Deterministically Defining Chambers in 3D-Scans of Caves

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Abstract

Increasingly, speleologists are employing terrestrial laser scanners to generate highly detailed 3D maps of caves, which can be used for quantitative analysis and comparison. Although their high precision allows very accurate volume computations, one of the key aspects of cave mapping – the identification of chambers for volumetric comparisons – still remains a manual post-processing step. Naturally, such manual steps are heavily influenced by subjective preferences and not suited for objective comparisons. In this paper, we present a novel algorithm that bridges this gap. Given an appropriate 3D model of a cave, our algorithm produces a unique and unambiguous segmentation of the cave into distinct chambers and passages. It is free of human bias and insensitive to scanning noise, scaling, and orientation of the model. The foundation of our work is a thorough analysis of cave geometry. We transfer the results of this analysis into a mathematical model and use state-of-the-art methods from computer graphics to derive the segmentation. We initially tested our approach with various cave models and a group of speleologists, which confirmed that our algorithm's results conform closely to manual segmentations. Therefore, it seems to be well-suited as a substitute for "classical" but ambiguous existing approaches to comparing chamber volumes, and can provide objective comparability to the process.

1. Introduction

In recent years, digital surveying of caves has become increasingly popular. Highly accurate laser scanners in combination with reference markers that help to assemble multiple partial scans to a single model have been used successfully to generate detailed three-dimensional maps of caves (McFarlane, et al., 2013) (Canevese, et al., 2013). For the first time, the availability of these maps allows precise measurement of cave sizes in terms of length, volume, or surface area up to an accuracy that is superior to any manual method.

However, an important piece of information is still missing that is required to measure chamber sizes: the actual borders of the chambers within a cave system. A scanning solution that acquires a cave's geometry is obviously not able to capture this semantic information since it is mainly dictated by convention and experience of professionals. Furthermore, the opinions of different professionals may vary slightly when asked to outline the chambers in the same cave. Thus, any advantage of the high-accuracy geometry would be lost immediately as soon as human interaction is involved in the process of defining chamber extents.

Instead, we present a fully automatic algorithm to solve the aforementioned problem: Given the result of a scanning expedition in form of a 3D model of a cave, our algorithm deterministically calculates the locations and extents of all chambers in the cave system, which allows objective size calculation without human bias. We developed our algorithm in conformance with the common sense in speleology, such that the results match manual segmentations from professionals closely. Yet, our algorithm provides enough degrees of freedom to alter the underlying definitions. The basis of our algorithm is a so-called *curve* skeleton (Cornea, et al., 2007), which is a network of paths through the cave. At every point of the skeleton, we then compute the perceptible size of the cave surrounding the skeleton point. This size measure is a generalized radius and captures the local extents of the cave. The change of the perceptible size along the skeleton gives important hints about entrances of chambers. More specifically, a sudden increase in size, which we determine from the first two derivatives, is a strong indicator that the corresponding skeleton path leads into a chamber. We gather all those indicators from the skeleton and generate a probabilistic model that describes the likelihood of entrances at every position of the skeleton. We then find the maximum-likelihood segmentation of the skeleton with respect to the probabilistic model, which allows us to uniquely classify each part of the cave model as either a passage or a chamber.

In this paper, we give a high-level overview of our algorithm. For a thorough explanation, we refer the reader to the according technical paper (Schertler, et al., 2017).

2. Input Data and Preparation

Our algorithm takes as input the watertight reconstructed surface from a series of scans, i.e. any holes are closed in the resulting 3D model. Such models can be generated easily from the raw point cloud data that virtually all scanning solutions expose, e.g. with Poisson Surface Reconstruction (Kazhdan & Hoppe, 2013).

Fine details in the cave's geometry are irrelevant for chamber recognition. Therefore, we reconstruct the surface with a low resolution and identify chambers in this coarse representation. Once the chambers are found, they can be mapped back onto a highly-detailed model, allowing accurate size calculation.

3. Curve Skeleton

The first step of our algorithm calculates the cave's curve skeleton by successively contracting the 3D model until a thin path network remains (Tagliasacchi, et al., 2012). Figure 1 shows the result of this procedure. As can be seen, the skeleton is a smooth path that is centered inside the cave and reflects the cave's



Figure 1 Curve skeleton represented as connected dots inside the Eisriesenwelt caves, Austria

overall topology, i.e. branching in the cave results in a corresponding branching in the curve skeleton.

Due to the contraction procedure, every point on the skeleton is also equipped with a set of corresponding points on the surface (i.e. those points that have been contracted to the according skeleton point). This correspondence allows to project the final segmentation from the curve skeleton back onto the cave surface. In perfectly cylindrical regions of the cave, these correspondences form a circle around the skeleton vertex, whereas more general cave shapes lead to irregular correspondence distributions.

We represent the curve skeleton in its discretized form, i.e. as a graph, consisting of vertices and edges. In the following step, we will calculate the perceptible size for every skeleton vertex and derive the first two derivatives on the edges. Intuitively, the first derivative corresponds to the direction of size changes and the second derivative represents how rapidly the change happens (cf. curvature).

4. Perceptible Size

The perceptible size at any skeleton position is the essential measure on which we base our segmentation algorithm. We define it in a way such that it corresponds to the perceived size of the cave for an observer located at the according skeleton vertex.

Our perceptible size measure is a generalized radius of the cave. E.g., for a cylindrical cave part, the size is equal to the cylinder's radius. Similarly, for elliptical cylinders, we use the average radius. In the following section, we extend this idea and explain how we calculate the perceptible size for arbitrary cave shapes, especially in the presence of branching.



Figure 2 Visualization of the cave part that is visible from the skeleton vertex at the intersection of the dark axes along with the corresponding valley line network on the surface used for perceptible size calculation visualized as orange dots. Gomantong caves, Borneo

The examples of the cylindrical caves have in common that the resulting perceptible size is the average radius over a circular line around the according cave part, where the radius is defined as the distance of the skeleton vertex and the cave surface in a given direction. We generalize this approach for arbitrary cave shapes as follows:

The cave part surrounding a skeleton vertex can be expressed as a spherical radius field. In this radius field, we find a closed network of valley lines that encompasses the vertex completely, i.e. the connected area on the unit sphere between the valley lines is smaller than a prescribed threshold. As a consequence, these lines are most compact in the sense that they would not contract further if they were rubber bands around the physical cave. As such, they naturally avoid incident passages and tend to align with the areas of smallest radius. Please note that the rubber band analogy was only chosen for demonstration purposes and is not completely accurate as there is no actual physical model in our calculation. Please refer to the technical paper (Schertler, et al., 2017) for a rigorous definition of this line network. An example network can be found in Figure 2.

Once this line network is found, we average the radius over the network to find the perceptible size. By construction, cylindrical caves produce networks that consist of a single circle with constant radius, resulting in the same perceptible size as in the introductory examples.



Figure 3 All possible label transitions for an edge between skeleton vertices v_i and v_j . The geometric characteristics that lead to high probabilities for the respective transitions have been annotated for three of the four transitions.

The steps to calculate the perceptible size over the entire data set are therefore as follows: For every skeleton vertex, we generate a spherical radius field. In this field, we find a network of valley lines and calculate its average radius. The result is then used as the skeleton vertex' perceptible size.

After calculating the perceptible size, we evaluate the first and second derivative numerically. These values are then used to guide the actual segmentation of the skeleton.

5. Segmentation

The goal of the segmentation step is to assign one of two possible labels (C or P) to every skeleton vertex that describes if the vertex belongs to a chamber or a passage. If this segmentation is known, distinct chambers can be separated easily by analyzing connected components.

To find the segmentation, we generate a *Markov* Random Field from the curve skeleton that describes the likelihood of every possible label transition for every skeleton edge in a probabilistic framework. Figure 3 shows the four possible transitions for a single edge. The underlying geometric properties on the edge (i.e. the first and second derivatives of the perceptible size) allow us to define the probabilities for every transition. E.g., a high absolute second derivative is characteristic for an area where the cave size changes rapidly and thus indicates a chamber entrance. Therefore, the two transitions $\mathcal{C} \to \mathcal{C}$ and $\mathcal{P} \to \mathcal{P}$ are very unlikely because they do not introduce an entrance on this edge. And depending on the sign of the first derivative, one of the two remaining transitions should have a higher probability than the other.



Figure 4 Segmentation result for the Eisriesenwelt caves, Austria. Chambers are visualized with distinct colors, passages are grey.

In this manner, we calculate all four transition probabilities for all edges of the curve skeleton. These partial probabilities then allow us to calculate a final objective function in form of the total probability: Given a specific labeling of the skeleton vertices, every edge is fixed to the according probability value defined by the labels of its two incident vertices. The product of all transition probabilities is then the total probability of the labeling given the underlying geometric properties. We finally maximize this objective function to find the most probable labeling with QPBO (Rother, et al., 2007).

Once the labeling is found on the curve skeleton, we find distinct chambers via connected component analysis. The result is then projected back onto the cave surface, such that every point of the 3D model is uniquely associated to a specific chamber or a passage.

6. Results and Conclusions

The chamber recognition algorithm presented in this paper leads to expressive segmentations of arbitrary cave data sets (cf. Figure 4). In a formal evaluation, we found that a reasonable parameterization achieves a similarity between automatic and manual segmentations from experts of over 95 %.

The high similarity with professional opinions makes our algorithm a perfect candidate to substitute the manual and potentially error-prone segmentation step in existing chamber size calculation pipelines. Furthermore, our algorithm is deterministic, i.e. running it multiple times on the same data yields exactly the same result, which is an obvious prerequisite for objective comparability. Although finding a good parameterization is not trivial, a rich data base of cave scans and manual annotations can help significantly in both improving the core algorithm and determining a global parameter set that is applicable to a variety of cave types.

7. References

Canevese, E. P., Forti, P. & Tedeschi, R., 2013. New Acquisition, 3D Modelling, and Data Use Methods: The Laser Scanning Survey of Re Tiberio Cave. *ICS Proceedings*.

Cornea, N. D., Silver, D. & Min, P., 2007. Curveskeleton properties, applications, and algorithms. *TVCG*.

Kazhdan, M. & Hoppe, H., 2013. Screened Poisson Surface Reconstruction. *ACM TOG*.

McFarlane, D. et al., 2013. Integrated Three-Dimensional Laser Scanning And Autonomous Drone Surface-Hotogrammetry at Gomantong Caves, Sabah, Malaysia. *ICS Proceedings*.

Rother, C., Kolmogorov, V., Lempitsky, V. & Szummer, M., 2007. Optimizing binary MRFs via extended roof duality. *CVPR*.

Schertler, N., Buchroithner, M. & Gumhold, S., 2017. Chamber Recognition in Cave Data Sets. *Eurographics (to appear)*.

Tagliasacchi, A., Alhashim, I., Olson, M. & Zhang, H., 2012. Mean curvature skeletons. *Computer Graphics Forum*.