

A Segmentation Technique for Flexible Pipes in Deep Underwater Environments

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This paper presents a novel segmentation technique for flexible pipes in deep underwater environments. It consists in finding regions of the pipe denominated *vertebrae* and has three stages. Firstly, the input image is pre-processed to reduce noise. Secondly, the pre-processed image is binarized by the proposed Multi-level Topological Binarization technique, resulting in an image which highlights (in white) the regions that are potential vertebrae (the *blobs*). Lastly, the pipe is segmented by finding the best sequence of blobs that fulfills a set of restrictions inherent to a pipe.

For improving the technique robustness, an alternating pattern of white (a vertebra) and black regions is marked on the pipe. Results show that the proposed technique can segment pipes even under harsh conditions such as: low contrast between pipe and background; uneven illumination of the pipe; and high level of noise due to floating particles. In particular, the proposed binarization technique achieves valuable results without any parameter, whereas state-of-the-art techniques did not achieve the same quality even after their parameters were fine-tuned for each condition.

Two blurring filters are used for pre-processing input image: a bilateral filter [5] removes small particles floating around, while preserving the vertebrae's edges; and a Gaussian filter uniformly smooths the images.

The proposed binarization technique finds peaks in the pre-processed image. This is done by "slicing" the image into a number of slices $s_{i,b}$ (i is its index and b is its level). A tree of slices is then constructed by hierarchically connecting nodes of consecutive levels (Figure 1a). Intuitively speaking, peaks are prominences similar to the first one exhibited in Figure 1b. More formally, a peak is a sequence of nodes denoted by $P = \{n_k\}_{k=1}^m = n_1, n_2, \dots, n_m$, such that: n_m is a leaf node of the tree; n_k , such that $1 \leq k < m$, is the parent node of n_{k+1} ; n_1 is the only element that has a brother node, or n_1 is the only element that has a parent with genus greater than zero, or n_1 is the root node. Nodes n_1 and n_m are respectively named the base and the top of a peak. Given a tree of slices, one has to traverse it from leaves to root in order to find its peaks. For example, Figure 1a contains three peaks: the first one is $P' = s_{1,2}, s_{1,3}$; the second is $P'' = s_{2,2}, s_{2,3}$; and the third is $P''' = s_{3,2}, s_{3,3}, s_{1,4}$.

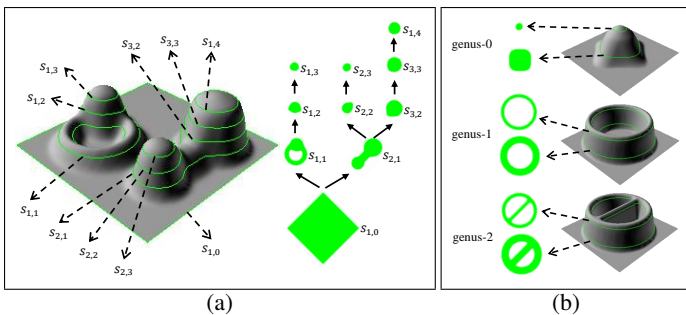


Figure 1: Surface plot of an image and the respective tree of slices in (a). Topological classification of slices obtained from different surfaces in (b).

The binarization stage produces a set of blobs $B = \{b_i : i \in \{1, \dots, n\}\}$ (the white regions depicted in Figure 2). The blobs due to the pipe vertebrae are selected by a backtracking algorithm. It searches for the longest chain of blobs that respects restrictions inherent to a pipe. This chain is denoted by a sequence $V = \{j_k\}_{k=1}^m = j_1, j_2, \dots, j_m$, where j_k is the index of a blob b_{j_k} . During the search, b_i is the current blob being tested to be inserted into V ; b_j is the last blob inserted into V ; and b_p is the blob inserted immediately before b_j .

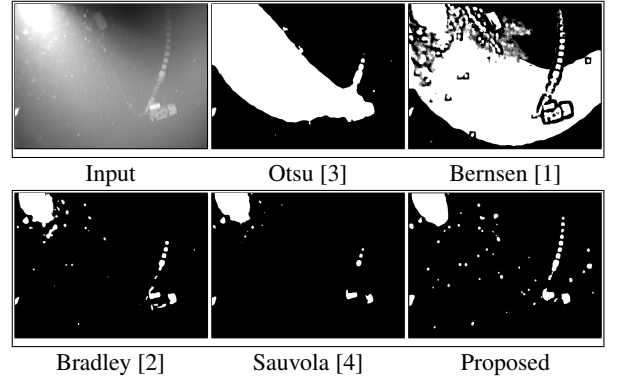


Figure 2: Input image depicting uneven contrast and noise. Results of Otsu, Bernsen, Bradley, and Sauvola binarization algorithms after parameters were fine-tuned. The proposed binarization technique extracts most of the pipe vertebrae without requiring any parameterization.

The first restriction limits the distance between the centroids of b_i and b_l , respectively c_i and c_l :

$$d(c_i, c_l) \leq d_{max}, \quad (1)$$

where d_{max} is the maximum acceptable distance. The second restriction limits the length of the gap between b_i and b_l . This gap is denoted by the line segment $\overline{o_i o_l}$, where o_i is the closest intersection point between the line segment $\overline{c_i c_l}$ and the contour of b_i (o_l is similarly defined):

$$d(o_i, o_l) \leq g_{max}, \quad (2)$$

where g_{max} is the maximum acceptable gap length. The third restriction limits the distance $d(o_i, c_l)$, which can be understood as a radius of b_i . This distance has an upper and lower limit:

$$\left(\frac{1}{1 + v_{max}} \right) \times d(o_i, c_l) \leq d(o_i, c_l) \leq (1 + v_{max}) \times d(o_l, c_l), \quad (3)$$

where $v_{max} \geq 0$ is a user parameter. The last restriction limits the exterior angle between $\overline{c_p c_l}$ and $\overline{c_l c_i}$, which is denoted by θ_i . Since three points are required to form an angle, this restriction only applies when there are at least two blobs already inserted into V :

$$\theta_i \leq \theta_{max}, \quad (4)$$

where θ_{max} is a parameter defined by consulting the pipe's specification.

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