A Robust Skeletonization Method for Topological Complex Shapes

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ABSTRACT

In this paper, we describe a skeletonization method effective and robust when applied to complex shapes, even if affected by boundary perturbations. This approach has been applied to binary segmented images containing bi-dimensional bounded shapes, generally not simply connected. It has been considered an external force field derived by an anisotropic flow. Through the divergence, we have examined the field flow at different times, discovering that the field divergence satisfies an anisotropic diffusion equation as well. Curves of positive divergence may be thought as propagating fronts converging to a steady state formed by shocks points. It has been proved that the sets of points, inside the shape, where divergence assumes positive values, converge to the skeleton. The curves with negative values of divergence remain static, so they may be directly used for edge extraction. This methodology has also been tested respect to boundary perturbations and disconnections.

KEYWORDS

Anisotropic Flow, Fourier Descriptors, Divergence Flow, Edge Extraction, Medial Axis, Not-Simply Connected Shape, Skeleton

INTRODUCTION

Skeleton detection is a fundamental issue for many computer graphics applications, such as object representation, shape analysis, data compression, computer vision and animation, medical and surgical applications. Skeleton is a one-dimensional curve that preserves the topological structure of the original form retaining much less points. Through skeletonization, a given shape is transformed in a contracted structure that is extremely simplified, consequently image processing algorithms will be facilitated in recognition and classification procedures. The present study is addressed to investigate a method for the simultaneously detection of edges and skeleton points for shapes even if not simply connected. After having performed a binary conversion of the original image, we have applied an approach for tracing skeleton of a given 2D bounded shape that relies on divergence of an anisotropic vector field flow. At first, we have generated a vector force field for edge extraction through the resolution of a generalized parabolic equation, initialized to the gradient of an edge detector. Therefore, we recur to the field divergence in order to better analyse its convergence. The
vector field varies over time, so its divergence will change as well. Thereby we focus our attention on its convergent behaviour because it will result of primary importance to skeletonize the extracted contour. Moreover, the analysis of convergence is very helpful in edge extraction, since it allows to enclose regions from which the field flow has been originated and to position any initial contour for shape reconstruction. This skeletonization method has a straightforward implementation and we have tested it with a wide set of training 2D binary shapes, even not closed or not simply connected. Since this approach is able to analyse not-simply connected objects with irregular boundaries, it turns out to be very suitable for image processing.

RELATED WORKS

Several computational approaches have been implemented during the last decades for skeleton extraction. Skeletonization provides an effective and compact representation reducing a 3D form to a surface and a 2D form to a one-dimensional structure. There are different classes of methods to compute skeleton of bounded objects. Methods based on Distance Transform (DT) generate a distance map, a graylevel image representing the distance to the closest boundary from each point of the shape. In this framework, the skeleton is described as being the locus of local maxima of a distance map (Blum, 1967), (Montanari, 1969). If this function is visualized in the three-dimensional space it appears as a not differentiable surface showing ridges formed by points that, when projected onto the image plane, define the skeleton structure. The topological thinning methods work eroding iteratively the shape until the skeleton is obtained (Ammann & Sartori-Angus, 1985), (Zhang & Wan, 1996).

In most cases the criteria used to delete a point are local, whereas the skeleton allows to capture global geometric features of a given shape (Pavlidis, 1980, Lam, Lee & Suen, 1992). Skeleton may be computed by Voronoi diagrams created using boundary points as anchor points (Ogniewicz, & Ilg, 1992). The main drawback of this approach is that a great number of anchor points are not relevant for skeleton generation and therefore additional skeleton branches are frequently introduced. The Field-based approaches evaluate skeletons recurring to potential functions, derived by the Electrostatic or Gravitational Theory. Boundary pixels are considered behaving like point sources of a potential field, as a consequence these methods require a reliable contour point localization. The resulting fields are diffused introducing an edge-strength function. In this context the skeleton is extracted through the level curves of the strength function (Grigorishin, Abdel-Hamid, & Yang, 1996).

SKELETONIZATION USING DIVERGENCE FLOW

Anisotropic Vector Field Flow

In this paper, we will mainly deal with edge and skeleton detection realized by an external force field (Kass, Witkin, & Terzopoulos, 1988), (Xu, & Prince, 1998). The external forces \( \vec{F}_{\text{Ext}}(\vec{x}) \) are derived by image data as a solution of the following anisotropic diffusion equation (Li, Li & Fox, 2005), (Kovács & Szirányi, 2011), (Xu & Prince, 1997), (Giuliani, 2012):

\[
\begin{align*}
\vec{v}_t &= \text{div} \left( g \left( |\nabla f| \right) \cdot \nabla \vec{v} \right) + \vec{F}(\vec{v}) \\
\vec{v}(x, y, 0) &= \vec{v}_0(x, y) = \nabla f
\end{align*}
\]

(1)

where \( \vec{v}(\vec{x}) = \vec{F}_{\text{Ext}}(\vec{x}) \) is the external field, \( \text{div} \) and \( \nabla \) are the divergence and gradient operators respectively, \( g(.) \) is the diffusion coefficient. In this prototypical parabolic equation, the initial condition \( \nabla f(x, y) \) is the gradient of an edge detector, whereas \( \vec{F}(\vec{v}) \) is a forcing term for the diffusion
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