**SculptStat: Statistical Analysis of Digital Sculpting Workflows**

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Figure 1: Models analyzed in the paper. Expert artists create the models with the specified number of strokes.

Abstract

Targeted user studies are often employed to measure how well artists can perform specific tasks. But these studies cannot properly describe editing workflows as wholes, since they guide the artists both by choosing the tasks and by using simplified interfaces. In this paper, we investigate digital sculpting workflows used to produce detailed models. In our experiment design, artists can choose freely what and how to model. We recover whole-workflow trends with sophisticated statistical analyzes and validate these trends with goodness-of-fits measures. We record brush strokes and mesh snapshots by instrumenting a sculpting program and analyze the distribution of these properties and their spatial and temporal characteristics. We hired expert artists that can produce relatively sophisticated models in short time, since their workflows are representative of best practices. We analyze 13 meshes corresponding to roughly 25 thousand strokes in total. We found that artists work mainly with short strokes, with average stroke length dependent on model features rather than the artist itself. Temporally, artists do not work coarse-to-fine but rather in bursts. Spatially, artists focus on some selected regions by dedicating different amounts of edits and by applying different techniques. Spatio-temporally, artists return to work on the same area multiple times without any apparent periodicity. We release the entire dataset and all code used for the analyzes as reference for the community.

1 Introduction

Content Creation. The human effort necessary to create 3D digital content is crucial in improving modeling workflows. User studies are employed to measure the performance of artists when performing creation tasks. The majority of these studies though are designed to validate particular algorithms rather than to characterize workflows as a whole.

SculptStat. In this paper, we statistically characterize digital sculpting workflows by analyzing artists’ behavior as they freely sculpt organic models. In sculpting, artists alter the model’s geometry by adopting an approach that is similar to clay sculpting, modifying parts of the model (i.e., vertices) using a set of different tools, whose effects span from minor surface modifications (like smoothing) to moving or extruding whole parts of the model. We chose to investigate sculpting since it is often used to define the shape of organic objects, such as characters, and since we are not aware of comprehensive user studies on this subject. We focus on detailed models, rather than simple edits, where overall workflow characteristics become apparent. Our experimental methodology is in stark contrast with most published literature in graphics, e.g. [Kerr and Pellacini 2009; Kerr and Pellacini 2010; Jarabo et al. 2014].

Experiment. We avoid using targeted experiments that would be limited to only a few aspects of sculpting and therefore provide no insight in the workflow as a whole. Instead, we let artists choose freely what to model and how. We only ensure that the chosen models span different types (head, bust, body), and that artists work both from scratch or base meshes. We analyze the data with sophisticated statistical methods that let us interpret this heterogeneous data. In contrast, most prior work guides artists with short tasks that have simple goals, requiring a relatively unsophisticated analysis. But workflows cannot be characterized with this data alone.

To keep datasets and analysis to a manageable size, we characterize workflows across model types, leaving inter- and intra-artist investigations to future work. Furthermore, we do not know how to...
We statistically characterize digital sculpting workflows when modeling organic characters. Within this model category, we let users freely choose what and how to model. Fig. 1 shows the models created for this paper. Tab. 1 summarizes statistics for the models. In general, we asked subjects to model organic characters of their choosing, spanning a variety of techniques using Blender. We considered heads, busts and full-bodies modeling, starting from scratch or using base meshes. Base meshes are shown in supplemental. Artists sculpted using subdivision modeling or dynamic topology [Stanculescu et al. 2011]. Models took between 29 minutes and 4 hours to create.

Subjects. We hired two experts to produce the models in this paper. We choose experts since they can create sophisticated models...
in relatively short time, without guidance in the experiment and interface. To limit the experiment to a manageable size, one can choose to either pick many subjects, each of which creates a model, or focus on a few subjects that create many models. We choose the latter since we wanted to establish a statistical methodology to characterize workflows from “freely-captured” data, validated across model types, rather than investigating inter- or intra-subject analysis. We chose subjects that are known in their community and are accomplished instructors. Their workflows are representative of best practices and what others are taught to do. Note that this practice is accepted in statistics.

Captured Data. We instrumented Blender to store all user actions and save mesh snapshots after each stroke. The instrumentation is fast enough to leave workflow unaffected. The models in this paper were created with between 816 and 4210 brush strokes and between 225 and 956 camera changes. This number of strokes is sufficient for detailed models. All models were created with mirrored strokes, and overall model size was left to the artists. We focus our analysis on the strokes since camera changes have been considered in [Chen et al. 2014].

Brush Types. We consider two groups of brush types: on-surface and freeform. For on-surface brushes, the interface determines the 3D position of a stroke point by projecting the 2D mouse location on the mesh. For freeform strokes, the 3D position is derived by the 2D mouse location by moving the point on a plane parallel to the camera. On-surface brushes are typically used to push or pull vertices along the surface normals or to add or remove volume like clay sculpting. Freeform brushes are mostly used to extrude new parts of the model or to apply freeform deformation to large areas.

Mesh Distances. In general, there is no simple relation between brush and stroke parameters and the corresponding mesh difference [Angelidis et al. 2006]. To measure the magnitude of the effect of a stroke, we compute the Hausdorff distance between the mesh before and after the stroke was applied, using [Cignoni et al. 1998]. We chose this metric since it correlates well (with an average Pearson’s $r = 0.99$, computed with a Fisher $z$ transformation of the individual $r$ of each model) with a simple estimate of stroke effect, computed as the product of stroke length, brush size and average pressure.

Reproducibility. To aid in further analysis, the supplemental material includes all captured data (strokes and meshes distances), the code used to perform the analysis, and detailed per-model diagrams.

4 Analysis: Overall Trends

We perform various types of analysis on stroke data and mesh distances. For each analysis, we qualitative illustrate trends using diagrams, and perform statistical estimation of model parameters and quality of fits. We include in the paper only representative diagrams, but provide all diagrams in supplemental. Tab. 2 summarizes the findings discussed in this section, shown in Fig. 3. We analyze features separately since we did not find significant correlation between them, but we included scatterplots for all the brush attributes analyzed, in supplemental.

Brush Type. For all models in the paper, on-surface strokes account for the majority of interactions, with no significant difference between model types. We believe that this can be easily interpreted considering that free form strokes are used for extrusions
and freeform deformations, two global operations that are rare. Furthermore, the statistics of on-surface and freeform strokes are close enough that we analyze them together and only highlight differences when present.

**Methodology.** For all brush attributes and mesh differences, we determine the theoretical distribution that best describe the data by choosing the best fitting model. We report mean or standard deviation of the process to quantitatively characterize it. We consider several well-known distributions (Normal, Log-normal, Student’s T, Cauchy, Inverse gaussian, as well as other main theoretical distributions), that maximizes the log-likelihood of the input given the set of parameters. We measure the goodness of fit with \( \chi^2 \) tests [Chernoff and Lehmann 1954]. We select the best distribution by picking the one with highest \( \chi^2 \) amongst the ones with high \( p \)-values (\( > 0.05 \)), minimizing distribution complexity (i.e.: number of parameters).

**Stroke Length.** The distributions of stroke lengths, shown in Fig. 3 are peaked near zero with long tails. This indicates that artists work mostly with quick and short strokes, but perform a good number of longer ones as well. For all models, stroke length is described best by an inverse gaussian distribution. The inverse gaussian, as a member of the exponential distributions' family, is well suited for extremely peaked data, also allowing for extreme values. The average stroke length differs for each model, since models have arbitrary scale. We observed that the mean length is related to model features: eyes and mouth’s width for heads, neck length and diameter for busts and arms and legs for full-bodies. The maximum stroke length exceed the model diagonal. This suggest that artists perform long straight strokes to adjust specific features, but also stroke back and forth on the same area, mainly for smoothing or texturing purposes. We will consider these two behaviours later.

**Brush Size.** The distributions of brush sizes, shown in Fig. 3 have similar shape to those of strokes’ length, that can be described well with an inverse gaussian distribution. Similarly to the length, artists work the majority of their time with small-sized brushes. In this case though, the tails have a less homogeneous descending trend, with smaller peaks along the whole tail itself. This latter observation can be explained if we consider that artists usually work for relatively long time spans at fixed camera and 2D brush size. The resulting brush size projected over the model are thus relatively similar, forming small peaks in the distributions. The average size is related to models’ features, but at a smaller scale compared to brush lengths: wrinkles and veins for the heads, eyes and ears for busts, hands and shoulders for full-body. The maximum size can reach the dimension of the whole model, and it usually happens with the use on freeform brushes when adjusting the proportion and the main structure of the whole model.

**Stroke Angles.** A useful feature to describe the stroking behaviors is the average angle between subsequent segments in a stroke \( \alpha_{12} = \arccos (\vec{s}_{e1}, \vec{s}_{e2}) \). We compute the angle projected in the camera plane since this is aligned with the mouse movements. In this case the fitting process was less obvious, as these distributions show (Fig. 3) two main peaks at 0 and \( \pi \). A deeper analysis showed that most of the strokes with broader angles were done with freeform brushes, demonstrating how artists favor long straight strokes for this kind of brushes. This is in opposition for what we observed analyzing angles for on-surface brushes. These distributions, which also in this case resulted to be better fitted by inverse gaussians, peak at zero, with long tails that only show a slow in-

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**Table 1: Statistics on the models used in the paper: name, interaction time, number of strokes and camera movements and model size (estimated as bounding box diagonal).**

| Model   | Artist | Time  | Strokes | Camera | Size    |
|---------|--------|-------|---------|--------|---------|
| alien   | A      | 1h12m | 2135    | 660    | 4.8841  |
| elder   | A      | 1h24m | 3062    | 519    | 18.1198 |
| ogre    | A      | 0h35m | 1435    | 324    | 20.0907 |
| merman  | B      | 0h58m | 2245    | 714    | 4.9031  |
| man     | A      | 1h11m | 1476    | 462    | 4.3839  |
| monster | B      | 0h40m | 816     | 492    | 6.8777  |
| sage    | A      | 1h04m | 1697    | 793    | 4.9185  |
| fighter | A      | 2h21m | 1551    | 459    | 2.0678  |
| gargoye | B      | 0h29m | 835     | 225    | 10.5912 |
| gorilla | B      | 3h43m | 2609    | 956    | 12.3074 |
| explorer| B      | 4h00m | 1700    | 808    | 17.2768 |
| engineer| A      | 0h54m | 844     | 785    | 2.0379  |
| elf     | B      | 1h37m | 4210    | 782    | 5.6241  |
creasing trend towards the end, although only accounting for less than 5% of the whole distribution. This indicates a strong preference for stroking back-and-forth in this kind of brushes, with a smaller percentage of long straight strokes.

**Stroke Pressure.** Strokes’ pressure distributions, shown in Fig. 3 are described well by gaussians, but with mean and standard deviation that differ significantly between on-surface and freeform brushes. On-surface brushes are used with a higher pressure mean and variance, demonstrated also by an higher index of dispersion on the distribution ($\text{iod} = 0.119$). On the other hand, freeform strokes are performed with less pressure, ranging in a statistically smaller spectrum of values ($\text{iod} = 0.051$). This supports the above observations that on-surface brushes are used for longer but detailed strokes, while freeform brushes are for quick but large adjustments.

**Mesh distances.** Hausdorff distances were fitted similarly to strokes’ length and brush size, using inverse gaussian distributions. We don’t supply any further interpretation for this data, as we think that the similar distributions’ behaviour supports the correlation measures presented in the previous section, thus reinforcing the conclusions presented above for those two attributes.

**Interpretation.** Before running the experiment, we expected lengths’ and sizes’ distributions to be gaussians, where artists naturally pick comfortable-to-perform strokes and work by repeating them throughout the model. The data supports a different interpretation. Most strokes focus on adjusting specific model features, where artists pick stroke lengths and brush sizes appropriate to the features’ sizes. This also partially explains the long tails, supporting the use of longer strokes that cover whole features (e.g.: eye vs. leg in a full body model). Artists also use quick taps, of length near zero, to precisely refine small features with on-surface brushes, or adjust the main proportion of the model with large freeform brushes, i.e. moving the whole head or an arm. Artists often perform back-and-forth strokes on the same area with on-surface brushes, usually for smoothing or texturing purposes. This suggest that to precisely control surface features, repeating simple strokes is easier than precisely configuring brush parameters or controlling tablet pressure.

5 Analysis: Temporal Trends

After analyzing global trends, we focus on their temporal aspects, by considering brush attributes and mesh differences over time as if they were time series, with the temporal progression given by the sequence of snapshots. Tab. 3 summarizes the results of our analysis.

**Exponential Smoothing.** To gain insights on temporal behaviors, we perform exponential smoothing to remove noise from the data [Prus et al. 2014]. We chose exponential smoothing over moving average since the former can provide a finer approximation of the series, giving more information on how the values are changing timely, that would instead be smoothed out by a simple moving average. Fig. 4 shows a representative diagram, while the remaining are included in supplemental. The diagrams show that neither brush attributes nor mesh differences have visible trends other than a repeating shocks without periodicity. We formalize the observations by modeling the temporal trends with an autoregressive moving average (ARMA) process [Whittle 1951], following the Box-Jenkins method [Box and Jenkins 1990]. First, we validate stationarity by visual comparison of autocorrelation plots with ARMA’s theoretical ones and by performing an augmented Dickey-Fuller test for unit root detection (test results are shown in Tab. 3). Second, we estimate the model’s parameters $p$ (order of the autoregressive part of the model) and $q$ (order of the moving average part of the model) with maximum likelihood estimation by optimizing the Akaike information criterion of the model given our data [Brockwell and Davis 1991]. Third, the goodness of fit was established analyzing the autocorrelation plot of the residual of the fitted values, performing a Ljung-Box Q test on them. Tab. 3 summarizes values of this procedure. As can be seen, ARMA fits our data very well, corroborating our qualitative observations.

**Hidden Markov Model fitting.** To better understand this bursting behavior, we fitted a Hidden Markov Model on the time series. We treated the bursts as one of the states in which the artist could work (e.g.: editing sparsely along the whole model versus focusing on a single area). The parameters of the HMM were fitted using an expectation-maximization approach, iteratively increasing the number of states of the model at each run. The metric used to evaluate the goodness of fit is the Bayesian Information Criteria: the fitting process was stopped when the BIC value of the new estimated model didn’t suggest any significant improvement from the previous one. A representative example of the trained HMMs is given in Fig. 4. In the estimated models, all states are characterized with higher probability of remaining in the same state, rather than transition to another one. States differ mainly in variance and transition probabilities distribution, where states with higher variance have also less probability to remain in the same state.

**Interpretation.** Before running this experiment, we expected artists to work in a coarse-to-fine manner, starting by roughly defining the whole model and proceeding with gradual refinements of increasingly smaller magnitude. Our analysis demonstrates a completely different workflow. Artists mainly work in bursts of activity, alternating periods of refinement and addition of small features to bigger and broader changes. Also, they don’t complete a single part of the model before working on another one, but instead going back and forth over the whole model during the bursts, often returning on the same parts.

### Table 3: Summary statistics of temporal distributions. Refer to the text for metric definitions.

|          | ADF test p | q | Q test | Peaks |
|----------|------------|---|--------|-------|
| alien    | -14.08     | 2 | 1      | 64.9  | 15   |
| elder    | -16.22     | 4 | 1      | 282.13| 15   |
| ogre     | -14.34     | 1 | 1      | 58.95 | 12   |
| merman   | -18.02     | 2 | 1      | 97.76 | 12   |
| man      | -12.62     | 3 | 2      | 162.36| 13   |
| monster  | -9.17      | 2 | 2      | 31.79 | 7    |
| sage     | -11.92     | 2 | 1      | 63.29 | 11   |
| fighter  | -12.9      | 4 | 2      | 94.64 | 7    |
| gargoyle | -8.94      | 2 | 1      | 64.37 | 5    |
| gorilla  | -15.59     | 4 | 2      | 94.23 | 18   |
| explorer | -15.74     | 4 | 2      | 72.74 | 8    |
| engineer | -8.31      | 3 | 1      | 30.59 | 3    |
| elf      | -17.06     | 4 | 1      | 76.92 | 35   |

6 Analysis: Spatial Trends

After investigating the temporal characteristics of sculpting, we focus on determining how brush attributes and mesh differences be-
|                  | Length | Size  | 2D angles | Hausdorff | Pressure | Density |
|------------------|--------|-------|-----------|-----------|----------|---------|
|                  | Avg    | Std   | Avg       | Std       | Avg      | Std     |
| alien            | 1.0472 | 1.6566| 0.1028    | 0.0951    | 0.2632   | 0.6206  |
| elder            | 1.7489 | 2.2930| 0.1915    | 0.1267    | 0.2321   | 0.5691  |
| ogre             | 3.3956 | 4.8483| 0.5356    | 0.4619    | 0.1909   | 0.6191  |
| merman           | 0.7547 | 0.9524| 0.0744    | 0.1026    | 0.1683   | 0.5192  |
| man              | 0.7886 | 1.4821| 0.0441    | 0.0375    | 0.2563   | 0.5812  |
| monster          | 2.9010 | 5.2696| 0.1525    | 0.2602    | 0.2404   | 0.6228  |
| sage             | 0.7832 | 1.4256| 0.0906    | 0.0951    | 0.1708   | 0.5702  |
| fighter          | 0.2588 | 0.3811| 0.0154    | 0.0078    | 0.2556   | 0.6502  |
| gargoyle         | 2.0315 | 5.2696| 0.1525    | 0.2602    | 0.2404   | 0.6228  |
| gorilla          | 3.4470 | 6.7520| 0.5274    | 0.3506    | 0.2777   | 0.6792  |
| explorer         | 3.9406 | 8.5568| 0.3808    | 0.6716    | 0.2486   | 0.6567  |
| engineer         | 0.7763 | 1.1086| 0.0184    | 0.0266    | 0.2282   | 0.6596  |
| elf              | 0.4032 | 1.4723| 0.1774    | 0.1246    | 0.4386   | 0.7797  |

**Table 2:** Summary statistics of parameter distributions.

![Figure 4](image_url)  
**Figure 4:** Stroke length and brush size for monster model plotted over time. Exponential smoothing is performed to reduce noise. Parameter values are colored according to their hidden Markov state. We highlight relevant peaks with vertical lines.

![Figure 5](image_url)  
**Figure 5:** Stroke density rendered over the mesh as reference. Red to yellow indicate low to high density.
The temporal analysis shows that artists don’t proceed in coarse-to-fine fashion, but alternate longer phases of small localized ad-
justments with phases of broader edits involving larger parts of the model. The spatial analysis shows artists’ tendency to concentrate on selected areas of the model. We now investigate the spatio-temporal relationship between edits.

**Spatio-Temporal Clustering.** To explore this behavior, we cluster strokes taking into account spatial (strokes’ centroids), non-spatial (path length, brush size, and mesh difference) and temporal (stroke time) information. To properly account for all information above, we used the ST-DBSCAN algorithm [Birant and Kut 2007], a density-based clustering method. The density-based component of the algorithm allows clusters to have any shape spatially. Temporal distance is accounted for with a moving window. All other properties are treated as a vector of floating point attributes. This kind of clustering is particularly useful in our context, because it can adapt well on non-flat geometries and uneven cluster sizes. Our data has these characteristics since strokes follow models’ shapes.

Fig. 7 shows clustered strokes and Fig. 8 shows representative results of the clustering properties plotted over time. Clusters overlap on the same mesh regions, indicating that artists work on the same regions at different times. Each time, brush properties stay similar within the activity burst, and artists stay on the region for a while before switching to another one. From the temporal plots we can see that stroke attributes are temporally related to the clusters.

**Interpretation.** The latter three analyses provide us with a clear picture about artists workflow. During sculpting, artists start focusing on some areas, dedicating them a good amount of work, then moving to a phase of adjustments and eventually coming back to the same spots for finer edits.

## 8 Discussion and Limitations

**Methodology.** Throughout the paper we employed a variety of state-of-the-art statistical methods to study digital sculpting behavior in an unguided experiment. The large dataset used (roughly 25000 strokes/mesh snapshots) allows us to extract statistically sig-
nificant trends even from “free-form” data. In particular, overall trends and spatio-temporal behaviors would not have been possible to measure with targeted experiments, since they bias artists and they generally use smaller datasets.

**Results.** We summarize here the main findings of our analysis.

1. A relatively small number of strokes is sufficient to create rel-
atively detailed models.
2. Brush parameters are changed rarely, indicating that artists prefer simple brushes used repeatedly than configuring com-
plex brush precisely.
3. Strokes length, brush size and mesh differences are described well by inverse gaussian distributions, made mostly of short strokes, but with a thick tail of longer strokes.
4. The average of stroke length and brush size is related to model features, suggesting that artists change their stroke patterns to adapt their workflow to the model.
5. Strokes are either very short for precise transformations, medium length and straight to follow a feature, or long with repeated back-and-forth movements for controlling surface “texture”.
6. Temporally, artists do not work in a coarse-to-fine fashion, but in bursts of activity on different parts of the mesh.
7. Temporal behavior is stationary with no significant periodic-
ity.
8. Bursts can be modeled as states in a hidden Markov model where they are stable, in that artists work in these states for a while before transitioning to another one.
9. Spatially, artists focus on some selected regions by dedicating different amounts of edits and by applying different techniques.
10. Strokes’ parameters are correlated with spatial location, proving that artists use different techniques on different parts of the mesh.
11. Bursts can be modeled as spatio-temporal clusters, showing that artists return on the same model region multiple times to perform different techniques.
12. Spatio-temporal clusters prove that a coarse-to-fine pattern in not present even locally.

Limitations: Experiment Size. As with all user studies, limitations often depend directly on experiment size in that more questions can be answered by increasing the number of subjects and workflows. For this work, the main limitation of this type is that we do not perform inter-subject analysis. The simple motivation for this is data scale. The dataset in this experiment takes roughly 100 GB to store compressed. The most complex analysis we performed took several hours of computation per mesh. We estimate that roughly 100 times more data would be needed for a statistically significant inter-subject analysis, but only if models choices are not left to subjects. This break our first desiderata. For these reasons, we did not perform this analysis. While it is possible that the conclusions of this work and the introduced methodology can be used to design a targeted experiment for inter-subject analysis, it remains unclear how to avoid the bias introduce by guidance. So we leave this investigation to future work. Similarly, we do not consider novice users, mainly since it remains unclear that users can model detailed meshes without training. It would still be interesting though to see whether simplified sculpting interfaces can be useful to such users. For this though, we would suggest an experiment design similar to [Jarabo et al. 2014].

Limitations: Exploratory Analysis. Throughout the paper we took the approach of interrogating data in an exploratory manner, rather than testing specific hypothesis of workflows characteristics. We tried the latter, but failed since we found that many hypothesis about artists behaviors made watching videos or discussed in the literature were not supported by the data. For example, coarse-to-fine trends are cited in most graphics literature. On the other hand, it is certainly useful to be able to answer very specific question doing hypothesis testing. For this very reason we release all our data.

Impact. We believe that a scientific characterization of content creation tasks is necessary to advance in this topic, now that our field is more mature. This paper is just a first step in doing it, producing statistically valid results for a specific creation task, namely sculpting. The impact of our work is twofold. First, using this data current interface might be improved. For example, it is clear that highly configurable brushes are not particularly useful since artists consistently prefer to use simpler settings with more strokes, since these provide better control. Note though that this is the opposite trend of many packages now. Second, artists routinely change models pro-
portion significantly after details have been created. This suggests the need for detail-preserving transformations that alter the mesh while maintaining its “texture” intact. Today, soft transformations deform details too significantly, leading to resculpting. More importantly, though we believe that the main impact of this work is our methodology that can be applied to other content creation tasks, such as material painting, environment-map lighting, and keyframe animation, etc.

9 Conclusions and Future Work

In conclusion, we present a methodology to statistically characterize 3D content creation workflows and apply it to investigate digital sculpting. We analyze the creation of several meshes, both from scratch and from base meshes. We use statistical methods to extract trends in the underlying data and ensure that such trends are significant. We plan to use a similar methodology for investigating other content creation tasks as future work.

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