DOI: 10.2478/aucts-2024-0002

ACTA UNIVERSITATIS CIBINIENSIS – TECHNICAL SERIES
Vol. 76 2024

AUTOMATIC HEMANGIOMA DETECTION ALGORITHM USING A CASCADE OF K-MEANS AND ACTIVE CONTOUR MODEL

NEGHINĂ Cătălina
Faculty of Engineering / Department of Computer Science and Electrical Engineering "Lucian Blaga" University of Sibiu, Romania, e-mail: catalina.neghina@ulbsibiu.ro

SULTANA Alina
Faculty of Electronics, Telecommunications and Information Technology / Department of Applied Electronics and Information Engineering, Polytechnic University of Bucharest Romania, e-mail: alina_elena.sultana@upb.ro

Abstract: Although mostly harmless, hemangiomas still need to be monitored and occasionally treated to avoid complications. The method presented for accurately segmenting the hemangioma pixels involves the automatic detection of the number of classes in an initial k-means clustering, followed by binarization, morphological operations and a further adjustment of region of interest using active contours. The method has been tested on a database containing a variety of situations, including multiple hemangioma areas, differently colored and textured skin and intrusive hair. Compared to the results before the addition of active contours, the mean global score shows an improvement of more than 1% (from 96.86% to 97.92%).
Key words: hemangioma, k-means clustering, active contour

1. INTRODUCTION

Hemangioma is a mostly harmless benign tumor originating in the cells of the vascular wall, being one of the most common tumors encountered in children [1]. Infantile hemangioma usually appears in the first weeks of life, and it looks like a reddish spot. It usually disappears by itself, leaving behind a slight skin atrophic scar. Most of the time, hemangiomas are harmless and asymptomatic. However, there are hemangiomas that can cause complications, such as cervico-facial hemangiomas, which can have negative effects on the affected structures (eyes, nose, lips, oral cavity) through compression, disfigurement or affecting the functionality of organs of sense. In these cases, it is necessary for these hemangiomas to be monitored to intervene with medical treatment.

Monitoring can be achieved by regularly examining patients to observe changes in the surface and color of the hemangioma. This process can be automated based on the analysis of hemangioma images and the extraction of various features, as has been done in previous works [2],[3],[4]. As the first step for such an automatic monitoring system, accurate segmentation is very important for the identification of the area of interest. This has been successfully done in various articles [5],[6],[7], resulting in accuracy over 90%. The proposed method attempts to further improve the accuracy and robustness of the segmentation by including active contours as a final step.

The remainder of the article is organized as follows: *Section 2* describes the database, *Section 3* presents the proposed model, *section 4* provides comparative results, while *Section 5* presents concluding remarks.

2. DATABASE

The database consists of 15 pictures with hemangioma that may also include skin, hair, a ruler (most of the images include a centimeter scale as a reference for area calculation) etc..To assess the performance of the segmentation algorithm, the area affected by the hemangioma was manually labeled in two classes for each image: pixels belonging to the hemangioma and pixels belonging to non-hemangioma regions, resulting in the creation of reference masks, as shown in *Figure 1*.

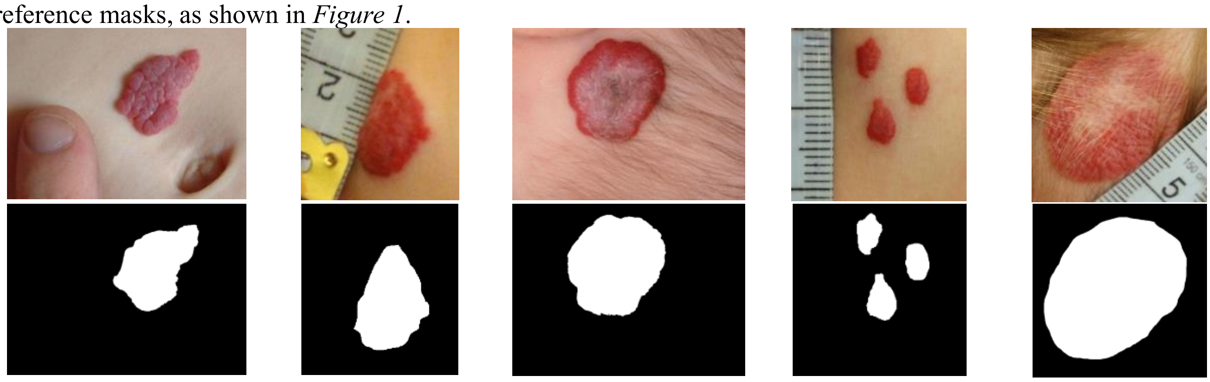


Figure 1. Images with hemangioma and their masks

3. THE PROPOSED METHOD

The images in which we aim to identify hemangioma pixels may contain one or more additional classes (such as hair, skin, etc.). Instead of determining the optimal number of classes after k-means clustering with classical methods such as silhouette [8], for which more classes are generally preferred, the proposed method establishes the number of classes in the image prior to implement the segmentation, by determining the number of local maxima in the histogram. Once the number of classes is determined, k-means clustering, binarization and morphological operations identify an approximate location of the hemangioma, which will serve as the starting point for segmentation using active contour. The overall structure of the algorithm is illustrated in *Figure 2*.

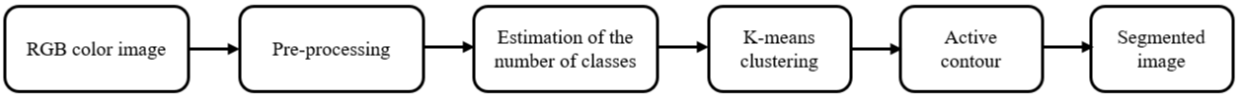


Figure 2. Structure of the algorithm

3.1. Preprocessing

Since hemangiomas typically appear as reddish spots, it is more practical to use the CIE L*a*b* color space for analyzing the images. In this space: **L*** indicates pixel intensity, distinguishing dark pixels (low **L*** values) from bright pixels (high L* values); **a*** represents colors ranging from green (negative **a*** values) to red (positive **a*** values); and **b*** covers colors from blue (negative **b*** values) to yellow (positive **b*** values). Only the **a*** layer was retained and linearly normalized to the [0, 1] interval, where high values are expected to correspond to hemangioma pixels, as shown in *Figure 3*.

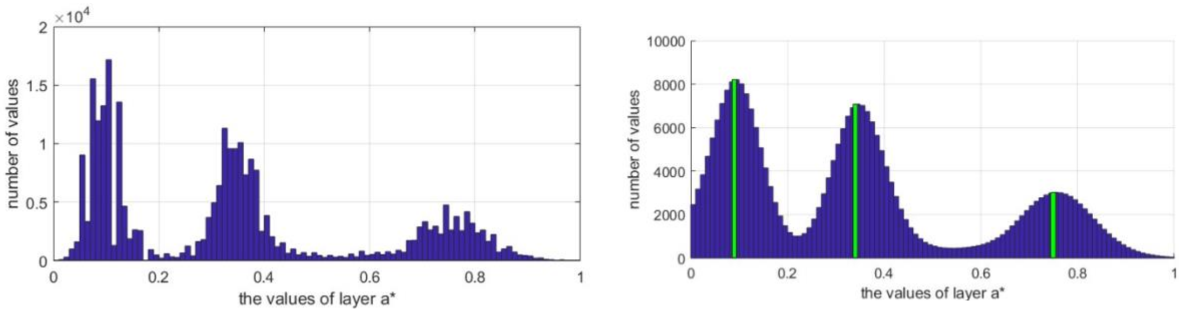
a.1 a.2 b.1 b.2

Figure 3. a.1) and b.1) images in RGB; a.2) and b.2) the **a*** layer from CIE L*a*b*

3.2. Estimation of the optimal number of classes

The algorithm implemented to automatically estimate the number of classes consists of the following steps:

- Computation of the histogram for the normalized values from the **a*** layer;
- Application of a gaussian smoothing filter in order to reduce noise and highlight underlying trends; the Gaussian filter's window size was set to 20 data points;
- Identification of local maxima in the smoothed histogram, corresponding to the number of classes for the K-means clustering.



a) b)

Figure 4. The estimation of the number of classes for the image presented in *Figure 3.b*

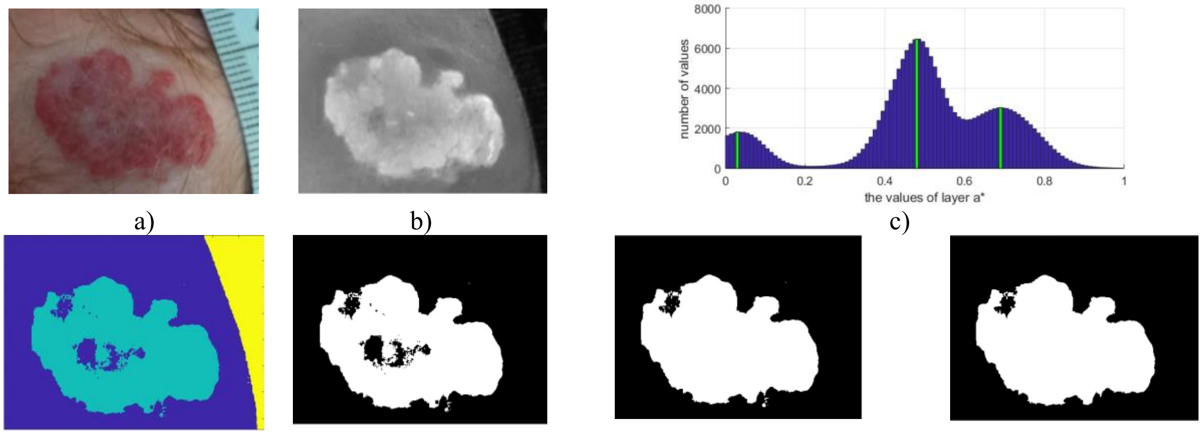
a) Histogram of layer **a*** b) Smoothed histogram with a gaussian filter with window size 20

Local maxima are marked green, so in this case there are 3 classes

3.3. Segmentation using k-means clustering

After determining the optimal number of classes from the image, a standard k-means clustering [9] was performed on the normalized **a*** layer. Since the red values in the RGB color space are the highest in the **a*** layer (and assuming there are no other red objects in the image), we concluded that the class of interest (from all the K classes identified by k-means) is the one with the highest average value. After binarization (0 for background and 1 for hemangioma), a morphological operation was performed to fill in the holes.

To eliminate regions that do not pertain to the area of interest, we focused on retaining only the largest regions, which collectively encompass at least 75% of the k-means selection in the binary image.



a) b) c) d) e) f) g)

Figure 5. a) RGB image; b) Layer **a*;** c) Smoothed histogram; d) k-means clustering; e) Binarization f) Binary image after filling the holes; g) Binary image after keeping the largest regions

3.4. Segmentation using active contour

The active contours, also known as the *snake* method [10], is a method which uses deformable curves that evolve through an image to detect object boundaries based on image features like edges and textures. The contour dynamically deforms to fit the object of interest within the image. It does this by balancing forces: pulling towards strong edges (external energy) while resisting excessive bending or stretching (internal energy). For the effective functioning of this algorithm, it is crucial to begin with an initial contour that closely approximates the target object boundaries. In our approach, the initial region is derived from the segmented area obtained through k-means clustering. The edges identified by k-means clustering will serve as the starting contour for the subsequent contour evolution process aimed at segmenting the image.


a) b) c)

Figure 6. a) Binary image with k-means b) Binary image with active contour c) Contour of the binary image obtained with active contour overlapped on the original image

4. RESULTS

All the images from the database have been segmented and for each segmented image the *True Positive Rate* (TPR) and *True Negative Rate* (TNR) were determined, along with the *Global Score* of classification (computed as the mean of TPR and TNR). The scores were computed for the segmented image obtained with k-means clustering and for the binary images obtained after active contour segmentation.

$$TPR = \frac{number\ of\ hemangioma\ pixels\ that\ were\ correctly\ classified}{total\ number\ of\ hemangioma\ pixels} \tag{1}$$

$$TNR = \frac{number\ of\ non-hemangioma\ pixels\ that\ were\ correctly\ classified}{total\ number\ of\ non-hemangioma\ pixels} \tag{2}$$

$$Global\ Score = \frac{TPR + TNR}{2} \tag{3}$$

The average Global Score for the segmentation performed using k-means across the entire database was 96.86%, while for segmentation using active contour, the average Global Score was an improvement to 97.92%.

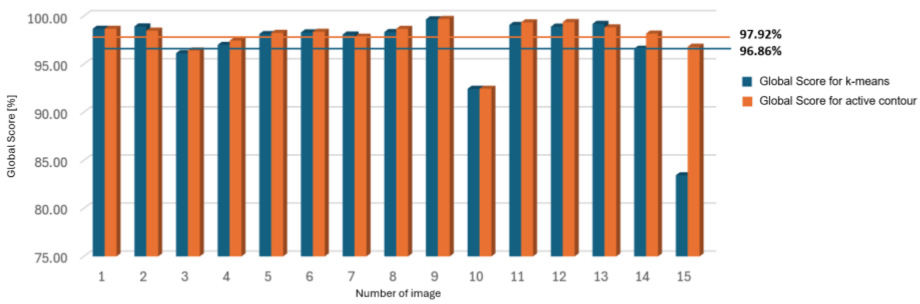
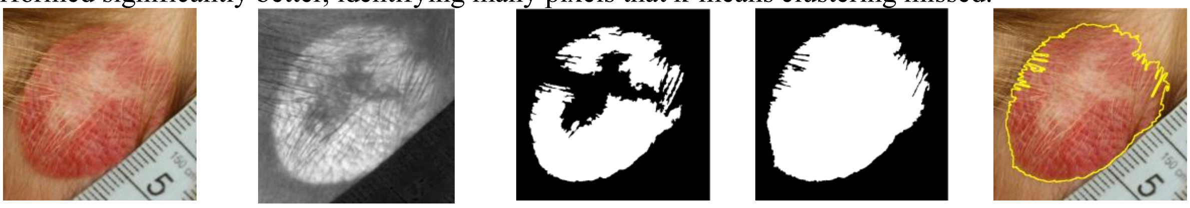


Figure 7. The result of segmentation for each image

Although the results from both methods are generally comparable, with the active contour segmentation achieving an average Global Score only about 1% higher than k-means, it's worth noting that for certain images (such as the one indexed 15 in *Figure 7* and shown in *Figure 8*), active contour segmentation performed significantly better, identifying many pixels that k-means clustering missed.



a b c d e

Figure 8. a) RGB image b) Layer **a*** c) Binary image with k-means d) Binary image with active contour e) Contour of the binary image obtained with active contour overlapped on the original image

5. CONCLUSIONS

This paper introduces an innovative segmentation approach using a combination of k-means clustering followed by active contour segmentation. Due to the hemangioma's reddish appearance, all subsequent analysis was performed on the **a*** layer of the CIE L*a*b* color space. To automatically determine the optimal number of clusters, the method identified the number of local maxima in the histogram. The k-means clustering yielded a segmentation accuracy of 96.86%, which improved to 97.92% after applying the active contour segmentation and reached a better performance for complex irregular atypical zones.

References

[1] O. Enjolras, M. Wassef and R. Chapot, "*Color Atlas of Vascular Tumorsand Vascular Malformations*", Introduction: ISSVA Classification. Cambridge University Press, pp. 1-11, (2012)

[2] S. Zambanini, R. Sablatnig, H. Maier and G. Langs, "*Automatic image based assessment of lesion development during hemangioma follow-up examinations*", Artificial Intelligence in Medicine, vol. 50, Iss. 2, pp. 83-94, (2010)

[3] C. Neghină, M. Zamfir, M. Ciuc, A. Sultana, M. Popescu, *"Automatic monitoring system for the detection and evaluation of the evolution of hemangiomas"*, International Conference on Image Processing Theory, Tools and Applications (IPTA), Oulu, Finland, (2016)

[4] Alina Sultana, Catalina Neghină, Marta Zamfir, *"Automatic Monitoring System for the Evolution of the Hemangiomas"*, Conference: 11th International Symposium on Advanced Topics in Electrical Engineering (ATEE), Location: Bucharest, ROMANIA, ISBN:978-1-4799-7514-3, (2019)

[5] C. Neghină, M. Zamfir, M. Ciuc, A. Sultana, *"Automatic detection of hemangioma through a cascade of Self-Organizing Map clustering and morphological operators"*, 20th Conference on Medical Image Understanding and Analysis (MIUA), Loughborough, UK, Published by Elsevier, ISBN: 978-1-5108-2708-0, Procedia Computer Science, Volume 90, pp. 145 – 150, (2016)

[6] Cătălina Neghină, Marta Zamfir, Alina Sultana, Elena Ovreiu, Mihai Ciuc, *"Automatic detection of hemangiomas using unsupervised segmentation of regions of interest"*, IEEE International Conference on Communications (COMM), pages: 69 – 72, ISBN: 978-1-4673-8198-7, București, Romania, (2016)

[7] Alina Sultana, Horvath BALAZS, Silvia OVREIU, Serban OPRISESCU, Catalina-Elena Neghina, *"Infantile Hemangioma Detection using Deep Learning"*, 13th International Conference on Communications (COMM), București, Romania, ISBN: 978-1-7281-5611-8, (2020)

[8] Neghina, M., Rasche, C., Ciuc, M., Sultana, A., & Tiganesteanu, C. "*Automatic detection of cervical cells in Pap-smear images using polar transform and k-means segmentation*", IPTA, (2016)

[9] Abiodun M. Ikotun, Absalom E. Ezugwu, Laith Abualigah, Belal Abuhaija, Jia Heming, "*K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data*", Information Sciences, Volume 622, Pages 178-210, ISSN 0020-0255, (2023)

[10] Kass, M, Witkin, A, Terzopoulos, D. "*Snakes: Active contour models*", International Journal of Computer Vision, doi:10.1007/BF00133570, (1988)