Automated abrasion segmentation in medical images

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Abstract: *The paper is attempt to automate the process of abrasion detection using active contour models. The benefits of the semiautomatic GVF algorithm are extended with prior knowledge of the medical images examined and providing initial region on interest. The initial detection is done using Bayes classifier trained with custom abrasion images database and with some technique for reducing false detected pixels.*

Key words: *GVF, Snake, Bayes, Medical images, Abrasions, Segmentations*

INTRODUCTION

Segmentation and edge detection plays important role in image processing. For medical images and in particular abrasions the procedure helps determine the size and location of the abrasion and how it changes in time. The main problem against the algorithm for image segmentation of medical images is that the abrasion is segmented in sub parts and the body part may look inconsistent – hand, face and etc. or body parts may look like abrasions – moles.

The proposed algorithm should be independent from the location of abrasion and should work automatically. Snake family algorithms are recognized as very convenient tool for finding contours of region but have some drawbacks as the need of initialization and has difficulties progressing into concave boundary regions. During research is found method that is applicable to solve the second problem described [1]. The first issue is analyzed and a solution is presented in current paper.

ALGORITHM IN STEPS

Most algorithms' optimizations attempt to solve the problem in general. The idea behind this work is to make it more domain specific, using it only for abrasion on human skin. In medical images there are a number of related works – mostly gray scale images detection.

Process of segmentation is split into three main stages – initial detection, contour initialization, GVF segmentation and it is shown on Figure 1 as overview.

Bayes method provides basic detection function over the tested model as it is trained with samples from the same dataset. This will provide the best results as the color model and noise will be in tolerated amplitudes.

The first stage of segmentation is detection of blood color in abrasions. That is achieved with Bayes classification, mentioned in previous work [3]. The color of skin and blood in particular is dependent primarily of melanin [3]. The model is generated from database with manually segmented abrasions. Database contains about a hundred images of recent abrasions and in RGB model the higher value are for R channel and G,B channels have similar lower values than R. For example [209, 72, 40] or [194, 51, 34] are one of the most detected colors. The final decision whether pixel represents blood is done by calculating formula (1), where P is probability and τ is currently initialized at 1.8.

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$$\frac{P(rgb|abrasion)}{P(rgb|non\ abrasion)} > \tau \quad (1)$$

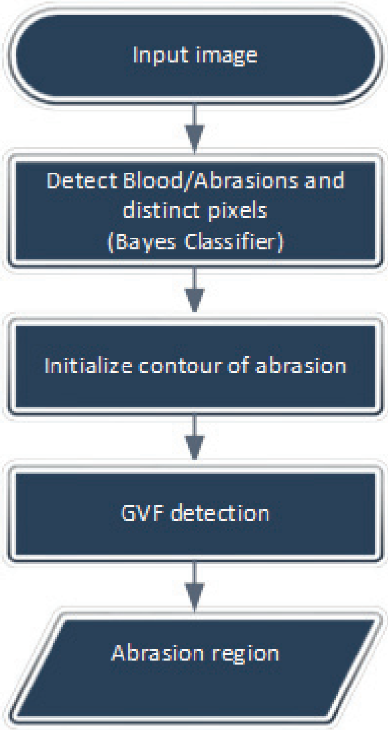
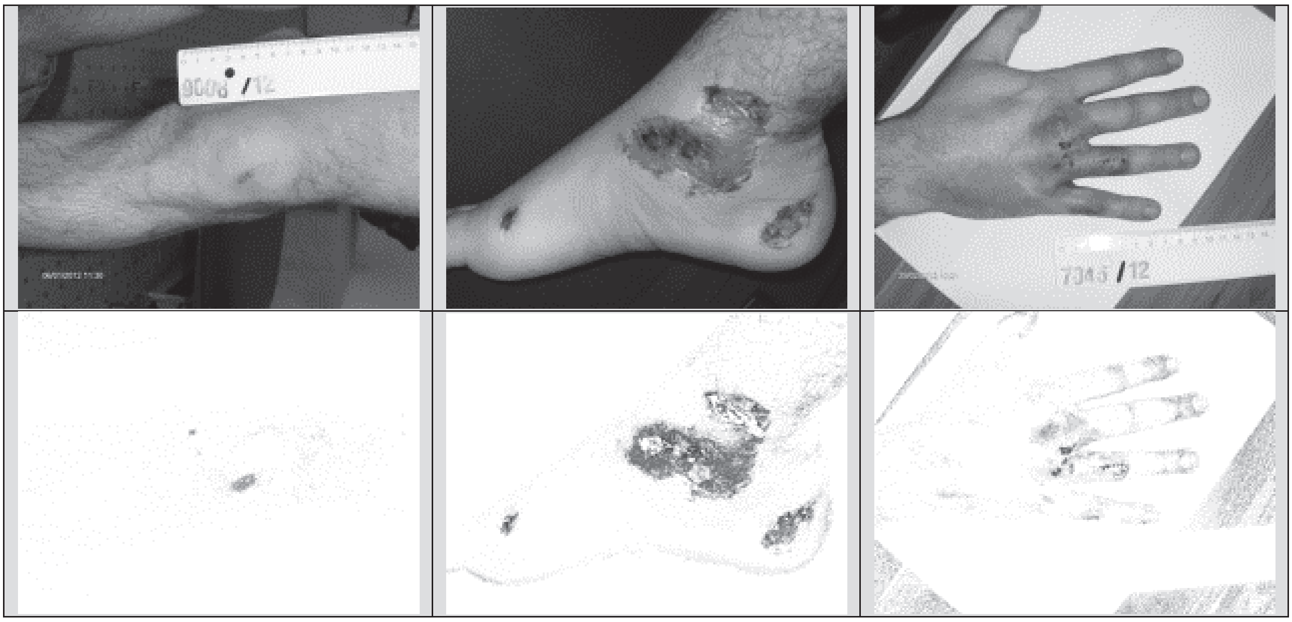


Figure 1 Algorithm overview

The initial detection is the most important step, as the whole algorithm success depends on the correct initialization. That is why for the pixel detection is used Bayes classifier with reduced uncertainty which will select the pixels that are most probably blood rather than background. The results obtained during tests are about TP=0.66, FP=0.04 measured in ROC ratios. Those results are good enough for starting point as seen in Table 1. As a result of the reduced uncertainty the initial region is not exactly the abrasion. That is why GVF algorithm is used as snake implementation as it could be initialized in the region of abrasion or in a distance.

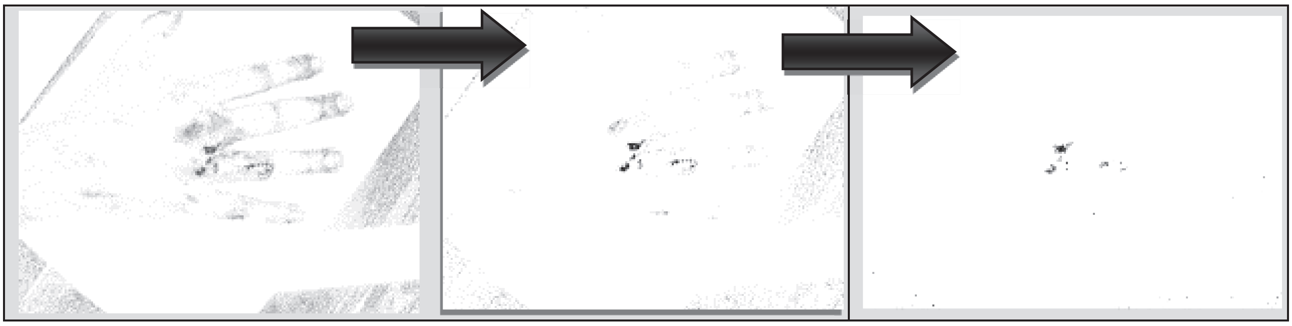
Other parametric or non-parametric models could be used as well. During tests simple threshold model and Gaussian model have been defined, however Bayes classifier outperformed the other tested methods with false ratio lower than 0,1.

Table 1 Abrasion detection results with Bayes classifier



On the most right column is seen a noise from wrongly detected pixels. To remove the noise threshold is used as next step to filter out pixels that have lower intensity (probably single pixels are not part of abrasion). The results are shown in Table 2 and as we can see even very small regions are detected correctly. On this step could be used other noise filter as well.

Table 2 Filtering result of false positive pixels



The last step in initializing GVF contour is to generate the ROI polygon. This is done by labeling image segments using the 8-neighbours region detection. The algorithm is suitable for this state of the process as it connects single pixels in blobs. The blobs’ borders are used as initialized active contour curve only for ones with distinctive region size (at least 50 pixels for label or depending on resolution of image, could be other number).

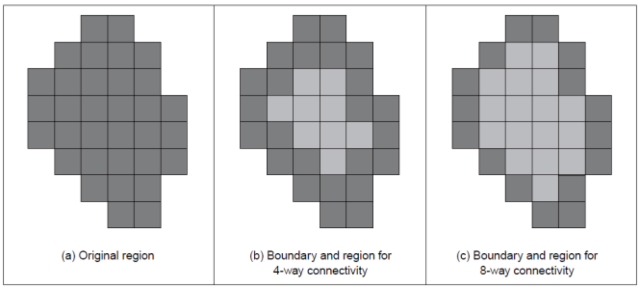


Figure 2 Boundaries and regions - 4-way and 8-way connectivity [4]

A boundary and a region can be defined using both types of connectivity shown on Figure 2 [4]. In the example the boundary is shown in dark grey and the region in light grey. We can observe that for a diagonal boundary, the 4-way connectivity gives a staircase boundary whereas 8-way connectivity gives a diagonal line formed from the points at the corners of the neighborhood [4]. In our case is used the 8-way connectivity as it provides lighter connections constraints as some pixels might be filtered out in previous steps.

The result is shown as the third column in Table 2. The purple, red and black blobs are the used ones and the yellow ones are skipped as they are not considered blobs. Depending on image resolution regions with area smaller than some p could be skipped as well. For 2 Mpx images $p = 50\, pixels$. This prevents initialization of small areas and the parameter could be adjusted for specific needs. The passed areas are stored as polygon lines overlaid on the edge map described in next paragraphs.

The final step is using GVF to finalize segmentation. The algorithm has been chosen as it is able to segment object even if it initialized in the region of object and this is requirement for current algorithm. Snakes may be understood as a special case of a more general technique of matching a deformable model to an image by means of energy minimization. Snakes do not solve the entire problem of finding contours in images; rather, they depend on other mechanisms such as interaction with a user, interaction with some higher-level image understanding process, or information from image data adjacent in time or space. This interaction must specify an approximate shape and starting position for the snake somewhere near the desired contour [5]. That was achieved in the first step of our algorithm and provides the initial state.

Unlike most other image models, the snake is active, always minimizing its energy functional, therefore exhibiting dynamic behavior [5]. Generally the snake model is represented with (2). Two energy functions are used to calculate the final curve – the external and internal energy. The internal forces are result from the shape of the snake, while the external forces come from the image. The snake is defined parametrically as $(s) = [x(s), y(s)]$, where $x(s)$, $y(s)$ are x, y coordinates along the contour and s ϵ[0, 1] [5].

$$E_{snake}^{*} = \int_0^1 E_{snake}\big(v(s)\big)ds = \int_0^1 E_{internal}\big(v(s)\big)ds + E_{image}\big(v(s)\big)ds + E_{con}\big(v(s)\big)ds \quad (2)$$

E_{image} has three components lines, edges, terminations. That is why the edge map is needed to calculate this argument [3]. Currently used map is the Canny edge detector. The pseudo algorithm for Canny is shown in Table 3 and it is described in details in [5].

Table 3 Canny edge detector pseudo algorithm

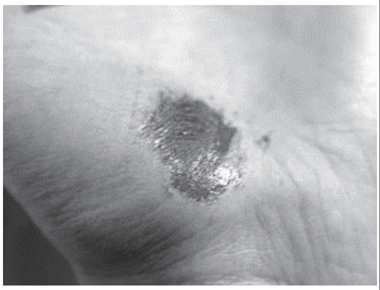
1. Convolve an image with a Gaussian of scale σ. 2. Estimate local edge normal directions n for each pixel in the image. 3. Find the location of the edges 4. Compute the magnitude of the edge. 5. Threshold edges in the image with hysteresis to eliminate spurious responses. 6. Repeat steps (1) through (5) for ascending values of the standard deviation σ 7. Aggregate the final information about edges at multiple scale using the 'feature synthesis' approach.

Detection with the hysteresis approach is used to eliminate problems with intensity variation and wrong edge detection. Current settings for detectors are: Hysteresis Low Threshold = 2.5f; Hysteresis High Threshold = 5f; Gaussian Kernel Radius = 2f; Gaussian Kernel Width = 16f;

GVF overall approach is to define a new non-irrational external force field, which is called the gradient vector flow (GVF) field. Using a force balance condition as a starting point (rather than a variational formulation) GVF field replaces the potential force field, defining a new snake, which is called *GVF snake*. The GVF field points toward the object boundary when very near to the boundary, but varies smoothly over homogeneous image regions, extending to the image border. The main advantages of the GVF field are that it can capture a snake from a long range - from either side of the object boundary - and can force it into concave regions [3].

On Table 4 are shown the final results for two cases on separate rows. The segments are not exactly subtracted but are close to the edges and provides sufficient results. They are obtained with the following parameters – k = 0.25 for 300 GVF field iterations and 500 for evolve iterations. This parameters are recognized as providing the best TP ratio for detected region. The second column shows the edge map and the third contains the original image with detected segments as overlay.

Table 4 Final segmentation results

CONCLUSIONS AND FUTURE WORK

The first step is most important for correct results and it is the main contribution in this work as the GVF is proved method for segmentation [1,3]. During tests average ROC ratios were about TP=0.66 and FP<0.1. That are the desired initial results as provides the reduced object border and white noise in the region which are tolerated during GVF segmentation. The final results shows that some parts are not detected due to initial error or small sizes or not correct snake properties. This leads to about 30% of the segments are not correctly set (measured according to training data) but visibly the results are satisfying. Analysis of the possible optimization and correction of the algorithm will be subject of future work.

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