# Segmentation Strategies in Dermoscopy to Follow-up Melanoma: Combined Segmentation Scheme

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**Abstract:** — Image processing techniques constitutes an important tool to improve skin cancer diagnose, whose early detection is still the most relevant prognostic factor.
Nowadays, the follow-up of suspicious melanocytic skin lesions using standard protocols is possible after the development of digital image technology, enhancing the early detection strategy of the skin cancer diagnose.
The correct selection of the borders in these particular images of skin microscopy is sometimes demanding, as these images possess particular artifacts (hairs and air bubbles).A stable algorithm to segment the border of the lesion is also important when the following up of suspicious melanocytic lesions uses quantitative markers, as accessing the geometry of the growth border, symmetry, area, among others. In this paper a new strategy to segment dermoscopy images is presented by merging two different approaches in image processing, the Empirical Mode Decomposition of the Hilbert-Huang Transform to remove common artifacts, followed by a Local Normalization to improve segmentation.

**Key words:** Segmentation, Local Normalization, Hilbert-Huang Transform, Dermoscopy, Melanoma.

## Introduction

Skin cancer is one of the cancer types with most prevalence and it is also one of the most common forms of malignancy in humans (Celebi, 2007). It is expected that its public health impact increases significantly in the coming decades in the absence of effective intervention today (Boyle, 2004).

Skin cancer is classified as a function of the cells from which it expands. Basal Cell Carcinoma (BCC) emerges from the lower layer of the epidermis, Squamous Cell Cancer (SCC) emerges from the middle layer of the epidermis and melanoma is derived from melanocytes, which are pigment producing cells. Although the melanoma type of cancer is least common, it is the most aggressive, the most likely to spread and, to suddenly become fatal (Kasper et al, 2007). Several studies in Europe have documented the increment of melanoma incidence in the last few decades (Baumert, 2005, Holterhues, 2010, Sant, 2009). In the particular case of Portugal, the estimated incidence for 2012 was 7.5 per 100000, mortality 1.6 per 100000 and prevalence at one, three and five years 12.08%, 33.99% and 53.93% respectively (Ferlay, 2012).

Melanocytic lesion is a term used to describe a region of the skin that differs in color from the surrounding area. This difference in color (discoloration) is often a benign nevus found in great number over the entire body and regularly called age-spot. A change in the melanocytic lesion characteristics triggers a marker of warmness and should be investigated. The early detection and monitoring of suspicions lesions is crucial for the disease prognosis. Dermatologists use epiluminescence microscopy, dermatoscopy or dermoscopy as is usually referred, to perform early diagnosis of melanocytic lesions and to track the progression thereof. Dermoscopy uses a polarized light source and a magnifying lens allowing the identification of dozens of morphological features such as pigmented works, dots/globules, streaks, blue-white areas, and blotches. A fluid is usually spread on the skin surface to minimize light scattering, and thus in-crease the performance of this technique. The use of this fluid together with the presence of hairs in the skin surface, conducts to conspicuous artifacts in dermoscopic images.

The classification of some melanocytic lesions is sometimes difficult, even for experienced specialists. The lesion border is especially relevant for diagnosis since it allows to gather information about the shape of the lesion, growth path, and growth rate. The lesion border detection algorithms applied to dermoscopic images have been widely used in recent works with dermoscopic images (Erkol, 2005, Iyatomi, 2006, Melli, 2006, Celebi, 2006, Huang, 1998). Currently dermatologists often resort to digital dermoscopes and computer storage of the information. Computers can also be used to perform automatic lesion border detection. This process in the presence of artifacts may induce artificial borders, thereby jeopardizing their efficiency. Therefore artifact removal is a required pre-processing step to improve the quality of detection.

  

## Segmentation in Dermoscopy

### Hilbert-Huang Transform

Hilbert-Huang Transform (HHT) is a time-frequency signal processing technique whose implementation is divided into two parts, Empirical Mode Decomposition (EMD) and Hilbert Spectral Analysis (HAS). EMD is an iterative and adaptive process designed to separate in components, known by Implicit Mode Functions (IMF), the original signal. Those components, which are signal derived, avoid the use of pre-defined basis functions as is the case when using classic Fourier Techniques. Hilbert Spectral Analysis (HSA) is employed to extract the instantaneous frequency to the previous components obtained after EMD. Further details relating to HHT can be found in (Fonseca-Pinto, 2009 and 2010).

### Image Empirical Mode Decomposition

The use of the first part of the HHT in the context of artifact removal in dermoscopic images was used before in a previous work whose results can be found in [15]. In that work the natural potential to identify common artifacts in dermoscopic images by using EMD is enhanced, and in particular in those images classified as "difficult" due the amount of hairs or air bubbles.
EMD was developed for one-dimensional signals but is possible to extend this procedure to two dimensional arrays, a process known by Image Empirical Mode Decomposition (IEMD). An image is an array of pixels that can be treated as a matrix. Each row of this matrix stands for the energy of this set of pixels, and therefore is possible to plot this information. By this way a one-dimensional signal is obtained and it is possible to apply EMD to this one-dimensional source. Performing EMD in succession to all rows, leads to a set of IMF's for each row, and the set of all IMF's of the same order constitutes a set of bi-dimensional IMF's (2dIMF's). The final set of 2dIMF's is obtained after each individual matrix processing, by summing up the results. An example of 2dIMF extraction by IEMD from a dermoscopic image is presented in Figure 1.

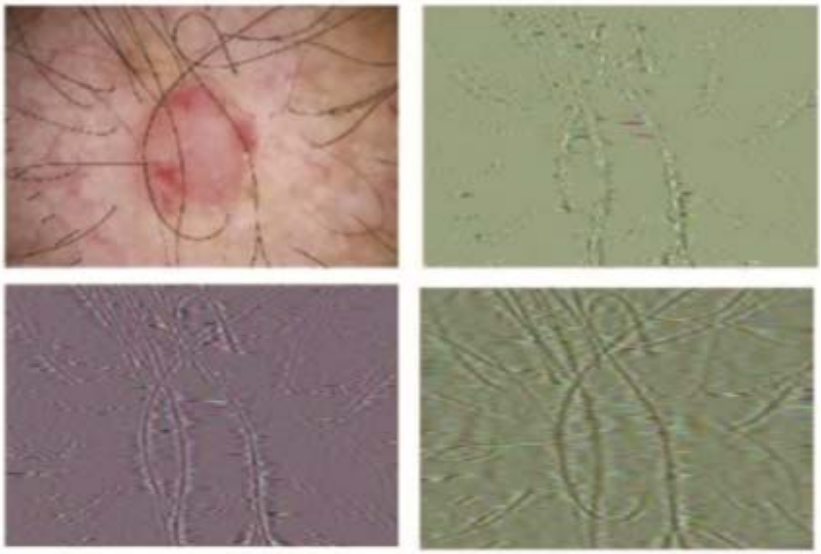

**Figure 1:** Dermoscopic image (top left), 2dIMF1 (top right), 2dIMF2 and 2dIMF3 (bottom images)

This 2dEMD extraction highlights artifacts, as is possible to see in Figure 1 by the identification of hairs. Artifact removal comprises two steps: 1) detection of corrupted pixels and 2) assignment of new intensity values associated to those pixels, while trying to minimize changes in the relevant image features. The above presented IEMD decomposition is used in this work to detect artifacts.
After the IEMD it is used the first component (2dIMF1) and the maximum (M) and minimum (m) energy value to calculate R=M+|m|, by using (1), where r is the number of rows in the RGB matrix and c the number of columns.

  

$$M = \max_{\substack{i=1,\dots,r \\ j=1,\dots,c}} \{2dIMF1(i,j)\}$$
$$m = \min_{\substack{i=1,\dots,r \\ j=1,\dots,c}} \{2dIMF1(i,j)\} \quad (1)$$

After this step, the reassignment of anomalous pixels can be made using several strategies. In (Haylo, 2001) a simple approach consisting in averaging the values of neighboring non-artefact pixel was used, conducting to interesting results. Contrary to the common filter procedures, this IEMD technique targets only those pixels where artifacts exist, leaving unchanged the remaining image. It is not a blind procedure, but rather an adaptive and oriented strategy to remove artifacts in dermoscopic images.

**Local Normalization**

Local Normalization (LN) processing is a center/surround operation based mainly on characteristics derived from human perception. Our perception of gray levels depends more on local characteristics rather than the absolute magnitude of the image signals. For example, we perceive a pixel with the same absolute gray level as darker if it is surrounded by light pixels, while we perceive the same pixel as light when it is surrounded by dark pixels. To incorporate this information into the processing of the image, LN separates the image into a local average or a low-frequency signal, and a surface detail or high-frequency signal. The locally normalized signal is then obtained by normalizing (i.e., dividing) the detail signal by the local average (Pereira, 2015).
The grayscale image is obtained after the RGB-averaged transformation shown in (2).

$$P_{i,j,m} = \frac{(p_{i,j,m})^2}{\sqrt{(p_{i,j,R})^2+(p_{i,j,G})^2+(p_{i,j,B})^2}}; for \begin{cases} i = 1,\dots,r \\ j = 1,\dots,c \\ m = R,G,B \end{cases} \quad (2)$$

where Pi,j,m represents the pixel (i, j) of the m channel in the image, c is the number of columns in the RGB matrix and r is the number of rows. LN can be computed by using (3)

$$LN = \frac{I-\bar{I}}{\sqrt{\overline{(I^2)}-(\bar{I})^2}} \quad (3)$$

where I is the original image and $\bar{I}$ is the output between a Gaussian kernel and I.
This LN strategy depends on the selection of a region of interest (ROI), which is computed in function of the size of the lesion and the Gaussian kernel. Using adaptive kernel orders, it is possible to detect and segment every skin lesion shape. An example of the output of this scale adapted normalization (Multiscale Local Normalization – MLN) joint with the lesion segmentation can be found in Figure 2.

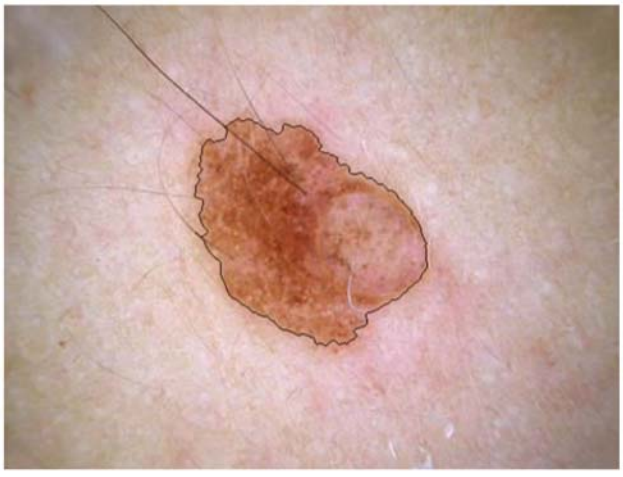

**Figure 2:** Output of the MLN in dermoscopy

  

**Combined Segmentation Scheme**

As reported in (Haylo, 2001), IEMD process shows good performance in removing artifacts, but the proposed methodology (the inpainting adopted scheme, and the segmentation based on a BW threshold) presents some drawbacks. On the other hand, LN and in particular the MLN shows good results when images are absent of difficult artifacts (in number and in quality). The proposed methodology combines MLN and IEMD to improve the segmentation output in those special cases where dermoscopic images are degraded by several and difficult artifacts, as result of a bad preparation of the skin, or related to the time consuming process in the acquisition.

## Results and discussion

In order to illustrate the performance of the combined segmentation two images with common artifacts are employed. In the first case depicted in Figure 3(A-C), the image has a large amount of small air bubbles, whose presence interferes with the automatic segmentation.
Figure 3C shows the segmentation using IEMD, where is possible to observe the non-dependence, in this process, of air bubbles. In particular in the top right is possible to see a bigger artifact who is ignored by the segmentation, yielding a realistic border. Another characteristic of the IEMD process is also present, the high sensibility of the segmentation algorithm in the borders.
Figure 3A presents the segmentation after MLN, whose results shows a dependence of the air bubbles in the border (red circle, top right) and a smooth border. The combined segmentation is shown is Figure 3B, allowing to observe a smooth and rational border, which is independent of artifacts.

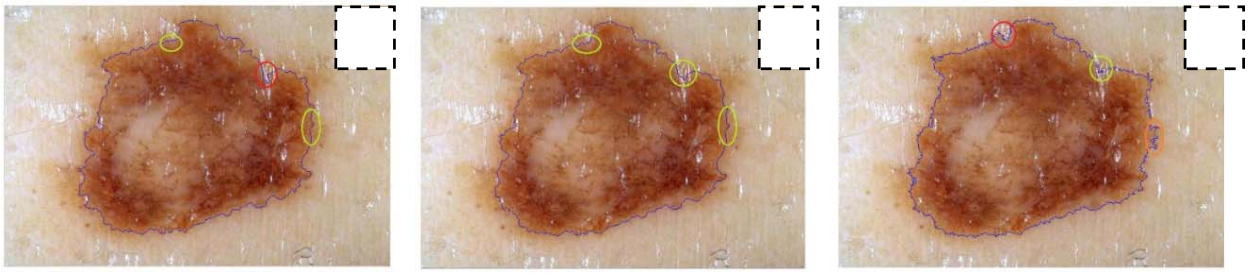

**Figure 3:** Segmentation strategies: A- segmentation after MLN, C - segmentation after IEMD, and B - proposed combined scheme segmentation.

In the second example (Figure 4) it is used a challenging image corrupted with hairs and air bubbles. Classical filtering and segmentation using commercial software in this image conducts to pour results. Figure 4A shows the segmentation after IEMD. It is possible to observe, as in the former case, a border irregularity and a good performance ignoring the top air bubbles in the image (red circles). In particular, it is possible to observe that the presence of hair in the bottom of the image (green circle) do not interfere with the correct segmentation. In the case of both artifacts, IEMD also demonstrates efficient results.
By using MLN, the segmentation is smoother, but in the presence of artifacts the algorithm follows the artifact path (Figure 4C, bottom, red circle). When the combined method is applied, as in Figure 4B, it is possible to observe a smoother, lesion correlated, and artifact independent segmentation, as in the former Figure 3B.

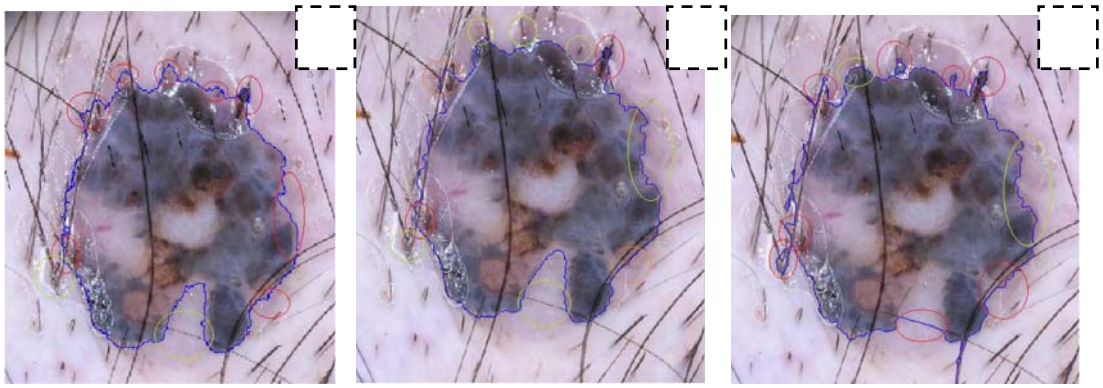

**Figure 4:** Segmentation strategies: A- segmentation after IEMD, C - segmentation after MLN, and B - proposed combined scheme segmentation.

  

## Conclusions

Strategies to follow the progression of melanocytic lesions are truly dependent on image processing techniques. A diagnosis based on quantitative markers is an important issue, implying a stable, lesion independent and accurate segmentation. In this work it is presented a combined scheme based on IEMD and MLN to segment dermoscopic images with high artifact density. The combined result proved to have a better performance than each one of their individual results. These are preliminary results, and more studies are being conducted related to the segmentation in dermoscopy in order to get independent artifact segmentation strategies. The segmentation output needs a ground truth with clinical correlation to compare results. This ground truth issue is an important open problem whose importance as led to clinical blind independent manual segmentation studies in dermatology. In the following of this work, this combined segmentation automated technique will be compared with manual segmentation.

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