Journal of Medical Systems (2019) 43: 190
https://doi.org/10.1007/s10916-019-1334-1

IMAGE & SIGNAL PROCESSING

Early Detection of Skin Cancer Using Melanoma Segmentation technique

Tammineni Sreelatha [1] · M. V. Subramanyam [2] · M. N. Giri Prasad [1]

Received: 12 March 2019 / Revised: 7 May 2019 / Accepted: 10 May 2019 / Published online: 20 May 2019

Abstract
The significance of pattern recognition techniques is widely enhanced in image processing and medical applications. Thus, lesion segmentation method is an essential technique of pattern recognition algorithms to detect the melanoma skin cancer in patients at earliest stage, otherwise, in further stages it becomes one of the deadliest disease and its mortality rate is very high. Therefore, a precise melanoma segmentation technique is introduced based on the Gradient and Feature Adaptive Contour (GFAC) model to detect melanoma skin cancer in earliest stage and diagnosis of *dermoscopic* images. In the proposed image segmentation technique pre-processing and noise elimination techniques are introduced to decrease noise and make execution faster. This technique helps in separating the required entity from the background and gather the information from the adjacent pixels of similar classes. Multiple Gaussian distributed patterns are adopted to extract efficient features and to get precise segmentation. The proposed GFACmodel is noise free and consist of smoother border. The segmentation model efficiency is tested on PH2 dataset. The superiority of the proposed modified gradient and feature adaptive contour model can be verified against various state-of-art-techniques in terms of segmented image, error reduction and efficient feature extraction.

Keywords Melanoma · Gradient · Feature extraction · Segmentation

Introduction

In recent years, the number of melanoma affected patients drastically enhanced due to high global warming. Melanoma is the most hazardous and lethalskin disease which often starts from the malignant tumors in skin pigment cells (melanocytes). According to a study, more than 70% deaths of skin cancer patients is due to malignant tumors of melanoma [1, 2]. Melanomais one of the widely spreading skin diseasewith high mortality rate [3]. In melanoma, the survival rate becomes significantly large if it is noticed at very early stages. Skin cancer melanoma if not diagnosed at initial periods, then it can affect the liver, bones, lungs and cerebrum and becomes very complex to diagnose. The melanoma is often assessed with the help of clinical photography for the clinical assessment at initial stage. *Dermoscopy*technique is often utilized for the assessment of melanoma lesions which is a non-invasive type image analysis technique [4]. In melanoma skin lesion cancer, *dermoscopy* is utilized to diagnose the patterns of Melanoma lesions. This technique can also diagnose the vascular components of skin lesions [5]. The device utilized to diagnose the vascular components is termed as *Dermoscope* which is a general microscope with significant lens quality and magnification quality of more than 10 times. So, the objective of the research work is to propose an efficient melanoma skin lesion recognition technique for early detection of skin cancer.

Thus, precise and clinical melanoma skin cancer detection for a*dermoscopic* images is of significant advantage. In melanoma skin cancer, lesion segmentation is one of the most essential technique and precision of lesion segmentation determines the performance of diagnosis and classification. However, lesion segmentation is a complex process due to varied lesion area, lesion structures, fuzzy borders, several skin colors and complex background areas etc. [6]. Moreover, the identification and separation of lesion from surrounding is very complex process using skin lesion

This article is part of the Topical Collection on *Image & Signal Processing*

✉ Tammineni Sreelatha
tamminenisreelatha.jntu@gmail.com

1 Department of Electronics and Communication Engineering, Jawaharlal Nehru Technological University Ananthapuramu, Ananthapuramu, Andhra Pradesh, India

2 Department of Electronics and Communication Engineering, Santhiram Engineering College, Nandyal, Andhra Pradesh, India

segmentation technique for *dermoscopic* images. The extra artifacts like hairand reflections make segmentation even more complex.

Moreover, the efficient diagnosis of *dermoscopic* images requires four stages namely lesion segmentation, artifacts exclusion, efficient feature extraction and classification. Image segmentation is utilized to segregate an image into its principal regions. Image segmentation described as the method of segmenting the desired object area. The main segmentation objective is the area separation of an image with high correlation and Region of Interest (ROI). In skin lesion *dermoscopic* images, the ROI extraction is one of the most essential stage after pre-processing [7, 8]. The efficient classification of skin segmentation depends on the effective feature extraction and ROI extraction.

The conventional state-of-art skin lesion segmentation techniquesrely upon the methods like region enhancing, thresholding and clustering have demonstrated minimum success in resolving these complex issues considering larger datasets [9–11]. Melanoma skin cancer tumor often starts from the moles and can be detected by its perimeter, symmetry, color and mole design and boundaries. Thus, the preciseness of the segmentation is very essential as it largely affects the skin lesion detection.

Various researchers have shown their interest in efficient segmentation of melanoma and immense amount of work has been provided for the diagnosis of melanoma in early stages. In [12], a lesion segmentation technique is introduced based on region growing method for *dermoscopic* images. Here, an efficient segmentation technique is introduced for the effective diagnosis of moles and lesions from the *dermoscopic* images. This technique provides a large contrast between skin lesion pixels and background. However, time complexity is more which depends on the tumor size. In [13], an automated skin lesion segmentation technique is adopted based on computer vison method for *dermscopic* images. This technique helps to enhance the contrast between skin lesion and false positive pixels of an image. This contrast and background pixels enhances the accuracy of the model. In [14], a skin lesion segmentation technique is introduced based on the convolution and de-convolutional networks for *dermoscopic* images. The skin lesion image segmentation can be enhanced based on the various color space data. This technique focuses on low-complexity. In [15], a pattern recognition technique is adopted to extract region of interest from the *dermoscopic* images to detect melanoma. The classification accuracy is significantly high using the proposed pattern recognition technique. Efficient texture and color gradients are extracted. In [16], a skin lesion segmentation technique is presented based on saliency in *dermoscopic* images. This technique helps in the identification of skin lesion melanoma in patients. However, computational complexity is higher using this technique. Therefore, several existing methods namely k-mean algorithm, automated computer aided method, saliency, convolution and deconvolution networks and fuzzy algorithms are presented by various researchers. However, efficient diagnosis and detection of melanoma in early stages is still an unsolved issue. Existing systems in place for *dermoscopic*skin lesion segmentation are predominantly computationally expensive and lack accuracy. Work presented here aims to improve segmentation accuracy for *dermoscopic*skin lesionsimages.

The contribution of work can be described as follows.

Therefore, to efficiently detect melanoma in early stages and to diagnose the melanoma skin cancer, a precise melanoma segmentation technique is introduced based on the Gradient and Feature Adaptive Contour(GFAC) model. Moreover, Gaussian analytical patterns are used to describethe heterogeneous objects/sections of *dermoscopic* images whose mean and variance can be varied. These Gaussian distributed patterns helps to express the gradient specialties of anlesion image. Gradient analysis of an image is a way of analyzing and exploring the huge amount of data and patterns corresponding to objects within. Here, the intensity of *dermoscopic* images can be varied based on gradient nature of an image. This technique helps to reduce errors present in naturally acquired*dermoscopic* images. The gradient features are utilized in adapting the segmentation contours. The proposed image segmentation technique is tested on PH2 dataset. The experimental result verifies the superiority and robustness of the proposed GFAC model which can be utilized for automated segmentation applications. Segmentation accuracy/correctness is expressed using Disc Similarity Coefficient (DSC), Accuracy (ACC) and Specificity (SPEC) metrics in this paper. The GFAC model is compared with state of art existing mechanisms in place and results presented prove its superior performance.

This paper is organized in following sections which are as follows. In section 2, we described our proposed methodology. In section 3, experimental results and evaluation shown and section 4 concludes our paper.

Literature survey

The need of detection of Melanoma at early stages and their better diagnosis is very much essential. The rate of mortality increasing day-by-day due to melanoma or skin diseases. Various researchers have shown their interest for the better diagnosis of these skin diseases which are very dangerous. In [25], a novel architecture is presented for the diagnosis of melanoma based on the deep learning framework and local encoding methods. These techniques providediscriminative features which can help in the detection of melanoma at early stages. In [26], a modern technique is proposed which generates texture and colorful components and this components are very essential in skin cancer evaluation. In [27], an automatic melanoma detection system is proposed for dermoscopic images. Here, SVM classifier is used to classify images in association with Gaussian radial basis kernel. In [28], an efficient machine learning technique is introduced for the detection of melanoma at early stages. However, these techniques cannot ensure high quality segmented images and ensure better classification.

In [10], six different types of algorithms are accessed these algorithm were mainly based on the active contours, regional information, level sets, regional information and adaptive thresholding and achieved best outcomes utilizing the algorithm of adaptive snake, whereas In [19], Delaunay Triangulatio is utilized to separate the image into many regions and segmented the lesion based on that.

In [20], the histogram based threshold algorithm is proposed to segment the lesion from background. In [21], the lesion segmentation via saliency detection methods is proposed to reconstruct the errors which is derived from the model of sparse representation coupled with background detection that can be more accurate and it can differentiate the lesion from the surrounding regions.

In [22], an unsupervised method is introduced to create two saliency scores, one is from the image color data and another is based on the image brightness data and then construct the last saliency map by joining these two saliency scores. In [23], the author has presented the classification of melanoma patients that can be performed by utilizing the features, they are extracted with the help of DLM (deep learning models), the performance of diagnostic is elevated significantly by separating the lesions. In [24], a supervised saliency detection technique is specially changed for the dermoscopic images based on the DRFI (discriminative regional feature integration). The proposed DRFI technique integrates the regional contrast, property, background descriptors, random forest regressor and multi- level of segmentation to produce the saliency scores for every single region in the image.

Therefore, to efficiently detect melanoma in early stages and to diagnose the melanoma skin cancer, a precise melanoma segmentation technique is introduced based on the Gradient and Feature Adaptive Contour (GFAC) model.

Proposed melanoma segmentation technique

This section describes about the method which is utilized to detect the melanoma and provides a detailed modelling of proposed gradient and feature adaptive contour model. In recent time, the number of melanoma patients has been drastically enhanced across all over the globe due to extensive global warming. The melanoma skin cancer especially found in United States and Australia and a major part of these countries are affected with melanoma skin cancer. According to a survey of World health Organization (WHO), around 13 million people become affected each and every year by deadly melanoma skin cancer [17]. Therefore, due to extensive mortality rate across the globe and higher medical diagnosis cost, the detection of melanoma skin cancer at earliest stages is becomes a mandatory requirement. Therefore, to efficiently detect melanoma in early stages and to diagnose the melanoma skin cancer, a precise melanoma segmentation technique is introduced based on the gradient and feature adaptive contour model. An efficient modelling of the proposed GFAC model is presented in next section.

Modelling of proposed gradient and feature adaptive contour model for image segmentation

In this section, an effective mathematical modelling is presented to detect the melanoma skin cancer in patients at earliest stage and for the diagnosis of melanoma *dermoscopy* images using segmentation technique. A following model is introduced to detect the gradient characteristics of an image of varied intensity. Here, fig. 1 demonstrates the flow map of the segmentation technique.

Here, assume that, an image domain can be expressed as φ, the input image can be represented as $J(a) : \varphi \to T$, the restored original signal can be expressed as $K(a) : \varphi \to T$ and unknown bias area can be denoted as $Y(a) : \varphi \to T$ and amount of noise present in the images can be expressed as $i(a) : \varphi \to T$ then the varied intensity of *dermoscopic* images based on gradient specialties can be expressed as,

$$J(a) = Y(a).K(a) + i(a) \tag{1}$$

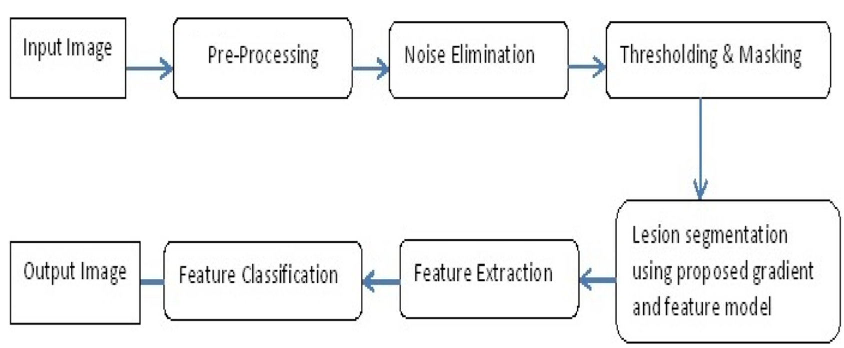

Fig. 1 Block diagram of proposed image segmentation model

Assume that, the image domain φ consists of number of objects/regions as I and can be expressed as φ_m of m^{th} domain. Let the original restored signal $K(a)$ is a piecewise constant for every image domain i.e. $K(a) = d_m$ for each $a \in \varphi_m$ where d_m represents a constant. In the image domain φ, the bias area Y always remains smooth. The Gaussian distributed pattern error can be expressed as i which consists of variance λ_i^2 and mean as $\mu = 0$. Then, Gaussian distributed pattern with variance λ_i^2 and mean as$\sigma_i = 0$ can be utilized to approximate the intensity of an image. Therefore, These Gaussian distributed patterns helps to express the gradient specialties of an image. However, single Gaussian distributed pattern cannot be efficient to get segmentation. Thus, several Gaussian distributed patterns are utilized to get the gradient specialties of an image of varied intensity for each image domain. The Gaussian distributed pattern to the respective image domainφ_m,

$$q(J(b)|\phi_m) = \left(\left((2\pi)^{1/2}\right).\lambda_m\right)^{-1} \exp\left(-(J(b)-\sigma_m(a))^2.\left(2\lambda_m^2\right)^{-1}\right) \quad (2)$$

Where, the Standard Deviation (SD) can be expressed as λ_m whereas statically varied mean can be denoted as $\sigma_m(a)$. The bias area changes very slowly and it can be treated as constant for small windows. Therefore, we can say that $\sigma_m(a) \cong Y(a)$. d_m and $\phi_m$can be expressed as$\phi_m = \{d_m, \lambda_m, Y\}$.

The adjacent central area can be denoted as $G_a$for every location a in the image i.e. $G_a = \{b | \|b - a\| \leq q\}$. Where, the radius of the adjacent central area $G_a$can be denoted as q. In an image domain $\varphi_m$of m^{th} objects, the non-overlapping objects can be represented as I, and then the image domain itself can be expressed as,

$$\varphi = \cup_{m=1,\ldots,I} \varphi_m \quad (3)$$

Where,

$$\varphi_m \cap \varphi_k = \theta, \forall m \neq k \quad (4)$$

The true image intensity domain $C(F)$ can be changed into some other domain $T(F)$ as,

$$\mathbb{J}(a|\phi_m) = (n_m(a))^{-1} \sum_{b\in \varphi_m \cap G_a} J(b|\phi) \quad (5)$$

Assume that, distribution of pixel intensity a is independent and $n_m(a) = \varphi_m \cap G_a$. Then, the respective probability function is of Gaussian type which can be expressed as,

$$\mathbb{J}(a|\phi_m) \sim I\left(\sigma_m, \lambda_m^2. \ (n_m(a))^{-1}\right) \quad (6)$$

Then, the smooth intensity function of Gaussian type can be expressed as,

$$\prod_{b\in \varphi_m \cap G_a} q\left(J\left(b|\phi_m\right)\right) = q\left(J\left(a|\phi_m\right)\right)^{n_m(a)} \propto I\left(\sigma_m, \lambda_m^2. \ (n_m(a))^{-1}\right) \quad (7)$$

Then,

$$q\left(\mathbb{J}\left(a|\phi_m\right)\right) = \prod_{b\in \varphi_m \cap G_a} q\left(J\left(b|\phi_m\right)\right) \quad (8)$$

Assume that, $C = \left\{\mathbb{J}\left(a|\phi_m\right), a \in \varphi, \ m = 1, 2, 3\ldots.., I\right\}$ and then probability function of the m^{th} object can be expressed as,

$$q(C|\phi_m) = \prod_{m\in\varphi} q\left(\mathbb{J}\left(a|\phi_m\right)\right) \quad (9)$$

Then, the combined probability function can be expressed as,

$$q(C|\Phi) = \prod_{m=1}^{I} q(C|\phi_m) = \prod_{m=1}^{I} \prod_{m\in\varphi} q\left(\mathbb{J}\left(a|\phi_m\right)\right) = \prod_{m\in\varphi} h(\mathbb{J}(a|\Phi)) \quad (10)$$

Where, $\Phi = \{\phi_m, m = 1, 2, .., I\}$.

$$h(\mathbb{J}(a|\Phi)) = \prod_{m=1}^{I} q\left(\mathbb{J}\left(a|\phi_m\right)\right) \approx \prod_{m=1}^{I} \prod_{b\in \varphi_m \cap G_a} q\left(J\left(b|\phi_m\right)\right) \quad (11)$$

Form eq. (7) and eq. (11), we can express the uni- variability of Gaussian distributed patterns,

$$h(\mathbb{J}(a|\Phi)) = \prod_{m=1}^{I} q\left(\mathbb{J}\left(a|\phi_m\right)\right) \propto I\ (\sigma, \beta) \quad (12)$$

Where,

$$\sigma = \beta \sum_{m=1}^{I} n_m(a).\sigma_m.\left(\lambda_m^2\right)^{-1} \quad (13)$$

$$\beta^{-1} = \sum_{m=1}^{I} n_m(a).\left(\lambda_m^2\right)^{-1} \quad (14)$$

Here, in eq. (10) the combined probability function represents the gradient intensities of several classes which are composed with every pixel of an image. The eq. (5) represents the adjacent pixels of similar class intensity which shows the proposed GFAC modelis noise free consist of smoother border. Using Gaussian distributed patterns eq. (11) segmentation contours similar to [10] are adapted to obtain accurate lesion segmentation.

Figure 2 represents the flow chart of segmentation process. Here, initially dermoscopic images are taken from PH2 dataset and then these images are pre-processed using pre-processing techniques like Gabor and Gaussian filtering. Then, the proposed segmentation model based on Gradient and Feature Adaptive Contour provides the highly qualified segmented images.

Result and discussion

This section describes about the performance of the proposed melanoma image segmentation technique based on gradient and feature adaptive contour model. Skin melanoma becomes one of the deadliest skin cancers in recent time across the globe which is very difficult to recognize in the early stages. However, detection of melanoma at early stages can be very helpful in diagnosis of skin cancer in patients. Therefore, here, to efficiently detect melanoma in early stages and to diagnose the melanoma skin cancer, a precise melanoma segmentation technique is introduced based on the gradient and feature adaptive contour model. This technique helps in separating the required entity from the background and gather the information from the adjacent pixels of similar classes. The segmentation approach ensures efficient melanoma segmentation of varied intensity. The efficiency of image segmentation technique is determined and compared with different existing techniques in terms of segmented image quality, error reduction and feature extraction. The proposed image segmentation model is tested on PH2 dataset [18].

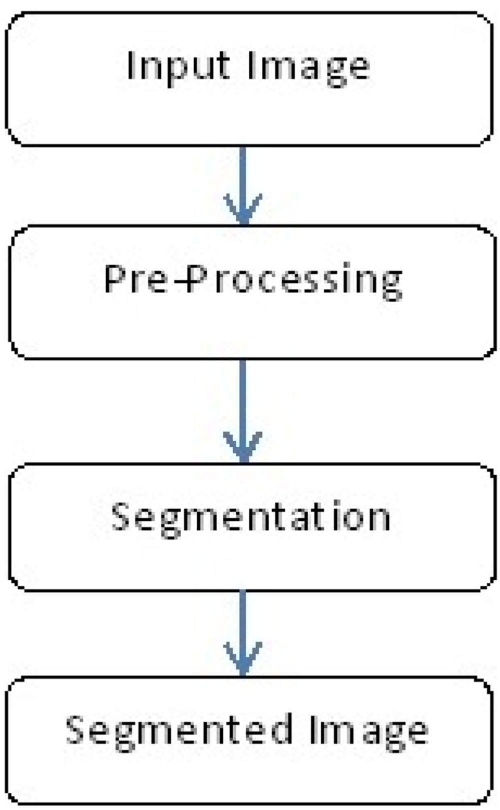

Fig. 2 Flow chart of segmentation process

The PH2 is adermoscopic image database, which is acquired at the Dermatology Service of Hospital Pedro Hispano, Matosinhos, Portugal. PH2 dataset contains clinical diagnosis, identification of many dermoscopic structures and manual segmentation that is performed by the professional dermatologist's in the set of 200 dermoscopic images. This dataset is developed for research and benchmarking purpose. The PH2 dataset consists of 200 melanocytic*dermoscopic* lesion images in which 80 images are common Nevus type, next 80 images are atypical Nevus type and remaining 40 images are Melanoma images. The proposed GFAC model helps in validating the classification methods. Moreover, PH2 dataset consist of two sets of $melanoma\ and\ non-melanoma$ images in which non-melanoma cases are more in number than actual melanoma images and contains various artifacts. The proposed modified image segmentation technique based on gradient and feature adaptive contours is simulated on 64-bit windows 10 OS with 16 $GB\ RAM$ which contains an $INTEL\ (R)\ core\ (TM)\ i5-4460$ processor. It contains 3.20 $GHz\ CPU$. This project is simulated using $MATLAB$ 2016B. Experimental results conclude the higher efficiency and robustness of the proposed GFAC model.

Comparative study

This technique demonstrates the performance comparison of proposed GFAC model with the existing techniques in terms of segmented images, efficiency of the model and feature extraction. The Classification accuracy can be enhanced with the help of pre-processing. This proposed gradient and feature adaptive contour model reduces Gaussian noise in an effective manner. The modified image segmentation technique helps to extract efficient contour features. The superiority of the proposed GFAC model can be verified against various state-of-art-techniques likeSilveira [10], Pennisi [19],Maglogianis [20], Ahn [21], Fan [22], Zamani [23], and DRFI [24]. Table 1 represents the average performance evaluation matrices (%) in terms of Disc Similarity Coefficient (DSC), Accuracy (ACC) and Specificity (SPEC). Here, the Disc Similarity Coefficient using the proposed image segmentation technique is 97.08 which is very high compare to any other existing technique. Similarly, accuracy and specificity using the proposed image segmentation technique is 98.64 and

Table 1 Average performance evaluation metrics (%)

Algorithm	DSC	ACC	SPEC
Silveira [19]	94.0	–	96.0
Pennisi [20]	–	89.4	97.1
Maglogianis [21]	90.0	92.8	97.0
Ahn [22]	91.5	–	–
Fan [23]	89.3	93.6	–
Zamani [24]	92.0	96.5	98.1
DRFI [25]	95.2	97.9	98.9
GFAC model	97.08	98.64	99.22

99.22respectively. Amongst all existing techniques considered for comparisons, DFRI reports superior performance when compared to its counterparts. Proposed GFAC model outperforms DFRI technique with an improvement of 1.88% in terms of DSC. Improvement of 0.74% and 0.32% is reported in segmentation accuracy and SPEC of GFAC model when compared to DFRI. Here, fig. 2 represents the visual segmentation results of original*Dermoscopy* images. Here, fig. 3(a) represents the original *dermoscopy* images, 3(b) represents the ground truth images and fig. 3(c) represents the proposed segmented images. The visual segmentation using the proposed GFAC model is very effective and precise.

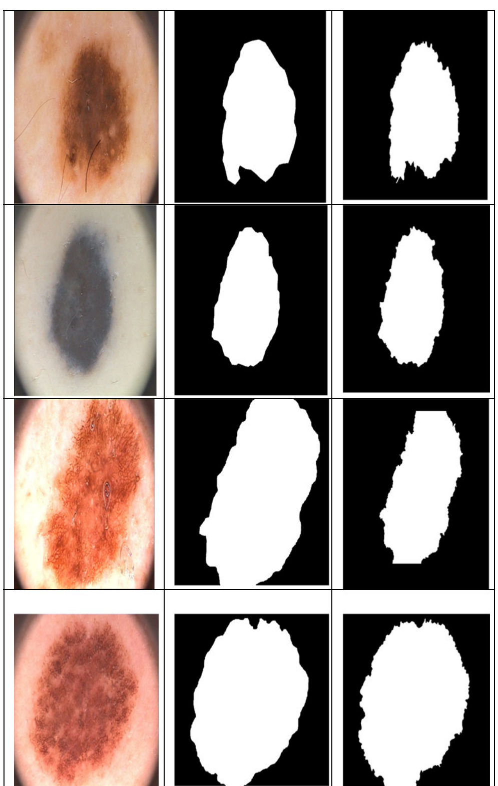

Fig. 3 Visual segmentation analysis of *Dermoscopic* images a) Original images b) Ground truth c) Segmentation using the proposed image segmentation technique

Results obtained prove that GFAC model described in this paper exhibit good segmentation performance of lesions present within *dermoscopic* images.

Conclusion

The significance of melanoma image segmentation is widely enhanced in this modern era due to presence of huge number of melanoma skin cancer patients across the world. However, the melanoma image segmentation is quiet challenging process due to presence of various artifacts, varied shape and structure. Therefore, to efficiently detect melanoma in early stages and to diagnose the melanoma skin cancer, a precise melanoma segmentation technique is introduced based on the gradient and feature adaptive contour model. Moreover, Gaussian analytical patterns are used to handle the heterogeneous objects whose mean and variance can be varied. The proposed technique helps to evaluate probability function of varied intensities considering different classes. An efficient mathematical modelling is presented for probability distributed function and to evaluate gradient and feature extraction of varied intensities. The performance of proposed image segmentation technique is tested on PH2 dataset. The superiority of the modified gradient and feature adaptive contour model can be verified against various state-of-art-techniques in terms of segmented image, feature extraction and segmentation accuracy in *dermoscopy* images. Here, the Disc Similarity Coefficient using the proposed image segmentation technique is 97.08 which is very high compare to any other existing technique. The accuracy and specificity using the proposed image segmentation technique is 98.64 and 99.22 respectively. In future, various classification algorithms like SVM, *AdaBoost* and Bag of Features (BoF) is utilized to determine the efficiency of the image segmentation technique.

References

1. Balch, C. M., Buzaid, A. C., Soong, S.-J., Atkins, M. B., Cascinelli, N., Coit, D. G., Fleming, I. D., Gershenwald, J. E., Houghton, A., Kirkwood, J. M. et al., Final version of the american joint committee on cancer staging system for cutaneous melanoma. *J. Clin. Oncol.* 19(16):3635–3648, 2001.
2. Freedberg, K. A., Geller, A. C., Miller, D. R., Lew, R. A., and Koh, H. K., Screening for malignant melanoma: A cost-effectiveness analysis. *J. Am. Acad. Dermatol.* 41(5):738–745, 1999.
3. Rigel, D. S. et al., The incidence of malignant melanoma in the United States: Issues as we approach the 21st century. *J. Am. Acad. Dermatol.* 34:839–847, 1996.
4. Kittler, H. et al., Diagnostic accuracy of dermoscopy. *Lancet Oncol.* 3:159–165, 2002.
5. Bahmer, F. A., Fritsch, P., Kreusch, J., Pehamberger, H., Rohrer, C., Schindera, I. et al., Terminology in surface microscopy. Consensus meeting of the committee on analytical morphology of the

ArbeitsgemeinschaftDermatologischeForschung, Hamburg, Federal Republic of Germany, Nov. 17, 1989. *J. Am. Acad. Dermatol.* 23:1159–1162, 1990.

6. Nascimento, J. C., and Marques, J. S., Improved Gradient Vector Flow for robust shape estimation in medical imaging. Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE. 4809–4812, 2010.
7. Shrestha, B., Bishop, J., Kam, K., Chen, X., Moss, R. H., Stoecker, W. V., Umbaugh, S., Stanley, R. J., Celebi, M. E., Marghoob, A. A., Argenziano, G., and Soyer, H. P., Detection of atypical texture features in early malignant melanoma. *Skin Res. Technol.* 16:60–65, 2010.
8. Sumithra, R. A., Suhilb, M., and Guru, D. S., International conference on advanced computing technologies and applications (ICACTA-2015). *Proc. Comput. Sci.* 45:76–85, 2015.
9. Korotkov, K., and Garcia, R., Computerized analysis of pigmented skin lesions: A review. *Artif. Intell. Med.* 56(2):69–90, 2012.
10. Silveira, M., Nascimento, J. C., Marques, J. S., Marçal, A. R., Mendonça, T., Yamauchi, S., Maeda, J., and Rozeira, J., Comparison of segmentation methods for melanoma diagnosis in dermoscopy images. *IEEE J. Sel. Top. Signal Process* 3(1):35–45, 2009.
11. Celebi, M. E., Iyatomi, H., Schaefer, G., and Stoecker, W. V., Lesion border detection in dermoscopy images. *Comput. Med. Imag. Graph* 33(2):148–153, 2009.
12. Agarwal, A., Issac, A. and Dutta, M. K., A region growing based imaging method for lesion segmentation from dermoscopic images. 2017 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON), Mathura. 632–637, 2017.
13. Agarwal, A., Issac, A., Dutta, M. K., Doneva, V. and Ivanovski, Z., Automated computer vision method for lesion segmentation from digital dermoscopic images. 2017 *4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON)*, Mathura. 538–542, 2017.
14. Yuan, Y., and Lo, Y. C., Improving Dermoscopic image segmentation with enhanced convolutional-Deconvolutional networks. *IEEE J. Biomed. Health Inform.* 99:1–1.
15. Sakeena, M., Riasat, R., Sadiq, A. H., Ahmad, Z., and Riaz, F., Dermoscopic image analysis using pattern recognition techniques from region of interest (ROI) for detection of melanoma. *Int. Conf. Mach. Learn. Cybernet. (ICMLC), Ningbo, China* 2017:162–168, 2017.
16. Ahn, E. et al., Saliency-based lesion segmentation via background detection in Dermoscopic images. *IEEE J. Biomed. Health Inform.* 21(6):1685–1693, 2017.
17. Skin cancer, Ultraviolet radiation and the INTERSUN Programme', World Health Organization (WHO).
18. Mendonça, T., Ferreira, P. M., Marques, J. S., Marcal, A. R., and Rozeira, J., PH 2-a dermoscopic image database for research and benchmarking,"in proc. EMBC 2013. IEEE. 5437–5440, 2013.
19. Pennisi, A., Bloisi, D. D., Nardi, D., Giampetruzzi, A. R., Mondino, C., and Facchiano, A., Skin lesion image segmentation using Delaunay triangulation for melanoma detection. *Comput. Med. Imaging Graph.* 52:89–103, 2016.
20. Maglogiannis, I., Doukas, C. N., and Member, S., Overview of advanced computer vision Systems for Skin Lesions Characterization. *IEEE Trans. Inf. Technol. Biomed.* 13(September):721–733, 2009.
21. Ahn, E., Kim, J., Bi, L., Kumar, A., Li, C., Fulham, M., and Feng, D. D., Saliency-based lesion segmentation via background detection in Dermoscopic images. IEEE J. Biomed. Heal. Informatics, p. Accepted to be printed, 2017.
22. Fan, H., Xie, F., Li, Y., Jiang, Z., and Liu, J., Automatic segmentation of dermoscopy images using saliency combined with Otsu threshold. *Comput. Biol. Med.* 85:75–85, 2017.
23. ZamaniTajeddin, N. and MohammadzadehAsl, B., A general algorithm for automatic lesion segmentation in dermoscopy images. 23rd Iranian Conference on Biomedical Engineering and 2016 1st International Iranian Conference on Biomedical Engineering (ICBME). 134–139, 2016.
24. Jahanifar, M., Tajeddin, N. Z., Goodya, A., and Asl, B. M., Segmentation of lesions in dermoscopy images using saliency map and contour propagation. arXiv preprint arXiv: 1703.00087, 2017.
25. Z. Yu *et al.*, Melanoma recognition in Dermoscopy images via aggregated deep convolutional features. *IEEE Trans. Biomed. Eng.*
26. Nezhadian, F. K. , and Rashidi, S., Melanoma skin cancer detection using color and new texture features. 2017 *Artificial Intelligence and Signal Processing Conference (AISP)*, Shiraz. 1–5, 2017.
27. Mustafa, S. and Kimura, A., A SVM-based diagnosis of melanoma using only useful image features. 2018 *International Workshop on Advanced Image Technology (IWAIT)*, Chiang Mai. 1–4, 2018.
28. Waheed, Z., Waheed, A., Zafar, M. and Riaz, F., An efficient machine learning approach for the detection of melanoma using dermoscopic images. 2017 *International Conference on Communication, Computing and Digital Systems (C-CODE)*, Islamabad. 316–319, 2017.