Layered Reconstruction of Stippling Art

Amal Dev Parakkat
LIX, Ecole Polytechnique CNRS

Pooran Memari
LIX, Ecole Polytechnique CNRS

Marie-Paule Cani
LIX, Ecole Polytechnique CNRS

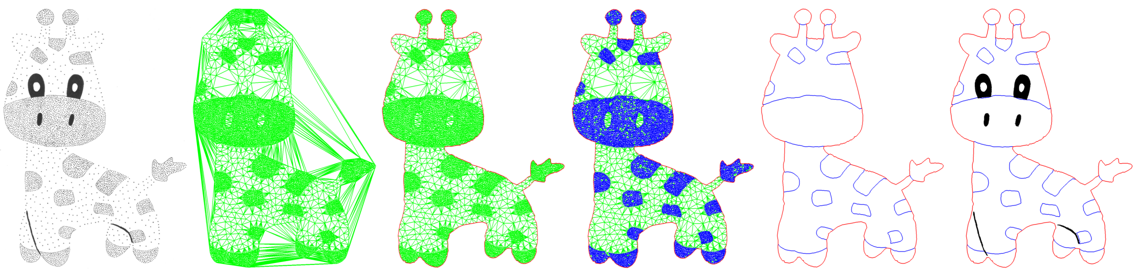

Figure 1: From left to right: Input stippled image, Delaunay triangulation of extracted stipples. Carving outer boundary. Trimming internal regions using α-shape. Output layered boundaries without and with non-stipple regions.

CCS CONCEPTS

• **Computing methodologies** → **Point-based models**; **Shape analysis**.

KEYWORDS

Delaunay Triangulation, Stippling Art, Reconstruction

ACM Reference Format:
Amal Dev Parakkat, Pooran Memari, and Marie-Paule Cani. 2019. Layered Reconstruction of Stippling Art. In *Proceedings of SIGGRAPH '19 Posters.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3306214.3338598

1 INTRODUCTION

Given a point set $S \subseteq R^2$, reconstruction refers to the process of identifying a vector shape that best approximates the input. Although this field was pioneered since 1983 by Edelsbrunner [Edelsbrunner et al. 2006] and has been heavily studied since then, the general problem still remains open, ill-posed and challenging. Solving it is essential for a wide range of applications, from image processing, pattern recognition and sketching to wireless networks.

The main motivation of our work is extend reconstruction to the case of stippled art (for eg. Hedcut drawings), as well as finding an inverse to the well studied problem of image conversion to blue noise (see for instance deGoes et al. [de Goes et al. 2012]). Solution to this problem is extremely difficult since we expect reconstruction to be consistent with human cognition and perception of the art piece, while possible feature extraction heavily depends on various parameters of the input point set (density, distribution etc).

In this work, we introduce a dedicated variant of traditional 2D reconstruction in which the input point set (a stippled image) can include different regions corresponding to different point densities. Our method converts this input into a layered, vector representation, which includes a main shape plus internal, closed regions, defined by their boundary. Providing such structured output eases subsequent editing and processing, such as generating shaded vector images from the stippled input [Orzan et al. 2008]. To achieve this, we first apply a layered reconstruction algorithm based on the detected regions in the input point set, and use the output for generating the outer and inner shape boundaries in the stippled drawing.

SIGGRAPH '19 Posters, July 28 - August 01, 2019, Los Angeles, CA, USA

ACM ISBN 978-1-4503-6314-3/19/07.
https://doi.org/10.1145/3306214.3338598

2 PROBLEM AND CHALLENGES

The problem can be formalized as follows: Let $R = \{R_1, R_2, ..., R_n\}$ be an image with regions $R_1, R_2, ..., R_n$, each region being represented by a set of points such that the adjacent regions have distinguishable point densities. Our goal is to extract a **Layered reconstruction** of this input, ie. to identify a set of regions defined by their boundary curves.

In this work, we only consider a simpler version of this problem, where the input point set has two distinct densities (region adjacency graph is two-colorable). We refer to these regions as low density and high density regions, respectively. We assume random point distributions on the input, since the latter can be hand-drawn.

Even in this simpler case, state of the art algorithms such as α-shape [Edelsbrunner et al. 2006] or the more recent *ec*-shape method [Methirumangalath et al. 2017, 2015] cannot handle stippled input. Figure 2 shows the results of various algorithms on such input. Though the α-shape is able to capture high density region with low α value, once we try to capture the region represented by low density points, the entire shape deteriorates (by filling the intended gaps between the high density regions; for example, the tail of goldfish shown in Figure 2). Whereas, random distribution of input points distorts the output of *ec*-shape algorithm. In the case of χ-shape [Duckham et al. 2008], the sculpting strategy based on edge length fails since the varying density cannot be taken into consideration. Also, the χ-shape cannot identify inner boundaries. Curve reconstruction is a very similar related problem, where the samples are generated only from the object boundary. Curve reconstruction algorithm cannot be used if there are interior points

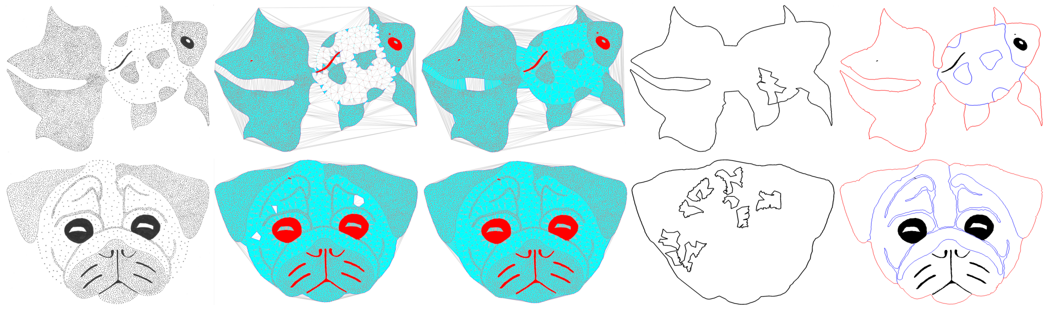

Figure 2: Comparison with existing methods. Left to right: Input stippled image, α-shapes (for two α values), ec-shape and our result.

(Figure 3 shows a sample result of a curve reconstruction algorithm [Parakkat and Muthuganapathy 2016] in this context).

Knowing that algorithms like α-shape and ec-shape perform well in reconstructing shape from a point set with single density, the key idea behind the algorithm we propose, as the name suggests, is to apply reconstruction in a layered fashion to individually extract and reconstruct regions represented by similar point densities.

3 PROPOSED APPROACH

We have no assumptions on the density of the stipples in regions. Our algorithm takes only two parameters that could be estimated from region densities (one for maximum boundary edge length in the carving step and the other is the α-shape parameter allowing to extract region boundaries in the trimming step).

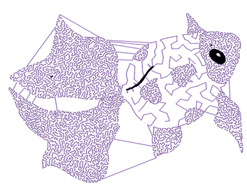

Figure 3: Result of a curve reconstruction

In carving step, we start from a Delaunay triangulation of the point set and progressively sculpt it as in the ec-shape method: starting from the exterior edges (edges not shared with any other triangle), edges are repeatedly removed until all the exterior edges satisfies the so-called diametric circle property (an edge ab is sculpted only if the circle with ab as a diametric chord is non empty). To avoid unnecessary blockages during sculpting, the algorithm removes an edge if its length exceeds a threshold (carving parameter).

Once the outer boundary (colored in red in Figure 1) is identified, trimming starts with the computation of α-shape lying inside the carved result. If the parameter α is chosen between low and high density values, only points lying in high density regions will appear in the α-shape. Therefore, extracting the boundary of α-shape leads to an automatic reconstruction of inner boundaries between low and high density regions (colored in blue in Figure 1).

As an application, we used the proposed algorithm to reconstruct shape from stippled drawings, given as raster images. Initially, the pixels in the input image are clustered together based on its 8-neighbourhood and each cluster is represented by a single point if it belongs to a stipple (so that non-stipple regions like eyes of the giraffe will be retained as such). The remaining non-stippled regions are separated before applying layered reconstruction and kept back after finding boundaries.

Algorithm 1 Reconstruct(Point set PS, low_density, high_density)

Compute Delaunay triangulation DT(PS)
Carving: Sculpt from Delaunay triangulation based on edge length denoted by low_density and diametric circle property to create shape S
Compute α-shape A based on high_density
Trimming: extract α-shape's boundary (retain edge $ab \in A$ if it is connected to a non-alpha point in DT and lies inside S)
Return the edges in carved shape along with the edges retained during trimming step

4 FUTURE WORK

Though the proposed algorithm requires two parameters (in order to automatically extract outer and inner boundaries between regions) we believe that they could be automatically computed based on local density estimation of the point set. This would be necessary for extending the method to the general case of stippled input with multiple densities, which is currently under development. Also, a complete system facilitating the creation of a shaded vector image from a stippled image, based on the point density and color information, is under progress.

REFERENCES

Fernando de Goes, Katherine Breeden, Victor Ostromoukhov, and Mathieu Desbrun. 2012. Blue Noise Through Optimal Transport. *ACM Trans. Graph.* 31, 6, Article 171 (Nov. 2012), 11 pages.

Matt Duckham, Lars Kulik, Mike Worboys, and Antony Galton. 2008. Efficient generation of simple polygons for characterizing the shape of a set of points in the plane. *Pattern Recognition* 41, 10 (2008), 3224 – 3236.

H. Edelsbrunner, D. Kirkpatrick, and R. Seidel. 2006. On the Shape of a Set of Points in the Plane. *IEEE Trans. Inf. Theor.* 29, 4 (Sept. 2006), 551–559.

Subhasree Methirumangalath, Shyam Sundar Kannan, Amal Dev Parakkat, and Ramanathan Muthuganapathy. 2017. Hole detection in a planar point set: An empty disk approach. *Computers Graphics* 66 (2017), 124 – 134. Shape Modeling International 2017.

Subhasree Methirumangalath, Amal Dev Parakkat, and Ramanathan Muthuganapathy. 2015. A unified approach towards reconstruction of a planar point set. *Computers Graphics* 51 (2015), 90 – 97. Conference Shape Modeling International.

Alexandrina Orzan, Adrien Bousseau, Holger Winnemöller, Pascal Barla, Joëlle Thollot, and David Salesin. 2008. Diffusion Curves: A Vector Representation for Smooth-Shaded Images. In *ACM Transactions on Graphics (Proceedings of SIGGRAPH 2008)*, Vol. 27.

Amal Dev Parakkat and Ramanathan Muthuganapathy. 2016. Crawl Through Neighbors: A Simple Curve Reconstruction Algorithm. In *Proceedings of the Symposium on Geometry Processing (SGP '16)*. 177–186.