features, which are a representation of shape features. To accomplish classification, primitives are further subdivided into part-models (or part- primitives), the consistency between part-primitives is established by relations among part parameters (see Sablatnig 1997 for details).
This method enables us to compute the confidence of a node by summing up the weighted tolerances of each attribute of the node and the overall confidence of the subgraph connected to this node. By computing the consistency for different descriptions, the one with the highest confidence value can be chosen if the confidence is above a certain threshold. For a given profile all primitives are represented in the description of the profile.

3. Fragment Matching

The optimal pairing of matching candidates obtained serves as input for the fragment matching part. Consequently we know those pairs of fragments which were probably adjacent in the original object. In order to represent the matching of two fragments, (G. Papaioannou et. al. 2001) describes seven pose parameters. In their approach the two fragments are first prealigned so that their broken facets face each other. In our case we know the orientation of a fragment; consequently we prealign two candidate fragments by simply aligning their axis of rotation. As a result, a two-degrees-of-freedom continuous search space is defined. The transformation which matches two candidate fragments consists of a translation along the z-axis with parameter T_z and a rotation around the z-axis with parameter R_z (see Figure 2).

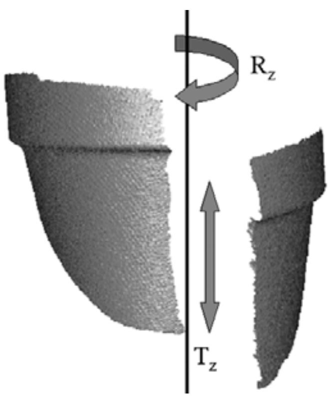

Fig. 2. Fragment Matching with 2degreesoffreedom.

The basic concept in our method for estimating is that the best fit is likely to occur at the relative pose which minimizes the point-by-point distance between the facing outlines. For this reason, we introduce a matching error ε_M based on the mean Euclidean distance between the corresponding points of the outlines of the candidate fragments with points $X = (x,y)$ and $X' = (x',y')$:

$$\varepsilon_M = \frac{1}{N}\sum_{i=1}^{N}\sqrt{\left(x_i - x_i'\right)^2 + \left(y_i - y_i'\right)^2} \tag{1}$$

where N is the number of data points used. The height of the fragment, limits the length of the matching segments. Different fragments types lead to the following matching possibilities:

A Rim fragments: firstn T_z is computed by aligning the rim along the orifice plane (Kampel 2003). Next R_z is estimated, so that the positioning transformation with the smallest matching error ε_M is considered to be the correct position.

B B Bottom fragments: first T_z is computed by aligning the bottom along the base plane. Next R_z is estimated in the same way as for rim fragments.

C Wall fragments: Candidates are first aligned along their profile sections. Next R_z is estimated in the same way as for rim fragments. Since it is not clear whether a new candidate fragment is in bottom up or bottom down position, we have to compute R_z and T_z for both positions. The positioning transformation with the smallest matching error ε_M is considered to be the correct position.

Matching algorithm

- Define reference fragment Fref with its axis of rotation ROT_{ref} : defines a new pot P, creates the pot coordinate system, ROT_{ref} is aligned to the z-axis.
- Prealignment of the candidate fragment F_{cand} by its axis of rotation ROT_{cand}: ROT_{cand} is aligned to ROT_{ref} . These results in a two-degrees-of-freedom search space: Translation T_z along the axis of rotation (up/down) and rotation R_z around the axis of rotation.
- Estimation of the translation parameter T_z: search for minimal distance d between all y-values (radius) of the profile of F_{ref} and the profile of F_{cand}. Exception A: Rim fragments are aligned along the orifice plane. Exception B: Bottom fragments are aligned along the base plane. When the candidate fragment is a wall fragment, the minimal distance d is computed for both positions, and the one with the smaller is considered to be the correct position.
- Estimation of the rotation parameter R_z by finding the position with the smallest matching error ε_M.

4. Results

In order to evaluate the results we have tested our method on synthetic 3D data of three parts of a synthetic pot. The orientation of the fragments is defined, which leads to three perfect matching parts. The experiment has shown a 100% theoretical accuracy of the approach.

In order to get data of matching fragments of a whole pot, we broke a flowerpot into 5 parts. We got three rim fragments, one wall fragment and one bottom fragment. Each part was digitized leading to a front and back view of each fragment. The biggest part (nr. 2) covers half of the pot and consists of 135070 triangles, whereas the smallest consists of 8210 triangles. Next we computed the orientation of the fragments, which leads to four matching candidates and one not processable object: a large part of the bottom fragment (Part 4) consists of flat area. It was therefore excluded from further processing due to its curvature being too low.

Starting with part one as reference fragment for each candidate a matching error was computed. Next part two was defined as reference fragment and again for each remaining candidate a matching error was computed. This procedure was continued until no candidate remained. Table 1 summarizes T_z, R_z and the matching errors for each possible candidate. RF_{nr} and CF_{nr} denote the number of the reference fragment and the number of candidate fragment respectively, and ε_M denotes the matching error. The value of ε_M for correct matches ranges from 1.12 to 0.63, the combination of part 3 and 5 shows an incorrect match with an error ε_M of 12.92.

Figure 3a displays the resulting match of part 1 and part 3 as both parts are rim fragments. Figure 3b shows the resulting match of part 1 and part 5. Since part 5 is a wall fragment the ε_M was computed for both possible positions, and the position with lower ε_M was finally chosen.

Figure 3c shows the final reconstruction of the pot. Correct matches for all four candidate fragments have been found. The missing bottom of the pot is due to part 4, not being processable because of its flat shape.

We applied our technique to real archaeological fragments (Nr: 319–71, 209–71 from the late Roman burnished ware of Carnuntum (Sablatnig and Kampel 2002)). Both pieces are rim fragments (Figure 4a and b). The alignment along the orifice plane allowed the estimation of T_z = 7.49 cm. The smallest ε_M = 0.31 was found R_z for = 3.35. Figure 4c shows the matched outlines of the two fragments and Figure 4d shows the final reconstruction.

Another example on real archaeological fragments was done on the common ware of Sagalassos Kampel 2003. One rim and two wall fragments were recorded and processed. Table 1 summarizes T_z, R_z and the matching errors for each possible candidate. Correct matches were found between part one and part two (ε_M = 1.32) and part two and part three (ε_M = 1.21). No correct match was found between part one and part three (ε_M = 14.81), because there was no alignment of the profile sections (part one is on top of part three). Nevertheless all three fragments were matched together, since the matching of part two succeeded for both candidates.

The results demonstrate the possibility of automatically matching adjacent fragments by our method. It works for fragments which can be oriented and classified by our approach with one exception: two adjacent fragments on top of each other cannot be matched by our method, because they do not have overlapping profile sections. Furthermore if the surface of the fragment is too flat or too small or the classification is not known, the fragment is not considered for reconstruction.

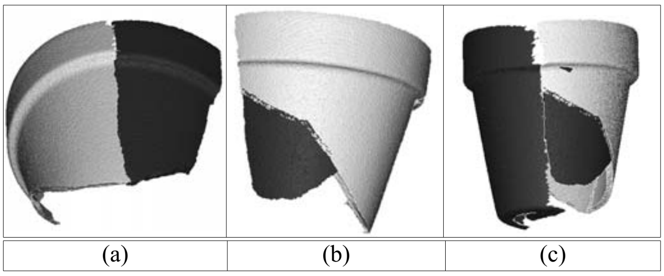

Fig. 3. Matched parts: (a) part 1 and part 3 (b) part 1 and part 5 (c) Matching parts 1, 2, 3, and 5.

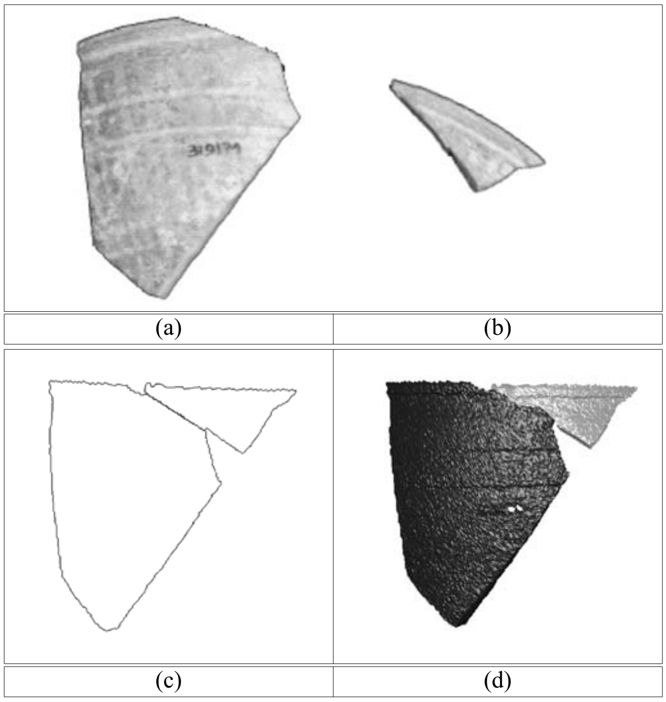

Fig. 4. Archaeological rim fragments: (a) Part1, (b) Part 2, (c) Matching outlines, (d).

Ware	RF_{nr}	CF_{nr}	T_Z (mm)	R_Z (mm)	ε_M
Flowerpot	1	2	12,03	22,81	1,12
Flowerpot	1	3	8,67	-41,29	0,81
Flowerpot	1	5	9,34	73,21	0,63
Flowerpot	2	3	-4,94	17,61	0,92
Flowerpot	2	5	-10,02	-26,75	0,71
Flowerpot	3	5	11,10	32,99	12,92
Carnuntum	1	2	7,49	3,35	0,31
Sagalassos	1	2	-4,29	11,70	1,32
Sagalassos	1	3	-1,61	7,59	14,81
Sagalassos	2	3	-5,19	15,76	1,21

Table 1. Results of the matching process.

5. Conclusions

We have proposed a method for the assembly of an object from pieces, which in our case means the reconstruction of an archaeological pot from its fragments. The outcome on vessel reconstruction out of multiple fragments was described by real 3D data. The ceramic documentation and reconstruction system described was recently integrated into the virtual excavation reconstruction project 3D MURALE. Future work will be directed towards setting up a pottery database with more then 100 fragments and applying the algorithm to find matching pieces.

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References

Burdea, G. C. and Wolfson, H. J., 1989. Solving Jigsaw Puzzles by a Robot. *IEEE Transactions on Robotics and Automation* 5(5), 752–764.

Hori, K., Imai, M., and Ogasawara, T., 1999. Joint Detection for Potsherds of Broken Earthenware. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR '99)*, volume 2, June 1999, 440–445.

Kampel, M., 2003. 3D Mosaicing of Fractured Surfaces. PhD thesis, TU-Vienna, Inst. f. Automation, Pattern Recognition and Image Processing Group.

Kanoh1, M., Kato, S., and Itoh, H., 2001. Earthenware reconstruction based on the shape similarity among potsherds. Society for *Science on Form* 16(1), 77–90.

Kong, W. and Kimia, B., 2001. On solving 2D and 3D puzzles using curve matching. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR '01)*, volume 2, 583–590.

Kosiba, D., Devaux, P. M., Balasubramanian, S., Gandhi, T., and Kasturi, R., 1994. An Automatic Jigsaw Puzzle Solver. In *Proc. of the 12th IAPR International Conference on Pattern Recognition*. Jerusalem, volume 1, 616–618. IEEEComputer Society Press.

Langenscheidt, 1989. *Langenscheidts Fremdwörterbuch*. Friedhelm Hübner.

Leitao, H. C. G. and Stolfi, J., 2002. A Multiscale Method for the Reassembly of Two-Dimensional Fragmented Objects. *IEEE Trans. on Pattern Analysis and Machine Intelligence* 24(9), 1239–1251.

Marques, F., Pardis, M., and Morros, R., 2002. Object matching based on partition information. In *IEEE Computer Society International Conference on Image Processing*, volume 2, 829–832.

Papaioannou, G., Karabassi, E., and Theoharis, T., 2001. Virtual archaeologist: Assembling the past. *IEEE Computer Graphics* 21(2), 53–59.

Sablatnig, R., 1997. A Highly Adaptable Concept for Visual Inspection. PhD thesis, TU-Vienna, Inst. f. Automation, Pattern Recognition and Image Processing Group.

Sablatnig, R. and Kampel, M., 2002. Model-based registration of front- and backviews. *Computer Vision and Image Understanding* 87(1), 90–103.

Üçoluk, G. and Toroslu, H., 1999. Automatic Reconstruction of Broken 3D surface objects. *Computers and Graphics* 23(4), 573–582.