

Contour filtering for smoother surface meshes

Justin Kinney

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1 Introduction

Neuropil reconstruction from EM images begins with a process called segmentation. The goal of segmentation is to divide each EM image into regions corresponding to different anatomical structures. For example the software program Reconstruct3D allows the user to outline regions with contours consisting of a set of discrete points defined by mouse clicks. After segmentation the regions are annotated by assigning names to the contours so that sets of contours belonging to the same object can be collected together. A surface mesh of the object can then be generated by passing the collection of all contours belonging to a particular object to a program such as VolumeRover that skins the contours by connecting adjacent contours with triangular polygons. The quality of the surface meshes is strongly influenced by the quality of the contour points. Erratic contour profiles with points located in haphazard fashion will contribute to noisy, uneven surfaces. In contrast contours with smooth profiles and uniformly spaced points will support the generation of smooth surfaces. This document describes the objectives, design, and operation of a c++ software program for filtering contour points before tiling to promote better output surface meshes.

2 Objectives

Reconstructing a chunk of rat CA1 neuropil has demonstrated a correlation between the quality of contour points passed to VolumeRover and the quality of surface meshes generated as output. A quality surface mesh is smooth with equilateral triangular polygons. We have found that (1) smoothing the contours and (2) controlling the distance between contour points to be near uniform before the tiling operation greatly increases the output mesh quality. Here we describe in more detail the motivation behind these two principal objectives of the software. To illustrate the need for contour filtering we will be referring to the trace in Figure 1 arbitrarily chosen as representative of input contour data to the tiling software.

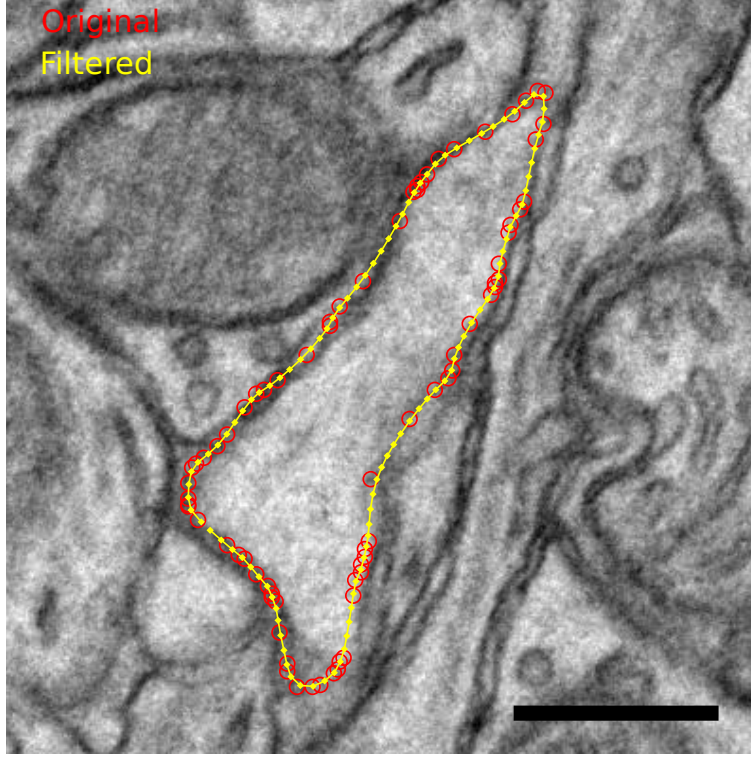


Figure 1: **Profile smoothness and interval uniformity are improved.** Our example data set is one of nine contours belonging to a large apical dendrite (d000) on section 99 in Kristen Harris' rat CA1 data set labeled R34CA1-B. Note that the contour points (red) as originally traced are slightly rough in profile (but not by much in this example) and have a high variance of intersample point distance. By fitting cubic splines to the original points and resampling, the filtered contour points (yellow) are smoother with a dramatic improvement in interval uniformity. Note that the splines do not necessarily interpolate the original points, a point discussed in more detail later. Scale bar is 250 nanometers.

2.1 Contour profile smoothing

To obtain smooth surface meshes the profiles of the contours are smoothed before tiling. So instead of using the original contour points directly, splines are fit to the input points and then sampled. Sets of four sequential contour points are used as control points for nonrational, uniform cubic B-splines. In general the number of splines used to describe a contour is equal to the number of original contour points. Rather than constrain the splines to precisely interpolate the contour points, the splines represent a weighted function of the control points and consequently simply pass near the control points (Figure 2). Consequently, the splines tend to smoothly transition from one contour point to the next.

Because the splines do not pass through the original contour points, the spline samples are likely to be displaced some nonzero distance away from the original contour. In fact, this

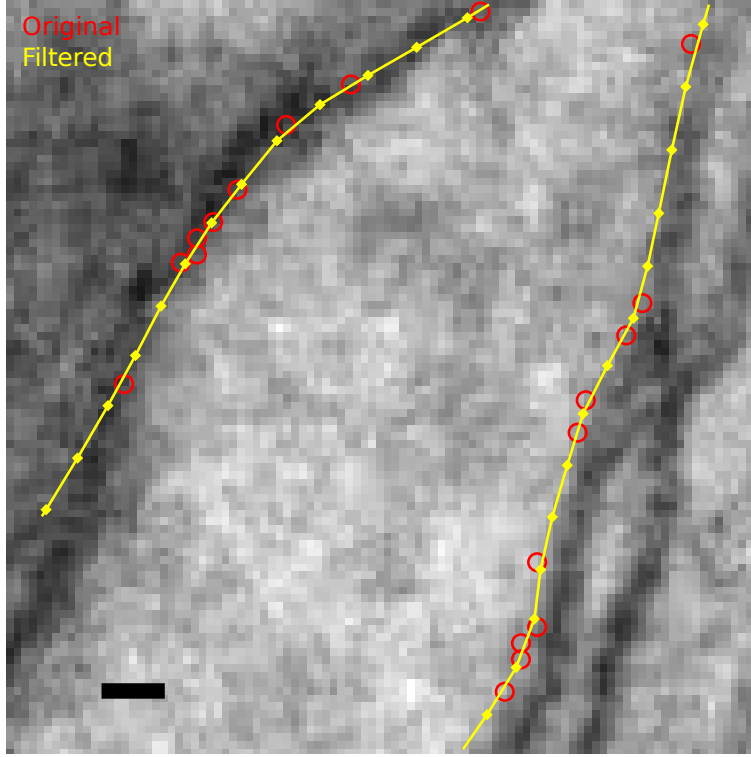


Figure 2: **Splines smoothly transition from one contour to the next.** B-splines are fit to the original contour points (red) and resampled yielding a smoother profile (yellow) than the original contour. In essence, the original contour is being run through a spatial low-pass filter. Scale bar is 20 nanometers.

deviation distance can be quite large. For example, the maximum deviation observed in the entire CA1 contour data set is larger than 40 nanometers. Consequently, provision is made in the software to constrain the deviation between spline samples and the original contour to be less than a user-specified deviation threshold (Figure 3).

2.2 Contour point interval uniformity

As important as contour smoothness for generating smooth surface meshes (if not more so) is the uniformity of the distance between contour points. The surface meshing process can be described as a search for the most parsimonious tiling that connects all the contour points on adjacent sections. As a result large differences in the distributions of contour points from one section to the next are not handled gracefully. Additionally for a given section thickness both very small and very large sampling intervals lead to undesirable high aspect ratio polygons. In contrast contours with near uniform intersample spacing are more easily tiled and lead to higher quality meshes based on our experience with the CA1 reconstruction.

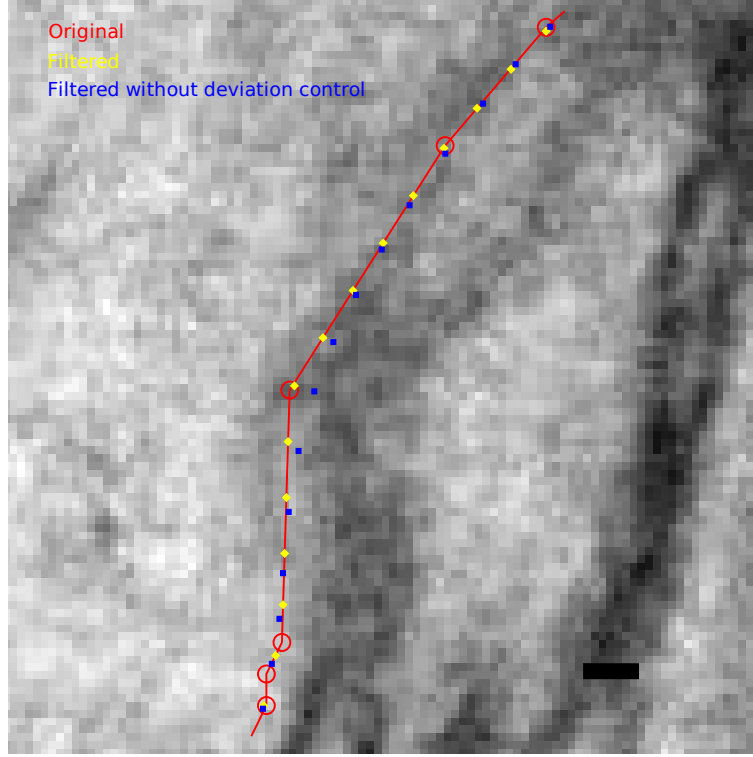


Figure 3: **Deviation between original contour and spline samples is constrained to be less than user-specified threshold.** Without deviation control the spline samples (blue) deviate from the original contour (red) by more than 6.5 nanometers (center red circle). However, imposing a maximum allowed deviation distance of 5 nanometers reduces the maximum deviation to less than one nanometer (yellow). Scale bar is 20 nanometers.

If the sample intervals are comparable to the section thickness, the output surface polygons are near equilateral and the surface is relatively more smooth. Because the distance between samples is so important to the generation of smooth surface meshes, the sample interval is controlled by the software (Figure 4).

We decided to explore two methods of controlling the sample intervals. First, we implemented by far the simplest approach which is to use uniform sample intervals. Second, we investigated an algorithm to place more points at contour regions of high curvature and less points at relatively straight contour regions. The rationale was that this method would increase the information of each point to either better represent the contour for a fixed number of points or represent a given contour equally well with less points. Both methods are available in the software.

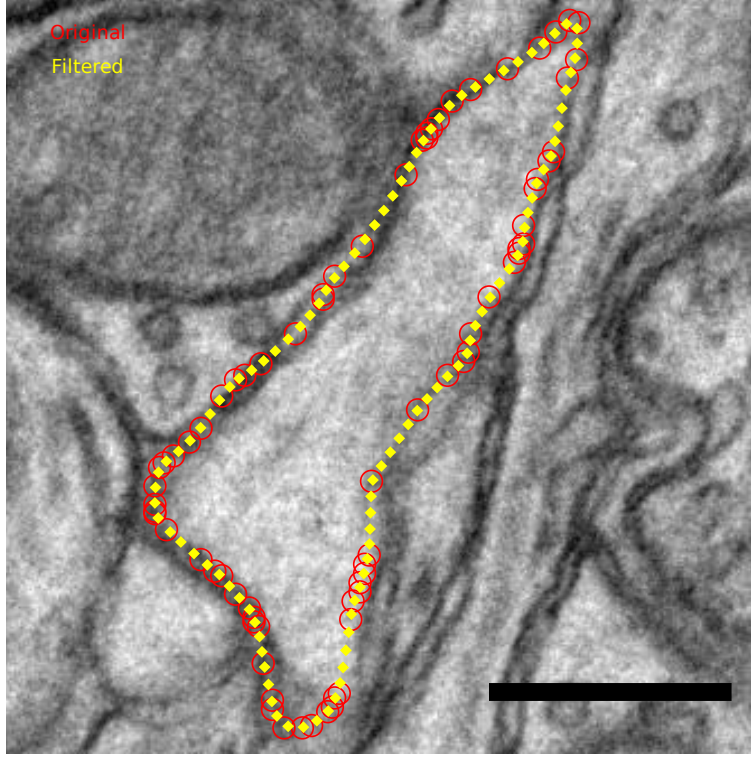


Figure 4: **Mesh smoothness is improved by controlling sample intervals.** The filtered points (yellow) correct three shortcomings of the original contour points (red). (1) The minimum sample interval was increased from 3 to 12 nanometers, thereby improving the aspect ratio of the thinnest polygons formed from the 50 nanometer section thickness. (2) The maximum sample interval was reduced from 90 to 20 nanometers also improving the aspect ratio of the thickest polygons formed from the 50 nanometer section thickness. (3) The variance of the sample interval was reduced by two orders of magnitude which will promote smooth meshing with contours on adjacent sections. Scale bar is 250 nanometers.

2.3 Error detection

The CA1 data set is contained in 101 input files defining 1640 different objects described by 29952 individual contours with a total of 1521831 points. As if that were not already an incredible amount of data, future reconstructions will contain orders of magnitude more. Because data sets this massive will certainly contain errors, the software needs to detect and handle a variety of errors in the contour data. For example, the CA1 data set presents missing contours, duplicate points, contours with less than three points, and contour names with characters prohibited in file names. These anomalies and others like them are correctly identified and dealt with appropriately.

3 Design

Piecewise-continuous cubic B-splines were chosen as the spline type for this application since the splines have sufficient degrees of freedom to represent the contour profile. Additionally, B-splines have the desirable property that at the join point the splines are continuous in position, slope, and curvature [1]. Finally, B-splines do not necessarily interpolate their control points which is exactly what we had in mind. The fact that B-splines are a weighted function of their control points and merely pass near them confers a degree of smoothness to the splines that we wish to leverage here.

We specifically chose to use uniform, nonrational B-splines for several reasons. First, the blending functions are the same for each spline segment which makes computation of spline points very fast. (There is no single set of blending functions for nonuniform B-splines, but there may be a work around by restricting the path parameter to the range 0 to 1.) Second, the spline can be pulled toward a control point by duplicating the control point once and even interpolate the point by copying again to get a triple control point. In this application the contour points are the control points, and it made sense to us to use them to control the shape of the splines (rather than knots as is done with nonuniform B-splines).

Because the sample intervals are so important for the generation of smooth meshes, we allow the user to specify a minimum and maximum sample interval size. For example, the default maximum sample interval size is set equal to the section thickness, and the minimum sample interval is set to one-fifth of the maximum sample interval. These two values are not used to enforce a strict sample interval policy; instead they are used to guide the sampling of the splines in a more flexible way. Specifically, the number of sample points per contour is constrained to be greater than the contour length divided by the maximum sample interval and less than the contour length divided by the minimum sample interval. If the sample intervals are near uniform then each interval is likely to fall within the range specified by the minimum and maximum values.

As mentioned above the software is designed to control sample intervals by two different methods: uniform sample intervals and curvature-dependent sampling. In the latter method the idea is to more densely sample splines where the radius of curvature is small and sparsely sample where the contour profile is more straight. We envision that the location of each sample point is determined by opposing forces. One force concentrates samples at regions of high curvature while an opposing force tries to spread out the samples for uniform sample intervals. Since the curvature of a cubic can be calculated exactly and the distance between samples is also readily computable, we chose to cast the task of sample point placement as an energy minimization problem and use simulated annealing to find a local solution [2]. Briefly, simulated annealing begins with a system at high "temperature" (i.e. randomized) and randomly explores the local state space of the system always accepting transitions that lower the energy of the system but also allowing with some probability changes that raise the energy of the system. Thereby, the system can escape local minima in search for the global minimum. As the algorithm proceeds the "temperature" of the system is lowered by reducing the probability of acceptance for moves that raise the system energy, ultimately

converging on a greedy algorithm. Theoretically, if the temperature is lowered slow enough the system will find the global minimum.

The resulting placement of samples after simulated annealing depends on the relative strength of the two opposing forces of curvature and sample proximity. By heavily weighting the proximity energy the algorithm returns samples more uniformly spaced irrespective of the curvature of the contour profile. In the limit of zero curvature energy, uniform sample intervals will be produced. Because the number of samples was chosen based on the minimum and maximum sample intervals provided by the user, then the uniform sample intervals will conform to these constraints. On the other hand by heavily weighting the curvature energy we retrieve samples densely concentrated in regions with low radius of curvature at the expense of high sample interval variance. In the limit of zero proximity energy then the distribution of sample intervals will be multimodal with several clusters at large intervals and a cluster at interval size of near zero. Because this scenario violates the minimum and maximum sample interval constraints provided by the user, for the curvature-dependent sampling method the balance of forces was carefully tuned by trial and error. For most of the contours in the CA1 data set the difference is small between the two sampling methods based on visual inspection (Figure 5).

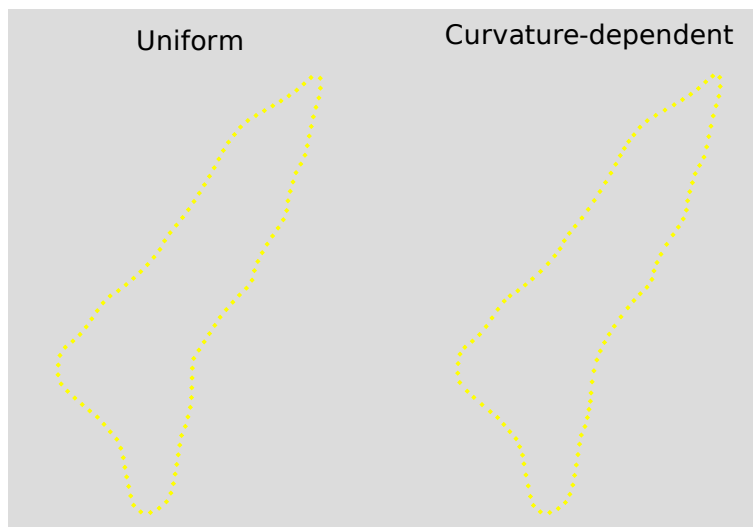


Figure 5: **Small difference between curvature-dependent and uniform sampling.** In this example the minimum sample interval was set to one-fifth of the maximum sample interval. Satisfying these constraints placed an upper bound on the relative weight of the curvature force with respect to proximity force. Consequently, the sampling patterns of the two methods are only slightly different.

The following sample interval statistics for the uniform and curvature-dependent sampling methods quantify the difference between the samples shown in Figure 5.

Uniform sampling

N	109				
min	0.0159219				
max	0.016907				
mean	0.0167317				
variance	2.09038e-08				

0 - 0	:	0		0.01669 - 0.01673	:	5
0 - 0.01646	:	6		0.01673 - 0.01677	:	24
0.01646 - 0.0165	:	0		0.01677 - 0.01681	:	28
0.0165 - 0.01654	:	2		0.01681 - 0.01685	:	9
0.01654 - 0.01658	:	1		0.01685 - 0.01689	:	9
0.01658 - 0.01662	:	3		0.01689 - 0.01692	:	6
0.01662 - 0.01665	:	4		0.01692 - 0.01696	:	0
0.01665 - 0.01669	:	12		0.01696 - 0.01691	:	0

Curvature-dependent sampling

N	109				
min	0.0121391				
max	0.0196499				
mean	0.0167482				
variance	1.81454e-06				

0 - 0	:	0		0.01639 - 0.01675	:	9
0 - 0.01423	:	3		0.01675 - 0.01711	:	8
0.01423 - 0.01459	:	1		0.01711 - 0.01747	:	6
0.01459 - 0.01495	:	4		0.01747 - 0.01783	:	11
0.01495 - 0.01531	:	4		0.01783 - 0.01819	:	0
0.01531 - 0.01567	:	1		0.01819 - 0.01854	:	10
0.01567 - 0.01603	:	20		0.01854 - 0.0189	:	4
0.01603 - 0.01639	:	21		0.0189 - 0.01965	:	7

4 Operation

The software has been tested in three basic modes of operation controlled via command line switches. In the simplest usage the user requests to get the original contour points back as output. In this mode the software will process all contours found in files matching the given name and section numbers in specified directory. The user has the option of including command line directives to ignore scratch work contours, especially exceptionally large contours. For instance, in the CA1 data set a contour named domain1 was found on all sections and measured over 4000 microns in size. The user may wish to run in this mode to simply get statistics on the sample interval of the original contour points. Alternatively, future advances in automatic tracing algorithms will deliver high quality contours that need no further processing.

In the second mode of operation the software linearly interpolates the original contour points by constraining the sample points to lie along straight lines between the original contour points. We chose to implement the linearity constraint by duplicating each original contour point twice as control points. In this way the cubic splines reduce to straight lines. While this approach is computationally more expensive than alternatives, the process flow inside the code was somewhat elegantly preserved. Because all straight lines have the same curvature, uniform sample intervals are the only outcome.

In the third mode of operation the software fits cubic splines to the contour points and samples the splines to generate new contour points. Because each spline is a weighted sum of four different control points, the splines does interpolate the contour points but instead

pass near. By changing the relative strength of the curvature force and proximity force, the splines sample intervals can be uniform or concentrated at contour regions of high curvature.

5 TODO

Perhaps the most important aspect of contour filtering that has not been addressed here or in the software concerns the coordination of contour points on adjacent sections. As discussed earlier the smoothness of the output surface meshes is strongly affected by gradients in the sample density on contours from adjacent sections. Large changes in the sample density degrade the quality of the resulting surface mesh.

Another topic of discussion is to decide whether to keep simulated annealing. It is expensive and uniform sampling may be sufficient. As the discussion above implies simulated annealing is used even when uniform sampling is requested. The simulated annealing could almost certainly be accelerated with a little work, but abandoning the annealing would be faster still.

6 Help Information

```
NAME
    reconstruct2contourtiler - generate contour_tiler input files from contours

SYNOPSIS
    reconstruct2contourtiler [options]

DESCRIPTION
    Converts reconstruct contour format to contour_tiler input format.
    All files in input directory are assumed to be
    of the form filename_prefix.section#.
    min_section to max_section is the section range to be converted.
    Section_thickness should be in same scale as x,y contour points.
    x,y and z coordinates of sampled splines will be multiplied by scale in output.
    CAPPING_FLAG=1 to attempt end capping.CAPPING_FLAG=0 to leave ends open.
    DEVIATION_THRESHOLD is the maximum allowed deviation of the spline from raw
    contour points in scaled units. Set
    DEVIATION_THRESHOLD to 0 to disable thresholding.

EXAMPLES
    reconstruct2contourtiler -i ./contours -f myContours -n 10 -x 100 -t .07 -s 1000 -o ./contour_tiler_output -d 2
    Read contours from directory './contours' and write contour_tiler output
    files to directory 'contour_tiler_output'. The input contour files have the
    name scheme 'myContours.#' where # is the section number which varies from
    10 to 100. The distance between contours in the direction of sectioning
    is .070 microns. The contour_tiler output data will be in nanometers as
    dictated by the 1000 scaling. Capping directives will be included in the
    output data. The interpolated contours will not deviate from the input contours
    by more than 2 (nanometers since scaling is 1000).

OPTIONS
    --no_capping
        Do not include directives in the output data to cap the meshes,
        thus creating open surface meshes.
        Default is to cap the meshes at the minimum and maximum sections
        thereby creating closed surface meshes.

    --print_detailed_info
        Print raw contour points, control points, s parameter
        values, etc as .log files in output directory.
        Default is to do nothing.

    --return_raw_contour_points
        Return input contour points unadulterated.
        Default is to fit splines to contour points and resample.

    --return_interpolated_raw_points
```

Return input contour points linearly interpolated to satisfy minimum and maximum sample interval constraints. Default is to fit splines to contour points and resample.

-n NUM, --min_section=NUM
The starting section number in the section range.
Default is '60'.

-x NUM, --max_section=NUM
The ending section number in the section range.
Default is '160'.

-t NUM, --section_thickness=NUM
Thickness of the sections. Each section is assumed to be of identical thickness.
Default is '0.05'.

-S NUM, --additional_points_factor=NUM
The number of sample points in contour will be determined by the ratio of contour length and maximum sample interval plus a fraction NUM of the samples described by the ratio of contour length and minimum sample interval. $0 \leq \text{NUM} \leq 1$.
Default is '0.5'.

-X NUM, --max_sample_interval=NUM
The linear distance between sampled contour points will be less than NUM.
Default is '0.05'.

-Y NUM, --min_sample_interval=NUM
The linear distance between sampled contour points will be greater than NUM.
Default is '0.01'.

-s NUM, --output_scale=NUM
The output data will be scaled by NUM.
Default is '1' which means output data has same scale as input data.

-d NUM, --deviation_threshold=NUM
The input contours are filtered before output. The deviation of the input and output contours is constrained to be less than NUM where units are input units scaled by --scale value.
Default is '0'.

no threshold is enforced.

-a NUM, --curvature_gain=NUM
A sample point contributes to energy in a manner proportional to NUM and inversely proportional to curvature.
Default is '1000'.

-b NUM, --curvature_exponent=NUM
A sample point contributes to energy in a manner inversely proportional to curvature to the NUM power.
Default is '1'.

-c NUM, --proximity_gain=NUM
A sample point contributes to energy in a manner proportional to NUM and distance between samples.
Default is '1'.

-e NUM, --proximity_exponent=NUM
A sample point contributes to energy in a manner proportional to distance between samples to the NUM power.
Default is '1'.

-T NUM, --high_temp=NUM
Starting high temperature of simulated annealing.
Default is '100'.

-i DIRECTORY, --input_data_dir=DIRECTORY
Directory containing input contours.
Default is current directory.

-o DIRECTORY, --output_data_dir=DIRECTORY
Directory where output data will be written.
Default is current directory.

-O STRING, --output_script=STRING
A bash script named STRING will be written to automate contour_tiling process.
Default script name is 'mesh_and_convert.sh'.

-f STRING, --input_filename_prefix=STRING
The input contours will be read from

```
'input_directory/STRING.min_section' to
'input_directory/STRING.max_section'.
Default is 'Volumejosef'.

-I STRING, --ignore_contour=STRING
    Contours with name STRING will not be processed
    and no output data will be written for these contours.
    Default is no ignored contours.

-h, --help
    Print reconstruct2contourtiler man page.
```

Justin Kinney Sep 10 2009

References

- [1] James D. Foley, Andries van Dam, Steven K. Feiner, and John F. Hughes. *Computer Graphics: Principles and Practice*. Addison-Wesley, second edition, August 1995.
- [2] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi. Optimization by simulated annealing. *Science*, 220(4598):671–680, May 1983.