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Region growing by sector analysis for detection of blue-gray ovoids in basal cell carcinoma

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Abstract

Blue-gray ovoids (B-GOs) are critical dermoscopic structures in basal cell carcinomas (BCCs) that pose a challenge for automatic detection. Due to variation in size and color, B-GOs can be easily mistaken for similar structures in benign lesions. Analysis of these structures could help further accomplish the goal of automatic BCC detection. This study introduces an efficient sector-based method for segmenting B-GOs. Four modifications of conventional region-growing techniques are presented: (i) employing a seed area rather than a seed point, (ii) utilizing fixed control limits determined from the seed area to eliminate re-calculations of previously-added regions, (iii) determining region growing criteria using logistic regression, and (iv) area analysis and expansion by sectors. Contact dermoscopy images of 68 confirmed BCCs having B-GOs were obtained. A total of 24 color features were analyzed for all B-GO seed areas. Logistic regression analysis determined blue chromaticity, followed by red variance, were the best features for discriminating B-GO edges from surrounding areas. Segmentation of malignant structures obtained an average Pratt's figure of merit of 0.397. The techniques presented here provide a non-recursive, sector-based, region-growing method applicable to any colored structure appearing in digital images. Further research using these techniques could lead to automatic detection of B-GOs in BCCs.

Keywords

Blue gray ovoids; basal cell carcinoma; cancer detection; feature extraction; region growing; dermoscopy; image analysis

Basal cell carcinoma (BCC) is the most commonly occurring cancer, with an estimated 3.5 million new cases annually in the US (1). For early detection of these skin cancers, physicians employ dermoscopy to visualize structures which cannot normally be seen with the unassisted eye. The classic BCC structures visible with the dermatoscope (3Gen LLC, San Juan Capistrano, CA; Heine Optotechnik, Herrsching, Germany) are called the BASAL features: Blue-gray ovoids and globules (B-GOs), Arborizing telangiectasia, Semitranslucency / Spoke wheel structures, Atraumatic ulcerations, and Leaf-like structures (2, 3).

B-GOs are roughly oval objects with indistinct borders, varying from very light blue to dark gray in color, as shown in Fig. 1. These objects represent nests of pigmented basaloid tumor

cells on histopathology (4). The blue hue is the result of the Tyndall effect—light reflected from the deeper basaloid cell clusters causes preferential reflection of the shorter blue wavelengths through the turbid cutaneous medium. Any pigment located as deep as the mid-dermis demonstrates the Tyndall effect, therefore benign mimics of the malignant B-GO structures are common. These examples of B-GOs show such a wide variation in shape, hue, brightness and size in these structures that significant overlap of benign and malignant structures is present. This poses a considerable challenge for automatic discrimination of B-GOs from benign structures. This article focuses on the problem of segmentation of these structures from the noisy surrounding areas using a novel region-growing technique.

Region growing is a widely used technique to merge areas within an image that have similar properties (5–10). The essential idea of region growing is that two adjacent regions, the existing region R_1 and the candidate region R_2 are joined if the merging criterion H is satisfied, where H is a similarity measure, e.g. gray level averages for R_1, R_2 :

$$H(R_1 \cup R_2) = TRUE \quad (1)$$

The merging criterion H is chosen to best represent the image domain. For domains such as medical dermoscopy images or satellite land images, color is often preferable to gray level (6, 11). The candidate region is generally 2×2 , 4×4 or 8×8 pixel blocks in size (5). In its simplest form, region growing proceeds from a seed point, iteratively testing the H criterion, and terminating when the H criterion fails.

Region-growing techniques have the primary advantage of overcoming noise, including weak edges present in the image (5). B-GOs lack sharp boundaries, therefore region-growing techniques are ideal for this application. The primary disadvantage of existing region-growing techniques is the inefficiency of recursive testing in the merging algorithm. A merging algorithm has recursive testing if the candidate region is added to the existing region before testing. The merging criterion H in Equation (1) has to be re-calculated n times for n merging operations for the initial R_1 region, making this step computationally intensive.

Another disadvantage of some existing techniques is the arbitrary selection of the H merging criterion rather than optimization of the H criterion/criteria based on the characteristics of the image domain. Ideally, the image domain has a single criterion after criteria optimization, but the use of more than one criterion in the merging step may yield more exact boundaries.

Finally, we note that a fixed candidate block size is generally used. Having an expanding block size allows for more efficient sector-based region growing.

This article presents a novel region-growing method that efficiently segments images to find B-GOs. This sector-based region growing method has improvements to overcome all disadvantages mentioned and yields satisfactory segmentation results in this difficult and noisy image domain by employing: (i) a seed area rather than a seed point, (ii) fixed control limits determined from the seed area, eliminating re-calculations for previously added regions, (iii) region-growing criteria based on logistic regression analysis, and (iv) sector-based expansion with expanding candidate regions that match circumference growth as the sector radius increases. The remainder of the article is organized as follows: (II) Materials and Methods, (III) Experiments and Results, (IV) Discussion

Materials and Methods

Merging criterion: Upper and lower control limit test Determining significant feature(s) for B-GO region-growing blue-gray ovoid center expansion

The color features and their corresponding calculations are shown in Table 1. These features were extracted from the margins of the B-GO structures within the lesion and areas immediately surrounding the B-GOs. In order to use the relative color method of Cheng (12), borders were drawn by a dermatologist for all 68 lesions within the images using a second-order spline function (13). Outlines were drawn around the B-GO structures using the same spline function, as shown in Figure 1. These spot masks were used to determine which color feature had the most significance in defining B-GO margins. A logistic regression procedure (SAS Proc Logit, SAS Inc., Cary, NC) was used to determine the significant color features. The most significant features, in descending order of multivariate χ^2 , shown in Table 2, were: (i) blue chromaticity, (ii) red variance, and (iii) red chromaticity. The three-feature expansion model showed no improvement over a two-feature expansion model, so only blue chromaticity and red variance were used in the border expansion of the B-GOs.

Pre-processing and seed block determination

A median filter (3×3) was applied as a preprocessing step to smooth out any noise, such as weak edges, that would interfere with the color calculations, negatively impacting the expansion procedure.

The B-GO centroids (centers of gravity) were found by calculating the moments of the hand-drawn B-GO masks. An 8×8 seed block around the centroid was used to mark the starting point of the B-GO expansion.

Establishing upper and lower control limits for region growing

The average μ and standard deviation σ for both blue chromaticity and red variance were calculated within the 8×8 seed block. These values were used to determine the upper and lower control limits, UCL and LCL. The natural process limits $\mu \pm 3\sigma$ (14), were selected for UCL and LCL:

$$\left. \begin{aligned} UCL_{\text{BlueChrom}} &= \mu_{\text{BlockBlueChrom}} + 3\sigma_{\text{BlockBlueChrom}} \\ LCL_{\text{BlueChrom}} &= \mu_{\text{BlockBlueChrom}} - 3\sigma_{\text{BlockBlueChrom}} \\ UCL_{\text{RedVar}} &= \mu_{\text{BlockRedVar}} + 3\sigma_{\text{BlockRedVar}} \\ LCL_{\text{RedVar}} &= \mu_{\text{BlockRedVar}} - 3\sigma_{\text{BlockRedVar}} \end{aligned} \right\} \quad (2)$$

$\mu_{\text{BlockBlueChrom}}$ denotes the average blue chromaticity within the initial 8×8 seed block; the other variables are similarly calculated.

Fig. 2 shows the application of the control limits to determine whether expansion is warranted. The blue chromaticity and red variance values for the candidate block must both fall between the UCL and LCL established from the seed block for block expansion to continue.

Sector-based, region-growing method Intra-sector expansion

Fig. 3 shows the plan for expansion of the first two sectors: the leftmost sector north of the seed block, labeled Sector North-1, and the adjacent sector, labeled Sector North-2. The blocks expand as the sector grows. The n th candidate block in North and South sectors has dimensions of $4 \times (2n + 2)$ pixels and the n th candidate block in East and West sectors has

dimensions of $4 \times (2n)$ pixels. Sector expansion proceeds until the control limit test fails (Fig. 2).

Sector expansion sequence

The expansion of each sector proceeds from Sector North-1, then Sector North-2, and continues clockwise until the 12th and last sector, Sector West-3. The time sequence of expansion is shown in Figure 4.

Experiments and Results

Data used

In this study, 68 contact, non-polarized dermoscopic images of basal cell carcinoma confirmed by dermatopathology were collected in the study SBIR R44 CA-101639-02A2 of the National Institutes of Health (NIH) and approved by the Phelps County Regional Medical Center Institutional Review Board, Rolla, MO, under the guidelines of the Belmont Report. All images were full-color images with 1024×768 resolution. These images were converted to binary image masks to assist with the computation of the color and texture features.

Comparing 12-sector expansion with 4-sector and 8-sector expansion

Before applying the 12-directional expansion algorithm for all B-GO masks, 4-directional and 8-directional expansion methods were applied to determine the minimum number of expansion directions needed. Each of these directional variants used the expansion criterion in (2) and sector-based methods in Section II. Comparison of 4- 8- and 12-sector expansion results are shown in Fig. 5.

As shown in Fig. 5, the 12-directional expansion includes additional area of the B-GO missed by 4- and 8-directional methods. We conclude that a minimum of 12-sector expansion is needed for best overall results. Thus, 12-sector expansion was used for region growing in B-GO segmentation.

Pratt's figure of merit for B-GO segmentation

For all images, the Pratt's figure of merit (PFOM) was calculated (15, 16). Other methods of error evaluation in skin lesion segmentation calculate non-congruent areas (17, 18). PFOM bears an advantage over these methods, since this metric calculates errors for edges summed over the boundary. PFOM is calculated below:

$$R = \frac{1}{\max(I_I, I_A)} \sum_{i=1}^{I_A} \frac{1}{1 + \beta d(i)^2}, \quad (3)$$

Where, I_I is the number of ideal edge points in the image, I_A is the number of edge points found by the edge detector, β is a scaling constant that can be adjusted to adjust the penalty for offset edges. For this study, the MATLAB default value for PFOM, $\beta = 0.11$, was used. $d(i)$ is the distance of a found edge point to an ideal edge point (Euclidian distance).

The average PFOM = 0.397 ± 0.216 for the entire set of 68 B-GO's. Four B-GOs with border results showing the sector-based region-growing border (dotted lines) and the manually-drawn dermatologist border (solid lines) are shown.

The final B-GO segmentation results show that the technique is able to overcome weak edges such as vessels (Fig. 5) and bubble edges (Fig. 6a). The figures show segmentation results better (Figs. 6a,b) and worse (Figs. 6c,d) than the average PFOM of 0.397.

Discussion

This study is the first to focus on segmentation of blue-gray ovoids (B-GOs) in BCCs. This is a step towards automatic detection of these structures, found in many BCCs. B-GOs vary in size, shape, hue, and brightness and therefore require an adaptive segmentation method. Accurate detection of these structures is important because these structures resemble similar structures found in other lesions, both benign and malignant (19).

Our method begins with a seed area rather than a seed point. The seed area provides more complete information than a seed point would permit. The seed area allows more precise color average determination and yields texture information not available from a point. This more complete information, in turn, enables fast non-recursive merging. Expansion then proceeds from the seed area, using the two test criteria found by statistical analysis of the seed areas. Since the two test criteria are tested only for the new candidate area, with no area tested again after merging, the merging criteria are non-recursive. The results, using the 3-sigma limits proposed, give satisfactory results, as measured by Pratt's figure of merit.

The criterion/criteria for region-growing merging, the H criterion in Equation (1), is/are often chosen empirically. We propose logistic regression to find the best separators for B-GO from non-B-GO regions. The analysis in Table 1 shows that the two most powerful criteria for B-GO expansion are blue chromaticity and red variance, which have the highest multivariate χ^2 by logistic regression. Since the merging is terminated in our system when any criteria in Equation (2) fail, our proposed method provides a powerful technique for selecting merging criteria from the B-GO margins. Our method of feature analysis at structure margins, comparing these features with surrounding areas, can be applied to find merging criteria for any colored structure in digital images. Thus data such as that in Table 2 can be obtained and used to choose region-growing criteria. The adjacency demand feature seen in Fig. 4 avoids creating holes and overfilling normally seen in region-growing methods.

Future work in this domain will extend these results to automatic detection of B-GOs. The key step necessary before automatic discrimination can be accomplished is user-independent determination of seed areas. Because of the widely varying B-GO features, an adaptive method will be used. Conversion of the image to the blue chromaticity space and determination of red variance in candidate seed areas is anticipated to allow fully automated detection of B-GOs.

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References

1. Rogers HW, Weinstock MA, Harris AR, Hinckley MR, Feldman SR, Fleischer AB, Coldiron BM. Incidence estimate of nonmelanoma skin cancer in the United States, 2006. *Arch Dermatol.* 2010; 146:283–287. [PubMed: 20231499]
2. Stoecker WV, Stolz W. Dermos-copy and the diagnostic challenge of amelanotic and hypomelanotic melanoma. *Arch Dermatol.* 2010; 144:1120–1127.

3. Altamura D, Menzies SW, Argenziano G, Zalaudek I, Soyer HP, Sera F, Avramidis M, DeAmbrosio K, Fargnoli MC, Peris K. Dermatoscopy of basal cell carcinoma: morphologic variability of global and local features and accuracy of diagnosis. *J Am Acad Dermatol*. 2010; 62:67–75. [PubMed: 19828209]
4. Agero AL, Busam KJ, Benvenuto-Andrade C, Scope A, Gill M, Marghoob AA, Gonz[notdef]alez S, Halpern AC. Reflectance confocal microscopy of pigmented basal cell carcinoma. *J Am Acad Dermatol*. 2006; 54:638–643. [PubMed: 16546585]
5. Sonka, M.; Hlavac, V.; Boyle, R.; Gonzalez, RC. Image processing, analysis and machine vision. 3rd edn.. Thomson; Toronto: 2008. p. 223-232.
6. Gonzalez, RC.; Woods, RE. Digital Image Processing. 3rd edn.. Prentice-Hall; Upper Saddle River, NJ: 2008. p. 785
7. Kang C, Wang W. Fuzzy based seeded region growing for image segmentation. Proc. 28th North American Fuzzy Information Processing Society Annual Conference, IEEE. 2009
8. Huang C, Liu Q, Li X. Color iamge segmentation by seeded region growing. Proc. 7th Int. Conf. Fuzzy Systems and Knowledge Discovery (FSKD 2010). 2010; 2:533–536.
9. Adams R, Bischof L. Seeded region growing. *IEEE Trans Pattern Anal Mach Intell*. 1994; 36:641–647.
10. Belongie S, Carson C, Greenspan H, Malik J. Color- and texture based image segmentation using EM and its application to content-based image retrieval. Proc Int Conf Comput Vis, IEEE. 1998:675–682.
11. Argenziano B, Soyer HP, Chimenti S, Talamini R, Corona R, Sera FF, et al. Dermoscopy of pigmented skin lesions: results of a consensus meeting via the Internet. *J Am Acad Dermatol*. 2003; 48:679–693. [PubMed: 12734496]
12. Cheng Y, Swamisai R, Umbaugh SE, Moss RH, Stoecker WV, Teegala S, Srinivasan SK. Skin Lesion Classification Using Relative Color Features. *Skin Res Technol*. 2008; 14:53–64. [PubMed: 18211602]
13. Gander W, Golub GH, Strebel R. Least-Squares Fitting of Circles and Ellipses. *BIT*. 1994; 34:558–578.
14. National Institute of Technical Standards NIST. Department of Commerce; <http://www.itl.nist.gov/div898/handbook/pmc/section3/pmc31.htm> [February 23, 2012]
15. Pratt, W. Digital Image Processing. Wiley; New York, NY: 1978.
16. Lim DH. Robust edge detection in noisy images. *Comput Stat Data Anal*. 2006; 50:803–812.
17. Hance GA, Umbaugh SE, Moss RH, Stoecker WV. Unsupervised color image segmentation with application to skin tumor borders. *IEEE Trans Med Biol*. 1996; 15:104–111.
18. Celebi ME, Iyatomi H, Malters JM, Schaefer G, Stoecker WV, Grichnik JM. An Improved Objective Evaluation Measure for Border Detection in Dermoscopy Images. *Skin Res Technol*. 2009; 15:444–450. [PubMed: 19832956]
19. Celebi ME, Iyatomi H, Stoecker WV, Moss RH, Rabinovitz HS, Argenziano G, Soyer HP. Automatic detection of blue-white veil and related structures in dermos-copy images. *Comput Med Imaging Graph*. 2008; 32:670–677. [PubMed: 18804955]

Fig. 1.
Dermoscopy images of blue-gray ovoids in BCCs. Note: 1) significant variation in shape, hue, brightness and size of objects and 2) weak edges in vessels and hairs.

Fig. 2.
Expansion Algorithm Flowchart

Fig. 3.

12-sector expansion technique around the central 8×8 seed area shows the first 3 expansion steps for the 4 North sectors and 2 East sectors. Each small square in the seed area represents one pixel.

Fig. 4.
Time lapse frames of the 12-directional expansion method

Fig. 5. (a) Comparison of 4-directional B-GO center expansion (solid border) and 8-directional B-GO center expansion (dotted border). (b) Comparison of 12-directional (solid border), 4-directional (dotted border) and 8-directional (dashed border) B-GO center expansion methods.

Fig. 6. Four B-GOs after sector expansion, using Pratt's FOM (PFOM) to compare with reference masks: a. PFOM = 0.717, b. PFOM = 0.573, c. PFOM = 0.307, d. PFOM = 0.317

TABLE 1

Twenty-four color features extracted from B-GOs

Color features	Description or Equations
Absolute RGB	Absolute R = Red average over spot Absolute G = Green average over spot Absolute B = Blue average over spot
Relative RGB	Relative R = Absolute R–Skin R Relative G = Absolute G–Skin G Relative B = Absolute B–Skin B
RGB chromaticity	R Chromaticity = $R/(R + G + B)$ G Chromaticity = $G/(R + G + B)$ B Chromaticity = $B/(R + G + B)$
Relative RGB chromaticity	Relative R Chromaticity = Relative R/Relative(R + G + B) Relative G Chromaticity = Relative G/Relative(R + G + B) Relative B Chromaticity = Relative B/Relative(R + G + B)
Relative lesion RGB	Relative color calculated by subtracting the absolute RGB values taken from the whole lesion from the absolute RGB values within the blue-gray spots. Example: Relative Lesion R = Absolute R_{SPOT} –Absolute R_{LESION}
RGB variance	R Variance = $\Sigma(R-total_R)^2$ G Variance = $\Sigma(G-total_G)^2$ B Variance = $\Sigma(B-total_B)^2$
Relative color ratios	Relative B/Relative R Relative B/Relative G Relative G/Relative R
Converting RGB color plane to XYZ color plane	R to X = $(R \times 0.49 + G \times 0.31 + B \times 0.20) / 0.17697$ G to Y = $(R \times 0.17697 + G \times 0.81240 + B \times 0.01063) / 0.17697$ B to Z = $(R \times 0.0 + G \times 0.01 + B \times 0.99) / 0.17697$

TABLE 2

Logistic regression analysis results obtained from SAS

Color Features	Pr > Chi-square	Chi-square score
Absolute red	0.0042	8.2026
Absolute green	0.0155	5.8578
Absolute blue	Not significant	Not significant
Relative red	Not significant	Not significant
Relative green	0.0020	9.5081
Relative blue	Not significant	Not significant
Red chromaticity	<0.0001	15.6139
Green chromaticity	Not significant	Not significant
Blue chromaticity	<0.0001	31.7005
Relative red chromaticity	Not significant	Not significant
Relative green chromaticity	Not significant	Not significant
Relative blue chromaticity	Not significant	Not significant
Relative-lesion red	Not significant	Not significant
Relative-lesion green	Not significant	Not significant
Relative-lesion blue	Not significant	Not significant
Red variance	<0.0001	23.7064
Green variance	Not significant	Not significant
Blue variance	0.0053	7.7722
Relative blue/Relative red	Not significant	Not significant
Relative blue/Relative green	Not significant	Not significant
Relative Green / Relative red	Not significant	Not significant
Red to XYZ	Not significant	Not significant
Green to XYZ	Not significant	Not significant
Blue to XYZ	Not significant	Not significant