Color Energy as a Seed Descriptor for Image Segmentation with Region Growing Algorithms on Skin Wound Images

José Luis Seixas Jr., Sylvio Barbon Jr., Claudia Martins Siqueira,
Ivan Frederico Lupiano Dias, André Giovanni Castaldin, Alan Salvany Felinto
Universidade Estadual de Londrina (UEL)
Caixa Postal 10.011 – CEP 86.057-970 – Londrina – PR – Brazil

***Abstract*—This paper presents a seed finding method for region growing segmentation approach using color channel energy in image regions. Instead of using the RGB system separated for each pixel, the proposal uses the energy on each color channel to improve the range of the possible values, then creates a more specific seed to detail different regions. Region size used to calculate energy was adjusted to verify the proposed method. Images used were real wound photos, taken from patients undergoing treatment at the university hospital. Results showed that energy on regions presents enough information to segment, leading to a high percentage of matching with experts marks.**

Keywords: Medical Computing, Image Segmentation, Skin Lesion Recognition, Region Growing Algorithm Seed.

I. INTRODUCTION

Incorrect diagnosis of skin diseases can lead to complications during the healing process, [1] mentions the case of pyoderma gangrenosum that has different causes and can have treatments that would not be recommended for patients with other kind of injuries. Injury recognition through characteristics such as size, severity, presence of infection, vascularity, has an important impact in determining the most appropriate treatment for each patient [2]. Most of skin lesions descriptors presented by [2] can be obtained by analyzing patients' lesion images segmentation, but a good segmentation is necessary to work with correct and reliable data. In [3] we can see that "image segmentation is essentially an application-oriented problem that demands either strong intervention of human experts or application specific solutions".

Color is the most informative low-level feature and might convey salience information of a given image according to [4], thus many algorithms turn to color-based segmentation to target areas of interest. [5] describes various algorithms and different proposals regarding the segmentation performed by color and cites region-based approaches as a good noise immune option. In skin lesions, algorithms based on region growth work satisfactorily because regions of injury are quite homogeneous.

The region growing algorithms disadvantage is the fact that the seed has very high impact on segmentation. Region merging techniques are implemented to reduce this impact, but consequently increase complexity regarding processing time and memory.

Lots of problems in medical analysis depends on or can be helped by images. These images depend on experts to describe each of them. And in some cases doctors cannot be with patient, in these cases, images are the option to send or keep the condition of this patient. The negative point is that doctor's analysis would still be necessary. The goal of this paper is to create a method that finds a region of certainty of injury by calculating the energy of each color channels, which would be input to region growing algorithms, in an attempt to reduce the need for these images to be seen by a doctor, since the amount of images and information is increasing steadily.

This paper is organized as follows: Section II, with a brief description of works with close characteristics or similar problems. Section III describes what is and how to use the color energy for the problem previously mentioned. In Section IV we have the descriptions of experiments, results of experiments and what they represent are addressed in Section V. Finally, Section VI will bring the conclusions that can be drawn from this work, along with suggestions for future work that may be performed based on this paper.

II. RELATED WORKS

To find articles regarding computational processes to help medical staff is not difficult as [6], or extracting features from images as [7] for cataract detection and [8] for renal segmentation.

[9] proposal is used on lower extremity skin ulcers as presented in this paper, but using near-infrared imagery, [10] segments skin diseases in phases, starting with a border detection then using contour merging, [11] focuses on clustering processes of the color components using HSI color model and mathematical representation of the skin ulcers morphology.

In [5] is described segmentation techniques such as histogram, fuzzy logic, regions approaches, borders and artificial intelligence. Segmentation is a very important step that must happen before image information extraction.

There are studies that seek descriptors for areas to be targeted as [12] and [13]. [14] uses the local binary pattern operator as texture feature descriptor. Also study techniques that use textures to help identify objects of interest as in [15] or [16], or using textures with edge detection such as [17] and [18].

978-1-4799-6644-8/14/$31.00 ©2014 IEEE

In [19] is presented an energy function that combines color and edge for the segmentation, as in [20] that also uses two techniques for region extraction using wavelets transform for texture and contourlet transform on boundaries. Or other segmentation is presented based on color and texture in [21].

But most similar paper from the proposal described in this paper is seen in [22], that selects seed points for region growing algorithms in breast ultrasound images. The similarity of proposals is on the fact of seed seeking and on using medical images as well, so difficulties dealing with medical images are part of the scope of both works.

III. Color Energy

The color energy on a region can describe the idea of how red, blue, or other color is the region taken. Color energy consists on squared channel value [23], when used this technique, values will have more disparity, improving range, making it easier to express a different value. A difference between two numbers is more visible when you look at them squared, specially when using computing techniques which depends on numbers, and most of all, depends on close numbers.

$$\varepsilon(x, y) = \sum_{a}^{b} |p(x,\ y)|^2 \qquad (1)$$

In Equation 1 is seen the formal expression to calculate energy on a pixel-based region. Given (x, y), energy is the sum of the values from an specific channel (red, green or blue) from a to b, where a is the upper left coordinates from used region and b (x, y) coordinates plus region size variation.

For instance, energy will show how important is this channel on region calculated and difference of importance from the channels gives the impact on how near the image taken is from the region supposed to be segmented.

The algorithm presented uses color channels energy to calculate how visible some of them would be on image, for example, when trying to segment some region that is too red, red channel energy will be much higher than others.

If the region is mostly yellow, blue channel will have energy much lower than others, in other words, it's possibly to "see" the color intensity on region based on how far the energy is on some channels at region being analyzed.

An example of how energy can be a better indicator would be the Pythagorean triangle, the triangle with sides 3, 4 and 5. If sides represent blue, green and red channels, respectively, summed values of blue and green, we would have a greater value than the red. But the comparison made with the values squared would equal them. Suppose now that sides are 3, 4 and 6, to blue, green and red, respectively. The sum of the values of blue and green still overcoming red, but when using squared values, we would have a better sense of the redness of the point in question, which is what is being sought by descriptor.

Just like in human perception, looking at a region and seeing that this region is mostly the color of some part of the image, will be assumed that this part belongs to the region being searched.

The method consists in calculating difference between two channels' energy for each part of image as possible. When some of the colors energy are overriding the appearance of others, in the case presented, the red channel influence is much higher than the others, so this was the difference wanted. Using the largest values of red difference, these areas was denoted as the foreground.

To complete segmentation, results of this calculation can be performed through two methods:

- **Small regions as seed:** Known algorithms as [24] and [25] uses seed to perform region growing segmentation. These methods don't demand a large set of data to start, so even with small regions, energy calculation will provide enough information for these algorithms to perform region growing on wound area.
- **Big regions as texture:** Texture segmentation needs more information than seed segmentation, because texture requires region and descriptors to generate patterns to be searched by algorithm. So when big regions are made, they are not good to be reprocessed as a seed, but has a good range of information to build descriptors patterns.

IV. Experiments

This research was approved by the Research Ethics Committee of Londrina State University (UEL Universidade Estadual de Londrina) in accordance with law 315/06 from 02/02/07 (amendment 1/2010). The subject was informed about research nature and signed an informed consent. Patients with chronic ulcers in lower limbs due to venous insufficiency were admitted. The survey was conducted in the CISMEPAR (Consrcio Intermunicipal de Sade do Mdio Paranapanema) in a partnership with Londrina University Hospital/UEL.

Images were acquired from 8 patients with different stages of injury, with a Sony camera model DSC-S1900, that allows high portability and manual settings. Settings were used in manual mode so there could be similarity in images, leaving only the focus to be automatic. Thus, the camera would need to be configured only once and medical staff itself could do following acquisitions.

Sets of images were acquired for variables adjustment that would be used for all acquisitions. Settings choice had as main purpose, maintain color quality and avoid light overexposure. Images used for parameters adjustment were not used in the construction of the algorithm, nor in tests. The set that best suited the purposes of this article had the following characteristics:

- Exposure value: -0.3;
- F-Number: 3.1;
- ISO: 400;
- Flash: disabled.

These images, acquired with cited settings, were marked by doctors at the hospital, so being possible to compare results regarding which area would be considered injury.

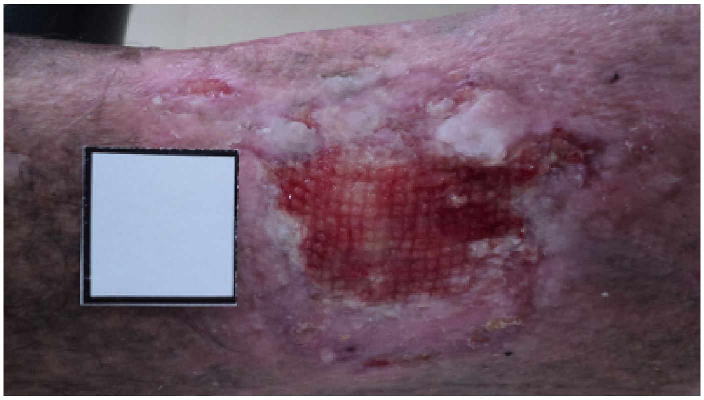

Fig. 1: Original image.

Figure 1 shows an example of acquired image. Images are very similar because standardized acquisition. 33 images were used in bitmap format with 400 x 225 pixels resolution, they were used with low resolution by the need to store regions in a list. Thus, regions search was treated in percentages rather than pixels, as will be described in subsection IV-C.

The white squares present in Figures 1 and 3 are markers for area calculation, since the segmentation procedure is a step towards lesion characteristics extraction, thus an object, easy to detect and with known size was placed in image as a reference. Moreover, the square was used as a good object for adjusting the white balance on the camera.

Fig. 2: Image with region marked by doctor.

In Figure 2 is shown a marked area. These images were obtained with doctors help who identified wound region in pictures of which region would be considered injury. Following this marking, the demarcated area was filled to facilitate the visualization and later comparisons.

A. Experiment 1

The goal of first experiment was to achieve the objective of this paper, namely to find a region where there is certainty of belonging to a injury region. And then, this region could be a seed for region growing algorithms.

Data: A wound image.
Result: A region that can be used as a seed for region growing algorithms.
Divide the image into small areas;
forall the *small areas* **do**
    Calculate the energy channels of red, blue and green;
    Subtract the value of the blue and green channels from red;
    Add in an ordered list by the value of this difference;
end
return the first region in the list;

Algorithm 1: Algorithm to get the highest energy region.

Note that is necessary to keep more information than just the difference calculated to get the first region in list, in our experiment, difference value to order the list was kept with coordinates x and y from upper left region corner. The order will be highest first.

As can be seen by Algorithm 1, to store a list for the simple fact of getting the region with the largest differential would not be needed, could just return the highest value as long as comparing calculated energies. However, described algorithm was used in further experiments that will be described later, which structure list storage was necessary.

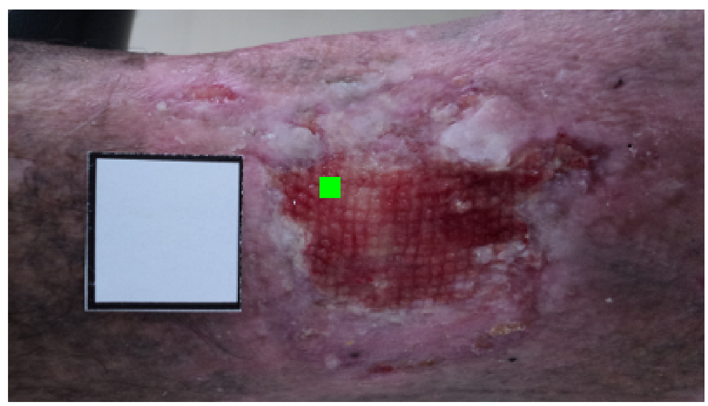

Fig. 3: Region of injury found by the algorithm.

Figure 3 shows region found by Algorithm 1, the green region denotes highest difference between energy of red channel from green and blue channels together.

B. Experiment 2

Second experiment aims to identify how many regions from ordered list would be part of injury region, i.e., how many times highest energies from list would find injury area. This experiment was conducted to identify other injury areas to use as seeds, in cases where lesion has less reddened areas or at different stages of wound.

Data: The ordered list from previous algorithm.
forall the *elements from the ordered list* **do**
    for *(w, h)* $\leftarrow (x, y)$**to**$(x + dx, y + dy)$**do**
        if *(w, h)* $\notin woundregion$**then**
            return *list index;*
        end
    end
end

Algorithm 2: Algorithm to get how many highest energies belongs to the lesion.

Algorithm 2 seeks how many regions actually belong to the injury. So it seeks in each region if there is any pixel that does not belong to injury. Comparison of belonging or not belonging to an area of injury was made using filled images as shown in Figure 2.

As can be seen in algorithm, any pixel that is not part of marked region by specialist, denotes this chosen region as a region outside the lesion. This assumption is quite extreme, since only one pixel would cause entire region to be considered outside area of interest, but it is essential for this paper. Thus, it would be guaranteed that chosen region would have no pixel that could cause noise in the seed for growing region segmentation. So even algorithms that operate on smaller regions and do not have good sensitivity to noise, would not have problems by not needing to treat them.

C. Experiment 3

As seen in subsection IV-A by analyzing the energy of the color channels is possible to find a region of injury. In third experiment, the same attempts were made, but with different region sizes for energy calculation. For algorithms where a small part of region would be sufficient for targeting, it would be interesting to keep a small area by not having to keep a lot of information in memory, small regions are also less susceptible to have noise. However, dividing the image into many regions would take more time in comparisons on which region should be chosen as seed. Therefore, with size variations on searching for appropriate region can generate precision possibilities or speed which can be decisive depending on application to which the algorithm is being used.

Alternative sizes were taken with percentage of image width and height, percentage was used so same method could be used for any size of input image.

Initially regions of 2% of the width and height were used, then this value was increased 2% until reach 10% of these measures, i.e., for our images of 400 x 225, there was regions of 8x4(2%), 16x9(4%), 24x13(6%), 32x18(8%) and 40x22(10%) pixels, calculated by method.

Moreover, some algorithms work best with larger regions that could provide a greater amount of information for later decision to join a new area. Seed made by small areas can become not interesting to keep, even though there was a reduction in memory consumption.

V. Results

According to [26], during the process of building a frequency table, to choose sub intervals that correspond to data needed is necessary, in this case, ranges that are or not part of the wound. These intervals were given by images marked by experts, since these images have settings which part of image is part of a group or another.

TABLE I: Wound regions found.

	Region Size				
File Number	2%	4%	6%	8%	10%
1	154	35	15	4	2
2	214	41	15	7	2
3	275	59	20	11	1
4	11	5	2	1	0
5	38	3	2	1	0
6	38	4	1	0	0
7	65	6	3	1	0
8	59	12	7	2	0
9	12	3	1	0	0
10	20	4	2	1	0
11	6	2	1	0	0
12	5	2	1	0	0
13	5	2	1	0	0
14	80	29	12	7	2
15	10	4	2	1	0
16	100	24	12	3	1
17	71	15	6	3	1
18	64	7	4	1	0
19	205	41	17	9	4
20	35	7	5	2	1
21	124	25	7	6	1
22	45	12	4	3	1
23	276	52	25	5	1
24	170	39	14	3	2
25	46	8	5	1	0
26	111	37	25	9	3
27	12	5	3	1	0
28	109	15	11	8	2
29	132	20	10	5	3
30	192	30	17	6	3
31	473	117	39	15	6
32	28	5	1	0	0
33	16	4	2	1	0

Table I shows that presented strategy can find at least one region of wound lesion that has sufficient size, i.e., the first element in the ordered list of energies is a region that would be useful as a region growing seed. Important to remember that counting energies regions are rectangular, so some curves in wounds or thin wounds can make slightly larger regions too large to fit perfectly into the wound.

Using 2% of width and height were possible to generate 2812 regions, 625 were generated with 4% regions, 286 regions of 6%, 155 of 8% and 102 of 10% were generated. Some pixels may have been used in more than one regions due to approximation.

Table I was built using the experiment described in Subsection IV-B, it was built by counting how many region is possible to find using different region sizes. The region got with largest energy difference that was marked as foreground was all inside wound region. Not even one single pixel touched a non-wound region.

With this, there are percentages where region does not fit the injury, these regions still can be used depending on the error that can be considered acceptable. We prefer not to work with false positives, i.e., better to have a smaller region that best fits in injury completely than larger region that crosses this area boundaries. The justification for this choice is that area of healthy skin takes a big part of picture and if used as seed, probably the region's growth would spread too much.

TABLE II: Execution time.

Region Size	Execution Time (Minutes)
2%	161" 52'
4%	39" 08'
6%	16" 46'
8%	9" 6'
10%	6" 9'

Table II has results from Subsection IV-C developed using a HP desktop, with Intel Core 2 Quad Q9505 processor, 2,83GHz, 8GB of RAM memory, using windows 7 professional 64 bits as operational system, algorithm was developed in Java language on version 1.7 with Eclipse Juno IDE.

The table obtained indicates time spent in phase of image division into regions and energy calculation, these execution time calculations are used to indicate the best case for different examples, so for cases where images contains small wounds would require a division into small regions, but process takes longer than larger regions. The results shown by execution time table shows times for all images of each region sizes.

In cases presented by this work, medium values can be possible to used, such as 6% which managed to secure at least one region entirely within the wound in all tests and were able to reduce processing time by almost 90%. Another factor that must be taken into consideration is how much information is needed to be passed to each algorithm. If the algorithm does not search for a point in image, but a region to look for patterns, regions can be seen in two ways:

- **Small region** (2%)**:** This types will have the same problem as single pixel approach, it may not have enough data to be a good perspective for segmentation and may not sufficient to describe the whole wound. Yet, as seen in the table, will have a longer run with image division into many small regions.
- **Big region** (10%)**:** In this case, some images will not have a wound big enough to provide data, so when the region taken is bigger than the wound, pattern taken by algorithm will include areas outside the wound. Even with a shorter execution, it may cause error in region growth, caused by inclusion of external pixels in seed.

VI. Conclusion

A wound region based on the difference between energies of color channels is possible to find, even with alternative sizes from region to avoid problems with performance. Alternative sizes of areas become applicable in different work situations of acquisition, thus, can be used in various medical imaging analysis.

Then, segmentation algorithms existing in the literature would be able to bring good results, as opposed to some cases that do not have good results due to not appropriate seed choice for region growing approach. As image will be used to analyze wounds, it is quite likely that object of interest will appear enough thus not being necessary to divide into very small regions.

Important to note that the proposed paper does not infer which region growing algorithm should be used. The paper shows how to find a good seed for segmentation that is a problem found in some of them and it is data inputs to others.

Therefore, developers can use known and implemented algorithms or propose a new solution using the data that can be extracted from the regions. This promotes alternative resources so that even people who do not belong to computer science field can use this strategy. So segmentation can be done with programs that already have growing region functions implemented.

As future work, energies can be analyzed in different ways, looking for other lesion areas that may be at different stages of disease. Thus, analyzes could include other wound characteristics and be more accurate. Another work could be based on specifying a particular algorithm for growing regions and trying to retrieve certain information that would be relevant in its use.

VII. Acknowledgment

The authors would like to thank CAPES and Fundao Araucria (Brazilian Agencies) for their financial support.

References

[1] R. H. Weenig, M. D. P. Davis, P. R. Dahl, and D. Su, "Skin ulcers misdiagnosed as pyoderma gangrenosum," *The New England journal of medicine*, vol. 347, no. 18, pp. 1412–1418, 2002.

[2] R. G. Frykberg, "Diabetic foot ulcers: Current concepts," *The Journal of Foot and Ankle Surgery*, vol. 37, no. 5, pp. 440 – 446, 1998.

[3] H. B. Kekre, T. K. Sarode, and B. C. Raul, "Color image segmentation using kekre's fast codebook generation algorithm based on energy ordering concept," in *Proceedings of the International Conference on Advances in Computing, Communication and Control*, ser. ICAC3 '09. New York, NY, USA: ACM, 2009, pp. 357–362.

[4] K. Fu, C. Gong, J. Yang, Y. Zhou, and I. Y.-H. Gu, "Superpixel based color contrast and color distribution driven salient object detection." *Sig. Proc.: Image Comm.*, vol. 28, no. 10, pp. 1448–1463, 2013.

[5] H.-D. Cheng, X. Jiang, Y. Sun, and J. Wang, "Color image segmentation: advances and prospects." *Pattern Recognition*, vol. 34, no. 12, pp. 2259–2281, 2001.

[6] L. Bi, X. Zhou, L. Zhang, and R. Zhang, "Multidimensional analysis for traditional chinese medicine diagnosis and treatment on hepatitis diseases," in *International Conference on e-Health Networking, Applications and Services*, 2012, pp. 52–56.

[7] M. Yang, J. Yang, Q. Zhang, Y. Niu, and J. Li, "Classification of retinal image for automatic cataract detection." in *International Conference on e-Health Networking, Applications and Services*, 2013, pp. 674–679.

[8] Y. Aribi, A. Wali, and A. M. Alimi, "An intelligent system for renal segmentation," in *International Conference on e-Health Networking, Applications and Services*, 2013, pp. 11–15.

[9] V. Bochko, P. Vlisuo, T. Harju, and J. Alander, "Lower extremity ulcer image segmentation of visual and near-infrared imagery," *Skin Research and Technology*, vol. 16, no. 2, pp. 190–197, 2010-05-01T00:00:00.

[10] O. Trabelsi, L. Tlig, M. Sayadi, and F. Fnaiech, "Skin disease analysis and tracking based on image segmentation," in *Electrical Engineering and Software Applications (ICEESA), 2013 International Conference on*, March 2013, pp. 1–7.

[11] P. M. Azevedo-Marques, S. M. Pereira, M. A. C. Frade, and R. M. Rangayyan, "Segmentation of dermatological ulcers using clustering of color components." in *CCECE*. IEEE, 2013, pp. 1–4.

[12] C. Jacquelin, A. Aurengo, and G. Hejblum, "Evolving descriptors for texture segmentation." *Pattern Recognition*, vol. 30, no. 7, pp. 1069–1079, 1997.

[13] N. Houhou, J. Thiran, and X. Bresson, "Fast texture segmentation based on semi-local region descriptor and active contour," *Numerical Mathematics: Theory, Methods and Applications*, vol. 2(4), pp. 445–468, 2009.

[14] X. Qing, Y. Jie, and D. Siyi, "Texture segmentation using lbp embedded region competition," *Electronic Letters on Computer Vision and Image Analysis*, vol. 5(1), pp. 41–47, 2005.

[15] D. E. Ilea and P. F. Whelan, "Image segmentation based on the integration of colour-texture descriptors - a review." *Pattern Recognition*, vol. 44, no. 10-11, pp. 2479–2501, 2011.

[16] S. Belongie, C. Carson, H. Greenspan, and J. Malik, "Color- and texture-based image segmentation using em and its application to content-based image retrieval," in *Proceedings of the Sixth International Conference on Computer Vision*, ser. ICCV '98. Washington, DC, USA: IEEE Computer Society, 1998, pp. 675–.

[17] J. Malik, S. Belongie, T. K. Leung, and J. Shi, "Contour and texture analysis for image segmentation." *International Journal of Computer Vision*, vol. 43, no. 1, pp. 7–27, 2001.

[18] Y. Xiaohan, J. Yl-Jski, and B. Yuan, "A new algorithm for texture segmentation based on edge detection." *Pattern Recognition*, vol. 24, no. 11, pp. 1105–1112, 1991.

[19] A. M. Us, F. Pla, and P. Garca-Sevilla, "A novel energy minimization criterion for color image segmentation." in *ICPR (3)*, 2004, pp. 206–209.

[20] N.-Y. An and C.-M. Pun, "Color image segmentation using adaptive color quantization and multiresolution texture characterization," *Signal, Image and Video Processing*, pp. 1–12, May 2012.

[21] J. Chen, T. N. Pappas, A. Mojsilovic, and B. E. Rogowitz, "Adaptive image segmentation based on color and texture." in *ICIP (3)*, 2002, pp. 777–780.

[22] J. Shan, H.-D. Cheng, and Y. Wang, "A novel automatic seed point selection algorithm for breast ultrasound images." in *ICPR*. IEEE, 2008, pp. 1–4.

[23] S. M. Smith and J. M. Brady, "Susan a new approach to low level image processing," *International Journal of Computer Vision*, vol. 23, no. 1, pp. 45–78, 1997.

[24] A. Likas, N. Vlassis, and J. J. Verbeek, "The global k-means clustering algorithm," *Pattern Recognition*, vol. 36, no. 2, pp. 451 – 461, 2003, biometrics.

[25] G. Friedland, K. Jantz, and R. Rojas, "Siox: Simple interactive object extraction in still images." in *ISM*. IEEE Computer Society, 2005, pp. 253–260.

[26] D. Stockburger, *Introductory Statistics: Concepts, Models, and Applications, Second Edition*, 2nd ed. Atomic Dog Publishing, 2001.