Sharpening Dermatological Color Images in the Wavelet Domain

Cláudio R. Jung and Jacob Scharcanski

Abstract—Tele-dermatology is becoming an important tool for early skin cancer detection in public health, but low cost cameras tend to cause image blurring, which affect diagnosis quality. Obtaining cost-effective images with diagnosis quality is a current challenge, and this paper proposes a novel method for enhancing the local contrast of dermatological images in the wavelet domain. The distribution of squared gradient magnitudes computed through an undecimated wavelet transform is modeled as a combination of chi-squared and gamma distributions, and a posteriori probabilities are used to discriminate coefficients related to edges from those related to noise or homogeneous regions at each scale of the wavelet decomposition. Consistency across scales is used to preserve coefficients likely to be edge related in consecutive levels of the wavelet decomposition, and local directional smoothing is used to reduce residual noise. Then, a non-linear enhancement function is applied to wavelet coefficients, so that low-contrast edge-related wavelet coefficients are increased. Our experimental results indicate that the proposed approach can effectively sharpen image details, without amplifying background noise. Preliminary validation by specialists indicate that the proposed sharpening algorithm improves the visual quality of dermatological images.

Index Terms—Color image processing, medical imaging, adaptive image denoising, adaptive image enhancement, wavelets, multisresolution analysis.

I. INTRODUCTION

In developing and in developed countries, controlling the incidence of skin lesions is a current public health challenge. For example, melanoma is one of the most life-threatening tumors with an alarming increasing incidence [2]. It is known that early diagnosed primary cutaneous melanoma has an excellent overall prognosis, whereas the prognosis of advanced melanoma is poor [26].

Despite the fact that early melanoma detection and diagnosis are important public health issues, the access to healthcare for persons with skin disease is coming under pressure in different countries for reasons such as the shortage of specialists, uneven geographical distribution of doctors and the long wait times for patients [39]. For example, the dermatology community tends to be clustered around urban areas, limiting access to specialists for many patients in less affluent and rural locations. Besides, an increasing proportion of patients with skin disease are being diagnosed and managed without ever seeing a dermatologist. Primary care physicians are attempting to bridge the widening gaps in the care network, despite the fact that many have no formal training in dermatology and that studies show their diagnostic agreement with trained dermatologists is only approximately 57% [19] [44]. Therefore, tele-dermatology is becoming an area of increasing interest and activity.

Mainly two approaches are currently used in tele-dermatology, namely, store-and-forward technology and live interactive technology [44]. The former is time and place independent, while the latter operates in real time via a video-conferencing link. In both approaches, low picture quality and information loss can lead to difficulties in interpreting dermatological images [44] [1].

Some studies show that experienced dermatologists have an accuracy of 64-80% using clinical diagnostic criteria [23], and this diagnostic accuracy tends to decrease in tele-dermatology. Some important difficulties to achieve high agreement rates in the evaluation of digital images in tele-dermatology are the loss of 3D information, blurring of image details, and color distortion [25].

There is active research in the areas of color image enhancement/sharpening [6], [35], [36], [38], [41] and denoising [3], [9], [30], [33], [40]. However, denoising and enhancement are somewhat dual problems: denoising tends to eliminate fine details, while enhancement tends to amplify noise as well. This paper presents a novel wavelet-based adaptive sharpening technique for color images that prevents the unwanted enhancement of noise, suited for dermatological images acquired with standard cameras. An undecimated wavelet transform is used to estimate color gradient magnitudes at different scales. Next, noise and edges are distinguished based on statistical properties of their gradient magnitudes. In order to further improve the discrimination of edges and noise, inter-scale and contour continuity constraints are applied. This paper also proposes a method for selecting of the number of dyadic scales used in the wavelet decomposition adaptively (i.e. more scales are used when noise contamination is higher). Finally, an adaptive edge enhancement procedure is applied for a better visualization of image details.

The rest of this paper is organized as follows. Section II presents an overview of state-of-the-art methods for color image enhancement. The wavelet transform used in this work is revised in Section III, and the proposed method is detailed in Section IV. Some experimental results are discussed in Section V, and our conclusions are presented in the final Section.
II. RELATED WORK

There are several different approaches to tackle the problem of color image enhancement, and most of them focus on global contrast enhancement. Some of these methods are designed to enhance the color contrast with hue preservation, and are discussed next. Kaiqui et al. [16] proposed a human visual system controlled color image enhancement and evaluation (HCCIEE) algorithm, which is based on multiscale representation of the luminance and color image components. This method can enhance details while avoiding color artifacts, producing images that have a natural look. Naik et al. [28] discussed the difficulty of keeping hue unaltered when color space transformations are used, causing the gamut problem, i.e., some values in the transformed color space may not have a correspondence in the original one. They propose a class of hue preserving contrast enhancement transformations, which generalize the existing gray scale contrast intensification techniques to color images. Murtaza et al. [27] claimed to have developed a hue preserving color enhancement technique that is faster and more effective than other available methods. The issue of color distortion after enhancement is analyzed by Dong and colleagues [10], and they proposed an algorithm that is faster and more effective than other available methods.

In this paper, we propose a combined approach to sharpen color images taking into account the existing relationship among different color channels avoiding color artifacts, preserving the color of homogeneous regions and enhancing region boundaries without amplifying background noise. This is particularly useful in tele-dermatology, where most information available to the specialist is the skin lesion image, and boundary details must be clearly identified in this image (e.g. for diagnosing melanomas).

III. WAVELET TRANSFORM AND COLOR IMAGE GRADIENTS

Let us consider a digital grayscale image $I[n, m]$, and the undecimated discrete wavelet decomposition proposed by Mallat and Zhong [22]. The wavelet transform of image $I$ returns two detail images (horizontal and vertical) $W^2_J f[n, m]$ and $W^2_J f[n, m]$, as well as smoothed images $S^2_J f[n, m]$, at each scale $2^j$, for $j = 1, ..., J$, where $J$ is the number of scales used in the decomposition. Furthermore, the original image $I$ can be reconstructed based on the smoothed image at the coarsest resolution $S^2_J f$ and the detail coefficients $W^1_J f$, $W^2_J f$, for $j = 1, ..., J$.

Since the chosen mother wavelet has approximately the shape of a derivative of Gaussian, detail images $W^2_J f$ and $W^2_J f$ provide good approximations for the local image gradients at scale $2^j$ (as in the ideal step edge detector proposed by Canny [5]). Consequently, edge magnitudes at scale $2^j$ are calculated based on these local image gradients, as follows [22]:

$$M^2_J f = \sqrt{(W^1_J f)^2 + (W^2_J f)^2}. \quad (1)$$

For color images, an estimate of the gradient magnitudes can be obtained by the following straightforward extension:

$$M^2_J f = \sqrt{\sum_{c \in \{R, G, B\}} (W^c_J f)^2 + (W^c_{2^j} f)^2}, \quad (2)$$

where $W^c_J f$ and $W^c_{2^j} f$ represent the horizontal and vertical details of color channel $c$.

In our color image sharpening approach, we discriminate noise-related and edge-related coefficients by performing intra-scale and inter-scale analysis of squared color gradient magnitudes $M^c_J f$. Then, noisy coefficients are shrunk to zero, while edge-related coefficients are enhanced. Finally, the inverse wavelet transform is applied to the modified coefficients, and the enhanced image is obtained. Our procedure is detailed next.
IV. THE PROPOSED DENOISING AND SHARPENING METHOD

In this Section, we detail how the proposed method analyzes coefficients intra- and inter-scales, directionally smooths noisy pixels, sharpens edges, and selects adaptively an adequate number of scales.

A. Intra-Scale Analysis

For each level $2^j$, a common approach for image denoising is to find shrinkage factors $g_j[n,m]$ satisfying $0 \leq g_j[n,m] \leq 1$, such that the detail coefficients $W^c_{2^j}f$ and $W^{c2}_{2^j}f$ are updated according the following rule:

$$NW^c_{2^j}f[n,m] = W^c_{2^j}f[n,m]g_j[n,m], \quad i \in \{1, 2\}, \quad c \in \{R, G, B\}. \quad (3)$$

The shrinkage factors are chosen to preserve relevant image structures, while image noise is reduced. For the intra-scale analysis, we assume that coefficients related to relevant structures (edges) have larger gradient magnitudes than those related to noise. To determine $g_j[n,m]$, we first find a non-decreasing shrinkage function $g_j : [0, \infty) \to [0, 1]$ such that $g_j[n,m] = g_j(M^2_{2^j}f[n,m])$. To obtain this shrinkage function, wavelet coefficients related to noise and relevant edges are modeled parametrically, and a posterior probability function is obtained, as explained next.

We assume that each color image channel ($R, G$ and $B$) is corrupted by uncorrelated Gaussian noise. If we apply the wavelet transform to each color channel, the corresponding coefficients $W^c_{2^j}f$ and $W^{c2}_{2^j}f$ at each scale $2^j$ may be considered Gaussian distributed [11], with standard deviation $\sigma_n$.

However, the detail coefficients $W^{c1}f$ and $W^{c2}f$ related to noise-free natural images usually do not follow a normal distribution [34]. In fact, several probabilistic models have been proposed to model distributions of detail coefficients in natural images, to name a few: two-parameter Generalized Laplacian distributions [34], Gaussian distributions with high local correlation [24], Generalized Gaussian distributions [7], [15], and Gaussian mixtures [8], [37]. It is important to notice that the extension of these probabilistic models for vector-valued images is not trivial, due to signal correlation in different channels.

In this work, we assume that detail coefficients related to the actual edges (exclusively) are approximately Gaussian distributed (i.e., if we disregard the sharp peak at the origin produced by homogeneous regions, the remaining distribution is roughly normal), as discussed in [32]. Although this Gaussian assumption may not produce an approximation as accurate as the other models mentioned above, it provides a simple and closed-form expression for squared color gradient magnitudes, as explained next.

The main difficulty in determining the shrinkage factors for noisy images relies on the discrimination between pixels that belong to noisy homogeneous regions, and pixels that are related to sharp transitions (or edges). In homogeneous regions, detail coefficients will be affected mainly by noise; at edges, detail coefficients will be influenced by both noise and the noise-free edges (i.e. edges with varying degrees of noise corruption). Hence, a detail coefficient $d$ of a noisy image, at a given subband and color channel, can be considered a random variable:

$$d = \begin{cases} x, & \text{if } d \text{ relates to a (noisy) homogeneous region} \\ x + y, & \text{if } d \text{ relates to a noisy edge} \end{cases} \quad (4)$$

where $x$ is a Gaussian random variable related to noise only (with variance $\sigma_n^2$), and $y$ is a Gaussian random variable related to noise-free image edges (with variance $\sigma_x^2$). Also, it shall be noted that $d = x + y$ is a Gaussian random variable as well (with variance $\sigma_n^2 + \sigma_x^2$), so that the distribution of detail coefficients in each subband and color channel is in fact a mixture of Gaussians. The distribution of squared color gradient magnitudes $r = M^2f$ will be also a mixture of two distributions:

$$p(r) = w_n p_n(r) + (1 - w_n) p_e(r), \quad (5)$$

where $p_n(r)$ is the distribution of squared magnitudes related to noise only, $p_e(r)$ is the distribution of squared magnitudes related to noisy edges, $0 \leq w_n \leq 1$ is the prior probability of the distribution $p_n(r)$, and $(1 - w_n)$ is the prior probability of the distribution $p_e(r)$.

If $X_1, X_2, \ldots, X_m$ are $m$ i.i.d. Gaussian random variables with standard deviation $\sigma$, then $Y = X_1^2 + X_2^2 + \ldots + X_m^2$ is chi-squared distributed random variable, and its probability density function is given by [14]:

$$p_Y(Y) = \frac{Y^{\frac{\alpha-1}{2}}}{2^{\frac{\alpha}{2}} \sigma^m \Gamma\left(\frac{m}{2}\right)} e^{-\frac{Y}{2\sigma^2}}, \quad (6)$$

Hence, if we assume uncorrelated Gaussian noise in the color channels and independence of noise-related detail coefficients, the distribution of squared magnitudes $p_n(r)$ related to noise only is obtained by setting $m = 6$ in Equation (6) (two detail images in each of the three color channels):

$$p_n(r) = \frac{1}{16\sigma_n^2 r^2} e^{-\frac{r^2}{2\sigma_n^2}}, \quad (7)$$

where $\sigma_n^2$ is the variance of noise-related detail coefficients. However, edge-related detail coefficients are not expected to be independent. In fact, an edge is expected to appear approximately at the same location, in different color channels and subbands. To model squared magnitudes related to noisy edges, we adopt a two-parameter gamma distribution, which generalizes the chi-squared distribution [29]:

$$p_e(r) = \frac{1}{\alpha^\beta / \Gamma(\beta)} r^{\beta - 1} e^{-r/\alpha}, \quad (8)$$

To obtain the parameters $\sigma_n$, $\alpha$, $\beta$ and $w_n$, which are needed to resolve Equations (5) and (8), we maximize the following likelihood function:

$$\ln L = \sum_{[m,n] \in \text{image}} \ln \left( p(M^2_{2^j}f[m,n]) \right). \quad (9)$$

Coefficients related to noisy edges usually have higher magnitudes than coefficients related to noisy homogeneous
regions. Therefore, we impose as a maximization constraint that the mean of \( p_n(r) \) must be smaller than the mean of \( p_0(r) \), which implies that the ML maximization is constrained by \( 6\sigma^2 < \alpha \beta \).

After estimating the parameters \( w_n, \sigma_n, \alpha \) and \( \beta \), we can compute the posterior probability function \( p(\text{edge}|r) \) using the Bayesian approach:

\[
p(\text{edge}|r) = \frac{(1 - w_n)p_c(r)}{p(r)},
\]

where \( p(\text{edge}|r) \) denotes the probability that a given coefficient with squared color gradient magnitude \( r \) is edge-related. It shall be noted that \( 0 \leq p(\text{edge}|r) \leq 1 \), \( p(\text{edge}|r) \) is close to one near edges, and close to zero in (nearly) homogeneous regions. Therefore, \( p(\text{edge}|r) \) is a good choice for the shrinkage function \( g \), i.e.,

\[
g_j[n, m] = p_j(\text{edge}|M^2_j f[n, m]),
\]

where \( p_j(\text{edge}|r) \) is the posterior probability at scale \( 2^j \), and \( M^2_j f \) are the squared gradient magnitudes at the same scale. Figure 1 illustrates a color dermatological image (489 × 550 pixels) and the respective shrinkage factors at scales \( 2^1 \), \( 2^2 \) and \( 2^3 \). As it can be observed, finer scales provide a local estimate of edges, while coarser scales indicate lower-resolution edges.

### B. Inter-Scale Analysis

In Section IV-A we described how the shrinkage factors \( g_j[n, m] \) are computed based on squared gradient magnitudes, separately, for each scale. Nevertheless, there are important information in the inter-scale analysis that should be also used. If noise contamination is intense, then noise-related coefficients can be associated with large gradient magnitudes, and their shrinkage factors can be close to one. This situation tends to occur mostly in finer resolutions of the WT, where the inherent smoothing effect (low-pass filtering) of the multi-scale WT is not as evident as in coarser resolutions. In practice, relevant edges (and edge-related coefficient magnitudes) tend to persist across scales, while noise (and noise-related coefficient magnitudes) tend to vanish across scales.

Therefore, we combine adjacent scale information to preserve coefficients whose shrinkage factors are close to one and persist across scales. In [21] and [20] the Hölder exponent was calculated in order to explore this property, while the direct product of wavelet coefficients in adjacent scales was used in [45] and [4]. In this work, we follow an approach similar to that used in [32], and combine the shrinkage factors \( g_j \) (instead of combining wavelet coefficients directly). Also, as noticed in [4], [32], [45], the support of an isolated edge increases by a factor of two across scales, and neighboring edges interfere with each other at coarse scales. Hence, it is more adequate to use only few adjacent scales (in this work, we use only two consecutive scales).

As explained in Section IV-A, the shrinkage factor \( g_j[n, m] \) represents the posterior probability that pixel \( [n, m] \) is edge-related at scale \( 2^j \). If \( g_j[n, m] \) and \( g_{j+1}[n, m] \) are close to one, then pixel \( [n, m] \) is likely to be edge-related in both adjacent scales \( 2^j \) and \( 2^{j+1} \). In fact, the product \( g_j[n, m]g_{j+1}[n, m] \) represents the joint posterior probability that pixel \( [n, m] \) is edge-related in both scales simultaneously (not considering inter-scale dependence). Hence, the direct product of shrinkage factors is used in this work to perform inter-scale consistency. The proposed procedure is applied in a coarse-to-fine manner: in the coarsest resolution \( 2^J \), we define \( g^*_j[n, m] = g_j[n, m] \), meaning that the coarsest shrinkage factor keeps unchanged. For \( j = J - 1, ..., 2, 1 \), the updated shrinkage factors using scale consistency are given by

\[
g^*_j[n, m] = g_j[n, m]g_{j+1}[n, m].
\]

It is interesting to observe that in [32] the harmonic mean was employed for inter-scale consistency. It is easy to show that the harmonic mean of two numbers is always greater than (or equal to) the direct product of those numbers. Hence, the procedure adopted in [32] produces larger scale-consistent shrinkage factors than the proposed approach, and tends to preserve more residual noise, particularly in images with higher noise contamination.

The scale-consistent shrinkage factors \( g^*_j[n, m] \) for dermatological image are illustrated in Figure 2. It can be noticed that spurious edges are reduced at scales \( 2^1 \) and \( 2^2 \) after using coefficient consistency across scales (as previously noticed, the shrinkage factor at the coarsest scale, \( 2^3 \), keeps unchanged).

### C. Local Directional Smoothing Along Edges

Let us consider the updated wavelet coefficients \( NW \), obtained with Equation (3), but using \( g^*_j[n, m] \) instead of \( g_j[n, m] \). If \( g^*_j[n, m] \approx 1 \), the corresponding wavelet coefficients are kept almost intact. However, such coefficients are usually corrupted by noise; since \( p_c(r) \) represents the distribution of squared gradient magnitudes related to noisy edges (i.e. edges plus noise). To further reduce the influence of noise in \( NW \), local directional smoothing is applied to the updated wavelet coefficients at each color channel and scale, as detailed next.

As noticed by Kanisza [17], edges usually occur along contours in natural images, and not isolated. Therefore, we analyze the shrinkage factors \( g^*_j \) along the local contour direction in the neighborhood of each pixel. Blurring is avoided by choosing small neighborhoods of analysis. In this paper, we consider a \( 3 \times 3 \) neighborhood only, and quantize the local orientation into 0, 45, 90 and 135°. More specifically, for each pixel \( [n, m] \) we compute the “local edge strength” along these four orientations as:

\[
\begin{align*}
S_0[n, m] &= g^*_j[n - 1, m] + g^*_j[n, m] + g^*_j[n + 1, m], \\
S_{45}[n, m] &= g^*_j[n - 1, m - 1] + g^*_j[n, m] + g^*_j[n + 1, m + 1], \\
S_{90}[n, m] &= g^*_j[n, m - 1] + g^*_j[n, m] + g^*_j[n, m + 1], \\
S_{135}[n, m] &= g^*_j[n + 1, m - 1] + g^*_j[n, m] + g^*_j[n - 1, m + 1],
\end{align*}
\]

and choose the direction that maximizes the local edge strength as the local orientation. Then, at each color channel and wavelet subband, a simple directional mean filter is applied to coefficients \( NW^d_{2^j} f[n, m] \) along the selected orientation.
Figure 3 shows the effect of the directional smoothing. The image on the left is a cropped and zoomed portion of the lesion shown in Figure 1, the central image is the processed image without directional smoothing, and the image on the right is the result with directional smoothing. As it can be observed, residual noise is attenuated along the contours when directional smoothing is applied. The procedure for edge sharpening is described next.

D. Edge Sharpening

The procedure described so far is suitable for wavelet shrinkage, which means that wavelet coefficients are only allowed to get smaller. However, the updated coefficients $NW_{2j}^2f$ can also be further modified to enhance low-contrast edges.

In this work, we extend the nonlinear enhancement function proposed by Velde [41]. In their approach, at each scale $2^j$, wavelet coefficients $W_{2j}^1f[n,m]$ and $W_{2j}^2f[n,m]$ are multiplied by enhancement factors $y(M_{2j}^2f[n,m])$, where $y : [0, \infty) \rightarrow \mathbb{R}$ is a nonlinear function given by

$$y(x) = \begin{cases} \left(\frac{m}{x} \right)^p, & \text{if } x < c \\ \left(\frac{m}{x} \right)^q, & \text{if } c \leq x < m \\ 1, & \text{if } x \geq m \end{cases}$$

In Equation (14), $c$ is related to noise estimates (the author suggests to set $c$ as the noise standard deviation); $m$ is a parameter such that coefficients having gradient magnitudes larger than $m$ would not be enhanced; and $0 < p < 1$ determines the function nonlinearity (the author suggests to use $p = 0.5$). Velde estimated the color gradient $M_{2j}^2f$ using the $L^{*}u^{*}v^{*}$ color space. Starck et al. [36] observed that this enhancement function has the drawback of amplifying both the signal of interest and the noise (linearly). Nevertheless, we can reduce the undesired noise magnification by applying Velde’s function to the updated wavelet coefficients $NW$ (in this case, the updated coefficients related to noise are shrunk to zero).

We apply the enhancement function $y$ to the squared gradient magnitudes $M_{2j}^2f$ in the RGB color channels, and we use $p = 0.5$ and $m = 0.25$ to account for this modification (since $(M_{2j}^2f)^{0.25} = (M_{2j}^2f)^{0.5}$). At each scale $2^j$, we set $m$ as the maximum squared gradient magnitude (such that all wavelet coefficients are enhanced). In our approach, the value of $c$ is chosen adaptively, based on the mean of the noise distribution $\mu_n(r)$, and is given by:

$$e_{j} = 6(\sigma_{n,j}^{2})^{2}.$$  \hspace{1cm} (15)

In order to allow the user to further adjust the amount of edge enhancement manually at each scale $j$, we include an additional enhancement factor $\kappa_j \geq 1$ (default value is $\kappa_j = 1$, for all $j$). The enhanced wavelet coefficients $EW$ are computed as follows:

$$EW_{2j}^c f[n,m] = \kappa_j NW_{2j}^2 f[n,m] y_j(\mu_{n,j}^2 f[n,m]),$$

and the inverse wavelet transform is applied to low-pass images $S_{2j}^c f$ and the enhanced detail coefficients $EW_{2j}^c f$, $EW_{2j}^2 f$, for $j = 1, \ldots, J_{\text{max}}$, $c \in \{R,G,B\}$, where $J_{\text{max}}$ is the number of scales used in the wavelet decomposition.

E. Adaptive Selection of the Number of Scales for Denoising

The whole point of using wavelet shrinkage before applying the enhancement procedure is to prevent noise from being amplified. However, the low-pass filter that is inherent to the wavelet transform smooths noise out as the number of scales...
increases, regardless of the shrinkage function. In fact, if too many scales are used, the image may be over-smoothed, and fine image details may be blurred or lost. In the proposed approach, wavelet coefficients are enhanced using Equation (16) up to a user-selected scale \( J_{\text{max}} \), but shrinkage is applied just to a scale \( J \leq J_{\text{max}} \), which is selected automatically based on an estimate of noise contamination.

As discussed in Section IV, noise and edge-related coefficients are discriminated by comparing the PDFs of edge-related squared magnitudes \( p_s^j(r) \) and noise-related squared magnitudes \( p_n^j(r) \) at each scale \( j \). The decision on whether the shrinkage function (i.e. denoising) will be applied to the scale \( j \) or not is based on the separability of the PDFs \( p_s^j(r) \) and \( p_n^j(r) \).^3

The Bayes classification error \([12]\) is given by

\[
\epsilon = \int_0^1 \min\{w_n p_n(r), (1 - w_n) p_e(r)\} \, dr,
\]

and it is limited by the Chernoff bound:

\[
\epsilon \leq \epsilon_c(s) = w_n^s (1 - w_n)^{1-s} \int_0^\infty p_n(r)^s p_e(r)^{1-s} \, dr, \quad \forall s \in [0, 1].
\]

Using the expressions for \( p_n(r) \) and \( p_e(r) \) given by Equations (7) and (8), respectively, the Chernoff bound can be written as

\[
\epsilon_c(s) = w_n^s (1 - w_n)^{1-s} \frac{\Gamma(s \beta - 3s + 3)}{\alpha^s \Gamma(\beta) (16 \sigma_n^2)^{1-s}} \times \frac{2\alpha \sigma_n^2}{2\alpha \sigma_n^2 + \alpha - \alpha s}^{s \beta - 3s + 3}.
\]

Given a threshold \( 0 < T_e < 1 \), we can say that edge-related and noise-related coefficients can be separated with at most an error \( T_e \) if

\[
\epsilon_c = \min_{0 \leq s \leq 1} \epsilon_c(s) \leq T_e,
\]

where \( \epsilon_c \) is computed numerically. As \( j \) increases (i.e. coarser scales are analyzed), noise is smoothed out, and the class separability is expected to increase. To select the number of scales \( J \) used for denoising, the scale \( j \) is increased until the maximum classification error is smaller than \( T_e \) according to Equation (20), i.e.

\[
J = \text{min} \left\{ j \mid \epsilon_c^j \leq T_e, \quad \text{for} \quad j = 1, \cdots, J_{\text{max}} \right\},
\]

where \( \epsilon_c^j \) denotes the bound for the classification error at the scale \( j \), and \( J_{\text{max}} \) is the total number of scales used for enhancement. In all examples, we used \( T_e = 0.2 \) based on empirical testing.

Figure 4 illustrates several enhanced versions of the image illustrated in Figure 1(a), using different enhancement scales \( J_{\text{max}} \) and factors \( \kappa_j \). As it can be observed, as coarser scales are introduced, larger structures/details are enhanced. Also, larger values for \( \kappa_j \) produce more edge enhancement.

\[\text{Fig. 4. Enhanced versions using different values for } J_{\text{max}} \text{ and } \kappa_j.\]

V. EXPERIMENTAL RESULTS

We applied the proposed image enhancement procedure for visual screening of typical dermatology cases. In these experiments, we focused our analysis on digital color images of superficial spreading melanomas, that were retrieved from the DermIS project web cite (http://www.dermis.net/dermisroot/en/17570/diagnose.htm), and from our personal database. In a preliminary validation phase, different enhanced versions of the same image from the DermIS database using combinations of \( J_{\text{max}} \) and \( \kappa_j \) were presented to specialists, who picked the to enhanced versions considered the best. The set of parameters that presented the best enhanced image varied for each individual image, since details are enhanced in different ways. However, \( \kappa_j = 1.25 \) with \( J_{\text{max}} = 1 \) or \( J_{\text{max}} = 2 \) presented the best overall results.

In a second phase, the original images were presented to the specialists along with two enhanced versions: version 1 (\( J_{\text{max}} = 1, \kappa_1 = 1.25 \)) and version 2 (\( J_{\text{max}} = 2, \kappa_1 = \kappa_2 = 1.25 \)). They picked the best of the two, and rated it in comparison to the original image using a scale from 1 to 5, where 1 means much worse, and 5 means much better. From all 71 images in the dataset, the best enhanced version produced equivalent visual results in 33.8% of them. In 59.2% of the cases, the enhanced version was classified as better, and in 7.0% the result was considered much better. In summary, the average score for the DermIS dataset was 3.7.

Figure 5 illustrates some of the images (original and en-
hanced versions 1 and 2) in the database\(^4\), in cases where the enhanced versions were considered equivalent to the original. Also, the fourth column in these Figure illustrates an enhanced version using the hue-preserving algorithm presented in [28], using a linear stretch followed by a S-type enhancement, as suggested by the authors. Figure 6 shows similar results, but for those cases where the enhanced version was classified as better or much better than the original. In images 51 and 68 (Figure 5), the enhanced version 2 was considered worse than the original, but version 1 was considered equivalent. Enhanced version 2 for image 8 (Figure 6) is one example of sharpening that was considered much better than the original. As it can be observed, the enhancement results using [28] did not improve the details in the interior of the lesions, and produced color distortion in most cases, as noticed by the specialists.

\(^4\)Some of the images in Figures 5 and 6 were cropped, to focus on the lesion.

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</tr>
<tr>
<td></td>
<td>Avg. 3.4</td>
<td>3.3</td>
<td>3.1</td>
<td>1.2</td>
</tr>
</tbody>
</table>

Besides testing our enhancement method on DermIS database images, we also used images from our personal database, captured under a variety of illumination conditions, distances from the lesion and focus adjustment, so that the lesions may appear at different resolutions and/or a little blurred. These images illustrate situations that are common in patients with non-melanocytic cutaneous neoplasies (i.e., not pigmented lesions), and some important clinical characteristics that are usually evaluated are the presence of telangiectasies (red vases), the clarity of the lesion boundaries, ulcerations and erosions in the interior of lesions, and lesion colors. Another clinical characteristic that is very important for the diagnosis is the palpation of the lesion, to evaluate the lesion relief. This last aspect is lost when only the image is available, and the enhancement of the lesion texture may help the dermatologist to infer the relief information.

Based on the clinical characteristic mentioned above, the specialists analyzed the enhancement results produced by the proposed approach using different values for \(J_{\text{max}}\) and \(\kappa_j\). The best enhancement result was selected for each image, and rated in a scale from 1 to 5 (as in the DermIS experiment) in terms of sharpness, texture/relief, lesion contour, and color. They also ranked the enhanced image produced using the method described in [28]. The obtained minimum, maximum and average scores for the visual aspects described above are summarized in Table I, for each one of the 9 lesion images from our database. As it can be observed, regarding sharpness, texture/relief and lesion contour, the proposed approach produced an enhancement result that usually is better than the original image (i.e., the result was rated with a grade \(\geq 3\) for all images tested). For some of the images, the dermatologist considered that the proposed approach downgraded the color aspect (minimum grade \(\leq 3\)), but in average the color of the processed image was improved as well.

Figure 7 shows some of the images of our database, along with the enhanced versions produced with the proposed algorithm. These enhanced image versions obtained high grades in terms of sharpness, texture/relief, lesion contour and color, and are considered good compromises in terms of these visual aspects. As it can be observed, our method enhances edges and lesion details without downgrading significantly color information, while the hue-preserve approach [28] presents significant color degradation.

The proposed algorithm was implemented in MATLAB, and experiments were performed on a Pentium Core 2 Duo 2.13 GHz PC computer with 2 GB RAM. Execution times depend on image sizes and number of selected WT scales, but typical running time for the images in the DermIS database is approximately 3.6 seconds using \(J_{\text{max}} = 1\) and 7.3 seconds using \(J_{\text{max}} = 2\). Clearly, an implementation of the proposed method in a compiled language would reduce running times.

### VI. CONCLUSIONS

This work presented a novel technique for sharpening color dermatological images, based on a non-decimated Wavelet Transform. In the proposed approach, a color edge map is computed at each scale, and squared gradient magnitudes are modeled by a mixture of chi-squared and gamma distributions to discriminate edge-related from noise-related coefficients. Then, a nonlinear function is used to enhance edges at different scales, without amplifying the inherent noise contained in the image.

The proposed method allows the selection of the number of scales for enhancement (which relates to the resolution of the lesions to be analyzed) and the individual enhancement factor for each scale. Results were validated in terms of visual improvement by specialists using a set of images of the DermIS database, and also using images from our database. Most of the enhanced images from both databases were considered better than the original. Although the method is intended to serve as an unsupervised tool for aiding tele-dermatology applications, the specialist may change the values of \(J_{\text{max}}\) and \(\kappa_j\) interactively to obtain optimal results for each individual image and aspect of analysis (e.g. sharpness, texture/relief, lesion contour and color).

Future work will concentrate on a thorough evaluation of the parameters \(J_{\text{max}}\) and \(\kappa_j\) in the visual quality of the sharpened images, and an extensive validation in terms of diagnosis accuracy. We also plan to improve the discrimination between noise and edges in textured regions within the lesions, and to apply the proposed algorithm to other types of multiband images.

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Fig. 5. Original images from DermIS database and enhanced versions - examples where the proposed approach did not improve visual analysis.

D’Elia (MD) and Nicolle Gollo Mazzotti (MD). They would also like to thank the anonymous reviewers, for their valuable contributions.

REFERENCES

Fig. 6. Original images from DermIS database and enhanced versions - examples where the proposed approach did improve visual analysis.


