Dynamic Aspects of Making and Personal Style

A Case Study in a Clay Relief Technique

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Abstract

Personal style in creative processes has been the topic of studies and discussions in different fields of the humanities, as well as the social and natural sciences, all aiming to understand the unique qualities of makers and their products. Nevertheless, due to technological restraints, the literature lacks satisfactory quantitative information regarding the correlation between artistic style and skill. In this work, we contribute a quantitative method to investigate the relationship between motor skills and personal and dynamic (time-variant) style in artistic tasks. We used a magnetic motion tracking system to track the 6DOF location of a carving knife in a clay-relief technique, then processed and analyzed the recorded data using digital-signal processing and machine learning tools.

The results demonstrate that such analysis allows us to observe both traditional and emerging aspects of artistic style. Based on our observations, we hypothesize that there is a time-variant dependency between personal style and motor skills in creative tasks, and foresee a future study on the development of users personal style as they develop their creative skills over time. We outline such study in the last section.

The structure of the document is as follows: first we bring a survey about style, both from the perspectives of humanities (specifically anthropology, archaeology, and art history) and of computer science. We then detail our algorithmic framework: two experiments with the clay-relief technique, including an analysis of the records of these studies; the domain-specific conclusions generated from these investigations; and the general implications for the study of dynamic style. Finally, we raise new directions for the computational study of dynamic style, outlining open questions regarding the introduction and integration of time in understanding creative style.

Acknowledgement

I would like to thank my family, for all of the support during my master degree, and to Dr. Amit Zoran for the patience and guiding throughout the process.

We deeply thank Dina Kahana-Gueller for the help in the early stages of the process, and for taking part in the second experiment.

In addition, we would like to thank to:

- Maya Dotan, Zuzana Gavorova, Naama Glauber, and Adi Yehezkeli, for participating in the first experiment.
- Past and current members of the Hybrid Lab, for all of the support during the process.
- Koral Goltseker (Tel-Aviv Uni.), for the helpful scientific comments during the later stages of this thesis.
- Chia Evers, for putting so much effort in editing this thesis.

Contents

1 Introduction

As personal qualities of stylistic performance leave a signature on the subject of manipulation, artists[1] create artifacts and visual experiences that display their makers' signature. Moreover, the acts of creation themselves generate complex and unique behavioral[5], cognitive [25, 45], and motoric [15, 46] interactions. Such stylistic signatures have been the topic of studies and discussions in different fields of the humanities, as well as the social and natural sciences, all aiming to understand the unique qualities of artists and their products. For example, scholars have studied the signatures of artists as shown in their complete works [16, 36]; how psychological and social conditions impact the development of their art [11, 21]; and how style and culture interweave [23]. Nevertheless, due to technological restraints, the literature lacks satisfactory quantitative information regarding the correlation between artistic style and skill.

New technologies now enable us to further investigate the connections between such aspects of an artist's work [10, 13, 40, 41, 46], and more specifically, between artistic style and the maker's skill [13, 46]. For example, digital tracking technologies enable us to detect, monitor and classify dynamic characteristics of artists' ways of working: the real-time qualities of the techniques artists use; the mathematical characteristics of the set of an artist's techniques; what physical features identify these techniques; and the statistical relationship between them [46].

In this work, we contribute a quantitative method to investigate the relationship between skill and personal and dynamic (time-variant) style in artistic tasks, allowing us to reveal qualities of personal style that traditionally were neither observed nor measured. We used a magnetic motion tracking system (MMTS) to track (in 60-120Hz) the 6DOF location of a carving knife in a clay-relief technique, then processed and analyzed the recorded data using digital-signal processing (DSP) and machine learning (ML) tools.

We conducted two user studies in a computer-tracked sculptor work: (i) in the first experiment we tracked and analyzed the work of five novice participants, each performing three simple tasks; (ii) in the second experiment we tracked four complex works created by a professional sculptor. The quantitative analysis of the data connected between the participants' motor-skills and a set of techniques based on unsupervised ML algorithms. We observe that novice participants have a distinct personal motor style; that over time participants' styles may diverge from each other; and that the working style of a single master artist varies depending on the model of the product (i.e., the mental model, which may call for extended future research).

The results demonstrate that such analysis allows us to observe both traditional and emerging aspects of artistic style. Based on our observations, we hypothesize that there is a time-variant dependency between personal style and motor skills in tasks such as sketching with a pen, drawing with a brush, and carving with a chisel. To validate this assumption, we foresee a future study on the development of users' personal style as they develop their creative skills over time. In the current work, we conclude that there is a need for a unified theory of artistic style to outline an investigation mapping the relationship between artistic style, an artist's manual techniques, and her or his making skill. As we will see, artistic style is a multi-aspect and *time-dependent* entity. We thus define *dynamic style* and outline fundamental research questions to structure the theoretical foundation of research in the field, and propose future studies and experiments to help in composing

[1]For simplicity, we refer to visual fine art or craft as art, while a practitioner in one of these fields is an artist, thus excluding music, dance, and other performative art forms

such a theory of dynamic style.

The rest of this document is as follows: the next section contains a survey about style, both from the perspectives of humanities (specifically anthropology, archeology, and art history) and of computer science. We then detail our algorithmic framework: two experiments with the clay-relief technique, including an analysis of the records of these studies; the domain-specific conclusions generated from these investigations; and the general implications for the study of dynamic style. Finally, we raise new directions for the computational study of dynamic style, outlining open questions regarding the introduction and integration of time in understanding creative style.

2 Style: Background and Definitions

Style describes a manner of doing something [42]. The research of artistic style is a multidisciplinary area that involves fields such as cognitive and behavioral sciences, sociology, anthropology and philosophy. On the whole, artistic style can be perceived as a subcategory of personal behavior: the way a person performs in the physical space, interacts with the environment, makes decisions, etc. Thus, a full survey exceeds the scope of this work, and a complete investigation of the matter may be overly ambitious.

In the context of our research, we wish to highlight attitudes that connect style to the behavioral basis of making art, seeing the mechanisms, causality, complexity, and other characteristics of style that can contribute to a theoretical (quantitative) framework.

During the second half of the 20th century, anthropologists, archaeologists and art historians engaged in a significant theoretical discussion concerning style. For scholars in these fields, style is both a pure subject of interest, and a tool for investigating societies, individuals or art. In all of these fields, the way scholars regarded style changed as the 20th century progressed. Anthropologists and archaeologists moved toward an active way of considering style, asking what social and cultural sources of aesthetics appear consistently. Art historians also suggested that style connects to broader structures, although during the 1970s, researchers doubted the importance of style as a tool in this field. Yet, none of these investigations executed technical experiments exploring how one develops a personal style, how this style evolves over time, and what the time-variant qualities of style (and manual skills) are, thus limiting the scope of the discussion to style as represented in the artistic product.

In the next section, we consider definitions of and attitudes towards style from several different fields. Then we discuss the presence of style in the digital world, which varies from well-defined algorithms and methods for stylization of images, to research on creativity and self-expression using digital tools. We specifically focus on HCI, computer graphics, and image processing. We suggest that increasing the connection between style and making in these fields may contribute to and deepen both, leading to our definition of *dynamic style*, and the fundamental open questions that structure the theoretical foundation of research regarding dynamic style. We end the section by proposing technical studies to help in composing a theory of dynamic style. First, to gain a better perspective on prior work, we turn to a discussion of style as studied in fields of material culture.

2.1 Style in anthropology and archaeology

Social and personal style differ, but they are linked to each other, and the connection between the two is complex. Some anthropologists and ethno-archaeologists focus on the social aspect of style, while others explore personal style and use it as a foundation for the correlation between culture and material culture. We begin with cultural aspects of style as they appear in anthropology, and specifically on the ideas of Franz Boas and Mayer Schapiro. Then we describe different definitions of style that focus on the individual, such as the works of Polly Wiessner. Finally we discuss the impact of cultural style on the individual maker.

Going back to the early days of modern anthropology, Franz Boas[2] defined style as the consistent and formal elements of aesthetics that appear in culture [34]. He studied culture empirically,

[2] Germany 1858–USA 1942

depicted visual elements in detail, and used them while analyzing the nature and role of making in culture. Boas's attitude to the research of cultures can be characterized as seeking empiricism and a historical point of view [12, 19] , with less attention on the individual. Boas was aware of the importance of the individual maker, and argued that *knowledge of the attitude and actions of the artists will contribute to a clearer understanding of the history of art styles*, yet he concluded that such empirical evidence was rare and unsatisfactory [12, p. 155].

Recent researchers take more flexible attitudes toward style. Mayer Schapiro[3] defines style as the constant elements, qualities, and expression in the art of individuals or groups[26, p. 287]. He consider it as a *concept*, rather than a pure and strict definition. Schapiro claims that although styles are socially dependent and not strictly defined, this concept is still useful in the study of culture and art [26, p. 288]. He mentions the importance of considering other social aspects in relation to style [26, p. 310–311], such as ideology, politics and economics, and writes that for the historian of culture, style reflects collective thinking and feeling [26, p. 287]. His article *style*, published in 1953, ends with the claim that a deeper theory of style, one that involves different aspects of making, such as psychological or historical, had not been created yet.

For archaeologists, style is the projection of cultural signals onto material artifacts. For example, Earle[4] shows how stylistic analysis of objects can be used to understand the politics of chiefly societies [6, chapter 8]. Yet as Conkey[5] shows, the interpretation of style separate from the culture produced it is a delicate task [6]. An important question is how societies are correlated with their material culture, and what can be reasonably inferred from style [6, chapters 1,3]. To answer such questions, ethnographers look for a deeper definition of style by investigating the social mechanisms of material culture. In this case, it is worth going back to the opening of Malinowski's[6] the *Argonauts of the Western Pacific*'s chapter 4, Canoes and Sailing[30, p. 80]:

> A CANOE is an item of material culture, and as such it can be described, photographed and even bodily transported into a museum. But—and this is a truth too often overlooked—the ethnographic reality of the canoe would not be brought much nearer to a student at home, even by placing a perfect specimen right before him [...] The canoe is made for a certain use, and with a definite purpose; it is a means to an end, and we, who study native life, must not reverse this relation, and make a fetish of the object itself...

Most researchers agree that style is a *way of doing something*, and involves a choice among different alternatives[18, p. 517–518], but different definitions focus on different aspects. Sackett concentrates style in different choices with the same functional end, being made by makers in a specific place and time. Such choices spread according to the specific social structure and may therefore reflect both social interaction and historical context[18]. Note that Sackett does not deal with *why* such choices are made. Wiessner, following Conckey and Wobst, uses the definition of style as formal variation in material culture that transmits information about identity[43]. She distinguished between different kinds of style, according to what can be learned about the maker, in what context, and for whom the message is intended[7], and specifically argues that understanding

[3] Lithuania 1904–USA 1996
[4] Timothy Earle, USA 1946 -
[5] Margaret Conkey, USA 1943 -
[6] Bronisaw Malinowski, Poland 1884–USA 1942
[7] Assertive and emblemic styles.

style depends on understanding the behavior that generates it[43]. Wiessner's theory connects variations in material culture to individuals' behavior and cognition, which is especially relevant to our own investigation of the dynamic characteristics of style, the relationship between style and manual skill, and the artist's mental model of the task. Moreover, Weissner specifically connects stylistic behavior to identification via comparison— that is, the establishment of self-image through comparison to both personal and social components in society [44, p. 191]. We touch upon this issue later on.

Furthermore, it has been observed that cultural style impacts personal style, too. Boas mentioned that style has the power to limit the creativity of the individual maker[12, p. 156]. Wobst widen this observation, and claims that style both depresses and challenges the individual's identity[34, p. 47], and allows individuals to shape their own identity with regard to it. It is important to note that the consensus regarding the relevance of cultural and social influence on one's style makes it challenging to analyze style in a controlled experiment, and requires a well-defined investigation, as will be discussed in the technical sections of our study.

2.2 Style in the history of the arts

Similar to anthropology, the issue of style in the history of art shifted greatly in the mid-20th century. Until then, social style was essential in the research of art, and was considered a formal and pure tool. At some point, art historians began to question the issue of social style, and shifted to the use of less-categorical attitudes, trying to look at the personal work of the creator through time-dependent and multidisciplinary criteria.

In his article *style*, Mayer Schapiro writes, "To the historian of art, style is an essential object of investigation" [33, p. 98]. Towards the first half of the 20th century, style was a dominant concern among scholars of art history [33, p. 98]. Works of art were described and analyzed by the representative aesthetics of their time and place, and this consideration aimed to be *formal*, to derive from the work of art itself. The meanings and the means (techniques, materials and aesthetics) were separated, narrowing the definition of style mainly to consistent aesthetics [26].

From the 1970s onward, an effort has been made to weaken such categorical and formal views within the history of the fine arts. In her article "Style is what you make it", published in 1978, the American art historian Svetlana Alpers writes [1, p. 158]:

> The study of styles and genres seems to me always in danger of extracting, by naming and singling out, the accomplishment of specific modes that seem by virtue of this nomination to have preeminence. But style is what you make it and the mode is in the making. The Renaissance model appeals to students of style and aesthetics because it produces the material for their study: works judged when completed, objective, outside the maker and prior to the viewer and presumably not tied to a function in the world. It is only certain modes that posit such an objective world and maker. Questions about style and iconography are appropriate for Renaissance art, but we want questions that are appropriate for all art. The main question, it seems to me, should be modal. And it goes something like this: "What would it (reality, the world) be like if the relationship between us and the world were to be this one? This formulation has the virtue of not distinguishing form and content, of not excluding function, of not choosing in advance between the parts played by the individual maker, his community, certain established

modes of perceiving the world, or the viewer.[8]

Alpers explores art and the making of it with a multidisciplinary attitude, trying to reveal the fundamental forces that brought art to be what it is. The idea that art simultaneously stands for itself but is also a manifestation of different and dynamic aspects of the contexts that produced it is a key idea in our approach to style.

2.3 Style and the digital world

As shown in the previous sections, the concept of style has changed dramatically in the humanities over the last two centuries. Yet, in the digital world, and specifically in HCI, we do not observe such a multi disciplinary and critical approach toward style. Indeed, while scholars use digital tools for investigating aspects of creativity, the common definition of *style* in the computer-science field is merely the visual representative properties (of the artists), not the dynamics that yielded them.

On the whole, artistic style can be perceived as a subcategory of personal behavior: the way a person performs in the physical space, interacts with the environment, makes decisions, etc. Because we focus on the physical results of one's actions in space, new technological methods of tracking and analyzing human behavior, in which we include both motor and more complex actions performed consistently, are especially relevant to our discussion. Such frameworks range from tracking brain activities that accompany a specific behavior [40, 41], to tracking a person's behavior long-term [7]. Yet a full survey of such frameworks exceeds the scope of this work. In the context of our research, we wish to highlight techniques that connect style to humans' motor-skills (and specifically, to making art). These methods may include wearable sensor systems [28, 20], automated analysis of photographed movements [9], or technologies like the smart milling tool Zoran et al. used to explore the motor structures of personal sculpting techniques [46].

We continue with the common (and direct) appearance of style in computer-graphics and image processing, elaborate on more complex frameworks for creativity and cognitive studies of creativity, and finally discuss general frameworks for human behavioral analysis.

2.3.1 Stylization in image processing and computer-graphics

Style appears in image processing and computer graphics mainly in the following contexts: (i) *stylization*, which is the application of desired visual properties to a still or moving image, and (ii) the exploration of art history using digital tools.

A body of work has been dedicated to extracting stylistic features from images: Sablatnig et al. used brush strokes to identify individuals' style [37]. Khan et al. used supervised machine learning with features such as color and shades to identify an artist [24]; and Leon et al. separated content and style to build a stylistic representation of an image using neural networks[14].

Stylistic feature spaces are also being used in the research of art history. Elgammal et al. used convolutional neural networks to classify large set of paintings [10], showing the similarity between traditional classifications by art historians and machine results. Rigaue et al. examined Van Gogh's different periods using information-theoretic tools [36], and Saleh et al. explored automated discovery of artistic influences [38].

[8] The mistake is in the original text ("no")

In computer graphics and image processing, such features are being used for *stylization*— changing a graphical element in a way that preserves the *content*, but brings its *appearance* closer to a reference. Van Gogh filters are an example of stylization using a famous artist's aesthetics [29]. Kypriandis et al. specify different methods for stylization using artistic techniques and genres, such as watercolors and abstraction [27]. Leon et al. apply the appearance of one image to another using neural networks [14]. Google's DeepDream uses neural networks to apply a psychedelic filter to an image by using a previously *trained* network[32].

2.3.2 Craft, making and creative environments

We end this section by specifying selected digital frameworks that enable or explore making and creativity. Works in this space vary in the way they combine real-world expertise with digital environments or virtual spaces. Examples include Google's TiltBrush— a pure virtual reality framework for drawing and painting in 3D[17], or Arisandi et al.'s framework for creating 3D models using virtual reality combined with digitalized hand tools [2]. Cho et al. presented an environment for digital pottery consisting of the detection of a user's fingers over a rotating wheel and virtual model of clay [4]. Other works take hybrid approaches while actually making objects: Devendorf et al. explore how to place digital fabrication activity in new environments [8]. Shilkrot et al. and Zoran et al. presented smart tools suggesting a balance between the certainty of digitized systems and the risk within making in practice [39, 46]. The last also lays the technical framework we used in our current research.

To summarize, we see a great potential in harnessing (computational) tracking, processing, and analytical technologies to gain a new and deep understanding of personal style, with the aim of expanding discussions about the creative process outside the computational terrain. We now move forward, and in the next three sections elaborate on our technical framework and experimental work, which is a continuation of [46], and a step towards establishing the concept of dynamic style.

3 A framework for investigating motor skills

3.1 A discretized view of making

Quantitative answers for questions concerning the maker's set of techniques require an exact definition of a *technique*. While watching sculptors work, we saw that each maker used a consistent set of motor skills, which may include the main states of the working tool, the main working movements, or a combination of the two. In this work we investigate these principal motor skills and how they vary among makers. This approach allows us to summarize the making process as a transition in time between different motor skills.

Figure 1-a shows the change in the roll angle of a sculpture tool being used in the clay relief technique. The tool's angle varies between a few dominant values, giving a sense of looking at the sculptor's work as a (statistical) transition between a limited set of states. However, it is important to note that the visualization of a maker's states is not always as clear as in this example; it depends on the maker, the technique, and even the feature being measured.

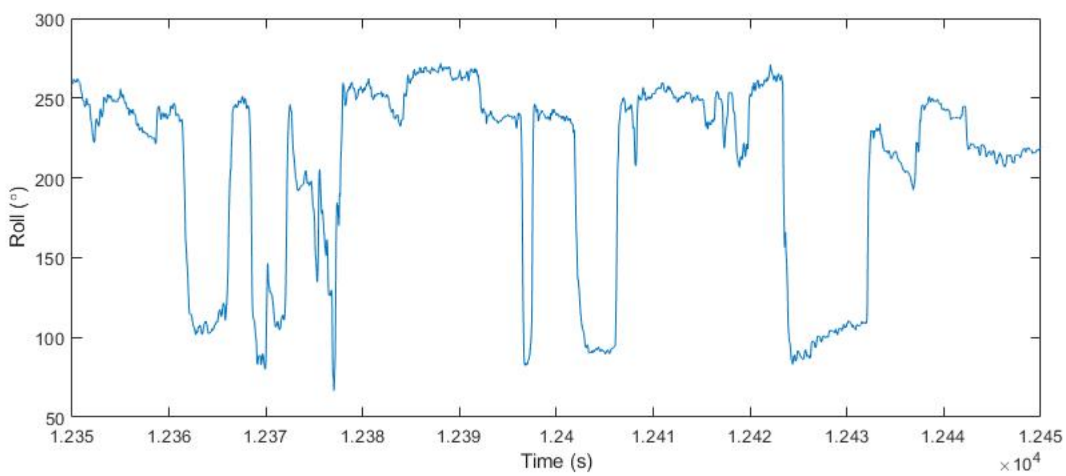


Figure 1: An example of how a tool's roll angle changes while a maker works with it.

3.2 Previous and current work

We performed two experiments in which participants carried out a set of sculptural tasks. We tracked the usage of the sculptural tool, then analyzed the principal motor skills and the transitions between them. We explored different questions in each of the two experiments. With the unskilled participants, we asked whether or not they consistently use the same set of techniques, and how similar or different they are to each other; with the experienced maker, we asked whether we can distinguish different tasks by observing only the techniques used.

In our quantitative analysis we followed [46] for extracting a set of principal working/tool states, with the following differences from the previous work:

- The tool we are using is a simple sculpture tool commonly used by clay artists, with a motion-tracking sensor but no other special capabilities.

- We separately observed a group of unskilled participants and a skilled maker.
- Each participant performed more than one task.

In the rest of this chapter we discuss the technical scope of this work, and describe our technical settings and algorithmic framework for both experiments. The mathematical background for the algorithms used is given in section 3.5.

3.3 Technical settings

Our framework consisted of (i) a Polhemus FASTRAK magnetic motion-tracking device, (ii) a simple sculptural hand tool with a motion-tracking sensor at the tip, (iii) a 20*20*4cm box-like terracotta clay body, and (iv) a constant light setting in the lab. The exact setup of the lab during the experiments appears in figure 2.

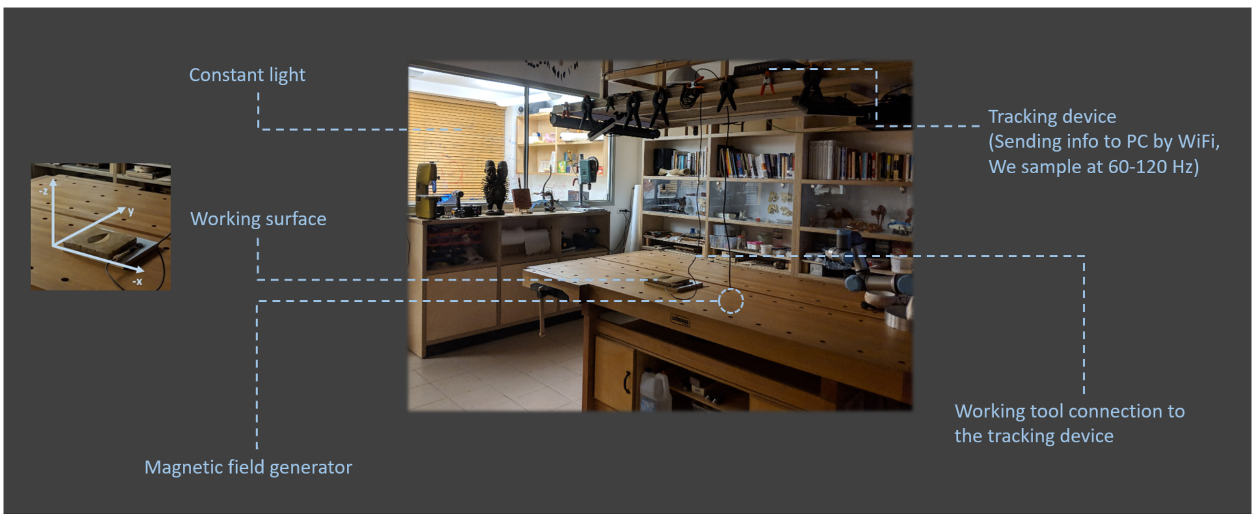


Figure 2: The lab's settings during the experiments. (a) is the working place of the participants; (b) is the position of the magnetic field source (under the table's plane); (c) is the position of the tracking device; (d) is the constant light configuration from the side room.

- *Tracking device* - we use the Polhemus FASTRAK magnetic tracking device, which allows 6 degrees of freedom (DOF) for 1-4 sensors with update rates of 120,60,40,30 Hz respectively. The technical manual of the device can be found here.
- *Tool* - the tool is a simple, knife-like, clay-manipulating tool. Its handle was designed and 3D printed so that the tracker's sensor fits within it. The tool has a knife-like tip which the experienced maker manually made from epoxy (figure 3). It is usually held with one hand, and can move freely in all directions, limited only by the long cables connecting it to the tracking device.
- *Clay* - the sculptured clay surface is a 20*20*4cm box-like clay body (figure 4 a). It consists of 2mm terracotta. Each such clay body was produced using the same square mold and left

in a loose nylon bag to solidify for 24 hours before being used. Terracotta has a warm reddish color that is neither too pale nor dark, and thus displays a broad range of shades in the light (figure 4 b).

- *Technique* - we focused on the clay relief technique, in which details are sculpted by manipulating a solid background of material. A key idea in this technique is that when a directed light hits a textured surface, different areas will appear at different levels of gray depending on their orientation. This technique can be considered as a discussion between the surface, light, and the absence of light.

  Historically, this technique has been used for a variety of purposes, such as decorating architecture (figure 5 a), monumental sculpture (figure 5 b-c), and fine art.

  This technique has particularly relevant characteristics for our work. First, it is a relatively basic technique, which allows inexperience participants to avoid the confusion and uncertainty of complex procedures. At the same time, as it lies on the border between 2D and 3D, it requires some practice even for those experienced with more common techniques such as painting or traditional 3D sculpture. Finally, it allows both coarse and highly accurate modes of working.

- *Light* - we imposed an identical arrangement of directed light within each experiment. In each session we turn off all light sources, except the warm lighting on the north side of the lab (minor sources such as computer screens were not considered). The lighting comes from one side of the participants, as observed in figure 2.

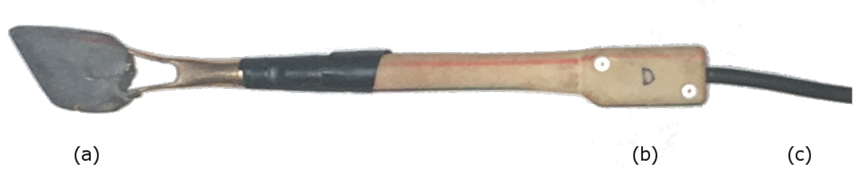


Figure 3: Main elements of the tool. (a) The tool's tip, which does all of the clay manipulation; (b) the sensor location; (c) the power cable for the sensor.

Figure 4: (a) An example of the clay body; (b) a terracotta variety of gray scales formed by light and orientation.

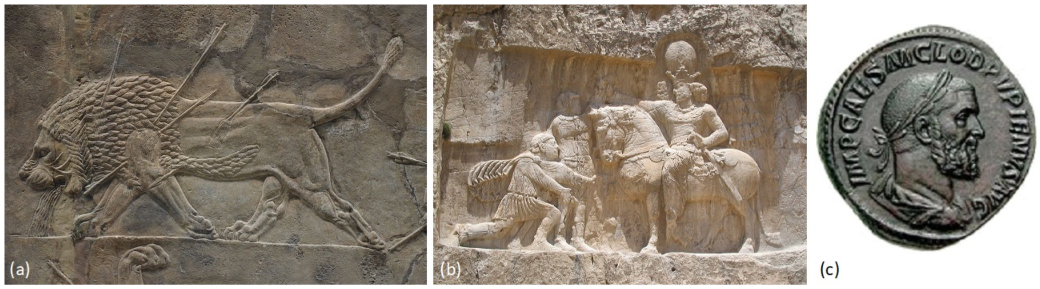


Figure 5: Examples of the relief technique (from Wikipedia) (a) Rock relief at Naqsh-e Rustam; (b) Assyrian relief, Lion Hunt of Ashurbanipal, North Palace, Nineveh 600-700 BCE. (c) low relief on Roman sestertius, 238 CE.

3.4 Algorithmic framework

We now describe the data analysis from the two experiments. Section 3.5 supplies the mathematical background for the methods and algorithms being used in this work. Sections 3.4.1.1 and 3.4.1.1 elaborate on the features by which we characterized each time sample, and explain why these features were chosen. As each feature has its own properties, we normalized each separately (section 3.4.1.2). As an initial investigation of the features space, we clustered it and considered each cluster as a principal working state (see section 3.4.1.4), and also explored the dynamics of the working states in time (section 3.4.2).

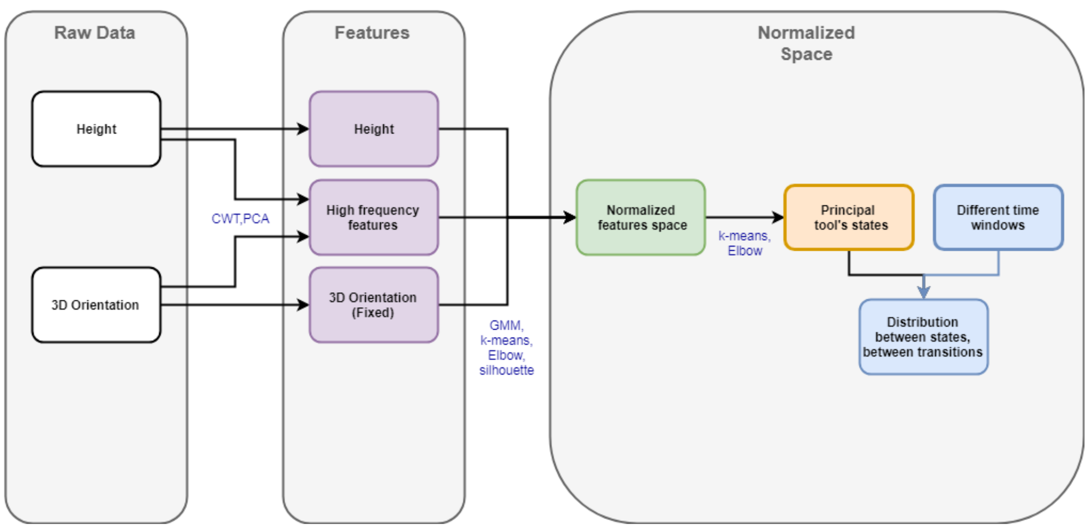


Figure 6: The algorithmic work flow of our data analysis. Main algorithms being used in each step are in blue.

3.4.1 Establishing the features space

3.4.1.1 Features

As previously mentioned, *techniques* are not well defined and involve different aspects of the maker's process, from motor skill to state of mind. Thus, it is necessary to ask which features should be quantitatively measured when investigating the maker's set of techniques. In this work we tried to characterize the tool's dynamics, focusing on the maker's typical motor skills with less attention to the specific image being produced. Thus, we characterized the tool's state by its height, orientation, and a signature of its local behavior at each time sample.

Other relevant features exist. For example, although speed is relevant to the maker's own motor skills, due to the repetitive nature of the movements in the relief technique, we used the high-frequency features instead. The transitions between different parts on the working surface may also be relevant, as changes in the location of the tool can tell us something about the makers technique for establishing the image. As we were not sure if and how the specific image being produced may affect the maker's behavior, we did not include the tool's location on the working surface (x, y plane); this is a matter for further investigation. We now describe the selected features in detail:

- Height

  The height of the tool is the tool-tip's Z coordinate. It is simply the third coordinate of the tracking device output with no further manipulations. The units of this feature are in centimeters.

  This feature contains statistical information on different aspects of the maker's motor skills, techniques and final result. Since the tip of the tool corresponds to the relief's face, this feature contains data such as the depth of the relief or the distribution between different heights along the process, indicating how the relief is physically being made. In addition, the maker's different motor skills, such as how she or he holds the tool at a certain height when thinking, appear in this feature. How such information relates to *technique* is an open question, as discussed in section 6.

- Euler angles[9]

  As mentioned also for the height feature, these orientation features are connected to a variety of aspects: the angle of the plane currently being manipulated, the makers' preference for which part of the tool's tip to work with (some prefer to manipulate clay with the edge of the tip, others with the flat part), and the motor skills of the maker (for example, whether they release their hands when thinking).

  Due to the cyclic nature of angles, an artificial discontinuity point occurs when crossing the feature's range (see figure 7). We considered two ways to deal with this issue:

  I. Embed this 1D angle feature in a 2D space.

     For each angle feature, we embed it in the 2D unit-circle using the mapping $\theta \mapsto (\sin\theta, \cos\theta)$.

[9] The description of the Euler angles appears in section 3.5.

II. Minimize the number of discontinuity points.

Given a feature f, if we build a histogram of f, this discontinuity phenomenon would appear as a split Gaussian in the limits of the features range (see figure 9a). We can select a value where the number of discontinuous points is low and shift f by it, resulting a minimal number of such discontinuity points. The disadvantage of this option is that discontinuity points still exist. The advantage is that we preserve the general structure of the data and are thus able to use more delicate mixture-model methods in later stages.

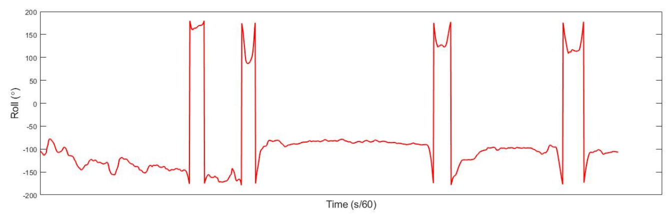
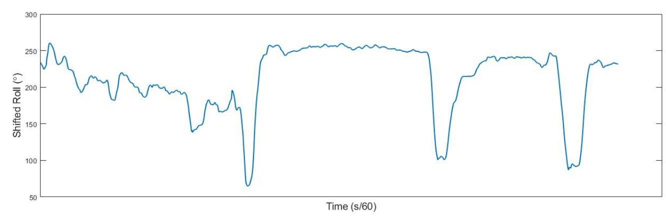
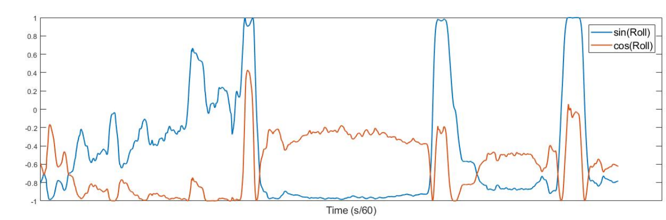


Figure 7: An example of the discontinuity of the roll signal.

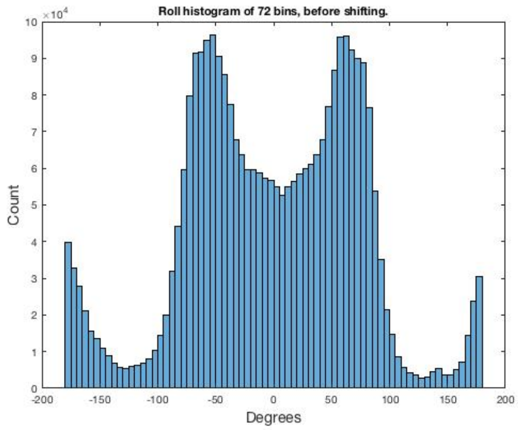


(a)

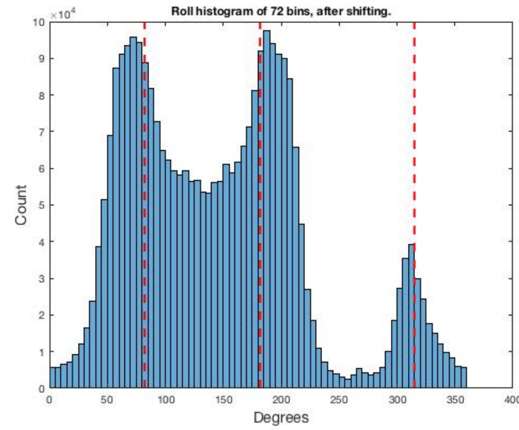


(b)

Figure 8: (a) Fixing an angle signal by shifting the entire feature; (b) and by embedding it into the unit circle of $\mathbb{R}^2$.



(a) Roll histogram before shifting.



(b) Roll histogram after shifting— red lines are the centers of the Gaussian mixture model (with three clusters) fitted for the fixed data.

- High-frequency features

As an indication for local behavior, we calculated a high-frequency corresponding feature for each of the previous features. The high-frequency h_f^s, corresponding to the feature f, was calculated as follows:

I. Calculate the continuous 1-D wavelet transform of f, as explained in section 3.5. Because we used CWT, we did not need to pre-define a fixed window when calculating the energy of each frequency. Moreover, due to its multi-resolution properties, it resulted in a better resolution for high frequencies without requiring the same resolution for lower frequencies.

II. Take the absolute of coefficients corresponding to frequencies greater than $s = 0.2$ Hz.

III. Use PCA to reduce the dimensionality of the feature such that 85% of the variance remains.

Figure 9 shows part of the tool's height signal and the corresponding CWT in the range of relevant frequencies.

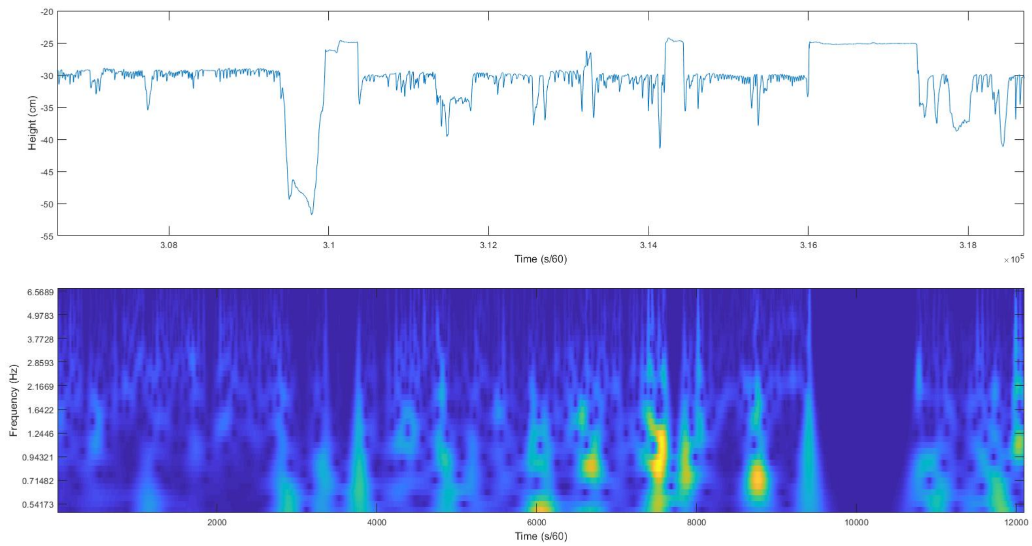


Figure 9: Part of the height signal and its corresponding CWT for frequencies greater than 0.5 Hz.

In the data analysis of our presented experimental work we used only the high frequency of the height feature, as we did not want the local behavior to become the main issue of our analysis.

3.4.1.2 Normalization of features

Different features exist in different dimensions and different units, and thus needed to be standardized before clustering the data. Given a feature f we transform each sample to a distribution of being in one of the main clusters of f. Thus our feature space becomes a space of distributions between different clusters of the data. More precisely, we are running the following algorithm for each feature f:

A. Estimate the number of clusters in f.

   Let k_f be the estimated number of clusters in f. Since clusters have no unique definition, we encountered two methods for this task:

   - The elbow method variant.

     Look at the percentage of variance explained as a function of the number of clusters, and set it in a way that explains at least 80% of the variance.

   - The silhouette criterion.

     Cluster the data for each cluster numbered between 1 and 30, and choose the number that gives the best result using the silhouette criterion.

   We observed that these two methods may give different evaluations for the number of clusters. Both methods suggest between two to four clusters for the low-frequency features and between two to 10 for the high-frequency features. As a rule of thumb, we used three clusters for the regular features and five clusters for the high-frequency feature.

B. Samples to distributions.

In the GMM variant case, the posteriors are usually part of the standard output and are calculated using the estimated parameters. In the *k-means* case the posteriors are integers, but we took a smoother approach. We use the output of the clustering algorithm to compute for each sample i, the distribution p_i of belonging to each of the clusters. Let f_i be the current sample, $(c_1, \ldots, c_{k_f})$ be the clusters centers, and $d_j = ||f_i - c_j||_2^2$, then the sample becomes $\frac{1}{\sum_j \frac{1}{d_j^2}}(\ldots, \frac{1}{d_j^2}, \ldots)$.

Another approach toward the normalization is to use a fixed and relevant set of points in space. For example, points uniformly sampled across the whole range of signals or points located near areas of interest (image and background, for example). Choosing which to use is a matter of what question is being answered.

3.4.1.3 Establishing the normalized features space

Overall, we checked two cases for the establishment of the normalized features space:

- GMM based analysis, where normalization of the features was done using the GMM algorithm. In this case, we fixed the angular features by shifting, as explained in 3.4.1.1, then used GMM on each feature in order to transform each sample to a distribution.

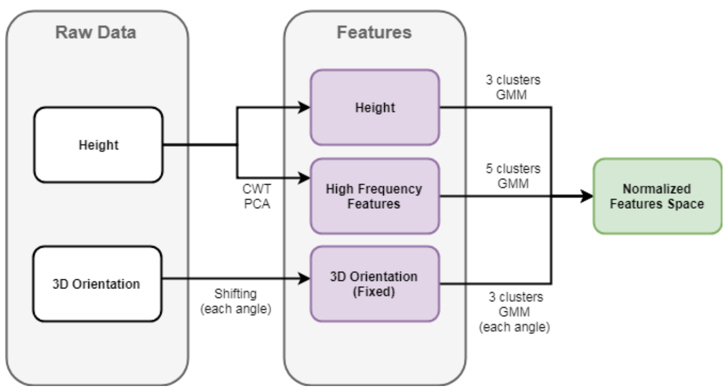


Figure 10: The GMM based process.

- k-means based analysis, where normalization of the features was done using the k-means algorithm. In this case, we embedded the angular features in the 2D unit-circle as explained in section 3.4.1.1. Then we used k-means to transform each sample to a distribution between the main clusters.

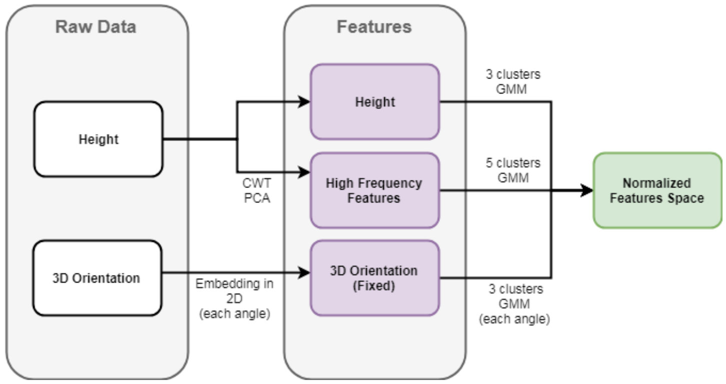
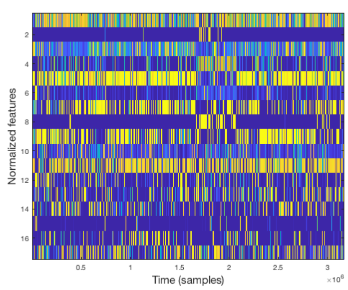


Figure 11: The k-means based process.

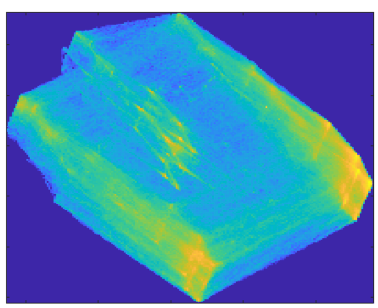
As can be seen in sections 4 and5, the results of the two approaches are similar. An example for the normalized feature space, projected on its first two principal components, appears in figure 12b.

3.4.1.4 Identify the principal tool's states

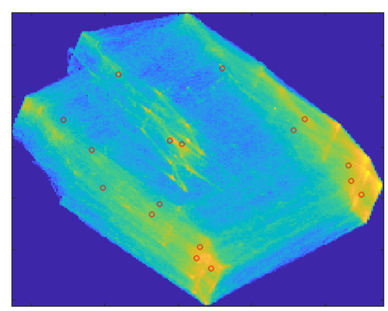
For each experiment, we used k-means to cluster the normalized feature space to $\hat{k}$ clusters, where $\hat{k}$ was calculated similarly to 3.4.1.2, but explained 90% of the variance. Figure 12c shows the clusters' centers in the space.



(a) The normalized features space of the experimental work.



(b) A 200 × 200 histogram (log scaled) of the normalized features space projected into 2D using PCA.



(c) Principal tool's states in the normalized features space.

Figure 12: Visualization of the normalized features space and principal tool states.

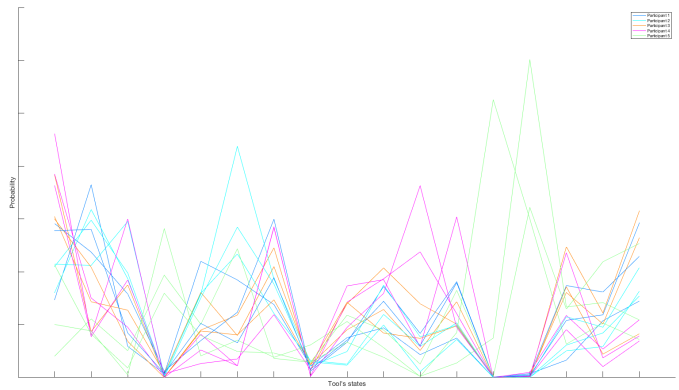


Figure 13: Probabilities between different tool states for first experiment's sculpturing sessions. Each participant in the experiment performed three different simple relief tasks.

3.4.2 Investigating the features space and the working sessions

After the previous step, each time slice can be regarded as a series of principal working states. As a step toward exploring motor skills in creative processes from a statistical point of view, we transformed a working series in time to a distribution between the $\hat{k}$ working states of a feature space, and the probabilities of transitions between them. This step allowed us to compare different time scales to each other, as each working window became an array of fixed length regardless of the original window's size.

Figure 13 shows an example of 15 distributions between different tool states, corresponding to 15 sculpturing sessions (30 minutes long) performed by five different participants (see next section). Interestingly, each participant's distributions are similar.

In this work we used the following similarity function to express the distance between two sculpturing sessions:

3.4.2.1 Distance between working windows

We transform each time segment s to two distributions:

- p_s is the distribution of any working state, the normalized histogram of s.
- q_s is the distribution of changing from state i to state j where $i \neq j$.

We then defined the distance $d(s_1, s_2) = D_{JS}\left[p_{s_1}||p_{s_2}\right] + D_{JS}\left[q_{s_1}||q_{s_2}\right]$, where D_{JS} is the Jensen-Shannon divergence, that is $D_{JS}[p||q] = 0.5\left(D_{KL}[p||\pi] + D_{KL}[q||\pi]\right)$ where $\pi = \frac{p+q}{2}$ and

$D_{KL}\left[p||q\right] = \sum_i p_i \log \frac{p_i}{q_i}$. Note that it is a real symmetric function, and thus practically convenient. We use d to quantify distance between different time segments, both of the same participant and between different participants.

3.5 Mathematical background

- Euler Angles

  The Euler angles are three angles describing the orientation of a rigid body with respect to the fixed coordinate system. The three Euler angles are:

  - ψ (azimuth) is defined in as a rotation of the X and Y reference axes about the Z reference axis, and let X_1 and Y_1 be the orientation of the X and Y axes after the azimuth rotation [35].
  - θ (elevation) is defined as a rotation of the Z reference axis and the X_1 transition axis about the Y_1 transition axis. Let Z_1 and X_2 be the orientation of the Z,X_1 reference axes after the elevation rotation [35].
  - φ (roll) is defined as a rotation of the Y_1 and Z_1 transition axes about the X_2-axis. Let Y_2 and Z_2 be the orientation of the Y_1 and Z_1 axes after the roll rotation [35].

- PCA

  - PCA Given a set of observations $X \in M(\mathbb{R})^{n\times k}$, and assuming the columns (features) of X_n have zero mean, we find an orthonormal basis $v_1,\ldots,v_k$ of $\mathbb{R}^k$ such that each v_j is the solution for the following problem:

    $$\begin{aligned} \underset{v}{\text{argmax}} \quad & \|X_n v\|_2 \\ \text{subject to} \quad & ||v||_2 = 1, \\ & v^T v_i = 0 \quad 1 \leq i < j \end{aligned}$$

    Since v is a unit vector, and the columns of X_n have zero mean, v_j can be interpreted as the line (direction) such that the projection of X_n on it has the most variance (among all such projections) that cannot be explained by projections on $v_1,\ldots,v_{j-1}$.

- Mixture models and EM algorithms

  Given observations of some population, a mixture model is a probabilistic model for associating individual observations with different sub-populations, without requiring that an observed data set explicitly identify this information. A Gaussian mixture model is a probabilistic model that assumes all observations are generated from a mixture of a finite number of Gaussian distributions (with unknown parameters).

  When fitting a Gaussian-Mixture model, we assume that there exists $\theta = (\pi_1,\ldots,\pi_k,\mu_1,\ldots,\mu_k,\sigma_1,\ldots,\sigma_k)$ where $\pi_1,\ldots,\pi_k,\mu_1,\ldots,\mu_k,\sigma_1,\ldots,\sigma_k \in \mathbb{R}_{\geq 0}$ and $(\pi_i)_{1\leq i\leq k} \in \Delta^k$, such that the empirical data was i.i.d sampled from the following process:

  A. Choose $1 \leq i \leq k$ by the distribution $(\pi_1,\ldots,\pi_k)$.
  B. Randomly choose a sample x by the distribution $\mathcal{N}(\mu_i,\sigma_i)$.

  Yet the parameter θ is unknown to us, and our goal is to estimate it by finding the θ that maximizes the likelihood $P(X_n|\theta)$ of the empirical data. Let C_n denote some outcome of stage A, and $\theta^{(t)}$ some estimation of θ. It holds that

  $$\log P\left(X_n|\theta\right) = L(\theta|\theta^{(t)}) + D_{KL}\left[P\left(C_n|X_n,\theta^{(t)}\right)||P\left(C_n|X_n,\theta\right)\right] + H\left[P\left(C_n|X_n,\theta^{(t)}\right)\right]$$

where $L(\theta|\theta^{(t)}) = \sum_{C_n} P\left(C_n|X_n, \theta^{(t)}\right) \log P\left(C_n, X_n|\theta\right)$.

Due to the non-negativity of the entropy and Kullback-Leibler divergence, for a fixed C_n we get that $L(\cdot|\theta^{(t)})$ is a concave lower bound for $\log P\left(X_n|\theta\right)$ that agrees with it for $\theta = \theta^t$. Thus we can use it to iteratively optimize the estimation by optimizing $L(\cdot|\theta^{(t)})$ (as sketched in figure 14). In general, we perform the following process:

- Expectation
  Having $\theta^{(t)}$, calculate $L(\cdot;\theta^{(t)})$.
- Maximization
  Having L, optimize the parameters by $\theta^{t+1} = \underset{\theta}{argmax}\ L(\theta;\theta^{(t)})$.

  This problem can be solved using Lagrange multipliers (as $(\pi_i)_{1\leq i\leq k} \in \Delta^k$):

$$\pi_k^{(t+1)} = \frac{1}{n}\sum_i P\left(C_i = k|X_n, \theta^{(t)}\right)$$

$$\mu_k^{(t+1)} = \frac{1}{n}\sum_i \frac{P\left(C_i = k|X_n, \theta^{(t)}\right)}{\pi_k^{(t+1)}} x_i$$

$$\sigma_k^{(t+1)} = \frac{1}{n}\sum_i \frac{P\left(C_i = k|X_n, \theta^{(t)}\right)}{\pi_k^{(t+1)}} \left(x_i - \mu_k^{(t+1)}\right)^2$$

The k-means algorithm can be considered as an extreme case of GMM.

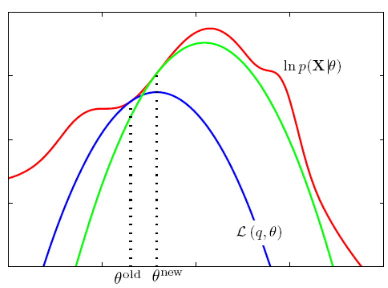


Figure 14: Sketch of optimizing $\log P\left(X_n|\theta\right)$ using the optimization of the concave $L(\theta|\theta^{(t)})$ (taken from [3]).

- Wavelets transforms

  The wavelet transform returns the continuous wavelet transform (CWT) for each time sample. It is an over-complete representation of the signal that uses inner products with a set of shifted and scaled mother functions, to measure the local behavior of the signal in different time scales. A more detailed survey can be found in [31].

- The elbow method

  The *elbow method* is a method for determining a reasonable number of clusters following variance considerations. It suggests choosing the number such that adding another cluster will not yield a significantly better result (compared with the variance that already been explained). When plotting the percentage of difference in variance as a function of the number of clusters, this number is chosen at the "elbow point"– that is the point where there is a dramatic reduction in the explained variance (at this point, the graph displays an angle; thus the name "elbow"). As this point is not well defined, and usually ambiguously identified, we search for the number of clusters that explain at least 80% of the variance.

- The Silhouette Criterion[22]

  The silhouette value is a measure of how similar an object is to its own cluster compared to other clusters. For a sample i, let $a(i)$ be the average distance between it and all other data within the same cluster, and let $b(i)$ be the lowest average distance of i to all other clusters, then the Silhouette value for i is $s(i) = \frac{b(i)-a(i)}{\max\{a(i),b(i)\}}$. Note that it follows from this definition that $-1 \leq s(i) \leq 1$. When $s(i) \approx 1$ it follows that $b(i) \gg a(i)$ and thus belonging i to its cluster is reasonable. When $s(i) \approx -1$ it follows that $a(i) \gg b(i)$ and thus it is reasonable that i should be part of one of the neighbor clusters. The silhouette grade for a clustering result is the average of $s(i)$ over all samples.

4 First experiment: short-term tasks by unskilled participants

This experiment involved a group of five unskilled participants. Although all of them had experienced other techniques, such as painting or other traditional crafts, none of the participants had worked with the clay relief technique before. In this experiment, we meta-ask:

1. Do unskilled makers have a consistent set of working states?
2. What is the variation of such consistency over time?

All participants were asked to perform three relatively simple tasks. In each task, a specific geometric pattern was sculpted on the clay body using the relief technique. The pattern for the first task was a simple, two-sided, leaf-shaped ornament; for the second task, a circular ornament divided into four equal sections; and for the last task, a purely circular ornament (figure 15). During the first task, which is the simplest of the three, the participants gain experience in the basic elements of the relief technique, such as the parting-line and differences in shades between two oriented planes that meet each other. In the second task, these elements were further developed by making planes in four different orientations that meet in a single point. The last task was the least-guided task, requiring participants to apply their experience from the two previous tasks while shaping the clay.

Each session lasted 30 minutes, and we notified the participants of the time remaining 15, 25 and 29 minutes. Each participant waited between one and two weeks between each task. At each session, a one-to-one model of the desired output was located next to the participant, and a sketch of the desired pattern appeared on the clay surface itself. Examples of the participants' reliefs are available in figure 16.

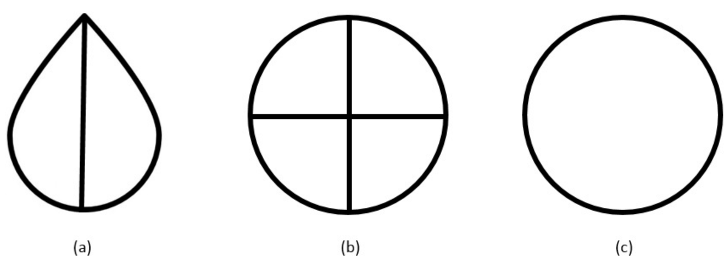


Figure 15: First experiment's sculpting tasks.

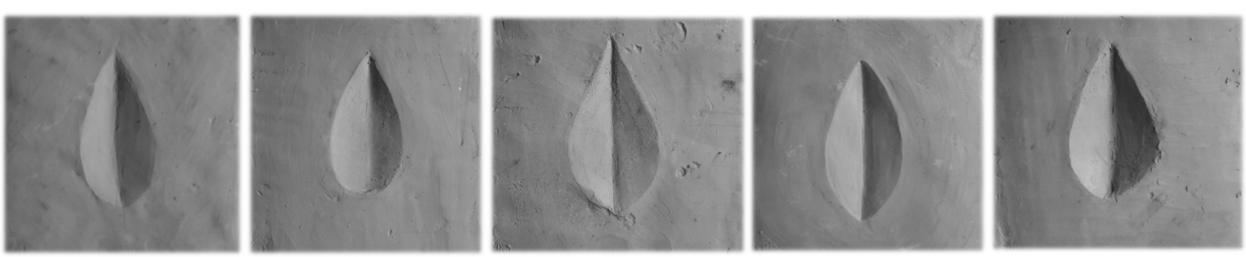


Figure 16: Reliefs from the first experiment's first task.

4.1 Results

We calculated the distances between all the working sessions, as explained in the previous section. We repeated this process for 10 repetitions, averaged the distance matrices, and embedded the sessions in 2D using the averaged distance matrix and non-classical MDS. Results for a single repetition gave very similar results, but we did the averaging for stability. Figures 17,18 and 19a show the embeddings.

4.1.1 GMM based analysis

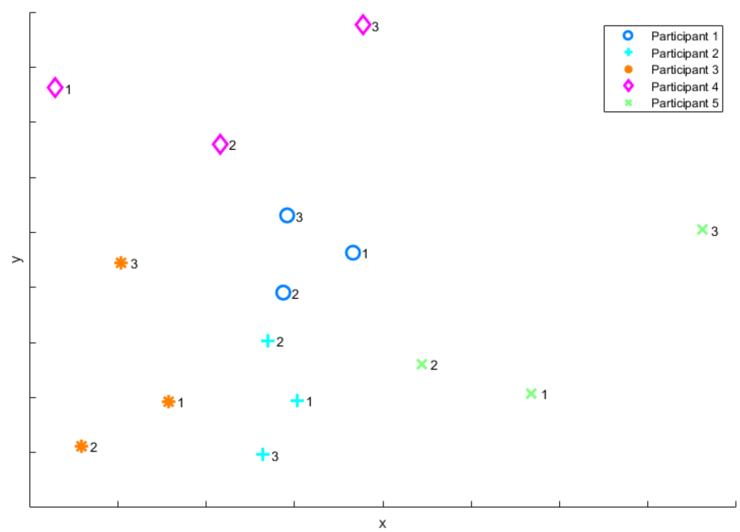


Figure 17: 2D embedding of the sessions, distance based on states distributions.

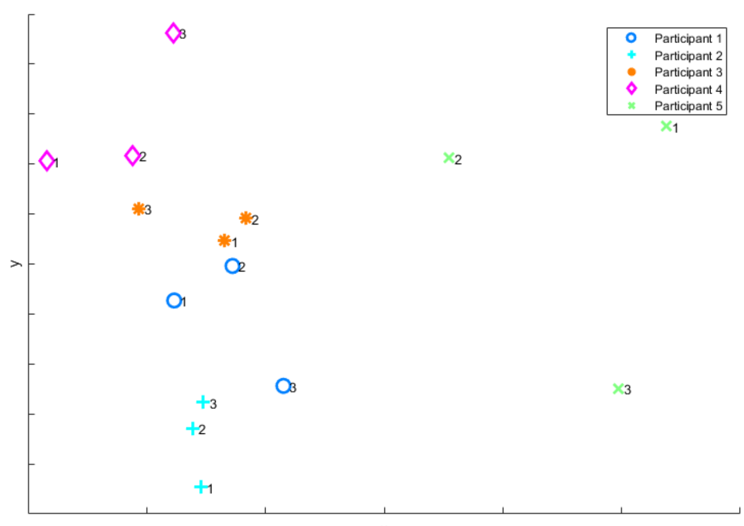
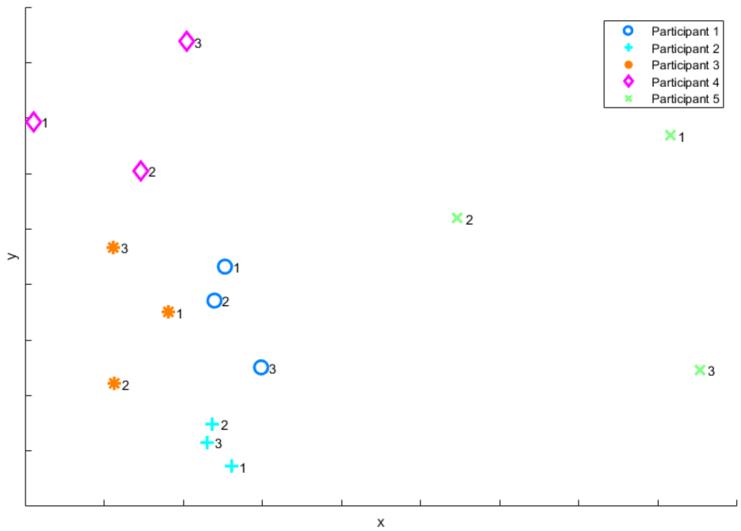
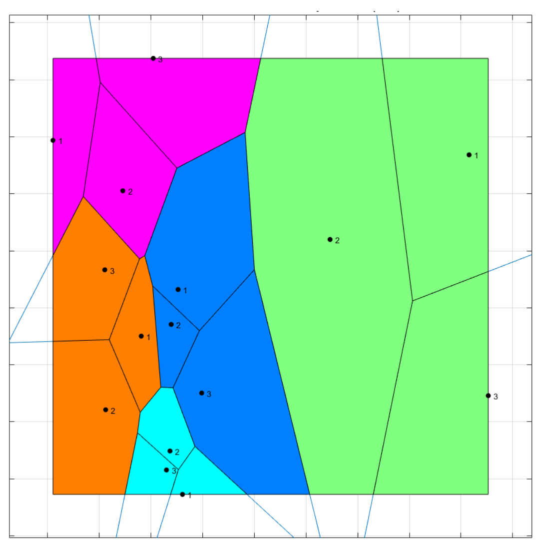


Figure 18: 2D embedding of the sessions, distance based on transitions distributions.



(a) 2D embedding of the sessions, distance based on sum of both distances.



(b) The Voronoi's diagram of the previous embedding

Figure 19: 2D embedding of the sessions, distance based on both states and transitions distributions.

4.1.2 k-means based analysis

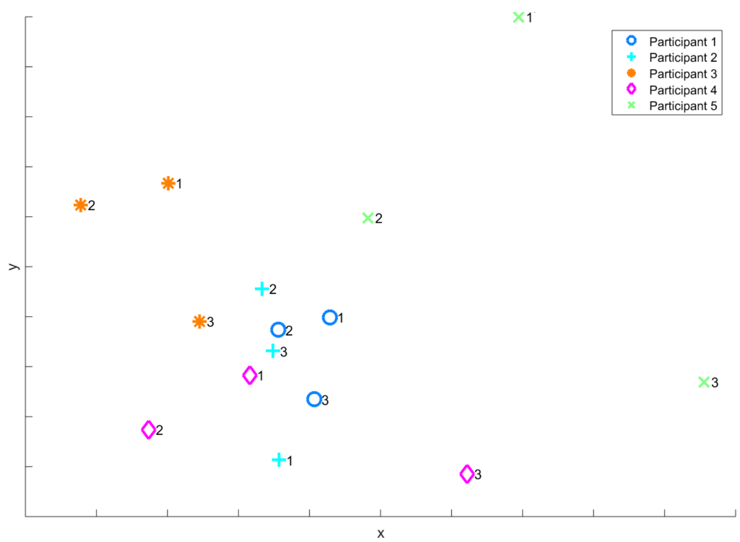


Figure 20: 2D embedding of the sessions, distance based on states distributions (k-means analysis).

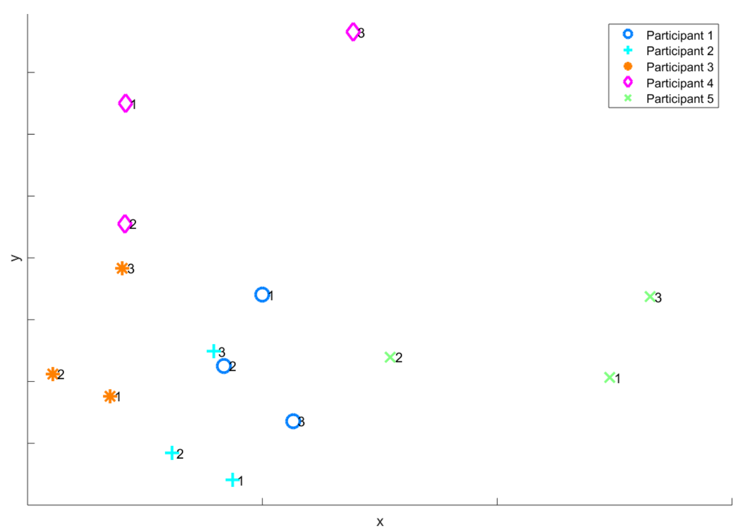
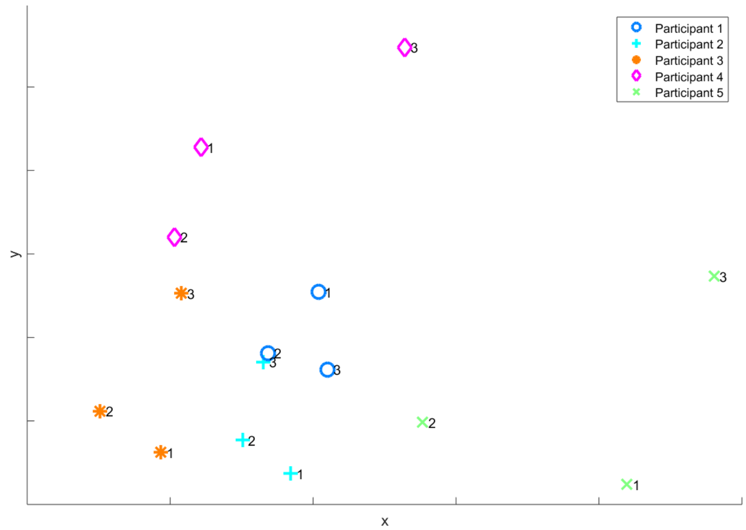
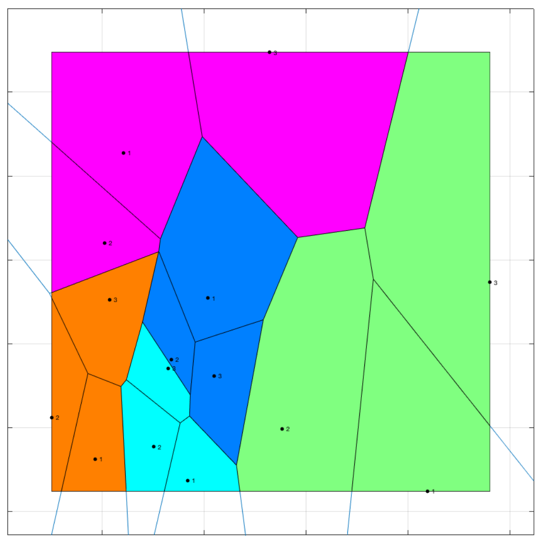


Figure 21: 2D embedding of the sessions, distance based on transitions distributions (k-means analysis).



(a) 2D embedding of the sessions, distance based on sum of both distances (k-means analysis).



(b) The Voronoi's diagram of the previous embedding

Figure 22: 2D embedding of the sessions, distance based on both states and transitions distributions (k-means analysis).

4.2 Discussion of the experiment's results

The results emphasize that even unskilled participants are relatively consistent in their motor skills, and the use of the sculpting tool. The participants did not form five separate clusters, but each participant's sessions are relatively close to each other, in terms both of states and the transitions between them. The Voronoi diagram in figure 19a show how space is divided by the embedding.

Figure 23 shows a 2D histogram of each session's contribution to the 2D histogram of the entire normalized features space (figure 12b). As can be observed, participant 5 owns an individual set of different tool states. The four remaining participants are relatively similar, although differences exist: for example, participant 1 visits participant 5's unique set of tool states from time to time, and participant 4's contribution exists mainly in the upper right area of the histogram.

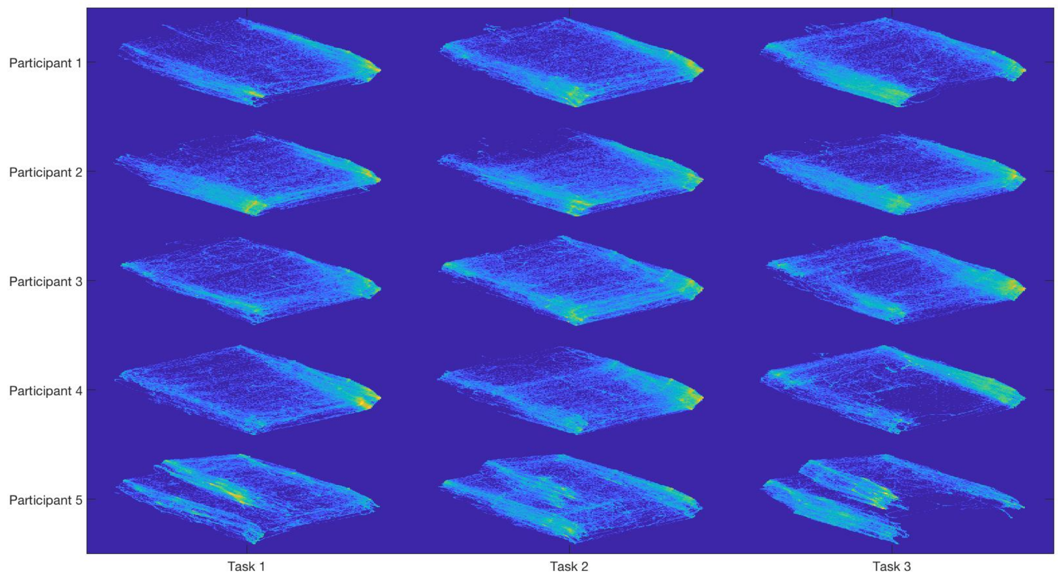
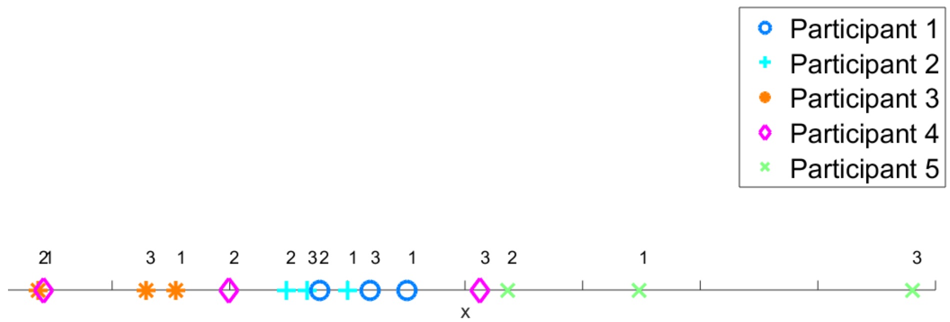
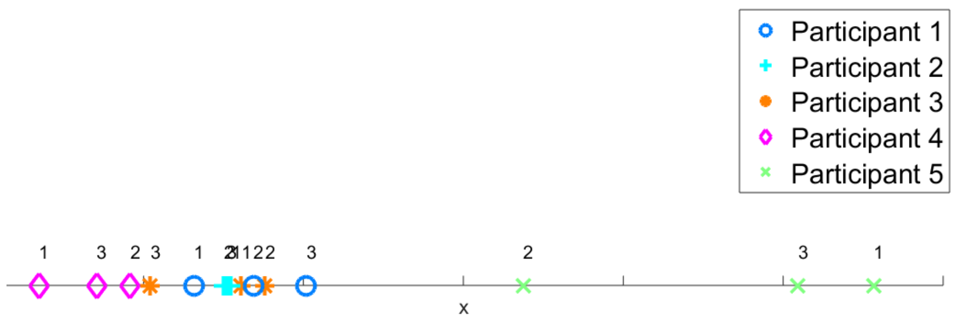


Figure 23: Each session's contribution to the 2D histogram of the entire normalized features space.

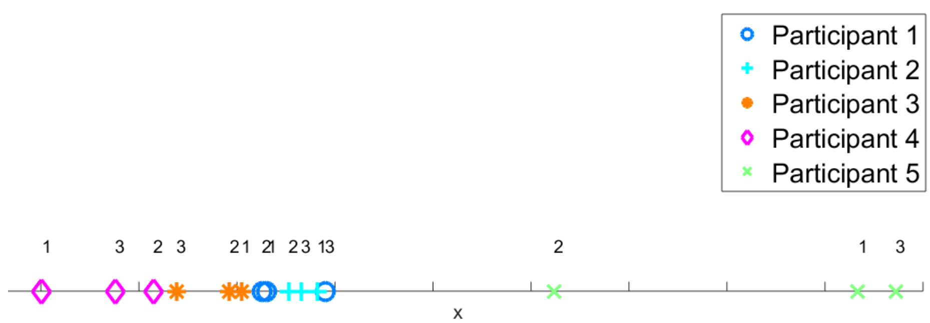
Embedding the sessions into 1D demonstrates the advantage of considering both distributions, between states and states' transitions. In this case, as can be observed in figure 24, considering both distributions reduces confusion between different participants when separating each of the three successive sessions.



(a) 1D embedding of the sessions, distance based on states distributions.



(b) 1D embedding of the sessions, distance based on transitions distributions.



(c) 1D embedding of the sessions, distance based on both distributions.

Figure 24: Embedding sessions into 1D (GMM case).

5 Second experiment: long-term process of a skilled sculptor

This experiment involves a single skilled participant. The participant is a professional sculptor with more than 20 years of experience with this technique, who teaches clay relief at an art academy.

sculpture and a teacher of the clay relief technique in an art academy with more then 20 years of experience with this technique. Alongside the skilled participant, an intern with a year of experience worked too. This intern is part of the experiments' organizers and thus its output is not a formal part of the final results, yet being brought as a supplementary material.

In this experiment we ask whether we can differentiate between different *sets* of techniques when observing an experienced maker. The experienced participant performed four advanced and long-term tasks. Each set of two of them related to a different type of clay-relief technique: two of the tasks involved a translation of a three-dimensional object (flower) to a relief, and the other two involved a flower-like geometric pattern. The sculptural tasks and the four final reliefs appear in figure 25. Both groups of tasks required the participant to produce a relatively large number of areas with different orientations, and to freely interpret a 3D/2D image to 2.5D. Yet some challenges are different between the two groups: in the flowers tasks (3D to 2.5D), the image is less geometric and more organic. In addition, the translation of the 3D object required the participant to make additional decisions about the organization and the specific interpretation on the clay surface. In the patterns tasks (2D to 2.5D), the image is more structured, and although the participant needs to decide about the orientation of each plane, the process is also more structured.

The whole process was divided into seven two-hour meetings. In each meeting, a 30-minute session was dedicated to each task, so that each task was 3.5 hours long in total. In each meeting, the order of the tasks was different.

Figure 25: The second experiment's sculptural tasks (above) and final reliefs (below).

5.1 Results

We calculated the distances between all the working sessions, as explained in the previous section. We repeated this process for 10 repetitions, averaged the distance matrices, and embedded the sessions in 2D using the averaged distance matrix and non-classical MDS. Results for a single repetition gave very similar results, but we did the averaging for stability. Figures 17,18 and 19a show the embeddings.

5.1.1 GMM based analysis

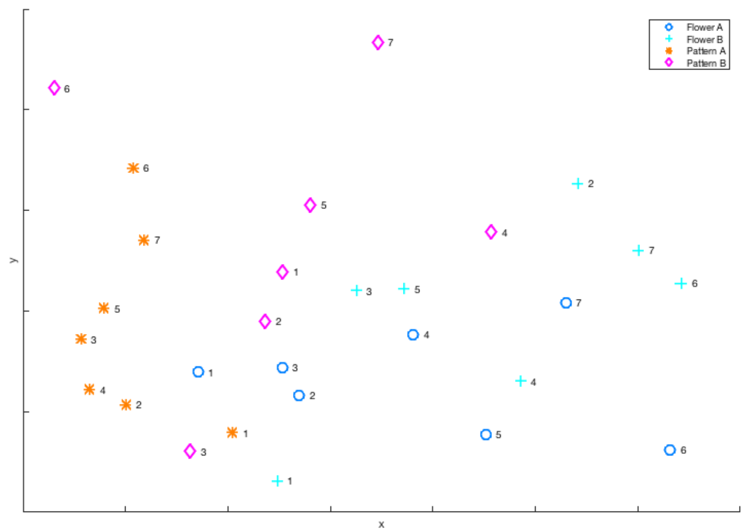


Figure 26: 2D embedding of the sessions, distance based on states distributions.

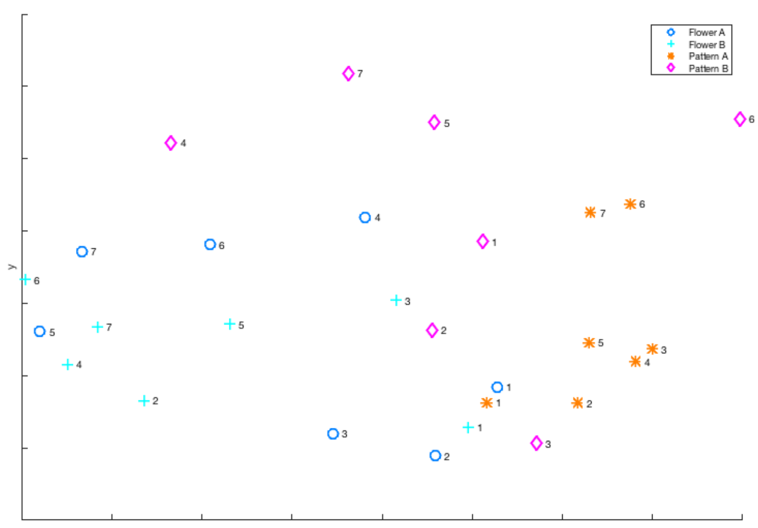
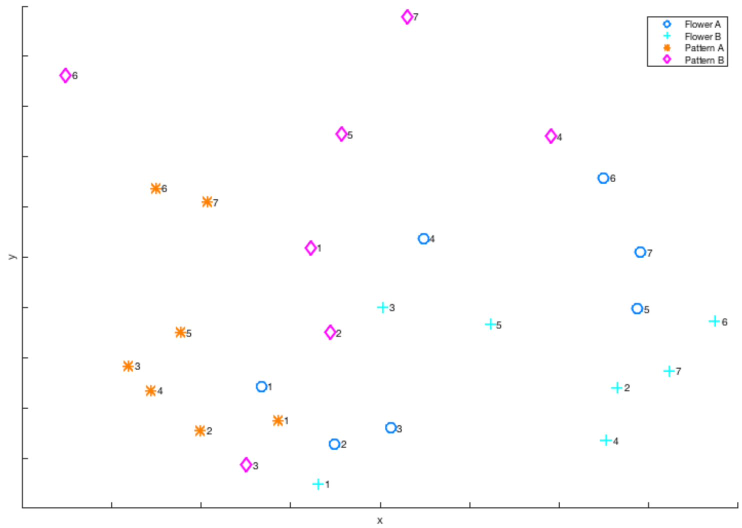
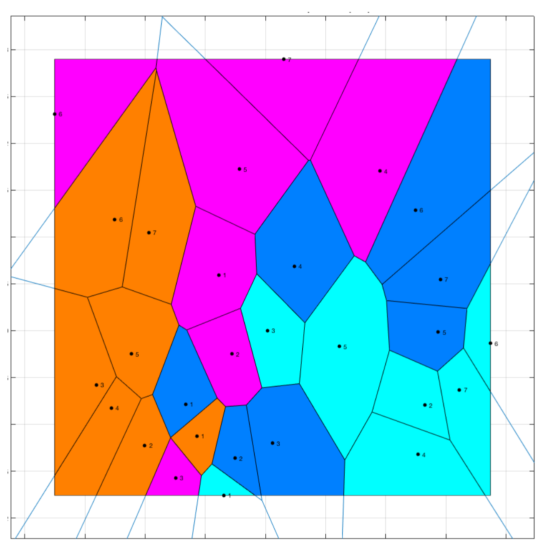


Figure 27: 2D embedding of the sessions, distance based on transitions distributions.



(a) 2D embedding of the sessions, distance based on sum of both distances.



(b) The Voronoi's diagram of the previous embedding

Figure 28: 2D embedding of the sessions, distance based on both states and transitions distributions.

5.1.2 k-means based analysis

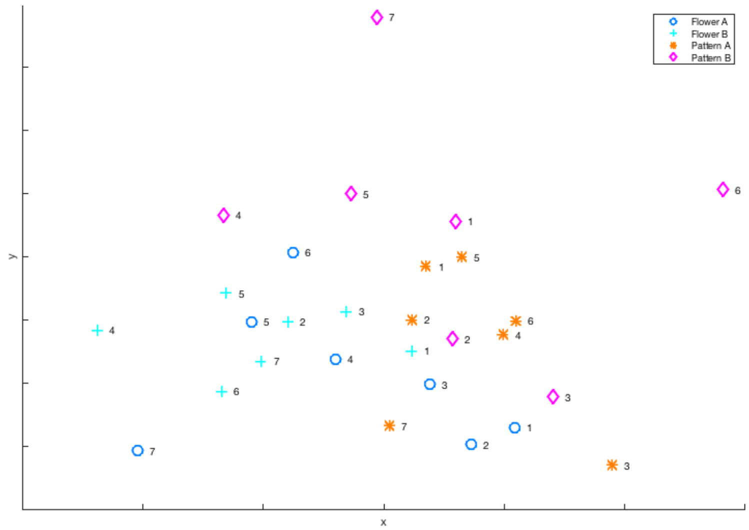


Figure 29: 2D embedding of the sessions, distance based on states distributions (k-means analysis).

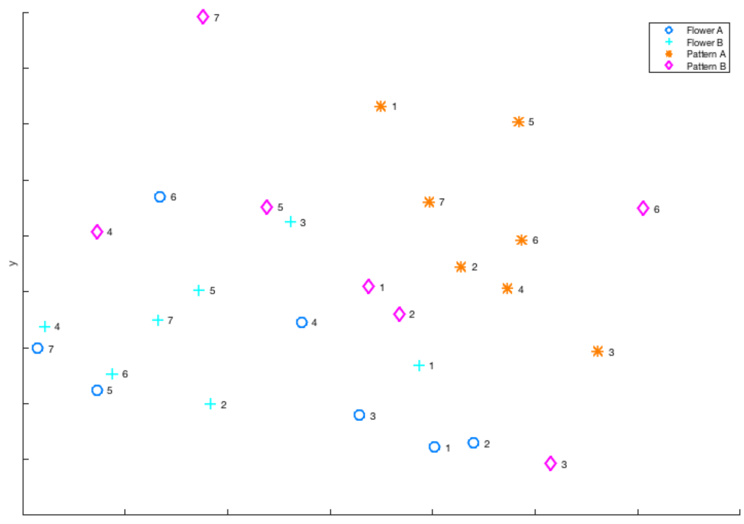
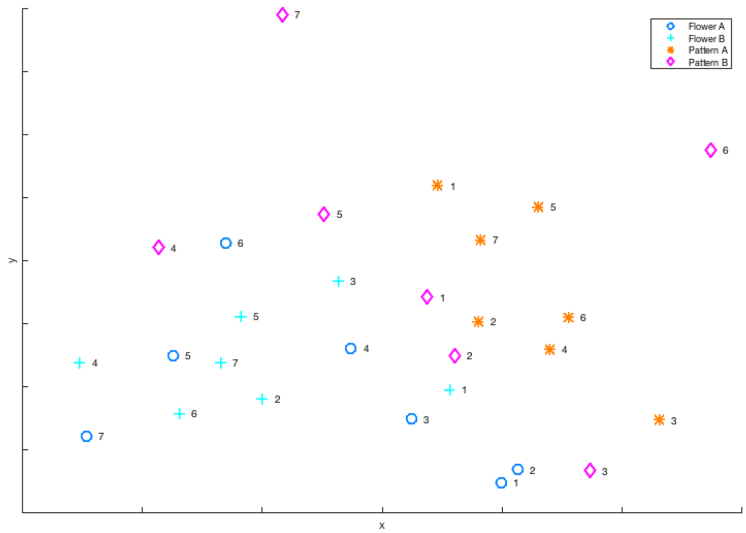
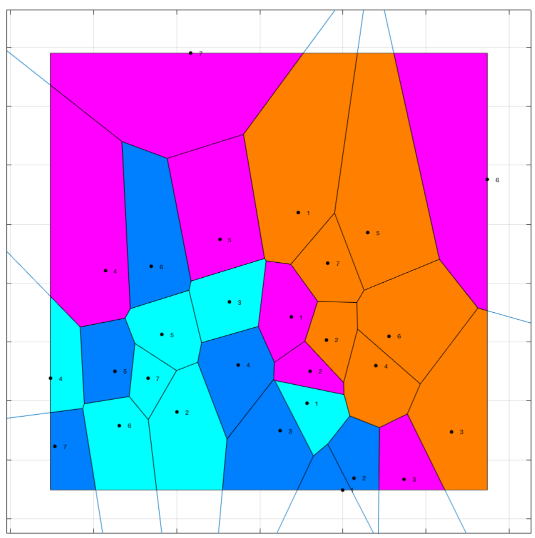


Figure 30: 2D embedding of the sessions, distance based on transitions distributions (k-means analysis).



(a) 2D embedding of the sessions, distance based on sum of both distances (k-means analysis).



(b) The Voronoi's diagram of the previous embedding

Figure 31: 2D embedding of the sessions, distance based on both states and transitions distributions (k-means analysis).

5.2 Discussion of the experiment's results

When embedding the sessions in 2D, there is almost a line separating between the two groups. This suggests that the skilled maker uses the tool differently for each of the two categories. Nevertheless, the two groups do not form two separate clusters, and some of the sessions in each group are closest to sessions in the other category. When projecting them into 1D there is no separation between the two groups.

The two flower reliefs are very different from each other, and thus we find it interesting that the sessions of these two tasks are mixed with each other in the 2D embedding (blue and cyan areas in the Voronoi diagram), and a better separation exists between the two pattern tasks. During the process, the experienced maker decided to give a more freely expressive interpretation to one of the patterns (pattern B, the third task in figure 25), where the other relief is a more classical geometric pattern. This may be the source of the better separation between the two, but this require further experimental work.

An interesting open question is whether the results reflect a change of technique **over time**. As can be seen in figure 28b, sessions in early stages are located in the lower middle-left side of the presented area, and later sessions spread toward the other three corners. This observation does not hold in the same way both for the GMM and k-means analysis (figures 28b, 31b), and it is clearer in the GMM case.

6 Conclusions and Discussion

6.1 Conclusions

During the experimental work, we asked question about both the motor and behavioral skills of makers and the computational possibilities for exploring them. We now summarize our conclusions about both of these aspects. Overall, we conclude that regarding making as a transition between different working states (the discrete view of making) provides a helpful summary of the process, and opens the door for using computational frameworks.

In our experimental work, we perceived different aspects of making: the consistency and individuality of makers, and the affection of different models and sub-techniques to the making process. The results of the first experiment indicate that even novice participants have individual and consistent motor skills, and the results of the second experiment show that an experienced maker apply different motor skills when dealing with two different sub-techniques. These results are not surprising, due to our knowledge of human behavior, but it is satisfying that we can computationally observe them using this framework.

Some of this research's original question were left open, especially the issue of time in the making process. This issue involves many interesting questions, such as the way makers' techniques change over time, or the existence of individual working rates and how to identify them. We believe that further experimentation with our framework can contribute to further understanding of these topics.

A very important open question is the relevance of the aesthetics in the definition and characterization of techniques. In this experimental work, there was no consideration of aesthetics when calculating the principal tool's states. Assuming that a participant has typical motor skills in holding the tool a certain way, is that immediately part of her or his technique? Or can we consider it as such only when aesthetic justification exists? It is not clear that a definitive answer to this question exists, but we believe that the question itself is fundamental, and further work on it may deepen our understanding of the connection between the makers motor skills and the result.

Due to the limited nature of discreteness, any such computational framework cannot fully characterize the entire making process. The main technical advantage of our framework is its simplicity and directness. This simplicity ensures the ability to easily investigate the results of each stage in order to understand their meaning regarding the experiments' original questions. Nevertheless, more sophisticated models may be useful, especially graphical models such as hidden Markov models. We represented the transitions between states in a simple way, but such advanced models may give more delicate observations (and involving aesthetics in the definition of techniques may be helpful).

We believe that these results, conclusions and open questions open the door for further investigation of making and personal style. In the next section, we describe a new approach and future work toward personal style and its dynamic aspects.

6.2 Dynamics of personal style

We suggest a general model for a deeper integration between making, style and aesthetics in HCI. The model emphasizes the dynamic nature of style— that is, that style is a time-dependent entity with multiple aspects. Different influences such as culture or iconography do not get enough attention when digital tools are used to produce visual experiences, and we hope our model will enable and deepen both the understanding and use of style in this context.

We define the maker's *dynamic style* as the set of relevant properties, abilities, and techniques, and the connections between them, while making. This set is dynamic and changes over time. We define the maker's *static style* as a projection of the *dynamic style* at a specific time within the space of aesthetics. Let us clarify the two definitions:

- The *static style* is a temporal interpretation of the maker's aesthetics. It is in some sense what has been referred to in HCI as *style*— a set of visual features connected to some known process or maker.
- The *dynamic style* encompasses all of the aspects that influence the maker's work over time, such as the maker's motor skills, temperament, or set of techniques. We foresee a hierarchical structure of the *dynamic style*, where different aspects depend on each other, alongside the establishment of and changes in personal style. This structure should allow us to add new aspects or change the relations between those that already belong to the model regarding the research of style.

Understanding the exact structure of the *dynamic style* may be difficult. It requires mapping the relevant influences on personal style, the relationships between them, and their dynamics over time. We suggest establishing a model for the *dynamic style* by a series of works, each exploring a specific question. As stated before, style raises physiological, behavioral, cultural and metaphysical questions, yet in this work we focus on questions regarding style and skill. We detail these questions for further investigation in the next section.

We end this section by clarifying how certain terms are used in this work. These definitions are specific to the scope of this work, and other interpretations exist.

- *Motor* relates to the individuals' typical muscular movements.
- *Technique* is the ability and way of performing a specific physical task.
- *Skill* is the ability and way of managing a process in a desired way.
- A sculpting *tool*, or *tool* refers to a simple material-manipulating tool. It includes all long, hand-held tools such that material is manipulated by the end of the tool.

6.3 Establishing the dynamic style

We now specify directions for further investigation of the dynamic style. First, we elaborate on general topics and give a short explanation of each. These topics aim to deepen understanding of the connections between motor, technique, and skill, and the role of these elements in the maker's personal style. We then derive a set of specific questions for further investigation.

I. The connection between time and style.

Time is of great importance for understanding makers, and different aspects of their style arise over different timescales. Over very short timescales, we can perceive highly specific details, such as the way the maker holds the tool. Over longer timescales, we may perceive meaningful changes in the general use of such a tool or a set of techniques. If we continoue on like this, we lose small details but get a general overview of the maker. Such different elements from different timescales are connected to each other, and a model of style should allow for some versatility over time.

II. The connection between style, technique and skill.

The maker's motor skills are an essential part of her or his making process, and a source of both confidence and uncertainty. Examples of skilled artists who know that "the hand will go exactly to the right place", as well as skilled artists who overcome great physical disabilities, exist. This suggests that the correlation between technique and motor skills is not given but dynamic and evolves over time. For example in the second part of this text, we presented two experiments regarding the motor skills of experienced and inexperienced makers while sculpting. Such experimental work may results in transitions matrix between different motor states that encodes the maker's techniques.

III. The maker's perception, image and aesthetics.

It is not only technique that evolves over time, but also the maker's mind and set of mental images. Some makers change them radically throughout their life, while others stay relatively consistent. The source of such changes may lie in a mental shift connected to experiencing the world and creating a visual form for such experiences. Thus it is worth exploring the connections between the makers' mental states and the sets of images and aesthetics used in their work.

IV. Relationship between cultural and personal aesthetics.

As previously noted, it is known that cultural style affects personal style and vice versa. It is clear that cultural style may limit the aesthetics of the individual, and that personal style enriches cultural style. Yet as Wobst suggested, the relationship between the two is more complex: cultural style has the power to simultaneously limit and encourage individuality. Although makers are individuals, they are also part of and interact with communities and other social structures.

In order to explore these topics, we suggest considering these specific issues:

- Do novice makers display a consistent and unique set of techniques when learning a new artistic technique?
- Do experienced makers display a consistent and unique set of techniques when learning a new artistic technique?
- How does a sculptor's technique and skill change over a long-term artistic process?
- In what way are master makers (not) consistent between different artistic techniques?
- What features are essential when exploring the maker's personal style?

- Is motor essential for characterizing the makers aesthetics?
- Does iconography affect a novice maker's motor or technique during the making process?
- Does iconography affect an experienced maker's motor or technique during the making process?

Other questions regarding different aspects of personal style will be suggested in future works.

References

[1] S. Alpers. Style is what you make it: the visual arts once again. *The concept of style*, pages 137–62, 1979.

[2] R. Arisandi, Y. Takami, M. Otsuki, A. Kimura, F. Shibata, and H. Tamura. Enjoying virtual handcrafting with tooldevice. In *Adjunct proceedings of the 25th annual ACM symposium on User interface software and technology*, pages 17–18. ACM, 2012.

[3] C. Bishop. *Pattern recognition and machine learning.* New York: Springer, 2013.

[4] S. Cho, Y. Heo, and H. Bang. Turn: a virtual pottery by real spinning wheel. In *ACM SIGGRAPH 2012 Emerging Technologies*, page 25. ACM, 2012.

[5] S. Cobbledick. The information-seeking behavior of artists: Exploratory interviews. *The Library Quarterly*, 66(4):343–372, 1996.

[6] M. W. Conkey and C. A. Hastorf. *The uses of style in archaeology.* CUP Archive, 1993.

[7] D. J. Cook, M. Schmitter-Edgecombe, and P. Dawadi. Analyzing activity behavior and movement in a naturalistic environment using smart home techniques. *IEEE journal of biomedical and health informatics*, 19(6):1882–1892, 2015.

[8] L. Devendorf and K. Ryokai. Being the machine: Reconfiguring agency and control in hybrid fabrication. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 2477–2486. ACM, 2015.

[9] H. Edgerton. Harold ”doc” edgerton — the edgerton digital collections project. `https://edgerton-digital-collections.org/`.

[10] A. Elgammal, M. Mazzone, B. Liu, D. Kim, and M. Elhoseiny. The shape of art history in the eyes of the machine. *arXiv preprint arXiv:1801.07729*, 2018.

[11] A. W. Foster and J. R. Blau. Art and society. *Readings in the Sociology of the Arts, New York*, 1989.

[12] B. Franz. *Primitive art.* Courier Corporation, 1955.

[13] E. Gandon, R. J. Bootsma, J. A. Endler, and L. Grosman. How can ten fingers shape a pot? evidence for equivalent function in culturally distinct motor skills. *PLOS one*, 8(11):e81614, 2013.

[14] L. A. Gatys, A. S. Ecker, and M. Bethge. A neural algorithm of artistic style. *arXiv preprint arXiv:1508.06576*, 2015.

[15] K. Glazek. Visual and motor processing in visual artists: Implications for cognitive and neural mechanisms. *Psychology of Aesthetics, Creativity, and the Arts*, 6(2):155, 2012.

[16] E. H. Gombrich. *The story of art*, volume 12. Phaidon London, 1995.

[17] Google. Tilt brush by google. `https://www.tiltbrush.com/`.

[18] M. Hegmon. Archaeological research on style. *Annual Review of Anthropology*, 21(1):517–536, 1992.

[19] A. A. Helm. Franz Boas and Bronislaw Malinowsky: a contrast, comparison, and analysis. *Lambda Alpha Journal of Man*, 2001.

[20] Y. Hoshen and S. Peleg. An egocentric look at video photographer identity. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4284–4292, 2016.

[21] G. Howard. *The Arts and Human Development: With a New Introduction by the Author*. Basic Books, 1994.

[22] L. Kaufman and P. J. Rousseeuw. *Finding groups in data: an introduction to cluster analysis*, volume 344. John Wiley & Sons, 2009.

[23] C. Kenneth. *Civilisation*. Hachette UK, 2015.

[24] F. S. Khan, J. van de Weijer, and M. Vanrell. Who painted this painting. In *2010 CREATE Conference*, pages 329–333, 2010.

[25] A. Kozbelt. Artists as experts in visual cognition. *Visual Cognition*, 8(6):705–723, 2001.

[26] A. L. Kroeber. *Anthropology today: an encyclopedic inventory*. Chicago: University of Chicago Press, 1953.

[27] J. E. Kyprianidis, J. Collomosse, T. Wang, and T. Isenberg. State of the "art: A taxonomy of artistic stylization techniques for images and video. *IEEE transactions on visualization and computer graphics*, 19(5):866–885, 2013.

[28] M. T. Lapinski and J. A. Paradiso. *A Platform for High-Speed Biomechanical Analysis Using Wearable Wireless Sensors*. PhD thesis, Citeseer, 2013.

[29] LunaPic. Free online photo editor — Van Gogh. `https://www140.lunapic.com/editor/?action=vangogh`.

[30] B. Malinowski. *Argonauts of the Western Pacific: An Account of Native Enterprise and Adventure in the Archipelagoes of Melanesian New Guinea [1922/1994]*. Routledge, 2013.

[31] matlab. *cwt*, 2018. `https://www.mathworks.com/help/wavelet/ref/cwt.html`.

[32] A. Mordvintsev, C. Olah, and M. Tyka. Inceptionism: Going deeper into neural networks. *Google Research Blog. Retrieved June*, 20(14):5, 2015.

[33] R. S. Nelson and R. Shiff. *Critical terms for art history*. University of Chicago Press, 2010.

[34] T. El Or. *Sandals, The anthropology of Local Style*. Am Oved, Tel-Aviv, 2014.

[35] Polhemus. *3SPACE® FASTRAK® USER MANUAL*, 2012. `https://polhemus.com/_assets/img/FASTRAK_User_Manual_OPM00PI002-G.pdf`.

[36] J. Rigau, M. Feixas, and M. Sbert. Informational dialogue with Van Gogh's paintings. In *Proceedings of the Fourth Eurographics conference on Computational Aesthetics in Graphics, Visualization and Imaging*, pages 115–122. Eurographics Association, 2008.

[37] R. Sablatnig, P. Kammerer, and E. Zolda. Hierarchical classification of paintings using face- and brush stroke models. In *Pattern Recognition, 1998. Proceedings. Fourteenth International Conference on*, volume 1, pages 172–174. IEEE, 1998.

[38] B. Saleh, K. Abe, R. S. Arora, and A. Elgammal. Toward automated discovery of artistic influence. *Multimedia Tools and Applications*, 75(7):3565–3591, 2016.

[39] R. Shilkrot, P. Maes J. A. Paradiso, and A. Zoran. Augmented airbrush for computer aided painting (cap). *ACM Transactions on Graphics (TOG)*, 34(2):19, 2015.

[40] N. Shourie, M. Firoozabadi, and K. Badie. Analysis of EEG signals related to artists and nonartists during visual perception, mental imagery, and rest using approximate entropy. *BioMed research international*, 2014, 2014.

[41] R. L. Solso. Brain activities in a skilled versus a novice artist: An fMRI study. *Leonardo*, 34(1):31–34, 2001.

[42] A. Stevenson. *Oxford dictionary of English.* Oxford University Press, USA, 2010.

[43] P. Wiessner. Style and social information in Kalahari San projectile points. *American antiquity*, 48(2):253–276, 1983.

[44] P. Wiessner. Reconsidering the behavioral basis for style: A case study among the Kalahari San. *Journal of anthropological archaeology*, 3(3):190–234, 1984.

[45] E. Winner and C. M Beth. 10 cognitive profiles of artists. *Emerging visions of the aesthetic process: In psychology, semiology, and philosophy*, page 154, 1992.

[46] A. Zoran, R. Shilkrot, S. Nanyakkara, and J. Paradiso. The hybrid artisans: A case study in smart tools. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 21(3), 2014.