

# Extracting Hand Grasp & Motion for Intent Expression in Mid-Air Shape Deformation : A Concrete & Iterative Exploration through a Virtual Pottery Application

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## Abstract

We describe the iterative design and evaluation of a geometric interaction technique for bare-hand mid-air virtual pottery. We model the shaping of a pot as a gradual and progressive convergence of the pot-profile to the shape of the user's hand represented as a point-cloud (PCL). Our pottery-inspired application served as a platform for systematically revealing how users use their hands to express the intent of deformation during a pot shaping process. Our approach involved three stages: (a) clutching by proximal-attraction, (b) shaping by proximal-attraction, and (c) shaping by grasp+motion. The design and implementation of each stage was informed by user evaluations of the previous stage. Our work evidently demonstrates that it is possible to enable users to express their intent for shape deformation without the need for a fixed set of gestures for clutching and deforming a shape. We found that the expressive capability of hand articulation can be effectively harnessed for controllable shaping by organizing the deformation process in broad classes of intended operations such as pulling, pushing, and fairing. After minimal practice with the pottery application, users could *figure out* their own strategy for reaching, grasping, and deforming the pot. Users particularly enjoyed using day-to-day physical objects as tools for shaping pots.

*Keywords:* Mid-air gestures, depth sensor, virtual pottery, shape deformation, hand grasp.

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## 1. Introduction

Mid-air gestures have been widely used as the *symbolic* means for expressing user's intent in 3D shape modeling [1, 2, 3, 4, 5, 6]. Gesture-based interactions enable the user to focus on the design task rather than dedicating significant time towards learning the usage of the tool itself [7]. With the recent commercialization of depth cameras, gesture-based interactions have become accessible to the common user; creative applications for free-form shape modeling [8] in mid-air have gained significant popularity. The user input in these applications is represented as a combination of some special hand posture (such as pointing with a finger), and the motion of a representative point (such as the palm or finger-tip) on the hand.

Hand and finger movements in real-world shaping processes (such as pottery or clay sculpting) are complex, iterative, and gradual. Such processes are essentially governed by the physics and geometry of contact between the hand and clay. Thus, the true expressive potential of finger movements remains underutilized despite advances in hand pose and skeletal estimation [9, 10]. This is what drives our research wherein, our intention is to bridge the gap between the user's expression of intent and the corresponding deformation of a virtual shape.

In this paper, we give an comprehensive account of our recent works [11, 12] by describing the iterative design and evaluation of a geometric interaction technique for bare-hand mid-air virtual pottery. Our broader goals are to (a) identify aspects of

real-world interactions that can be emulated in free-form 3D shape deformation, (b) understand the expression of design intent in shape deformation in terms of the user's hand grasp and motion, and (c) design an interaction that integrates the geometric information in user's actions with shaping operations in virtual space.

### 1.1. Contributions

This paper is an extension of our recent work [12], where we modeled the shaping of a pot as a gradual and progressive convergence of the pot's profile to the shape of the user's hand represented as a point-cloud (PCL). We presented a method that uses the kernel-density estimate (KDE) of the hand's PCL to extract the grasp and motion for deforming the shape of a pot in 3D space. This feature of our method directly allows a user to shape pots by using physical artifacts as tools without the need for computing any finite set of gestures or hand skeleton. In doing so, we demonstrate that it is possible to achieve controllability in bare-hand mid-air shape deformation using raw PCL data of the user's hand.

There are two differences between this paper and our prior works [11, 12]. First, we present the complete evolution of our algorithm in three stages of iterative design (section 3.3). At the end of each stage, we describe a user evaluation that informs the algorithm development of the subsequent stage. Second, we evaluate our KDE based approach in comparison to our prior work [11]. Our evaluations help reveal two core aspects

53 of mid-air interactions for shape deformation, namely, intent &  
54 controllability. We characterize user behavior in pottery design  
55 in terms of (a) common hand & finger movement patterns for  
56 creating common geometric features, (b) user perception of in-  
57 tent, and (c) engagement, utility, and ease of learning provided  
58 by our approach.

## 59 2. Related Work

### 60 2.1. Mid-air Gestures

61 Gestures can be designed effectively for pointing, selec-  
62 tion [13, 14], and navigation, since they define an unambigu-  
63 ous mapping between actions and response. Such tasks are im-  
64 plemented using deictic gestures [15] and can usually be seg-  
65 mented into discrete phases, with each phase triggering an *event*  
66 or a *command* [16]. Pointing in the direction of a virtual ob-  
67 ject creates the association between the user and the object. A  
68 recent study [17] shows dwell-time to be an effective method  
69 of pointing and selecting objects without hint to the users. In  
70 manipulative tasks such as ours, a direct spatial mapping is re-  
71 quired between the user’s input and the virtual object [18, 15].  
72 Particularly in our case, such an association would be in terms  
73 of the proximity of the user’s virtual hand to the shape being  
74 deformed.

### 75 2.2. Gestures for 3D Modeling

76 Let us consider a mid-air interaction scenario of selecting  
77 and displacing a mesh vertex for deforming a 3D mesh. Since  
78 the user’s hands are interacting in the air, there is no physical or  
79 natural mechanism for triggering events. Here, gestures could  
80 serve two fundamental purposes. First, they help define a be-  
81 ginning (e.g. reaching and clutching some region of interest)  
82 and end (e.g. de-clutching the region after required deforma-  
83 tion) of an interaction [16, 19]. Secondly, they help define the  
84 exact operation from a set of operations defined in the context  
85 of the application. For example, the type of deformation could  
86 be selected by using different gestures (e.g. fist to pull, point to  
87 push, open palm to flatten).

88 On these lines, most existing bare-hand interaction tech-  
89 niques for 3D shape conceptualization, use gestures combined  
90 with arm and full-body motions. Segen and Kumar [1] showed  
91 examples of computer-aided design (CAD) with their *Gesture*  
92 *VR* system, using computer vision for general virtual reality  
93 (VR) applications. Wang et al. [2] presented *6D Hands* to demon-  
94 strate CAD using marker-less hand tracking. The modeling  
95 of sweep surfaces using hand gestures and body motion was  
96 demonstrated by Vinayak et al. [4, 5]. Han and Han [3] demon-  
97 strated an interesting surface-based approach with particular fo-  
98 cus on audiovisual interfaces for creating 3D sound sculptures.  
99 Holz and Wilson proposed *Data miming* [7] as an approach to-  
100 wards descriptive shape modeling wherein voxel representation  
101 of a user’s hand motion is used to deduce the shape which the  
102 user is describing. This approach uses hands without the ex-  
103 plicit determination of gestures for recognizing the user’s de-  
104 scription of an existing shape.

### 105 2.3. Hand Grasp

106 Prehension is a common phenomenon in real-world inter-  
107 actions. Jeannerod [20] notes two functional requirements of  
108 finger grip during the action of grasping, (a) adaptation of the  
109 grip to the size, shape, and use of the object to be grasped and  
110 (b) the coordination between the relative timing of the finger  
111 movements with hand transportation (i.e. whole hand move-  
112 ments). Intended actions strongly influence motion planning of  
113 hand and finger movements [21]. This suggests that the intent  
114 for deformation can be recognized before the user makes con-  
115 tact with the surface being deformed. Grasp classification [22]  
116 and patterns of usage and frequency [23] have been integral to  
117 robotics research. Literature in virtual reality [24, 25] has stud-  
118 ied and implemented grasping in the context of object manip-  
119 ulation (pick-and-place). Kry et al. [26] implemented a novel  
120 hardware system to emulate grasping for desktop VR applica-  
121 tions such as digital sculpting. It is worth noting that the pri-  
122 mary methodology for investigating grasp taxonomies is mostly  
123 derived from the geometry of the hand in relation to a physical  
124 object that is held or manipulated by the hand. What we aim to  
125 do is to understand what is the minimal and sufficient character-  
126 ization of the user’s hand and finger movements, that could be  
127 used for mid-air deformation. Our goal is not to explicitly de-  
128 tect the hand grasp, but to design a deformation approach where  
129 the grasp is automatically and implicitly taken into considera-  
130 tion.

## 131 3. Overview

### 132 3.1. Intent & Controllability

133 The general term *intent* is literally defined as “*the thing that*  
134 *you plan to do or achieve : an aim or purpose*”. In our case,  
135 intent (*what one wants to achieve*) can be described in terms  
136 of the context of shape deformation (*what operations one can*  
137 *perform on the shape*). Based on Leyton’s perceptual theory  
138 of shapes [27], Delamé et al. [28] proposed a process gram-  
139 mar for deformation by introducing structuring and posturing  
140 operators. Here, structuring operators involve adding/removing  
141 material to the shape, while posturing operators allow for modi-  
142 fications such as bending or twisting some portion of the shape.  
143 Since our context is that of deformation, we define the intent in  
144 terms of two basic operations: pulling and pushing. These are  
145 analogous to structuring operators.

146 We see controllability as the quality of intent recognition  
147 and disambiguation *as perceived by the user*. Specifically, in  
148 our context, controllability is defined as a function of two fac-  
149 tors: (a) the disparity between what a user intends for the shape  
150 to be and what the shape actually becomes after the deforma-  
151 tion and (b) the responsiveness of the deformation. The goal is  
152 to minimize the disparity and optimize the responsiveness.

### 153 3.2. Rationale for Pottery

154 We have two goals in this paper. First, we seek a con-  
155 crete geometric method that takes a general representation of  
156 the user’s hand (PCL) and allows the user to deform 3D geom-  
157 etry. Second, we want to investigate this geometric method in

light of intent and controllability. Thus, our focus here is not to build a comprehensive and feature-rich 3D modeling system. Instead, we intend to investigate spatial interactions for 3D shape deformation with an unprocessed representation of the hand.

In a general shape deformation scenario, an arbitrary triangle mesh is the ideal and generic shape representation. However, a controlled study is prohibitively challenging in such a case, for two reasons. First, the hand PCL data obtained from a single depth sensor is partial and noisy. Second, dynamic and complex finger motions add further complexity to the occlusions and noise. Subsequently, designing interaction tasks for a quantitative evaluation is difficult, particularly for users that have no prior experience with mid-air interactions for free-form 3D modeling. Hence, it is essential to constrain the geometric representation of the object being modified.

Our broader motivation in this work is to cater to the creative needs of individuals that are inclined towards 3D modeling and design and but do not have the expertise require for working with design tools. With this in view, we use pottery as our application context for two reasons. First, it offers a well-defined and intuitive relationship between the use of hands and the shaping of pots to a user. This allows us to concretely construct a geometric relationship between the shape of the hand PCL and the corresponding user intent. Secondly, the simplicity of the geometric representation and deformation lends itself to quantitative measurement of the user’s response to our system.

### 3.3. Approach

Given the context of pottery, our approach involved the following three stages:

**Stage 1:** Using hand as one-point manipulator, we implemented *proximal-attraction*, an interaction technique for clutching and de-clutching without hand gestures. Our technique (section 4) generalizes the notion of *dwelt-time* in the context of mid-air shape deformation. We conducted a preliminary study to evaluate the feasibility and effectiveness of this technique.

**Stage 2:** We extended the *proximal-attraction* method to the whole shape of the hand (section 5) [11]. Here, the hand was represented as a collection of multiple points (i.e PCL) obtained via a depth sensor. Each point in the PCL deformed a small local region on the pot using the proximal-attraction approach. On the whole this amounted to a gradual and progressive convergence of the pot-profile to the shape of the user’s hands. Through experimentation, we found that users had significant difficulty in creating convex (pulling) and flat (fairing) features on the pot. This method was also found to be agnostic to the user’s grasp and hand movements.

**Stage 3:** Based on our experiments, we implemented our final technique for pot deformation using hand PCL (section 6). We used kernel-density estimation to characterize the contact between the hand and the pot. This allowed us to classify the

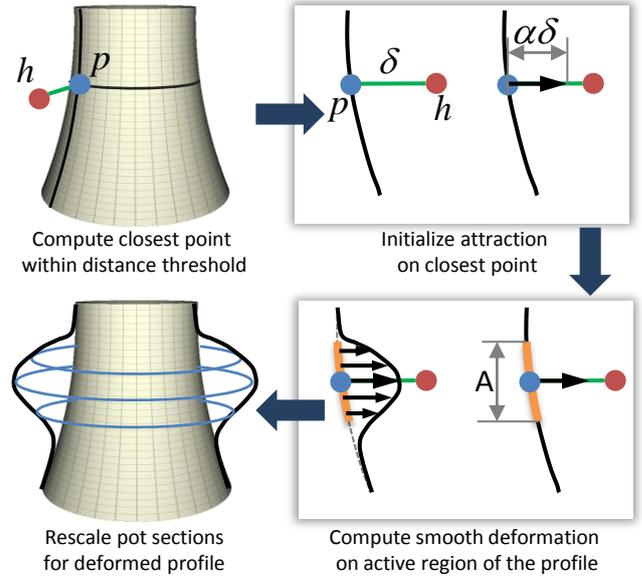


Figure 1: Algorithm for one-point pot deformation is illustrated for proximal-attraction. The pot is gradually deformed by attracting the profile towards the hand (represented by a point). Subsequently, each section is re-scaled to obtain the deformed pot surface.

users’ intent to push, pull or fair the surface of the pot depending on the hand grasp, finger movements, and motion of the hand on the pot’s surface. We conducted a final user evaluation to investigate the efficacy of this approach.

### 3.4. Pot Representation & Deformation

The deformation algorithm for the pot evolved through iterative implementation and evaluation. Here we describe the basic geometric representation of a pot and the general computational setup of deforming the pot.

We represent a pot as a simple homogeneous generalized cylinder. The surface of the pot is defined as a vertical stack of circular sections. Each section is a polygonal approximation of a circle, i.e. a closed regular polygon. Note that a sequenced list of pairs (radius, height) is the *profile curve* of the pot. The deformation of a pot is achieved by deforming the profile curve, i.e by modifying the radii of each section. For a 3D pot, this essentially corresponds re-scaling each section by the corresponding amount of deformation.

## 4. Hand as a Point: Clutching by Proximal Attraction

In the first stage, we developed a method wherein the hand is represented as a single point manipulator, as is the case with many gesture-based methods. The main goal was to allow users to deform the surface of the pot without using hand gestures for clutching and de-clutching the pot.

### 4.1. Technique

Let  $h$  be the location of the hand in 3D space and  $p$  be the point on the pot that is closest to  $h$ . The main idea of proximal-attraction is to deform the pot gradually by attracting  $p$  towards

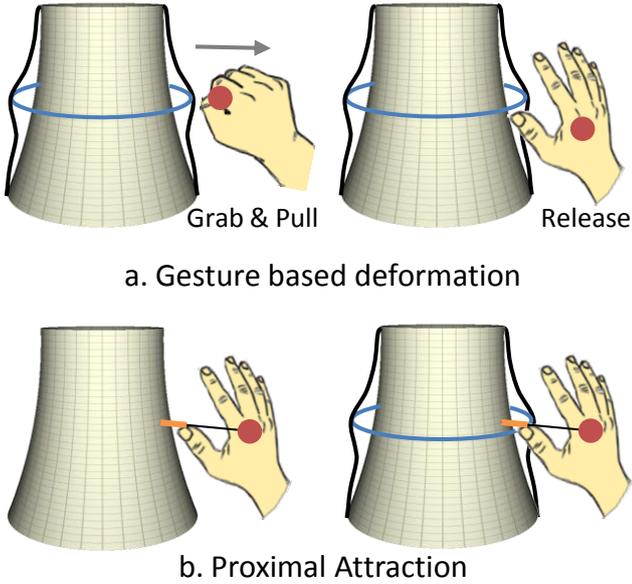


Figure 2: Two strategies are shown for clenching and deforming a pot using hand as a single point. In the first approach (a) grab and release gestures. The second (b) is the proximal-attraction approach

241  $h$  in the *horizontal* plane. The condition of proximity is that  
 242 the distance between  $h$  and  $p$  should be less than a pre-defined  
 243 threshold (say  $\epsilon$ ). We implement the approach in the following  
 244 steps:

- 245 1. Given  $h$  and  $A$ , compute  $p$
- 246 2. if( $\|h - p\| < \epsilon$ )
  - 247 (a) Set  $\delta$  to horizontal distance between  $h$  and  $p$
  - 248 (b) Set attraction at  $p$  to  $\alpha\delta$
  - 249 (c) Compute smooth deformed profile using Laplacian  
 250 smoothing ( $\nabla^2\delta = 0$  for all points in  $A$ )
- 251 3. Rescale pot sections

252 Here,  $\alpha \in [0, 1]$  is the rate of attraction where  $\alpha = 0$  implies  
 253 no attraction and  $\alpha = 1$  implies maximum attraction. Our idea  
 254 is inspired by exponential smoothing [29]. The main step was  
 255 to determine the right balance between the rate of attraction and  
 256 the distance threshold. The responsiveness of deformation is di-  
 257 rectly proportional to both, attraction rates and distance thresh-  
 258 old. From our pilot studies, we found  $\alpha = 0.3$  and  $\epsilon = 0.05$   
 259 to be the optimal values. Here, the distances are in the nor-  
 260 malized device coordinates. In our current implementation, we  
 261 pre-defined the active region  $A$  to be 50% of the total profile  
 262 length.

#### 263 4.2. Preliminary Evaluation

264 Our main goal was to examine the feasibility and effec-  
 265 tiveness of the proximal-attraction approach for pot shaping  
 266 in terms of user performance and behavior. We also wanted  
 267 to determine the differences between our method and a typical  
 268 gesture-based approach. Additionally, we wanted to understand



Figure 3: An example of common behavior is shown wherein users shaped their hands to express their intent for deformation.

269 the reception of a creative application such as pottery for a wide  
 270 variety of participants - particularly those without prior knowl-  
 271 edge of CAD tools. For this, we conducted a two-day field  
 272 study<sup>1</sup> in an exhibition setting.

273 *Apparatus.* Our hardware setup consisted of a ThinkPad T530  
 274 laptop, a 60" display, and the Microsoft Kinect camera. The  
 275 Kinect camera was placed on a tripod below the display facing  
 276 a user standing at a distance of around 1.5 – 2.0 meters from  
 277 the display. Our pottery prototype was developed in C++ and  
 278 OpenGL.

279 *Implementation.* We implemented two versions of our pottery  
 280 application, one using mid-air gestures and the other based on  
 281 the proximal-attraction approach. We first obtained the posi-  
 282 tion of the hand using the skeletal tracking algorithm provided  
 283 by the *openNI* API. Owing to the nature of the venue, the study  
 284 was not conducted in a controlled environment leading to dis-  
 285 turbances in skeletal tracking, posture recognition, and ambient  
 286 noise. Thus, appropriate measures were taken to isolate the user  
 287 from the audience.

288 The gesture-based prototype uses two simple hand postures,  
 289 *grab* and *release*, which correspond to closed and open palms  
 290 respectively (Figure 2(a)). We used the random forest algorithm  
 291 for posture recognition as detailed in [5]. The grab and release  
 292 postures allowed the user to *clutch* and *de-clutch* a certain re-  
 293 gion of interest on the pot. The user could create concave and  
 294 convex profiles of the pot by *grab-and-push* and *grab-and-pull*  
 295 actions at the desired location of the pot surface in 3D space. In  
 296 the second prototype, we implemented our proximal-attraction  
 297 technique (Figure 2(b)).

298 *Participants & Procedure.* Participants within a wide age range  
 299 (5–60 years) were invited to use our pottery prototype wherein,  
 300 the task for each participant was to create a pot as per the par-  
 301 ticipant's liking. Although we did not carry out a formal demo-  
 302 graphic survey, we found that the participants were from a vari-  
 303 ety of backgrounds including non-technical users, engineers,  
 304 designers, artists, and professional potters. Our evaluation was  
 305 mainly informal and observational wherein we recorded videos  
 306 of sessions subject to the participant's permission and the time  
 307 taken to complete the creation of a pot. Due to the nature of our  
 308 venue, we constrained the maximum time for each participant  
 309 to about 8–10 minutes.

<sup>1</sup>MakerFaire, Bay Area (2013)

Table 1: Behavioral observations in our preliminary evaluation

Age	Value	Behavior
5-10	Fun, Play	Excitement, Random hand movements
11-15	Entertainment, Education	Controlled movements, Explored tool features
16-30	Entertainment, Art, Education	Controlled movements, Investigated pot behavior
30-60	Entertainment, Meditative	Controlled movements, Expected real-world like response

310 A total of 360 participants responded to our invitation and  
 311 used our prototype to create pots. In the first session (day 1),  
 312 180 participants used the prototype implemented using the grab  
 313 and release gestures. In the second session (day 2), 180 partic-  
 314 ipants used the proximal-attraction technique for pot deforma-  
 315 tion. There were participants that were either completely unable  
 316 to create any meaningful shape of the pot or did not find the re-  
 317 sulting shape as the intended one. These attempts we removed  
 318 from our database leaving us with the recorded times for 113  
 319 participants per session (i.e. 226 participants in total).

#### 320 4.3. Results

321 We categorized the perceived value and user behavior dur-  
 322 ing the use of the pottery applications on the basis of age. Young  
 323 participants (5-10 years) were mostly interested in simply play-  
 324 ing around with the application and usually applied arbitrary  
 325 hand movements during the deformation of the pot’s profile.  
 326 Participants in the age range of 11-15 years provided more con-  
 327 trolled movements of the hands during pot shaping with slower  
 328 and more careful hand movements and accurate hand gestures.  
 329 They also adopted a more exploratory approach towards the ap-  
 330 plications in that they were primarily interested in the various  
 331 software features rather than the realism in the pot’s deforma-  
 332 tion.

333 However, in case of participants above the age of 15, we  
 334 observed that they instinctively shaped their hands according to  
 335 geometry of the pot on the screen. Specifically, users within  
 336 16 and 30 years of age were mainly interested in investigating  
 337 how the gesture and motion of the hand was related to the de-  
 338 formation of the pot. They would frequently expect the pot to  
 339 deform according to how they shaped and moved their hands  
 340 on the pot’s surface. This strongly suggested that the internal  
 341 learning of physical interactions, combined with some prior ex-  
 342 pectation of the pot’s response, increased with the participants’  
 343 age. In case of the gesture-based approach, this was also a cause  
 344 for intermittent gesture misclassification, resulting in user fru-  
 345 stration. Despite their simplicity, the *grab* and *release* gestures  
 346 were tedious to use while using virtual tools. This was mainly  
 347 the case with participants who were completely new to inter-  
 348 faces developed for RGBD cameras.

349 On the other hand, users found the proximal-attraction ap-  
 350 proach easier to learn and use. The participants could immedi-  
 351 ately start deforming the pot, and at the same time they could  
 352 shape their hands as they saw fit. A common mental model that

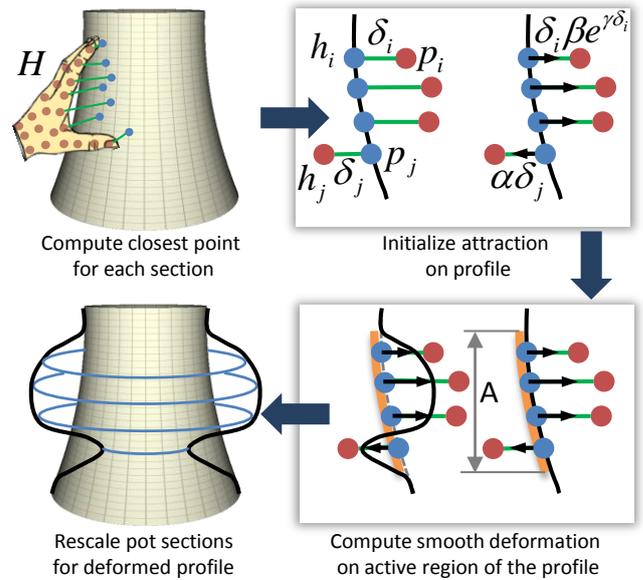


Figure 4: Algorithm for pot deformation is illustrated for proximal-attraction. The profile is deformed based on the proximity of the points on a given hand PCL. Subsequently, each section is re-scaled to obtain the deformed pot surface.

353 the users seemed to create was that of a surface which “sticks”  
 354 to their hands upon coming close. Thus, the users were in-  
 355 variably slower while approaching the pot (so as to reach the  
 356 right location) and retreated faster when they wanted to release  
 357 contact with the pot. For some users, fast retreat also caused  
 358 accidental deformation leading to frustration.

#### 359 4.4. Takeaways

360 The two main insights we gained were: (a) the intent for de-  
 361 formation directly translates to how users shape their hand and  
 362 (b) the rate of attraction for pulling and pushing must be deter-  
 363 mined separately so as to make them consistent. We found that  
 364 full-body interactions caused significant fatigue and difficulty  
 365 in controlling deformation. Thus, our subsequent stages, we  
 366 implemented interactions at close range wherein a user could  
 367 perform pottery sitting in front of a desktop or a laptop com-  
 368 puter.

### 369 5. Hand as a PCL: Shaping by Proximal Attraction

370 Our main objective in this stage was to adapt the proximal-  
 371 attraction method that could use the shape of the whole hand to  
 372 deform the pot. Thus, we used a representation of the hand as  
 373 a collection of multiple points (i.e PCL) obtained via a depth  
 374 sensor.

#### 375 5.1. Technique

376 Consider the hand  $H$  as a set of points  $\{h_i\}$  in 3D space. Each  
 377 point in the PCL deforms a small local region on the pot using  
 378 the proximal-attraction approach. On the whole this amounts to  
 379 a gradual and progressive convergence of the pot-profile to the  
 380 shape of the user’s hands (Figure 4).

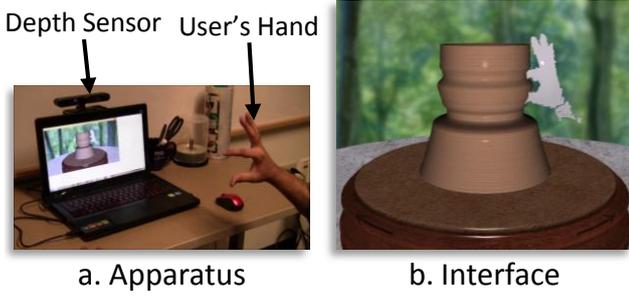


Figure 5: The apparatus (a) consists of the user, a computer and a depth camera. The user sees a PCL of their hand deforming a rotating pot (b).

381 *Pushing vs. Pulling.* A push is characterized by an inward displacement ( $\delta < 0$ ). This is the simplest case wherein a user would typically approach the pot and subsequently recede away once the desired deformation has occurred. A pull is characterized by an outward displacement ( $\delta > 0$ ). This is a non-trivial intent to recognize since a user would invariably approach the surface first and then recede to pull. The overall motion of the hand is similar to that of a push. In order to distinguish pulling and pushing, we used two different rates of attraction. For pulling, we defined the attraction rate as a smooth function of the distance between the hand point and pot. The function is given by  $\beta e^{\gamma \delta_i}$ . For pushing, we defined the rate of attraction as  $\alpha$ . This essentially allows the user to first approach the pot without deforming it during the process of approach. The algorithm is as follows:

- 396 1. For each section  $i$ 
  - 397     Compute unique  $h_i$  such that  $\|h_i - p_i\| < \varepsilon$  is minimum.
  - 398     Set  $\delta_i$  to horizontal distance between  $h_i$  and  $p_i$
- 400 2. Set  $\delta_r$  to  $\delta_{max} - \delta_{min}$
- 401 3. Set  $\gamma$  to  $\frac{0.1}{\delta_r}$
- 402 4. For each  $i$  on profile
  - 403     if ( $\delta_i < 0$ ): Set attraction at  $p_i$  to  $\alpha \delta_i$
  - 404     else: Set attraction at  $p_i$  to  $\beta e^{\gamma \delta_i} \delta_i$
- 405 5. Compute Active region  $A$
- 406 6. Smooth deformation ( $\nabla^2 \delta = 0$  for all points in  $A$ )
- 407 7. Compute deformed profile
- 408 8. Rescale pot sections

409 *Initialization Time.* In order to avoid accidental or unintended deformation of the pot, we implemented an that allows for the pot to deform only when contact with the pot is maintained for a sufficient amount of time. We achieved this in two steps. First, we reset  $\alpha$  and  $\beta$  to 0 at every new contact that the hand made with the pot. Subsequently, we linearly increase them to their

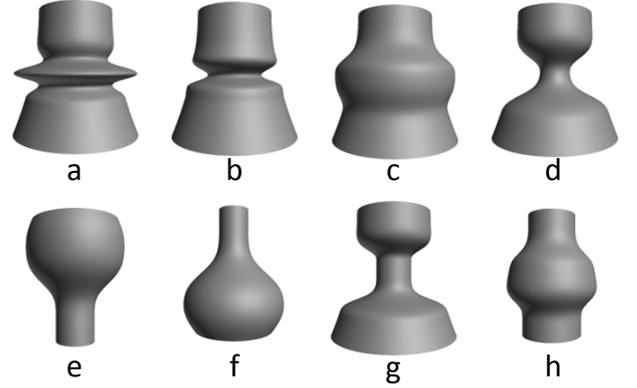


Figure 6: Eight pre-defined pots were shown to participants in the quiz. These are: (a, b) thin convex and thin concave, (c,d) fat convex and concave, (e, f) round and flat, and (g, h) flat at center and ends. (from Vinayak et al. [11])

415 maximum values within a stipulated amount of time  $T$ . We call this the initialization time. Intuitively,  $T$  is the time taken by the pot to gradually initiate the response to the user's hand after a contact is made.

## 419 5.2. Experiment

420 We conducted a lab experiment to evaluate the proximal-attraction approach. The results of this experiment led us to develop the final approach in this work. In the paragraphs below, we will describe selective details of our prior work for the sake of completeness. For a comprehensive analysis of this experiment, the reader can refer to our prior published work [11].

426 *Apparatus.* Our setup consisted of a Lenovo ideaPad Y500 laptop computer with an intel i7 processor and 8GB RAM, running 64-bit Windows 8 operating system with a NVIDIA GeForce GT 750M graphics card, and the SoftKinetic DS325 depth sensor (Figure 5(a)). SoftKinetic DS325 is a close range (0.1m-1.5m) time-of-flight depth sensor that provides a live video stream of the color and depth image of the scene. Every pixel on a given depth image can be converted to a 3D point using the camera parameters.

435 *Implementation & Interface.* After segmenting the hand from the scene, we use the SoftKinetic iisu API for tracking the hand PCL. However, the tracking method provided in this API does not work with hand-held objects - a feature that we required in order to allow users to utilize physical objects for deformation. Thus, we used a pre-defined a volumetric workspace as the active region in front of the computer screen. Our interface comprises of a 3D scene with a rotating pottery wheel on natural outdoor background (Figure 5(b)). The user sees the potter's wheel and the PCL of their hands, or the tools held in their hands. We designed this interface based on the guidelines provided by Stuerzlinger and Wingrave [30]. Finally, we provided keyboard shortcuts to the allow the participants to undo and redo a particular deformation at any time. Additionally, we also made provisions for the participants to reset the current shape to the blank pot.

451 *Participants.* The participants of this evaluation comprised of  
 452 15 (13 male, 2 female) science and engineering graduate stu-  
 453 dents within the age range of 20 – 27 years. Out of the 15  
 454 participants, 5 participants self-reported familiarity with mid-  
 455 air gestures and full body interactions through games (Kinect,  
 456 Wii). Due to engineering background, most participants (12 of  
 457 15) reported familiarity with 3D modeling and computer-aided  
 458 design. Incidentally, we also had 3 participants who had prior  
 459 experience with physical ceramics and pottery.

460 *Procedure.* The total time taken during the experiment varied  
 461 between 45 and 90 minutes. We began the study with a demo-  
 462 graphic surface where we recorded participants’ background re-  
 463 garding their familiarity with depth cameras, full-body games,  
 464 and pottery. Subsequently, we provided a verbal description  
 465 of the setup, the purpose of the study, and the features of the  
 466 pottery application. This was followed by a practical demon-  
 467 stration of the pottery application by the test administrator. The  
 468 participants were then asked to perform the following tasks:

469 **P Practice:** To get an overall familiarity with the interac-  
 470 tion of their hands with the pot surface, each participant  
 471 was allowed to practice with our interface for a a max-  
 472 imum time of three minutes. The participants were al-  
 473 lowed to ask questions and were provided guidance when  
 474 required.

475 **T1 Quiz:** A pre-defined target shape was displayed on the  
 476 screen and the participant was asked to shape a “blank”  
 477 pot so as to roughly match the most noticeable feature of  
 478 the target shape. We showed a total of eight target shapes  
 479 in a randomized sequence (Figure 6). The participants  
 480 were allowed to undo, redo, and reset the pot at any given  
 481 time and for as many times as they required.

482 **Q1 Questionnaire 1:** Each participant answered a series of  
 483 questions regarding the association of the deformation to  
 484 the shape of the hand, responsiveness of the deformation,  
 485 and consistency of pushing and pulling.

486 **T2 Composition:** The participants were asked to think of  
 487 (and verbally describe) a set of *intended* pot shapes and  
 488 subsequently create those shapes using their hands. Al-  
 489 though the maximum duration of time for each shape was  
 490 fixed to five minutes, we allowed the participants to com-  
 491 plete their last composition that was started before the  
 492 end of the specified duration.

493 **Q2 Questionnaire 2:** Finally, each participant answered a se-  
 494 ries of questions regarding enjoyability, ease of use and  
 495 learning. The participants also commented on what they  
 496 liked and disliked about the application, interface and in-  
 497 teraction.

### 498 5.3. Results

499 The following paragraphs briefly summarize the observa-  
 500 tions that we have detailed in our prior work [11].

501 *Reaching, Grasping, & Deformation Strategies.* Each user had  
 502 a different perception of the process necessary to achieve the  
 503 profile of a given target shape. Most users attempted the quiz

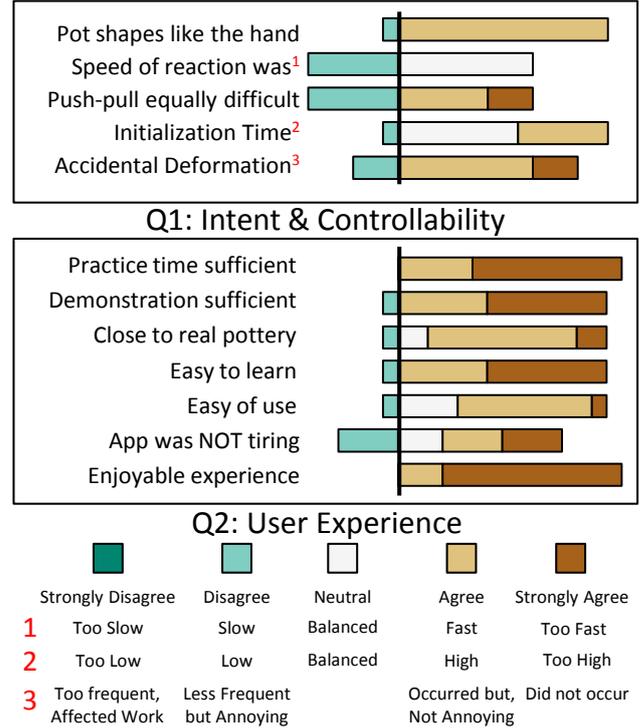


Figure 7: User response to are shown for proximal-attraction. The main issue in terms of controllability (a) was the slow response and difficulty of pushing in comparison to pulling. (from Vinayak et al. [11])

504 problems in multiple trials, wherein they would refine their strat-  
 505 egy to deform the profile in every trial. However, we observed  
 506 that these strategies of reaching, grasping, and deforming the  
 507 profile converged to patterns common across users (Figure 8).  
 508 Typically, users would first estimate the size and shape of the  
 509 grasp according to the geometric feature of the profile and then  
 510 move the whole hand in the intended grasp to deform the pro-  
 511 file [21]. The most common usage pattern observed across  
 512 users was the recursive smoothing and refining of the pot after  
 513 deforming the profile reasonably close to the target shape. This  
 514 was typically done by moving the hand vertically along the sur-  
 515 face of the pot (Figure 8). This was the cause of frustration for  
 516 two reasons. First, the accidental contact of the hand with the  
 517 pot’s surface resulted in unintended deformations. Second, the  
 518 proximal attractions did not allow for an explicit way to smooth  
 519 or straighten a region of the pot. Despite being reminded of the  
 520 undo, redo, and reset functionalities, most users preferred us-  
 521 ing their hands for reversing an accidental deformation. For the  
 522 thin-convex profile, most users first created a convex feature in  
 523 the center followed by pushing the top and bottom portions in-  
 524 ward. For concave features, users first pulled the top and the  
 525 bottom portions of the pot and subsequently pushed the cen-  
 526 tral region of the pot (Figures 9(a)). This was an interesting  
 527 common pattern since we had assumed that users will create  
 528 concave features in a single inward action. This was also the  
 529 case with flat-round features (Figures 9(b)) wherein many users  
 530 first pulled out the round feature followed by straightening the

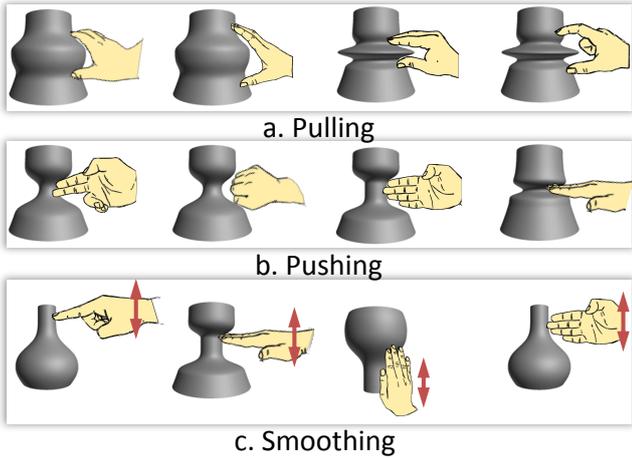


Figure 8: Common user patterns are shown in terms of grasp and motion performed by users for each target shape (in decreasing order of occurrence along columns). The hand images represent the grasp and the arrows (red) show the motion of the hand. The most successful strategies are indicated by blue boxes for each target shape.

531 flat regions of the pot. The *pointing* posture of the hand was  
 532 commonly observed during the creation of thin concave fea-  
 533 tures. However, in subsequent trials, most users resorted to us-  
 534 ing an open palm. This was because the *pointing* pose limited  
 535 the depth to which the users could push the surface inwards,  
 536 owing to the interference of the fingers other than the index  
 537 finger. The cupping of the hands in conjunction with vertical  
 538 movement of the hands was a common approach for round fea-  
 539 tures.

540 The use of two hands was particularly prevalent for round-  
 541 flat combinations. Due to arm fatigue, some users also changed  
 542 from their dominant hand to the non-dominant hand. This was a  
 543 cause for frustration due to the limited volume of the workspace  
 544 and unintended deformations caused by the asynchronous mo-  
 545 tions of two hands. Most users commonly approached the pot  
 546 from the sides. The reason, as stated by a user, was: ”*my own*  
 547 *hand blocks the view of the pot*”. Difficulty in depth percep-  
 548 tion caused many users to inadvertently reach behind the pot’s  
 549 surface. This caused further unintended deformations when the  
 550 user did not expect one, or the lack of response when it was  
 551 expected.

552 *Intent & Controllability.* In general, users agreed that the shape  
 553 of the profile behaved in correspondence to shape of the hands  
 554 (Figure 7(a)). However, only 50% of the users agreed that the  
 555 response speed of the deformation was balanced. There was a  
 556 common agreement on the initialization time and robustness to  
 557 accidental deformation. There were two common and expected  
 558 difficulties that the users faced. These were: (a) pulling specific  
 559 regions of the pot and (b) creating straight and flat features on  
 560 the top portion of the pot. As a user stated: “*Pushing seems*  
 561 *easier than pulling. Part of the reason I suspect is the visual*  
 562 *feedback. It is easier to determine if my hand starts to touch*  
 563 *the pot, while it’s not as easy to determine if my hand is still*  
 564 *attached with the pottery or leaving it.*”. This indicated that

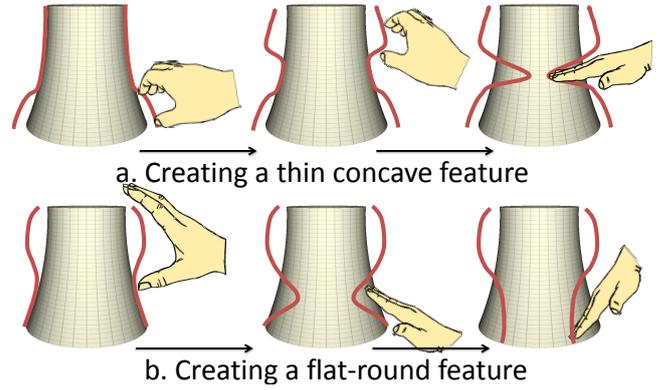


Figure 9: Two examples are shown of common deformation strategies are shown through which users created (a) thin concave and (b) flat-round features. (from Vinayak et al. [11])

565 perceiving the depth difference between the hand and the pot  
 566 was difficult for the users.

#### 567 5.4. Takeaways

568 There were two main issues with the proximal-attraction ap-  
 569 proach. First, pulling was clearly more difficult since the rate  
 570 of attraction was *designed* to be lower than that of pushing.  
 571 Secondly, the users clearly distinguished between several op-  
 572 erations of fairing, straightening, carving, pulling and pushing.  
 573 However, the proximal-attraction approach, was not designed  
 574 to explicitly identify or classify the type of operation the user  
 575 intended to perform. Our main goal in our third and final stage  
 576 was to resolve these two issues. Our first step was to identify  
 577 the main characteristics of users’ preferences towards grasp-  
 578 ing to pull and motion patterns for smoothing the pot. Subse-  
 579 quently, the aim was to design a geometric approach that could  
 580 recognize these identified characteristics and broadly classify  
 581 the intended actions from the hand PCL.

## 582 6. Hand as a PCL: Grasp + Motion

583 Our observations strongly indicated that users distinguished  
 584 their intent in three broad categories: pulling, pushing, and  
 585 smoothing. In our final stage, we implemented a grasp and mo-  
 586 tion based approach to identify these three classes of intent.

### 587 6.1. Technique

The basic idea of the *grasp+motion* approach is to *summa-*  
*riize* the grasp of the hand *in relation* to the surface of the pot and  
 subsequently classify the user’s action (Figure 10). We achieve  
 this by using kernel-density estimation of the point cloud on  
 the axis of the pot. In our context, this kernel-density estimate  
 (KDE) is essentially a smoothed histogram of the distribution  
 of the hand’s PCL on the pot’s. We use the exponential func-  
 tion to determine the KDE. For a given section  $i$ , the KDE is  
 given by:

$$\phi_{i,j} = \sum_{j=1}^{j=|H|} e^{-\alpha \|\delta_{i,j}^2\|} \quad (1)$$

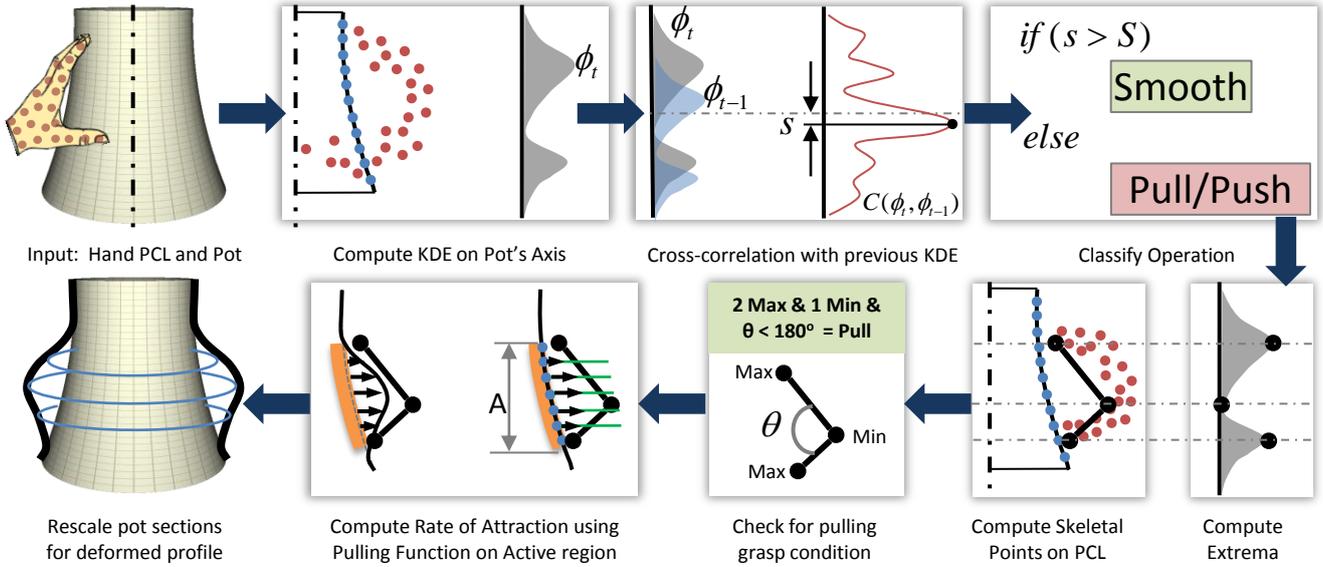


Figure 10: Algorithm for grasp+motion technique is illustrated. The main steps involve computation of axial KDE for hand PCL, detection of intent for smoothing, differentiation between pulling and pushing, and deformation of the pot. In this example, we show the details of the pulling deformation (row 2).

588 There were three main observations (Figure 8) that helped  
 589 us use the KDE to classify the user's intent. First, users moved  
 590 their hands in a fixed pose along the surface of the pot to express  
 591 their intent for smoothing. This corresponds to detecting  
 592 the vertical shift of the KDE. We used normalized cross-  
 593 correlation [31] between the two consecutive KDE signals to  
 594 determine the shift. Secondly, for pulling the pot, we observed  
 595 that users used specific grasps. In this case, we note that the  
 596 KDE has two maxima and one minima (Figure 11). Here, each  
 597 maxima corresponds to the fingers making contact with the pot  
 598 and the minima corresponds to the center of the grasp. This  
 599 essentially allows us to track a basic skeletal representation  
 600 of the hand. We then define the attraction rate using a based on  
 601 the angle of grasp ( $\phi$ ) (Figure 12). Finally, all actions that do  
 602 not correspond to either smoothing or pulling, are assigned as  
 603 pushing. For pushing, we use the proximal-attraction approach  
 604 for deformation. The steps of the algorithm are:

- 605 1. Compute the KDE  $\phi_t$  at time  $t$
- 606 2. Compute normalized cross-correlation  $C(\phi_t, \phi_{t-1})$
- 607 3. Compute Active region  $A$
- 608 4. Set  $s$  to the shift of correlation
- 609 5. if ( $s < S$ ): Smooth pot profile in  $A$
- 610 6. else:
  - 611 Compute extrema
  - 612 Detect skeleton
  - 613 Compute  $\theta$
  - 614 if ( $\#maxima = 2$  &  $\theta < 2\pi$ ): Apply pulling in  $A$
  - 615 else: Apply proximal-attraction in  $A$

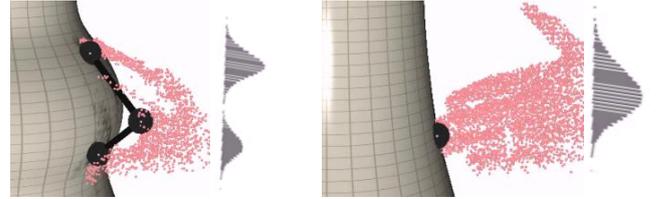


Figure 11: KDE functions are shown for a pulling (left) and pushing (right) intents.

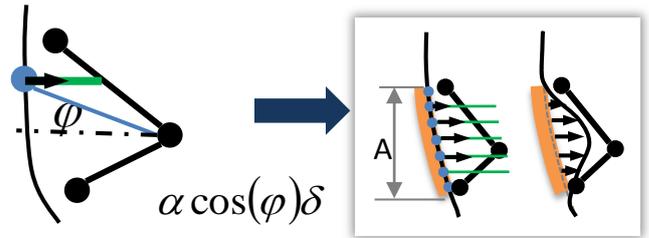


Figure 12: Computation of attraction rate using the angle of grasp.

- 616 7. Smooth deformation ( $\nabla^2 \delta = 0$  for all points in  $A$ )
- 617 8. Compute deformed profile
- 618 9. Rescale pot sections

## 619 6.2. Experiment

620 We used identical apparatus and interface to evaluate our  
 621 final stage. Additionally, we made two important modifications  
 622 to the interface. First, we added a shadow of the hand on the  
 623 surface of the pot. The goal was to enable users to estimate their

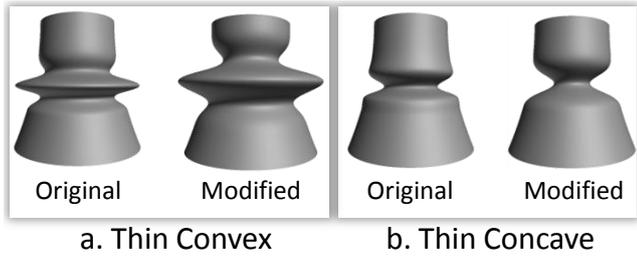


Figure 13: The thin convex and concave features were modified according to the capability provided by the *grasp+motion* technique.

624 proximity to the surface. Secondly, we clamped the hand PCL  
 625 so as not to allow points on the hand to reach behind the surface  
 626 of the pot.

627 *Participants.* We recruited 15 (11 male, 4 female) participants  
 628 within the age range of 19 – 30 years. None of these partici-  
 629 pants had prior knowledge of mid-air interactions or had partici-  
 630 pated in any of our previous studies with pottery interface.  
 631 All participants were from science and engineering background  
 632 wherein 10 participants had familiarity with mid-air gestures  
 633 and full body interactions, and 11 participants reported familiari-  
 634 ty with 3D modeling and computer-aided design. 5 participants  
 635 reported that they had practical familiarity with real ceramics  
 636 via informal workshop sessions but did not pursue pottery as a  
 637 regular activity or professional practice.

638 *Procedure.* Our overall experimental procedure was identical  
 639 to the one that we used for evaluating the proximal-attraction  
 640 approach (Section 5.2, *Procedure*). However, we made three  
 641 modifications to the evaluation procedure as listed below:

- 642 1. One of the main goals of our work was to enable users to  
 643 invoke their tacit knowledge of deforming physical objects. To this end, we designed the *grasp+motion*  
 644 approach such that it is geometrically-driven and can potentially be used even for user inputs that used other physical  
 645 objects as tools in addition to the use of hands. In order to verify the generality of our approach with respect to user input,  
 646 we added another composition task (**T3**) wherein participants were given a duration of five minutes to create pots using a set of physical artifacts as  
 647 tools. Our “tools” comprised of day-to-day objects (e.g. white-board marker, pair of scissors, ruler) and also some special objects such as Shapescapes<sup>TM2</sup>.  
 648
- 649 2. In order to understand user experience with physical objects tools, we also added questions to the questionnaire  
 650 **Q2** regarding the utility, ease of use, and preference of tools over hands.  
 651
- 652 3. We modified the target shapes for the thin convex and concave features (Figure 13). The rationale behind this  
 653  
 654  
 655  
 656  
 657  
 658  
 659  
 660

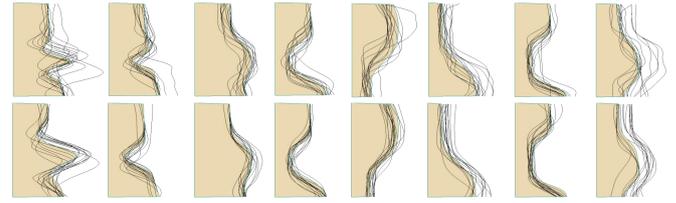


Figure 14: User created pot profiles (black curves) are shown relative to the target shapes (light brown cross sections). The top and bottom rows shows the results for proximal-attraction and *grasp+motion* approaches respectively. Visual inspection evidently shows improvements in the creation of flat, round and smooth features. More significant improvements were observed in the creation of fat convex features in comparison to proximal-attraction.

661 modification was that the *graph+motion* technique is sen-  
 662 sitive to the size of the hands, finger thickness. Thus, the  
 663 detection of single-point pulling intent is not possible, as  
 664 in the case of proximal-attraction.

665 For each participant and task (**T1**, **T2**, and **T3**), we recorded  
 666 the completion time and the profiles of the pots shaped by the  
 667 users. Even though we designed **T1** towards statistical analysis,  
 668 we observed that each user perceived the target shapes differ-  
 669 ently and consequently the measured data did not provide suf-  
 670 ficient insights regarding the strengths and weaknesses of our  
 671 approach. With this in view, we present a visual comparison of  
 672 the numerical data recorded during the evaluation of proximal-  
 673 attraction and *grasp+motion* techniques.

### 674 6.3. Results

675 *User Performance (T1).* Visual similarity with respect to the  
 676 target shapes evidently increased in comparison to the proximal-  
 677 attraction approach (Figure 14). This was primarily due to the  
 678 explicit smoothing. Overall, the completion time (Figure 15(a))  
 679 was reduced as expected. Surprisingly, the maximum comple-  
 680 tion time across all users and all target shapes was recorded for  
 681 the thin-concave feature (14.4 minutes) followed by the thin-  
 682 convex feature (13.2 minutes). The mean completion time was  
 683 highest for the thin-convex feature (3.4 minutes) followed by  
 684 the central-flat feature (3.3 minutes). The main aspect that we  
 685 sought from **T1** was the quality of the final outcome across par-  
 686 ticipants for a given quiz problem. We used curvature cross-  
 687 correlation (*CCC*) as a measure of the quality of user created  
 688 profiles (see [11] for details). As expected, the smoothness of  
 689 the results was notably superior in comparison to the proximal-  
 690 attraction (Figure 15(b)). We also recorded the number of tri-  
 691 als per user per target shape (Figure 15(c)). The global maxi-  
 692 mum number of trials were 7 and 5 for proximal-attraction and  
 693 *grasp+motion* techniques respectively. In case of *grasp+motion*,  
 694 most users required only one trial for fat-convex, central-flat,  
 695 and top-bottom-flat features. On the other hand, thin-concave  
 696 and thin-convex features required more iterations.

697 Each user perceived and approached a given target shape in  
 698 different ways. Consequently, there was no evident correlation  
 699 between the time taken by each user and the quality (*CCC*) of  
 700 the final pot created by the user for any of the target shape. To

<sup>2</sup>www.shapescapes.com

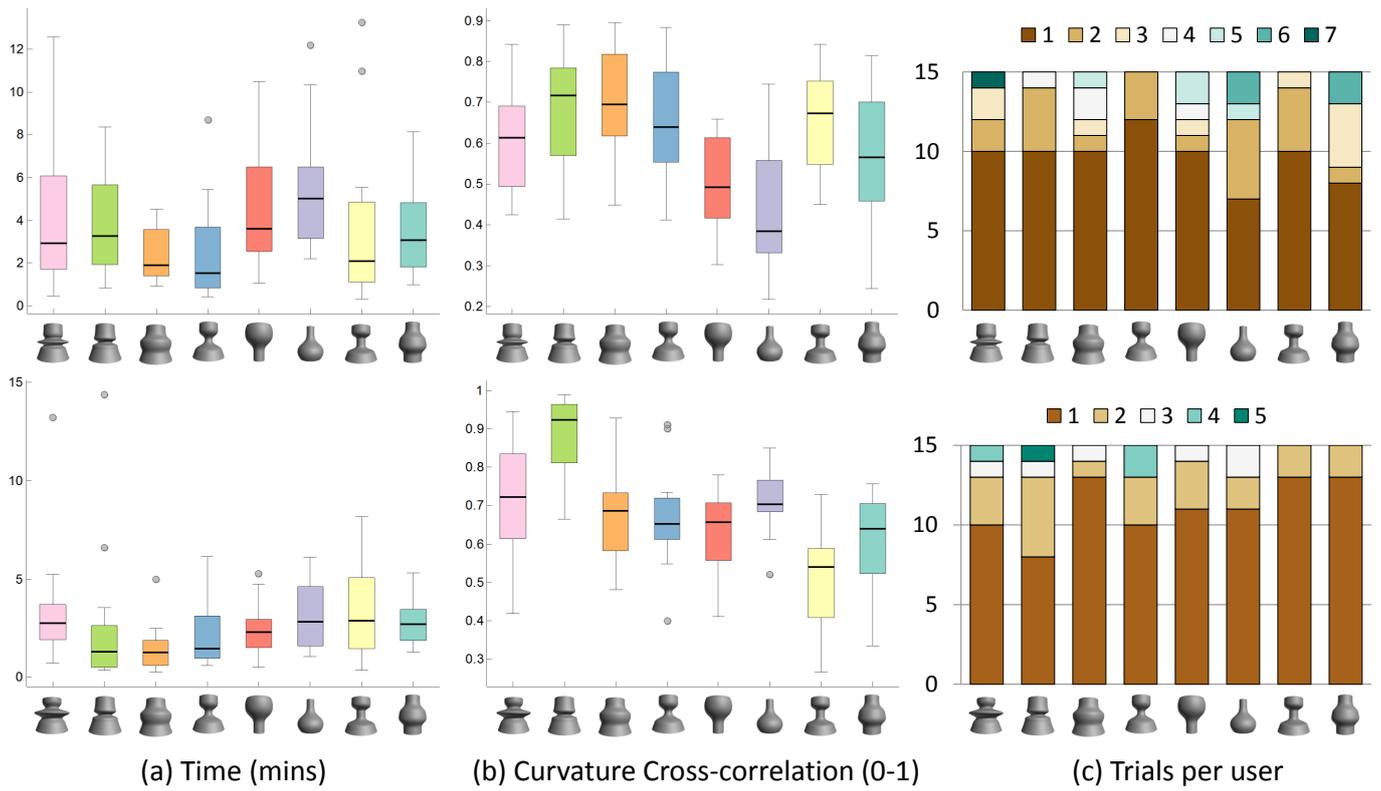


Figure 15: A comparison between proximal-attraction (top row) and grasp-motion (bottom row) is shown in terms of (a) the time taken by users to shape a target profile, (b) the quality of users' responses in terms of curvature cross-correlation of profiles, and (c) the distribution of users with respect to the number of trials per target profile.

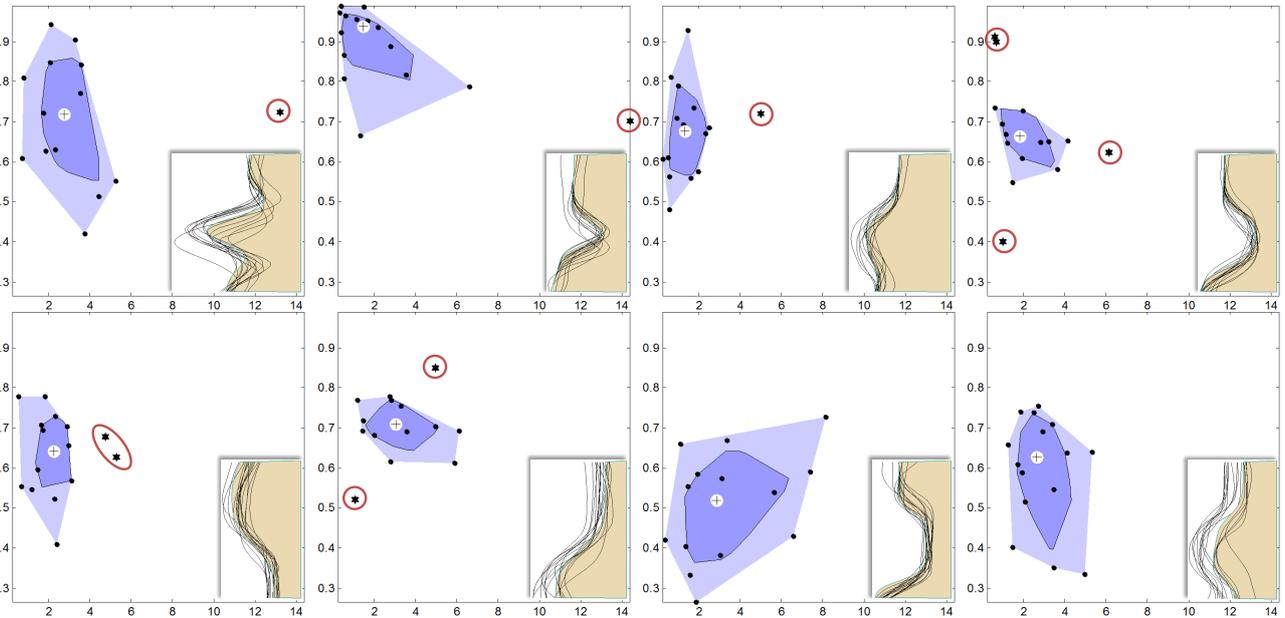


Figure 16: User performance is shown for the each quiz problem as a bag-plot. The x-axis is time in the range [0, 14] minutes and the y-axis is the curvature cross-correlation in the range [0, 1]. The dark and light blue regions show the bag and fence regions, respectively. The white circle is the Tukey depth median and the points marked with red circles are the outliers. The insets show the actual pot profiles (black lines) created by the users in comparison to the target shapes (beige region) of the Quiz. The coordinates of the depth median (C) and the spread (Sp) are provided for each target shape.

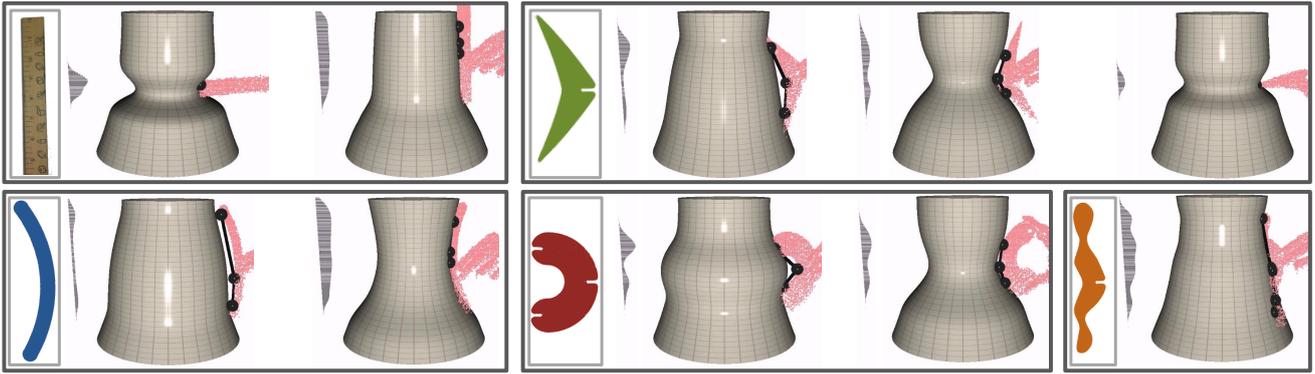


Figure 17: The characterization of tool geometry is visualized for five different physical objects. The objects were chosen to represent concave, convex, flat, and round contacts for deformation.

701 account for this, we represent the user performance as a bivari-  
 702 ate dataset given by the ordered pair of the response quality and  
 703 completion time. We visualize performance as a bag-plot [32]  
 704 (Figure 16). Here, the spread of the data (i.e. variations in user  
 705 responses) is given by the area of the *bag*. Users clearly per-  
 706 formed best for thin-concave targets with Tukey median value  
 707 of (0.94, 1.46). Performance was most consistent for the fat-  
 708 concave feature (Figure 16(d)). Users also performed consis-  
 709 tently for round-and-flat features (Figures 16(e) and (f)). Vari-  
 710 ations were significant for central flat feature (Figure 16(g)).  
 711 Further, the pot-profile quality was very low for the central-flat  
 712 and top-bottom-flat features (Figures 16(g) and (h)). This was  
 713 mainly because users typically spent considerable time pulling  
 714 and smoothing the top and bottom regions after performing an  
 715 initial push. Consequently, the median completion times were  
 716 also higher for the round-flat and central-flat features (Figure  
 717 16(f) and (g) respectively).

718 *Hand Usage (T1)*. The general user behavior in terms of reach-  
 719 ing the pot was similar to the proximal-attraction approach.  
 720 Both the algorithm and its description was different in this case.  
 721 The users were explicitly made aware of pushing, pulling and  
 722 smoothing as three distinct operations. This obviously led to  
 723 variation in user behavior as compared to proximal-attraction.

724 *Hand Usage (T2)*. On average, users created 5 pots (max: 12,  
 725 min: 2) within 5.80 minutes (std: 0.66 min). We made two in-  
 726 teresting observations in **T2**. First, we found that users were  
 727 able to repeat the process of getting from an initial shape to  
 728 the same final shape across multiple trials. Similarly the users  
 729 could also deform a current shape back to some previous shape,  
 730 akin to the *undo* operation, but with the hands. In fact, most par-  
 731 ticipants preferred using their hands to *undo* a pot deformation  
 732 instead of the keyboard-shortcut. One user stated: “*I thought it*  
 733 *was easier to learn the software when I was trying to make my*  
 734 *own pot not a model one*”. This was expected because of the  
 735 learning and practice that the users had during the quiz (**T1**).  
 736 However, during **T1**, users mentioned that their attention was  
 737 divided due to the need to intermittently look at the target shape  
 738 during the shaping process. Thus, they generally perceived **T1**  
 739 to be more demanding than **T2**.

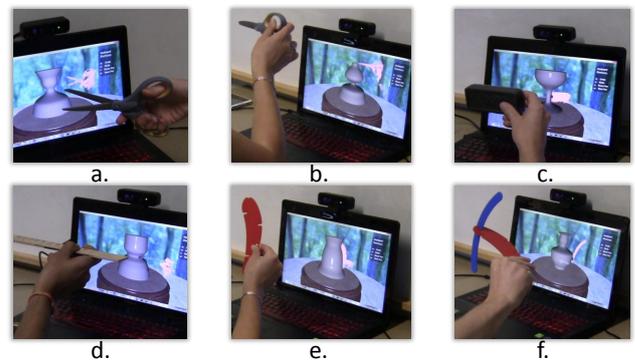


Figure 18: Examples of tool usage are shown.

740 We made two observations that were not evident in the ear-  
 741 lier stages. First, we found that the ability to repeat the process  
 742 of getting from an initial shape to the same final shape. Simi-  
 743 larly, the ability to get to some previous state from the current  
 744 state was increased substantially. We observed that most of the  
 745 participants were successfully able to use their hands to *undo* a  
 746 pot deformation instead of the keyboard-shortcut.

747 *Geometric Characterization of Tools*. The choice of everyday  
 748 objects and ShapeScapes<sup>TM</sup> was mainly helpful in providing a  
 749 reasonable variety of geometric profiles for pot deformation.  
 750 However, in order to better understand how users would use  
 751 these objects, we wanted to pre-determine how the intent of  
 752 pulling and pushing translates to the use of physical objects.  
 753 Thus, we conducted a set of experiments (Figure 17) to ver-  
 754 ify if the users could in fact extend their understanding of the  
 755 grasp+motion approach and apply it to the use of physical tools.  
 756 Our experiments showed that the geometry of the tool can in-  
 757 deed be interpreted in terms of the nature of the KDE of the  
 758 tool’s PCL and the grasping angle of the skeleton computed  
 759 from the KDE. Below, we summarize how this observation came  
 760 into play during the usage of tools by our participants.

761 *Tool Usage (T3)*. Users showed immediate enthusiasm during  
 762 the use of tools. Almost all users first inspected the objects

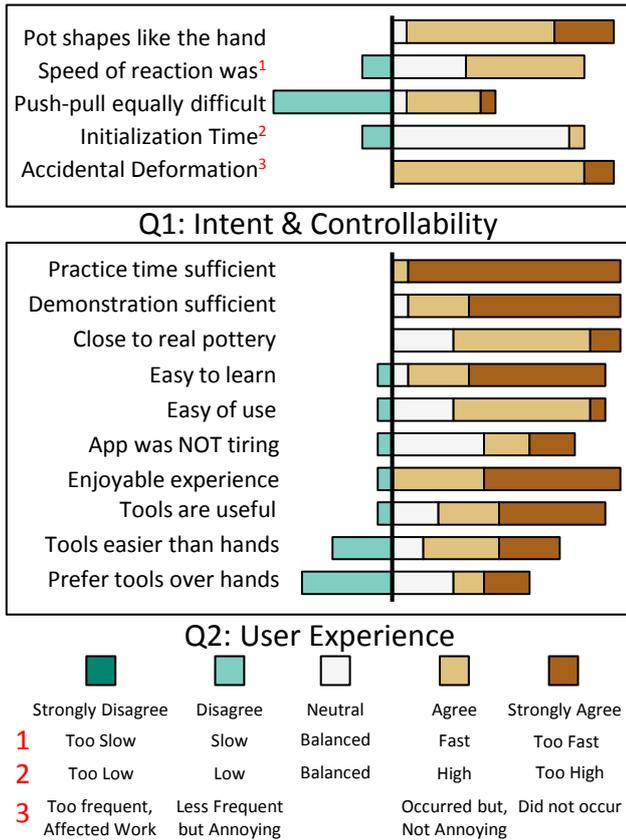


Figure 19: User response to are shown for grasp+motion. While the robustness to accidental deformations was perceived to be negligible (a), many users still perceived pulling to be difficult. Users agreed regarding the usefulness of tools but were not in general agreement about preferring them over hands.

763 provided to them and planned how to use them for shaping the  
 764 pots. Users created 4 pots on average (max: 8, min: 2) within  
 765 6.0 minutes (std: 0.8 min). In contrast to the use of hands,  
 766 we observed exploratory behavior in users while using tools.  
 767 Rather than creating pots, most users were more interested in  
 768 finding out the effect of each of the objects provided to them.  
 769 This explained the decrease in the average number of pots in  
 770 the composition task. One of the difficulties with the use of  
 771 hands was the inability to create thin concavities. With the use  
 772 of tools (Figure 18(a),(d)), users could achieve this easily. The  
 773 most interesting behavior that was observed was the tendency to  
 774 create convex deformations, which the users achieved by combin-  
 775 ing two different objects, so as to simulate a grasping hand.  
 776 This was evident from the users’ fascination with scissors (Fig-  
 777 ure 18(b)). Another important observation was the direct associa-  
 778 tion the users made between the shape of the tool and the  
 779 purpose it could be used for. The motion of the hand was af-  
 780 fected by this association. For instance, while using a white-  
 781 board eraser (Figure 18(c)), the most common motion was that  
 782 of smoothing the pot. Similarly, for objects with grasp-like ge-  
 783 ometries, users invariably tried convex deformations by pulling  
 784 (Figure 18(e)). One user fashioned a new tool by combining  
 785 different Shapescapes™ parts. This provided the convenience  
 786 of holding the tool at the “handle” and deforming the pot using

787 fine hand movements (Figure 18(f)).

788 *Intent & Controllability (Q1).* We see evident improvements in  
 789 the perception of intent recognition quality, initialization time,  
 790 and robustness to accidental deformations (Figure 19). How-  
 791 ever, despite the decrease in completion time (task T1) there  
 792 was no significant improvement in the user’s perception of in-  
 793 consistency between pulling and pushing. In this case, reason  
 794 for this perception was primarily related to the visual and tactile  
 795 feedback rather than the algorithm for pulling itself. This was  
 796 evident from the user’s comments such as: “I think the reason  
 797 pushing and pulling were different were because the pulling you  
 798 had to 2 contacts with the pot and pushing you only needed one.  
 799 I had a hard time understanding the depth of the pot making it  
 800 hard to get two contacts on the pot”. One user also suggested:  
 801 “I think it would be better if I get some feeling when I touch the  
 802 pottery. It [would] make me feel more real and easier to control  
 803 my hand. Then it would be better to have some sounds when I  
 804 touch the pottery”.

805 *User Experience (Q2).* The experience was mostly positive,  
 806 similar to the proximal-attraction approach (Figure 19(b)). In  
 807 particular, users liked the use of tools and the smoothing opera-  
 808 tion the most. One user commented: “The freeform design with  
 809 tools was the most fun, as I could spend most of my time focus-  
 810 ing on the design aspect as opposed to focusing on minimizing  
 811 errors.”. According to another user: “The pottery changing ac-  
 812 cording to my hand shape is so real. While smoothing, I could  
 813 shape it as well, I like to do it this way a little bit.”.

#### 814 6.4. Limitations

815 Our method is currently implemented for pottery, which is  
 816 essentially a one dimensional deformation. Further, we ob-  
 817 served that the use of 2D displays is a factor due to which users  
 818 tend to use side configurations. We believe that 3D visual feed-  
 819 back will encourage users to access the front and back faces.  
 820 One user noted: “This application with haptic feedback could  
 821 train people for pottery before they actually perform it”. This  
 822 strongly indicates that the lack of tactile feedback is a critical  
 823 component that is missing from our current system.

824 Severe occlusion resulting from camera position and hand  
 825 orientation is an issue particularly for skeletal based gesture  
 826 recognition. We partly addressed this challenge using our PCL-  
 827 based approach which can make use of partial data even when  
 828 the full hand skeleton is intractable. However, occlusion is an  
 829 inherent problem in any camera-based method. Investigation of  
 830 optimal camera position and use of multiple cameras at strate-  
 831 gic locations is important. Secondly, we provided a method for  
 832 temporally adaptive persistence.

833 In our current implementation, the definition of active re-  
 834 gions is in terms of 2D profile topology rather than actual dis-  
 835 tances in real space. Thus, our implementation is dependent on  
 836 PCL sampling relative to the mesh resolution of the pot. Inde-  
 837 pendence from the sampling resolution may be addressed with  
 838 an adaptive approach wherein new sections could be added ac-  
 839 cording to manipulators or old ones removed based on geomet-  
 840 ric properties of the pot profile such as curvature.

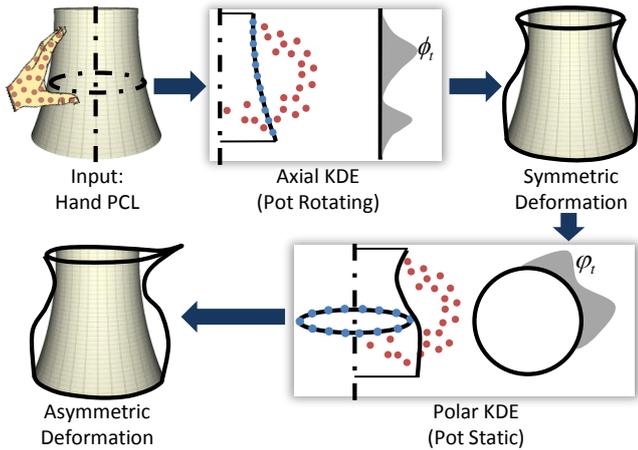


Figure 20: Asymmetric deformation can be applied to a pot in two steps. When the pot is rotating, we apply the *axial* KDE (top row) of the hand PCL for deforming the profile of the pot. Subsequently, users can stop rotating the pot and deform the pot locally using the *polar* KDE (bottom row).

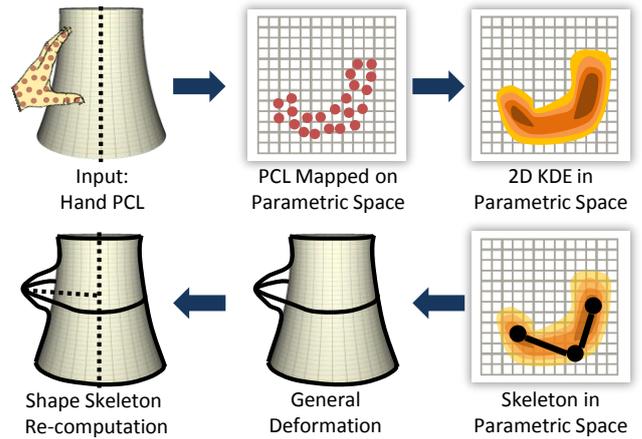


Figure 21: The computation of two-dimensional KDE in the parametric space of a cylindrical surface leads to the computation of grasp and motion for an arbitrary orientation of the hand PCL with respect to the surface. This allows for arbitrary deformation of the surface. Recomputing and segmenting the deformed surface using the method of Bærentzen et al. [33] provides a generalized deformation approach using our KDE based approach.

841 In terms of our evaluation approach, our participants were  
 842 primarily from science and engineering background. Even though  
 843 some users had prior experience with creative tasks such as pot-  
 844 tery and computer-aided design, studying our approach with art  
 845 students would provide additional insights on user experience  
 846 and utility of our approach.

## 847 7. Discussion

### 848 7.1. Spectrum of Expressiveness:

849 One aspect that is both advantageous and disadvantageous  
 850 in our approach is that different users can achieve the same  
 851 target shape using different strategies for grasping, reaching,  
 852 and deforming a shape. While this provides flexibility and in-  
 853 tuitiveness to the user, it also results in increasing the time  
 854 taken by the user to reach to a desired shape. The evalua-  
 855 tion of proximal-attraction evidently indicated that there needs  
 856 to be a balance between completely free-form interaction and  
 857 symbolic approaches. This is what we attempted through the  
 858 grasp+motion approach. The main advantage that our process  
 859 provided was the discovery of relevant grasp information that  
 860 is useful to design continuous operations such as shape de-  
 861 formation. Our grasp based approach can serve as a starting point  
 862 for designing grasp-based interactions using cleaner data such  
 863 as hand-skeleton [10].

### 864 7.2. Definition of Intent:

865 We began with a simple classification of intent through the  
 866 analogy of structuring operators inspired by Delamé’s [28] work.  
 867 However, users’ description of actions and expectation strongly  
 868 indicates towards a richer and more complex mental model for  
 869 deformation processes. To this effect, we had to include a third  
 870 class of operation, namely “smoothing” which evidently im-  
 871 proved the performance of the user. Though this aspect is not  
 872 new in 3D modeling in general, this aspect of refinement is cer-  
 873 tainly worth investigating from a perceptual point of view.

### 874 7.3. Generalization:

875 Although we demonstrated intent classification for rotation-  
 876 ally symmetric shapes, the general approach of computing KDE  
 877 to characterize grasp and motion can be extended to the de-  
 878 formation of arbitrary shapes. Here, we propose such an extension  
 879 in two steps. First, we will consider asymmetric deformation  
 880 in the context of pottery itself. For this, we begin by noting  
 881 that our approach summarizes the hand grasp and motion by  
 882 computing a one-dimensional *axial* KDE of the hand PCL on  
 883 the pot’s surface. In the same way, we can also compute the  
 884 one-dimensional *polar* KDE of the PCL (Figure 20). Thus, by  
 885 combining two one-dimensional KDE computations (axial and  
 886 polar), we can enable users to create asymmetric features on the  
 887 pots.

888 To see how these ideas can be used to conceptualize an arbi-  
 889 trary deformation of a shape, we make two observations. First,  
 890 the pot is a cylindrical shape with a simple parametric repre-  
 891 sentation and the axis of the cylinder is essentially its skeleton.  
 892 Thus, given the hand’s PCL in an arbitrary orientation with re-  
 893 spect to the cylinder’s surface, its two-dimensional KDE can be  
 894 computed in the parametric space as a simple means to deter-  
 895 mine the grasp and motion of the hand (Figure 21). The con-  
 896 sequent deformation of the cylinder would inevitably result in  
 897 the need for re-computing the skeletal structure of the surface.  
 898 This is where we invoke our second observation that an arbi-  
 899 trary 3D surface model can be converted to a set of connected  
 900 cylinders using the recent work by Bærentzen et al. [33] that  
 901 demonstrates the conversion of arbitrary triangle meshes into  
 902 polar-annular meshes (PAM). The PAM representation effec-  
 903 tively segments 3D shapes into generalized cylinders. Thus,  
 904 the combination of two-dimensional KDE with the PAM repre-  
 905 sentation can be used for deforming arbitrary meshes.

#### 906 7.4. Precise & Selective Reachability:

907 One user aptly commented: “Sometimes it is hard to use the  
908 palm because it may deform the surface too much. The context  
909 of barely touching does not seem too well implemented. How-  
910 ever, if you do this very carefully you can do the barely touching  
911 but may make your arm tired a little.”. This is the problem of  
912 precise and selective reachability wherein one is required to  
913 reach and manipulate a local region of an object without affect-  
914 ing neighboring regions. There is extensive volume of work  
915 that investigates *distal* selection, manipulation, and navigation  
916 [34, 35, 36] of objects. We believe that precision and selectivity  
917 are problems worth investigating for close-range, i.e. *proximal*  
918 3D manipulations in mid-air.

#### 919 8. Future Directions & Conclusions

920 Our first goal is to extend the grasp+motion approach for  
921 arbitrary meshes. This would involve several computational  
922 challenges since distance computations and KDE computation  
923 would be on 2-manifolds. Secondly, we intend to study how  
924 user perception and performance is affected by adding 3D visual  
925 feedback and also tactile feedback. Finally, with our approach,  
926 it is not possible to perform deformation using existing hand  
927 skeleton tracking approaches. We intend to investigate this in  
928 comparison to the PCL based hand representation. One key ad-  
929 vantage of using tracked skeletons is that there is a direct corre-  
930 spondence between the fingers and palm which can give useful  
931 movement information for better intent detection. This would  
932 help segmenting users intentional and unintentional movements  
933 [37]. One of the main observations in our preliminary explo-  
934 ration was that users from different backgrounds and age group  
935 had different ways of using the pottery tool. In our future works,  
936 we want to understand how experience, performance, and cre-  
937 ative outcomes will change with respect different user groups  
938 such as artists, engineering designers, and young participants.

939 We presented a spatial interaction technique that uses hand  
940 grasp and motion for intent expression in virtual pottery. This  
941 approach enables a paradigm shift from existing gesture-based  
942 procedural events towards non-procedural and temporally con-  
943 tinuous processes in the context of shape deformation. In other  
944 words, our work enables users to achieve what they intend in  
945 the way they see fit. To the best of our knowledge, no existing  
946 hand-based spatial modeling scheme offers such diverse con-  
947 texts of user input, for instance the use of everyday real objects  
948 as tools for virtual shaping, with controllable outcomes. The  
949 idea creates new pathways for further research exploring cre-  
950 ative design contexts in a “what you do is what you get” frame-  
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