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Noise-resistant Digital Euclidean Connected Skeleton for graph-based shape matching ☆

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ABSTRACT

The skeleton is an essential shape descriptor providing a compact representation of a shape that can be used in the context of real object recognition. However, due to the discretization, the required properties to use it for graph matching (homotopy to the shape, consequently connectivity, thinness, robustness to noise) may be difficult to obtain simultaneously. In this paper, we propose a new skeletonization algorithm having all these properties, based on the Euclidean distance map. More precisely, the algorithm cleverly combines the centers of maximal balls included in the shape and the ridges of the distance map. Post-processing is then applied to thin and prune the resulting skeleton. We compare the proposed method to three fairly recent methods and demonstrate its good properties.

1. Introduction

Let us consider the recognition of 2D shapes, which could result from an image segmentation step. To deal with this recognition problem, one of the methods consists of extracting a set of features, referred to as signature, on the shape to be recognized (to be classified) and on the shapes of the database, or on representative shapes of the database, and comparing such signatures.

The goal here is to represent the shape with as little information as possible while keeping the overall appearance of the shape. In particular, the first properties that we expect for a skeleton is to maintain the topological properties of the initial shape and its geometric properties (ramifications and elongated parts for example).

To compare skeletons extracted from shapes, the idea is to convert skeletons into graphs (branches being edges and, junction points and ending points being vertices) and then to perform graph matching. In fact, a graph is a representation more compact than the shape itself. Moreover, many effective graph matching methods have been proposed in the literature [1–3].

However, in order to easily convert the skeleton into a graph, it is necessary for this skeleton to have at least the following properties, which are not obviously obtained when the shape is represented by points in $\mathbb{Z}^2$:

- it has to be connected: if the skeleton is not connected, the graph obtained from this skeleton will not be connected. Consequently, the graph and the shape will not have the same topology;
- it has to be thin (1-pixel width): a thick skeleton generates path extraction problems.

Moreover, to obtain effective and pertinent matchings in the context of reals objects, it is necessary to construct skeletons robust to noise. Note that this last property is rarely satisfied by the algorithms of the literature, for which the slightest deformation of the border usually generates a branch [4].

Let us consider now skeletonization algorithms. We can classify them as follows:

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- skeletonization methods based on thinning [5–9]
  In an intuitive manner, it consists of "peeling" the shape for the purpose of obtaining a set of connected points with a single pixel width, which preserves the topology of the shape. In other words, thinning is an operation that aims to remove non-terminal simple points in a parallel or sequential manner. The main advantage of these algorithms is the preservation of the shape topology [5,6].
- skeletonization methods based on a distance map [10–15]
  The objective is to identify the key points on the distance map, where each pixel is labeled with the value of its distance to the nearest background pixel. Different distance maps approximate or compute exactly the Euclidean distance:
  - Chamfer (approximation of the Euclidean distance by local mask) [16];
  - squared Euclidean distance [17];
  - signed Euclidean distance [18];
  - honeycomb (based on hexagonal grid) [19].

The next step is to search for the medial axis defined as the set of centers of maximal balls contained in the shape. A maximal ball is a ball contained in the shape not entirely covered by another ball contained in the shape.
The extraction of the medial axis is a reversible operation if the information on distance of each point to the nearest background pixel is retained. Hence, the original shape can be obtained with the medial axis [13]. The main advantage is that the skeleton is centered and the reconstruction is possible. However, such algorithms do not guarantee connectivity.

As stated previously, object recognition requires a shape representation which is invariant to minor changes, but the main drawback of the skeleton is its sensitivity to noise on the shape boundary. This is the reason why it is customary to use a regularization procedure, which can be of two types:

- smoothing the boundary of the shape: this is done before the computation of skeleton points, for the purpose of removing unwanted boundary noise and discretization artefacts [20,12]. In this case the result is rather biased as the boundary smoothing changes the boundary location. Consequently, the skeleton position will be different from the one computed directly on the shape without smoothing. The difficulty here is differentiating between significative boundary information and noise.
- deleting unwanted branches: this is a post-process called pruning [21–23]. It is based on local or global salience measures. The difficulty here is removing "noisy branches" without removing any meaningful parts of the skeleton.

Even if it could belong to the category of skeletons based on distance map, the proposed algorithm, called Digital Euclidean Connected Skeleton (DECS), computes maximal balls but also exploits the distance map in a novel way to connect centers of maximal balls to each other. The main contribution is the propagation and fusion of centers of maximal balls taking into account the ridges of the distance map, which are obtained by filtering this map. The obtained skeleton is then connected, thin and robust to noise. This is brought out by experiments in Section 4.1.

Before describing the proposed method in detail, in Section 3, we detail in Section 2, three methods from the literature we consider as state of the art for their properties: parallel thinning based on critical kernels, namely Bertrand and Couprie's method [5], extraction of the Euclidean skeleton based on a connectivity criterion, namely Choi's method [10] and the Hamilton–Jacobi skeleton method [12]. These methods will be compared to our method in Section 4.

2. Methods used for comparison

We chose to compare our method (DECS) against three existing methods: Bertrand and Couprie's method is a recent parallel thinning method, Choi et al.'s method and Hamilton–Jacobi Skeleton are two methods based on distance maps, like the proposed method.

2.1. Bertrand and Couprie's method [5]

This is a recent parallel thinning method based on critical kernels. The main idea is to gradually thin the shape until stability. This algorithm is based on a general framework for the study of parallel thinning in the context of abstract complexes. The principal is to parallely delete simple points, which are points that may be deleted without changing the topology of the shape. This definition is based on the collapse operation which is a classical tool in algebraic topology and which preserves the topology. It is based on the fact that, if a subset Y of X contains the critical kernel of X, then Y has the same topology as X. We can observe in Fig. 1, an example of skeleton obtained with Bertrand and Couprie's method.

Note that although Bertrand and Couprie's method has no parameter to tune, like most thinning algorithms, but experiments, in Section 4, will show its shortcomings in terms of resistance to noise.

2.2. Choi et al.'s method: Euclidean skeleton based on a connectivity criterion [10]

This method generates a connected Euclidean skeleton. This algorithm starts with the computation of the 8-connected Signed Sequential Euclidean Distance map (8SSED) [18].

The next step is the extraction of the skeleton based on a connectivity criterion using a threshold ρ. The complexity of this algorithm is linear with respect to the number of pixels in the image. As illustrated in Fig. 2, the degree of branching of the skeleton decreases as ρ increases. This raises the issue of finding the appropriate threshold value with respect to the desired application. This method is interesting because it has been used for graph matching [3]. Moreover, it is a skeletonization method based on a distance map, like DECS.

2.3. Siddiqi et al.'s method: Hamilton–Jacobi Skeleton [12]

Like the previous method, Siddiqi et al.'s algorithm [12] generates a Euclidean skeleton with a single pixel width. Their method relies on an initial continuous modeling of the Euclidean distance

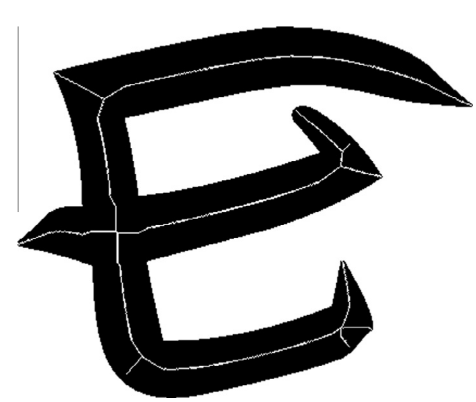

Fig. 1. Skeleton of a letter obtained with Bertrand and Couprie's method.