# Click&Draw Selection

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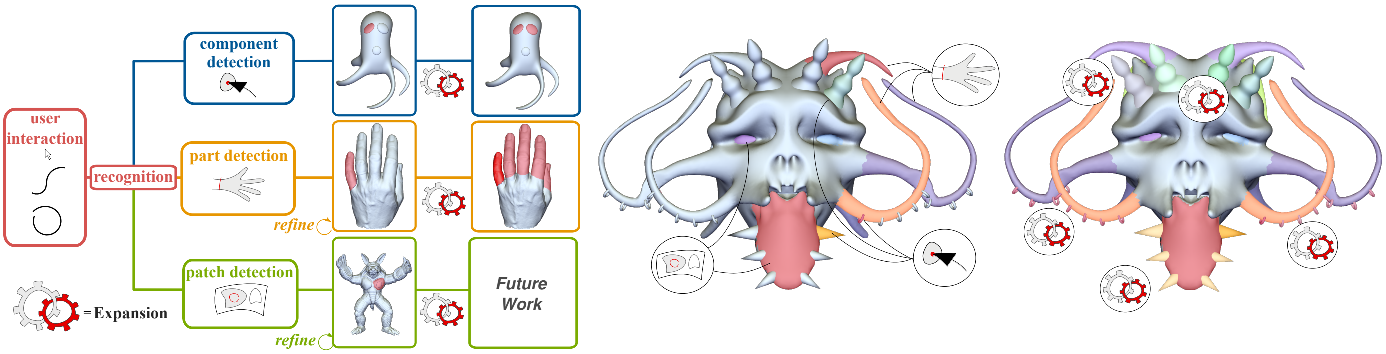


**Figure 1:** ***Left:*** *click&draw overview.* ***Middle:*** *user selection.* ***Right:*** *results.*

## 1 Introduction

In interactive shape modeling, surface selection is one of the basic, cornerstone interaction: this task may be performed hundreds of times by the user for the modification of a single shape. Despite the numerous automatic selection methods introduced in the literature, this remains a cumbersome operation in a number of scenarios, where the user is ultimately asked to paint over everything she wants to select. Without imposing a full visual grammar, we observe that a more effective selection process can be designed around a simple classification of the user interaction: *point click*, *open* and *close strokes*. Our basic idea is to relate this simple classification to a specific set of selection algorithms, targeting the three main classes of surface selections: *connected components*, *parts* and *patches*. We also address the problem of repetitive similar selections by providing an automatic *expansion* process which captures regions which are detected as similar to the selected one.

## 2 User Interaction & Selections

We state that the interaction should carry more or less information based on "how evident" the selection is for the user. Based on this simple observation, our tool classifies user interactions from a single click to multiple strokes and matches each of them with a particular selection algorithm. Connected components are selected by point clicks, parts (resp. patches) by open (resp. close) strokes.

**Connected Component Selection :** When loading the mesh we perform a flood filling algorithm to link each face with it connected component. When the user clicks on a triangle, we simply select all the faces which have the same component number.

**Patch Selection :** We compute a principal component analysis on the user stroke to find a local frame $F_c$. This frame is used to roughly classified faces as selected, not selected, or unclassified. Then a flood filling algorithm, started from the selected faces and driven by a normal-based metric, sets all unclassified faces as selected or not. We evaluated a panel of different metrics, and eventually found that the $L_{2,1}$ distance [Cohen-Steiner et al. 2004] and the $L_{cross}$ distance [Zheng and Tai 2010] give the best results.

**Part Selection :** Isolines of a harmonic field, guided and progressively refined by user strokes, are used as cutting boundaries for the selection of a part. The field is obtained as the solution of the following system:

$$\begin{bmatrix} L \\ \hline W_0 P_0 \\ W_1 P_1 \end{bmatrix} \Phi = \begin{bmatrix} 0 \\ \hline W_0 B_0 \\ W_1 B_1 \end{bmatrix}$$

where $L$ is the mesh Laplacian (cotan scheme), $W_0$ and $W_1$ are positional weighting matrices, $P_0$ and $P_1$ are positional constraints matrices, $B_1 = (1..1)^T$ and $B_0 = (0..0)^T$.
We set 0 and 1-constraints on each side of the user stroke. The system is factorized only once when the mesh is loaded. Then we update it only from the few dynamic constraints during interaction. To handle meshes with multiple connected components, we set 0-constraints on all the components not touched by the stroke.

## 3 Expansion

To find similar connected component selections, we compute the area of each component and select the closest ones to the selected reference. This simple strategy happens to be surprisingly effective in practice.

For parts selection expansion, we use the conformal factor [Ben-Chen and Gotsman 2008] as a similarity map to detect similar parts. This is computed once by solving: $L\Phi = K^T - K^{origin}$, where $K^{origin}$ is the mesh gaussian curvature and $K^T$ is the average gaussian curvature. To find similar parts, we compute the average conformal factor of the user stroke and find isolines with a similar value: they act as potential selections. For each isoline we apply the part selection process and we compare the potential selection found with the reference one based on their conformal factor distributions. The algorithm is efficient because it uses the locality of the part selection and the globality of the similarity map to find the best similar selections.

## 4 Results

We compare our selections with human selections strokes from the benchmark of Chen et al. [Chen et al. 2009]. For all the models we were able to find similar selections in a small amount of time and using few strokes. In future work, we plan to define a unified framework for the expansion process.

## References

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