Development of methods for the processing of mining images using genetic algorithms

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In this paper we describe the extension of system FOTOM capabilities with respect to segmentation of specific mining images. We focus on methods that are inherently resistant against noise present in experimental pit at VSB Technical University. Here, we describe procedures employing proven active contours and evolutionary algorithms for recognizing points of interest in the images that may serve in determining various parameters and properties of analyzed objects. We use the evolutionary algorithms to optimize the parameters of the gradient vector flow field and the parameters affecting the geometrical properties of closed curve used to approximate the location and shape of object boundaries. We suppose that evolutionary algorithms can be used to find the desired global solution. As the computation of gradient vector flow field and also the evolution of active contour are computationally very expensive, we incorporate the GPU acceleration. In conclusion, we compare our approach with common numerical methods on real industrial images segmentation.

Keywords: *mining image, image segmentation, active contour, GVF, SOMA*

Introduction

In this contribution, our aim was to explain the analysis and evaluation processes, for objects of interest present in mining images, and to assess the progress or regressions illustrated in these objects.

The FOTOM system developed at the Department of Computer Science FEECS VSB-TU Ostrava is used for digital image processing and analysis. The system was originally designed to measure mine pits, but over time it has expanded into a system with many modules offering detection and visualization of objects of interest especially in medical images. The FOTOM system is useful in diagnosing and measuring of mining devices and providing 3D modeling capabilities. This system also provides a simple solution for analyzing images obtained during specific exams and time intervals, while assessing progression or regression between exams.

In addition, this article describes procedures that employ common principles and methods for recognizing regions of interest in images that may serve in finding and determining the coordinates, shape properties and other valuable parameters of analyzed objects. There exists an entire class of algorithms and methods for extracting segments with certain parameters from rather specific class of mining images. The rest of the paper is organized as follows. The first part briefly describes the architecture of the system FOTOM.The second part addresses some common mathematical tools for image segmentation. In the third part, we focus on active contours. In the fourth part, we briefly describe the optimization of active contour parameters by SOMA. The last section brings short conclusion. The contribution follows the issues described at [1].

The architecture of the system FOTOM

System FOTOM contains many specialized modules for various kinds of measurements. The architecture of FOTOM follows.

- 2D Fotom1 modeling module. Six types of objects of interest are proposed: points, borders, apexes, circles, ovals, and polygons. These objects are defined in the pixel editing mode. Other forms of 2D modelling are called "relative spinning" and "distance between objects".
- Measuring objects in a series of Fotom2 module images. In this module, the user performs a synthesis on several images. This means that the user can observe all parameters of objects of interest with relevance to time (dates or hours) produced by images. With this feature, the module can evaluate deviations from average and original values while comparing two measurements.

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- 3D modelling in a series of Fotom3 module images. The FOTOM3 module is a full-value analytical tool that enables 3D modelling of objects in 4 windows, graphic illustrations, 3D animation, 3D deviation modelling, and many other functions.
- 2D Animation measuring process with the Fotom4 module. This module provides animated images and animated objects engaged in image measuring, regardless of whether they are transformed or not.
- Recognizing objects of interest and objects in the Fotom5 module (versions 5.1 and 5.2). This module enables entirely new efficient solutions for recognition of points and objects of interest.

Image segmentation and objects of interest recognition

Image segmentation and indexing are the most important and most complicated steps in the entire procedure of image analysis. The aim here is to divide an image into regions that are closely related to boundaries of captured real objects. Thresholding is one of the most conventional and simplest segmentation methods, but it is still one of the fastest. During the thresholding process, individual pixels in an image are marked as foreground pixels if their value is greater than the given threshold value (assuming an object is brighter than its background). Unfortunately it is often difficult to set the appropriate threshold value. Most methods for automatically determining thresholds presume that the image histogram is either bimodal or multimodal. This means that they posses at least two clearly separated local apexes. The Rosin method, first presented by Paul Rosin in [2], is very simple, yet effective, and works well with unimodal histogram images. Another method which works good, especially with unimodal histograms, is the method for determining thresholds using Tsallis entropy [3]. In the case of irregular brightness levels in various parts of the image (e.g. due to irregular lighting) it is impossible to find one threshold level to correspond with all image parts. To overcome this problem, we can use the method of thresholding with varying thresholds. The key to thresholding with varying thresholds lies in splitting the original image into several smaller parts. The threshold of newly created part is now calculated as the average of maximum and minimum brightness value in the given part. Resulting binary (or indexed) images can be further processed by mathematical morphology operators like erosion and dilation [4]. Another useful operation is also thinning. The aim of thinning is to represent objects as linear forms. Thinning may be executed with repeated erosion.

In an effort to recognizing objects of interest we can utilize neural networks as a recognition mechanism. The most common types are three-layer networks and the back propagation algorithm is used to calculate the gradient of the error of the network with respect to the network's modifiable weights. Another type of neural networks are competitive networks which are created with two-layer neural networks, where the lower layer represents input units that are interconnected with all output layers, within which all neurons are again mutually interconnected. Each neuron in the output layer is tacked onto itself (i.e. a self-existing link or inhibition link) and onto the other neurons, as well. This method of interconnection strengthens the excited neuron that was most excited at the beginning of the process. At the end of this process, the neuron is excited to the maximum, and the remaining neurons are totally suppressed (this event is called lateral inhibition). Each neuron then represents an object, or a class of objects, from the input area.

Active contours

In the previous part we have described some common methods for image segmentation and recognition. Those methods are well suited especially for unimodal or bimodal images with compact regions. In this section we will focus on noisy images with multimodal histograms and spongy-like structure of regions of interest.

Active contours (known also as snakes) are parametric (or geometric) curves defined over an image domain and their shape is governed by two types of forces. The first one, called internal force, comes from the curve itself and restricts expansion and bending of the curve. The second one usually represents the edges in the analyzed image in some way. Original version of active contours suffers from two main difficulties. The contour should be initialized near the desired contour otherwise the process will converge to the wrong result. Many attempts address this issue (e.g. pressure forces, distance potentials and multiresolutional methods) but problems still prevail. The basic idea is to extend the capture range of the external force. The second problem is related to boundary concavities. And again, although many solutions have been proposed (e.g. pressure forces, control points, domain-adaptivity, directional attractions and solenoidal fields also known as an incompressible vector fields), none of them is satisfactory. In [5] authors present a new class of external forces for active contour models called gradient vector field (GVF) that addresses both problems. GVF is dense vector fields derived from images by minimizing certain energy functional in a variational framework. The main advantage of GVF is large convergence area of initial contour and the ability to move inside the boundary concavities.

The parametric curve $\mathbf{x}(s) = [x(s), y(s)], s \in < 0, 1)$ representing the contour is defined over the spatial domain of the image I. The main goal is to minimize the following energy functional

$$E = \int_0^1 \frac{1}{2}[\alpha|\mathbf{x}'(s)|^2 + \beta|\mathbf{x}''(s)|^2] + E_{ext}(\mathbf{x}(s))ds \tag{1}$$

where α and β represents the weighting parameters that control the tension and rigidity of the curve. External energy is represented by the function denoted E_{ext} and can be computed in several ways. We use the following form, which is suitable for most cases

$$E_{ext}(x,y) = -|\nabla[G_\sigma(x,y) * I(x,y)]|^2 \tag{2}$$

where G_σ stands for two-dimensional Gaussian function with standard deviation σ and ∇ is the gradient operator. During our experiments with GVF snake we have observed that proper selection of the parameter σ is essential for successful segmentation. The convolution the image with Gaussian kernel also enables us to use this method for very noisy image. A contour $\mathbf{x}$ that minimizes the energy functional must satisfy the Euler equation

$$\alpha\mathbf{x}''(s) - \beta\mathbf{x}''''(s) - \nabla E_{ext} = 0 \tag{3}$$

so that $\mathbf{F}_{int} = \alpha\mathbf{x}''(s) - \beta\mathbf{x}''''(s)$ prevents the curve from excessive stretching and bending and $\mathbf{F}_{ext} = -\nabla E_{ext}$ attracts the curve to the edges in the image. As we want to find the solution to the Eq. 1, we threat the contour as a function of time t yielding

$$\mathbf{x}_t(s,t) = \alpha\mathbf{x}''(s,t) - \beta\mathbf{x}''''(s,t) - \nabla E_{ext} \tag{4}$$

After discretization step, Eq. 2 represents the receipt how to iteratively find the solution of Eq. 1. Now we are still missing the definition of external force $\mathbf{F}_{ext}$. According to [6] $\mathbf{F}_{ext} = \mathbf{v}(x,y)$, where $\mathbf{v}$ represents gradient vector flow (GVF) field. After substituting the term ∇E_{ext} in Eq. 2 by $\mathbf{v}$ we get the following equation

$$\mathbf{x}_t(s,t) = \alpha\mathbf{x}''(s,t) - \beta\mathbf{x}''''(s,t) + \mathbf{v}(\mathbf{x}(s)) \tag{5}$$

The Eq. 3 can be also solved numerically by discretization and iteration like in the case of classic snake [6]. Finally we need to evaluate the GVF field $\mathbf{v}(x,y) = [u(x,y), v(x,y)]$ that minimizes the energy functional

$$\varepsilon = \iint \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2|\mathbf{v} - \nabla f|^2 dxdy \tag{6}$$

where $f(x,y) = -E_{ext}(x,y)$ is called edge map[5]. It is advisable to normalize the edge map prior further computations. With the aim of calculus of variation [7] and the following set of Euler equations

$$\mu\nabla^2 u - (u - f_x)(f_x^2 + f_y 2) = 0 \tag{7}$$

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we can find the GVF field minimizing the functional from Eq. 4. Discretization and numerical implementation of Eq. 5 is straight forward. Further details and conditions of convergence are discussed in more details in [5]. The computation time is significantly larger for GVF than for the other traditional forces mentioned in the beginning of this section. Thus we have implemented both parallel CPU and GPU version of algorithm for GVF computation. GPU version was implemented using CUDA.

Experimental results are provided in Fig. 2 and Fig. 3 - left. We use artificial image of U-shape image with superimposed noise. Initial contour shape was circular (Fig. 2 - right, largest outer circle) and the curve was iteratively evolved into its final state corresponding with desired shape contour. Fig. 3 - left shows GVF field after 1.000.000 iterations computed with following parameters: smoothing Gaussian kernel width equals 11 pixels, $\mu = 0.01$, $\alpha = 0.02$, $dt = 0.1$, $dx = 1$, $dy = 1$. Result was obtained in 39 s for an 640 ×480 pixel image on NVIDIA GTX 460. In case of CPU version, we obtain the same result in 107 minutes on 4-core Intel Xeon 3220 at 2.4 GHz. Using CUDA we were able to achieve up to $160 times$ speedups over CPU version.

We have also evaluated our implementation on numerous mining images (two of them are shown in Fig. 4. The main problem was to reset the right values controlling the generation of GVF and the following curve evolution. In Fig. 3 - right is example showing our attempt to extend 2D GVF to 3D space. Main difficulty related to active surface is reparametrization of triangular mesh. Also the memory requirements, especially in case of high resolution images, are significantly higher (e.g., roughly 1.3 GB in case of 200 × 512 × 512-voxel volume).

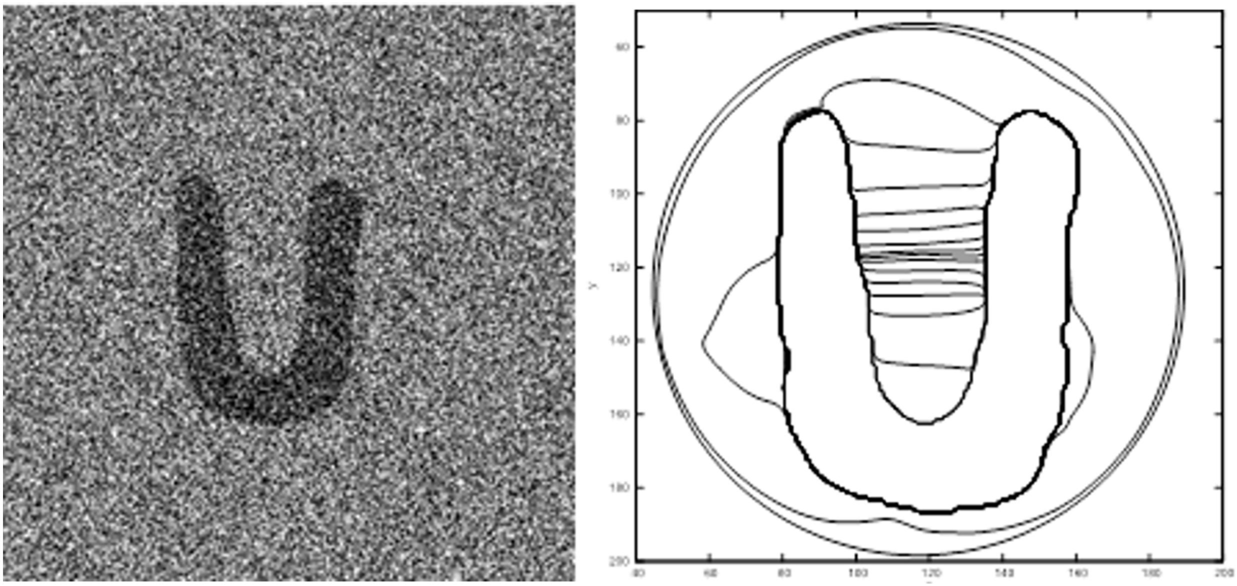

Fig. 1. Left) Example of active contour evolution - noisy artificial test image. Right) Image shows iterations of snake evolution from initial circular shape to final contour.

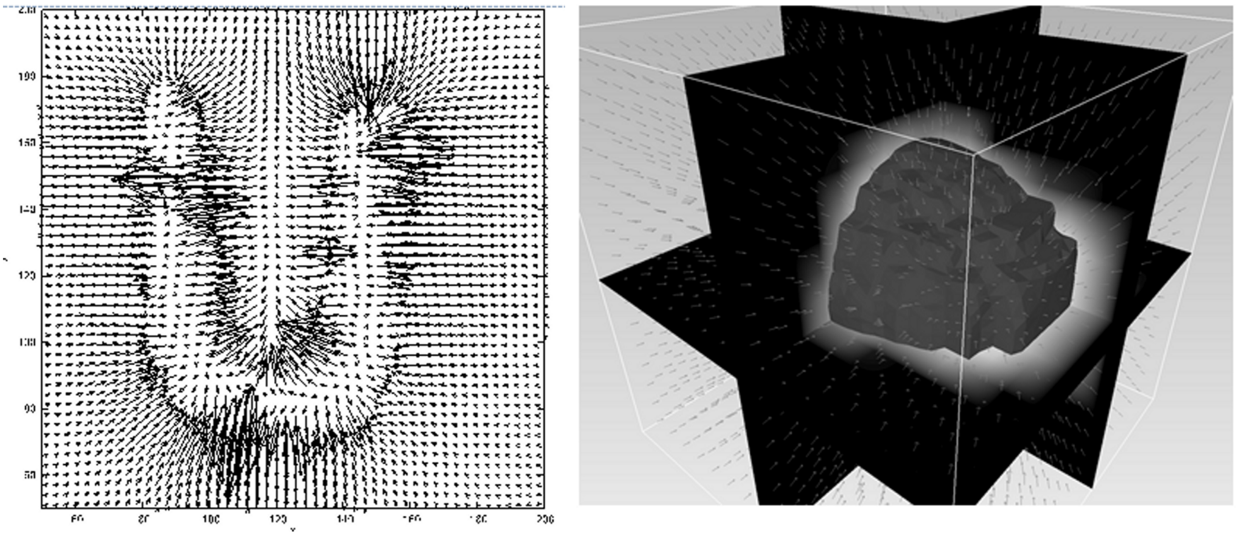

Fig. 2. Left) Images of corresponding GVF fields. Right) Example of 3D surface reconstruction from volumetric data.

Selected parameters optimization

To obtain the desired contour, we should investigate every possible combination of selected GVF field and contour evolution parameters. We have selected 4 distinct parameters, namely α, β, μ and Gaussian kernel width. To reduce the dimension of searched space, we constrain the center and the radius of initial circle to be constant. Those parameters are forming 4-dimensional parameter space. Evolutionary algorithm (EA) is expected to find the minimal contour energy function value in significantly lesser number of steps in comparison to the naive approach when the user is responsible for setting the right parameters for every processed image.

To find the optimal values of selected parameters for active contour algorithm, we have used Self-Organizing Migration Algorithm (SOMA) [8]. It is a member of the evolutionary algorithm class because of similar results obtained with EA that are equivalent to the results from one generation derived by the classic EA except the fact that there are no new individuals - offspring. It also behaves like Genetic Algorithms (GA) and Differential Evolution (DE). Algorithm works with populations that are evolved in migration loops in which only the best suited individuals will survive. SOMA is based on vector operation what makes this algorithm similar to DE and Particle Swarm Optimization (PSO). The principles of SOMA can be described as follows. Each specimen is fully described by vector of parameters. Each parameter is of certain type (e.g. real or integer) with some predefined upper and lower borders representing the valid range of values. The population consists of many individuals and can be represented as an

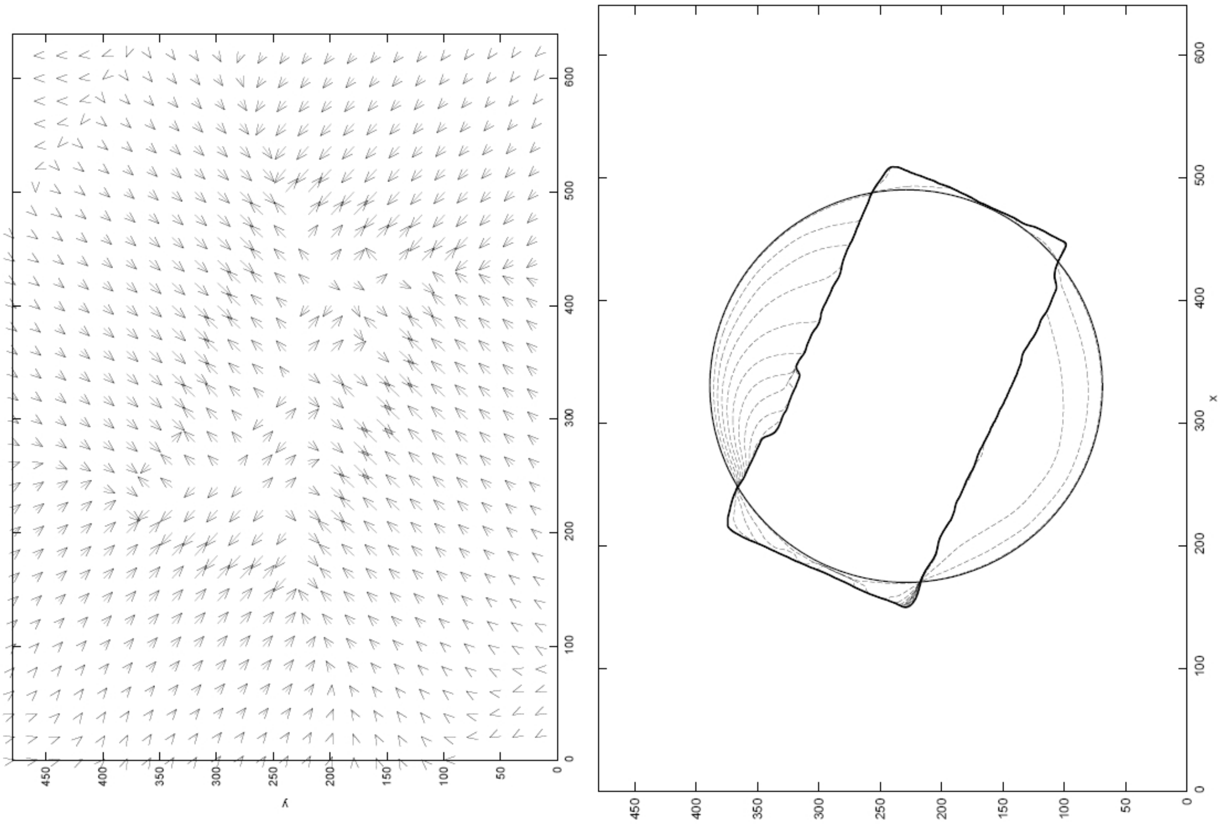

Fig. 3. Left) Images of corresponding GVF fields. Right) Image shows iterations of snake evolution from initial circular shape to final contour.

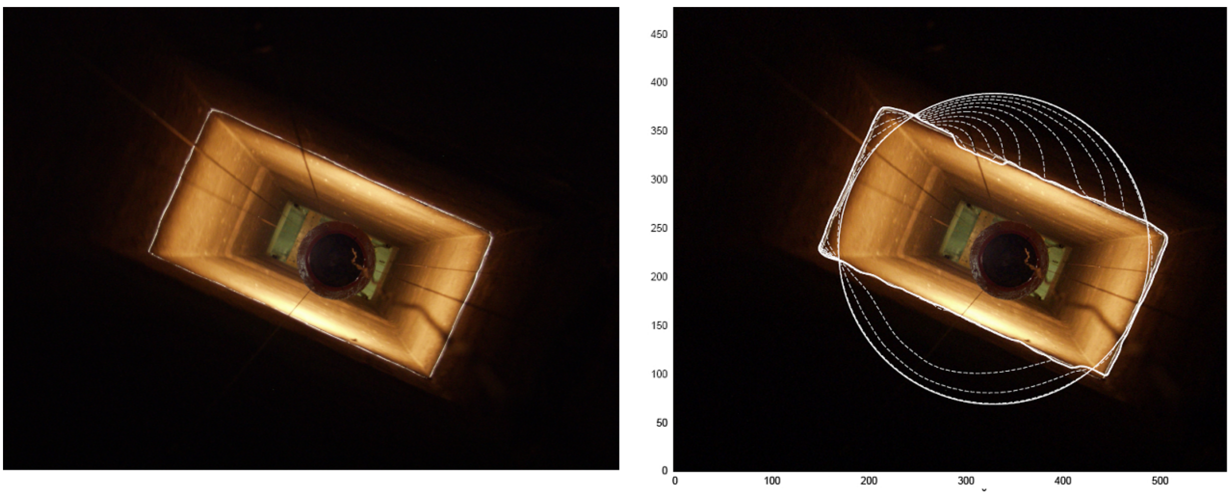

Fig. 4. Left) Example of real image Right) Image shows iterations of snake evolution from initial circular shape to final contour.

M $\times$ N matrix, where M stand for number of parameters and N represents number of individuals. Each individual represents an estimate trying to minimize the cost function. The cost function is defined in such a way that if we get closer to desired solution (in our case it is the desired shape of contour), the value of that function will decrease. We define the cost function that penalizes the deviation of generated curve from the predefined reference contour. In the ideal state when we get exactly the desired solution, value of the cost function will be minimal. It is clear that such a function is multimodal and is difficult to find its global minimum. At the beginning of the evolutionary process we randomly initialize each specimen of the population as follows in Tab 1.

Intrinsic parameters of SOMA algorithm were set according the guidance of [8]. After 805 migrations we were able to obtain valid values of selected parameter for the example in Fig. 4.

Tab. 1. Ranges of selected parameters representing each specimen.

Parameter	Lower boundary	upper boundary	Step
α, β	0.01	0.10	-
μ	0.0001	0.100	-
G. kernel width	1	25	2

Conclusion

In this paper we have described our experience with mining image segmentation. We focused on active contour algorithm based on GVF field for segmenting challenging images of various industrial parts. We implement the GPU based version of the above mentioned algorithm and CUDA technology has proved its usefulness especially in the demanding area of mining imaging. To accommodate the algorithm for using at area of mining engineering we use the SOMA algorithm to automatically refine the parameters of GVF computation and active contour evolution part. In the further development we would like to extend the number of those parameters (e.g. parameters of initial curve) to handle wider range of images. The aforementioned methods and algorithms have been tested and proven at the experimental pit at VSB Ostrava, Czech Republic.

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