An invisible DWT watermarking algorithm using noise removal with application to dermoscopic images

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Abstract. A new approach for the digital watermarking process is proposed to be part of the pre-processing stage of a computer-aided diagnosis system. We propose to embed a denoised image acting as the watermark image in the original host image with the final goal of improving the quality of dermoscopic images for further image processing operation related to CAD. The proposed algorithm uses Discrete Wavelet Transform (DWT) corroborated with some basic properties of Human Visual System such as Contrast Sensitive Function (CSF) and Noise Visibility Function (NVF) with the goal of correlating the texture properties and noise. This approach hides the watermark (i.e. denoised version of the host image) in high-pass subbands that are focused on image features. The main concern is to evaluate the distortion produced to the host image by watermarking and an objective quality measure function, i.e. Weighted Peak Signal-to-Noise Ratio (WPSNR), is used to evaluate the existing differences between the original and watermarked images. The proposed approach is tested using the available skin lesion images from the digital image archive of the Department of Dermatology of the University Medical Center Groningen. The experiment results show the improved performance of the proposed scheme against a 3 × 3 median filtering attack in comparison with the a 5 × 5 median filtering attack.

1. Introduction

Digital watermarking deals with embedding information into another signal, which can be in our case a dermoscopic image. The result will be a new image. The aim of this paper is to analyze the effect of watermarking on the dermoscopic image quality with the declared goal of improving the computer-based diagnosis of skin lesions process. Specifically, we are focused on increasing the visibility around image features like lines, pseudopods, circles, globules. As a future goal, this study will aim to be able to differentiate nevi from melanomas.
A lot of studies devoted to digital watermarking are reported and different digital watermarking techniques are proposed. It is well known that the Human Visual System (HVS) is sensitive to noise and various watermark schemes can be affected. Noise is independent of frequency and the human eye is almost insensitive to high frequency variations so, a rather weak watermark will be performed in this frequency range. Also, according to Kankanhalli et al. [1] the HVS sensitivity to noise is higher for smooth and textures areas whilst a weak sensitivity exists for image edges. HVS performs the visual perception based on contrast sensitivity (CSF) or contrast masking features. The contrast sensitivity ability allows us to perceive degradation artifacts existing in both uniform and strongly textured areas as well as in the dark and bright areas of a digital image. However, the artifacts are more visible in uniform and bright areas. From a perceptual point of view, noise is more detectable around edges than in textured areas [2, 3]. The contrast masking effect describes the reduction in visual perception due to the masking effect of some image components to another image components having a similar location and frequency content [4].

From the literature survey, the frequency domain watermarking based on transforming the original image into the frequency domain by the use of Discrete Wavelet transforms (DWT) has captured greater attention due to the quality of the watermarked images [5-9]. The hidden information into image can be detected if this image is previously DWT transformed. The main advantage of DWT consists of its attractive time-frequency domain localization properties. A digital image is decomposed into a set of resolutions and facilitates to detect image features. Also, the coefficients of the DWT sub-bands are important for the watermarking transformation. The magnitude of the coefficients is correlated to the energy and information contained into image as well as to the robustness of the watermark. Usually, a low frequency sub-band (LL) image is an approximation of the original image with a smoother spatial distribution. The coefficients in the LL sub-band are mostly dominated by the effect of luminance and are involved in the CSF definition. In the high frequency sub-bands (HH – the diagonal details), sharp variation such as edges and textures areas contribute to image features that are mostly used to define Noise Visibility Function (NVF) [10, 11]. HVS model operating in the DWT domain is originated from the HVS sensitivity response that is different in DWT sub-bands [12]. NVF allows to characterize the textured and edge regions into image being inversely proportional to the local image energy defined by the local variance (variance of the visual noise is an HVS parameter). CSF mask weights the wavelet coefficients relative to their perceptual importance while NVF describes the local image properties through the texture and edges (i.e. a large local variance indicates the presence of edges or highly texture areas).

The weighted Peak Signal-to-Noise Ratio (WPSNR) is a quality metric based on the prediction of a human observer’s responses. It is used to estimate the image degradation produced by embedding watermarks [13, 14]. WPSNR provides a better estimate of distortions based on its ability to localize the visual errors [15].

An invisible watermarking approach for gray scale images is our main goal. The proposed algorithm transforms an image and operates on the transform domain. Firstly, it uses a median filter to pre-process and generate the watermark image. Then, the DWT coefficients extraction on the carrier image is performed. Simultaneously, the host image is DWT transformed and a coefficients extraction is also carried out. The decomposed wavelet coefficients of the original image are used to generate the CSF rule. Simultaneously, a NVF rule related to the wavelet coefficient variance for several resolution levels and according to each direction is set up with the assistance of HVS’s most important characteristics: luminance and the texture sensibility of the human eye. Also, a study on the detection thresholds for DWT coefficients has been carried out. The magnitude of the CSF coefficients of the DWT sub-bands allow us to compute the so – called scaling factor and the modulation rate as the global characteristics of the host and watermark images. All these parameters, i.e. the decomposed wavelet coefficients of the original and watermark images and the NVF function will generate the watermarked image. At the end, the inverse DWT (IDWT) is applied to the combined watermarked coefficients to obtain the watermarked image [16]. WPSNR will estimate the embedding capacity of the algorithm. The proposed approach is tested using images from the digital image archive of the
Department of Dermatology of the University Medical Center Gröningen with the final goal of improving the quality of demoscopic images for further image processing operation related to CAD.

Method

2. Contrast Sensitive Function CSF

The CSF provides a characterization of HVS’s frequency response dealing mainly with the relationship between contrast sensitivity and spatial frequency. The global contrast measure is defined as:

$$C = \frac{(L_{\text{max}} - L_{\text{min}})}{(L_{\text{max}} + L_{\text{min}})} = \frac{1}{\text{CSF}(f)}$$  \hspace{1cm} (1)

Where $L_{\text{max}}$ and $L_{\text{min}}$ denote the maximum and minimum luminance values. CSF is the reciprocal of the contrast threshold that describes the minimum luminance differences perceived by HVS. CSF for grayscale image is as follows [17, 18]:

$$\text{CSF}(f) = 2.6 * (0.0192 + 0.114 * f) * e^{(-0.114* f^2)}$$  \hspace{1cm} (2)

where the spatial frequency is $f = \sqrt{f_x^2 + f_y^2}$, and $f_x$, $f_y$ are the spatial frequencies in the horizontal and vertical directions, respectively. Larger $f$ values will produce larger ranges of luminance.

CSF masking [12] is employed in the DWT to weight the wavelet coefficients of the original image relative to their perceptual importance. Masking effect characterizes the variability of the image component visibility due to neighboring components frequency and orientation. For each approximation and detail sub-bands, the weights in the mask were computed. The small weights are correlated to noise or less important details while the large weights are due to important image features. For the last ones, HVS becomes more sensitive. For each sub-band, the scaling factor $\alpha_{\lambda, \theta}$ is derived as:

$$\alpha_{\lambda, \theta} = 1 - \frac{(2.74 - r_{\lambda, \theta})^2}{2.74^2}$$  \hspace{1cm} (3)

where $r_{\lambda, \theta}$ are the CSF wavelet coefficients of the perceptual importance weight for each sub-band, $\lambda (=1,2,3,4,5)$ denotes de decomposed level and $\theta (=1,2,3,4)$ is the orientation. Watermark embedding is effective for perceptually significant coefficients. The best CSF approximation is obtained for the maximum weight in the case of a 3-level wavelet pyramidal decomposition. The average value of 2.74 over the 170 images in our database was computed and the corresponding weights are displayed in Table 1.

**Table 1.** The average weight values for CSF masking for a 3-level DWT pyramidal decomposition for considered dermoscopic image database.

| Orientation Levels | HH | HL | LH |
|-------------------|----|----|----|
| 1-level           | 1.7| 1.52| 1.52|
| 2-level           | **2.74**| 2.22| 2.22|
| 3-level           | 2.2| 2.02| 2.02|
2.1. Noise Visibility Function (NVF)
NVF characterizes the local image properties and identifies the textured and edge regions. In order to control the robustness of the watermark we use a content adaptive NVF function based on the wavelet coefficient variance for several resolution levels and according to each orientation. NVF is defined as [14]:

$$NVF(i, j) = \frac{1}{1 + \sigma_{\delta}^2(i, j)}$$  \hspace{1cm} (4)

with

$$\sigma_{\delta}^2(i, j) = \frac{1}{(2L+1)^2} \sum_{k=-L}^{L} \sum_{l=-L}^{L} \left( x(i+k, j+l) - \bar{x}(i, j) \right)^2$$

$$\bar{x}(i, j) = \frac{1}{(2L+1)^2} \sum_{k=-L}^{L} \sum_{l=-L}^{L} x(i+k, j+l)$$  \hspace{1cm} (5)

where $\sigma_{\delta}^2(i, j)$ is the local variance of an image in a window of width $L$, centered on the pixels with coordinates $(i, j)$. $\bar{x}(i, j)$ denotes the local mean around the window $L$ having the values $x(i+k, j+l)$ as the center of the window. The NVF approaches 1 in smooth regions and 0 in highly textured regions. If NVF $\sim$ 1, the strength of the embedded watermark approaches zero and the watermark information is almost lost in these areas.

Finally, to consider the watermark intensity, the luminance CSF is further correlated to the decomposed wavelet coefficients of the watermark through the modulation rate $\beta_{\lambda, \theta}$ defined as follows:

$$\beta_{\lambda, \theta} = 0.01 - \frac{(2.74 - r_{\lambda, \theta})^2}{2.74^2}$$  \hspace{1cm} (6)

2.2. Embedding stage
The watermarked image is determined as a weighted combination between the DWT coefficients of the host image weighted by the scaling factor $\alpha_{\lambda, \theta}$ and the DWT coefficients of the watermark image weighted by the modulation rate $\beta_{\lambda, \theta}$. Additionally, a $NVF_{\lambda, \theta}$ function related to the wavelet coefficient variance for several resolution levels and according to each direction is taken into account. For watermarking, the composite DWT coefficients formula is given by:

$$Y_{\lambda, i, j, \theta} = \alpha_{\lambda, \theta} \times X_{\lambda, i, j, \theta} + \left( 1 - NVF_{\lambda, i, j} \right) \times \beta_{\lambda, \theta} \times S_{\lambda, i, j, \theta} + NVF_{\lambda, i, j} \times K \times S_{\lambda, i, j, \theta}$$  \hspace{1cm} (7)

where, $K$ is an empirically determined constant. A typical value is 0.08 [5].

2.3. Filtering and performance comparison
The median filter calculates the median value of a pixel in a $3 \times 3$ or $5 \times 5$ square neighborhood and the central pixel is replaced with the corresponding resulted value [13]. The main advantage of this filter consists of the insignificant influence on the discontinuities such as edges that are not affected in terms of gray-level intensity. Only a small shift by a few pixels is produced during filtering operation. On the other hand, it has the potential to completely remove the “sand and pepper” type of noise without any severe degradation of the edges or image characteristics. The filtered image $f(i, j)$ uses the following equation:
\( f(i, j) = \text{median}\{g(i, j)\} \)  

(8)

where \( S_{xy} \) is a sliding window of size \( x \times y \) pixels centered at the original value of the pixel \((i, j)\). The quality of the watermarked image is assessed with respect to the original image by using the Weighted Peak Signal-to-Noise Ratio WPSNR. For any two images \( I_1 \) and \( I_2 \), WPSNR is calculated by the relation:

\[
\text{WPSNR} = 10 \log_{10} \left( \frac{255^2}{\text{NVF} \times \text{MSE}} \right)
\]

(9)

where and \( \text{NVF} \) is given by eq. (4) and the mean square error \( \text{MSE} \) for the watermarked image \( I_2 \) (approximation of the original \( I_1 \) in this case) is as follows:

\[
\text{MSE} = \frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \left[ I_1(i, j) - I_2(i, j) \right]^2
\]

(10)

both images have a \( m \times n \) size [13].

2.4. Proposed embedding algorithm

To obtain a robust watermarking result, the steps involved in the process of embedding are as follows:

1. A host image (original image) is first transformed into the frequency domain by using the DWT (discrete wavelet transform). The host image is decomposed into three-level multiresolution structures and the decomposed wavelet coefficients are determined.

2. The watermark consists of filtered images. The detection reliability is related to the watermark characteristics, so to optimize the data detection, a median filter and two masks of size \( 3 \times 3 \) and \( 5 \times 5 \) were used to perform the noise removal. Once again, the denoised image is transformed into frequency domain by using the DWT and three-level multiresolution. The decomposed wavelet coefficients were determined.

3. The wavelet decomposition coefficients are used to compute the CSF mask coefficients of the associated sub-bands. CSF mask weights the wavelet coefficients relative to their perceptual importance.

4. Also, NVF in relationship to the various spatial frequencies (frequency sub-bands) is computed. NVF describes the local image properties through the texture and edges (i.e. a large local variance indicates the presence of edges or highly texture areas).

5. Each pixel of the watermarked image is established as the weighted linear combination between the host weighted pixel value, the weighted watermark pixel value along with the CSF masking and NVF.

6. The obtained composite watermarked DWT coefficients are used to employ the inverse transform of the DWT (IDWT) to obtain the watermarked image.

7. The quality of the watermarked image is assessed by using WPSNR.

The flow chart of the proposed algorithm is shown in figure 1.
2.5. Image database
In our proposed watermarking experiment, 170 digital dermoscopy images (70 malignant melanoma images and 100 nevus (benign) images) are chosen from the Digital Archive of the Department of Dermatology of the University Medical Center in Groningen (UMCG)\(^2\).

3. Results and discussion
The watermark image adopted in our experiment consists of filtered images using a median filter and two masks of size 3 × 3 and 5 × 5 for noise removal. Both images, i.e. the host (original) and denoised (watermark) images are transformed into frequency domain by using the DWT (discrete wavelet transform). They are decomposed into three-level multiresolution structures and the decomposed wavelet coefficients and were determined.

Figure 2 shows an example of a host image (Fig. 2a), the corresponding watermark representation for median filtering with 3 × 3 and 5 × 5 masks (Figs. 2b and 2c) and the resulting watermarked image (Figs. 2d and 2e), for both filtering conditions.

\(^2\) http://www.cs.rug.nl/~imaging/databases/melanoma_naevi/
Figure 2. Images watermarked with denoised images

The original and watermarked images were used to establish the contrast threshold (CT) values. The contrast has been determined using eq. (1), then the image was modified according to computed CSF values. The higher CT values will determine the quality of the watermarked images for the HVS model which operate in transform domain of DWT and is combined with contrast thresholds. For nevus original images, the average CT value was 0.76 ± 0.03, while for nevus watermarked image a value of 0.78 ± 0.02 was computed. Similarly, for original melanoma images a value of 0.66 ± 0.02 was determined, while for watermarked images it becomes 0.68 ± 0.019. The average contrast threshold values are slightly higher for watermarked image getting a better visual quality of the results.

The composite watermarked DWT coefficients (eq. 7) are used to employ inverse transform the DWT (IDWT) to obtain the watermarked image. An example is displayed in figs. 2d and 2e.

Data in Tables 2 and 3 contains the WPSNR values (displayed as average ± standard deviation) for nevus and melanoma images. WPSNR was computed to compare the similarity between the original ($I_1$) and extracted watermarks ($I_2$) and is a good tool for an objective quality assessment based on HVS as it uses the NVF which is a texture masking function. In this case, WPSNR reflects the difference between images, for each perceptual sub-band, more precisely.

**Table 2.** M ± SD values of WPSNR (dB) after 3 × 3 median filtering and for 3-level DWT

| Sub-bands | LL1     | HL1     | LH1     | HH1     |
|-----------|---------|---------|---------|---------|
| Nevi      | 39.55 ± 10.33 | 108.57 ± 5.52 | 108.93 ± 4.72 | 120.09 ± 4.82 |
| Melanoma  | 44.70 ± 10.80 | 110.77 ± 5.68 | 110.41 ± 7.15 | 121.13 ± 6.00 |

| Sub-bands | LL2     | HL2     | LH2     | HH2     |
|-----------|---------|---------|---------|---------|
| Nevi      | 25.71 ± 10.35 | 94.32 ± 6.84 | 95.95 ± 5.57 | 105.94 ± 5.50 |
| Melanoma  | 30.87 ± 10.83 | 98.40 ± 7.43 | 98.36 ± 8.10 | 108.41 ± 7.48 |

| Sub-bands | LL3     | HL3     | LH3     | HH3     |
|-----------|---------|---------|---------|---------|
| Nevi      | 11.88 ± 10.37 | 79.07 ± 9.08 | 81.05 ± 7.56 | 90.85 ± 6.97 |
| Melanoma  | 17.02 ± 10.84 | 84.71 ± 11.02 | 83.40 ± 9.68 | 96.39 ± 9.37 |

**Table 3.** M ± SD values of WPSNR (dB) after 5 × 5 median filtering and for 3-level DWT

| Sub-bands | LL1     | HL1     | LH1     | HH1     |
|-----------|---------|---------|---------|---------|
| Nevi      | 36.53 ± 9.82 | 103.63 ± 5.59 | 103.93 ± 5.51 | 119.81 ± 4.75 |
| Melanoma  | 39.85 ± 8.62 | 105.03 ± 6.30 | 105.02 ± 8.25 | 120.66 ± 5.66 |

| Sub-bands | LL2     | HL2     | LH2     | HH2     |
|-----------|---------|---------|---------|---------|
| Nevi      | 36.53 ± 9.82 | 103.63 ± 5.59 | 103.93 ± 5.51 | 119.81 ± 4.75 |
| Melanoma  | 39.85 ± 8.62 | 105.03 ± 6.30 | 105.02 ± 8.25 | 120.66 ± 5.66 |
The low frequency sub-band (LL) image is the approximation of the original image with a smoother spatial distribution and it is critical during the reconstruction of the image. The coefficients in the LL sub-band are driven by the effect of luminance, are involved in the CSF definition and, in order to preserve the quality of watermarked image only small values of parameters are intended. In the high frequency sub-bands (HH – the diagonal details), sharp variation such as edges and textures areas contribute to image features that are mostly used to define NVF. For for 3-level DWT decomposition, HH sub-bands combine the information that are neither horizontal, nor vertical, being insensitive to orientation. As we are focused on the invisible watermark and higher WPSNR values, for HH sub-bands, indicate a robust watermark with better results. Also, higher WPSNRs for 3×3 median filtering attack demonstrate that the proposed watermarking scheme has better visual appearance than 5×5 median filtering attack. In this case, fewer details are lost and the images are less distorted.

4. Conclusion
A new approach of the digital watermarking process was proposed as a method able to improve the quality of medical images without the embedding process affecting the diagnosis to be part of the pre-processing stage of a computer-aided diagnosis system. A median filtered image acted like a watermark image and was embedded in the original host image with the final goal of improving the quality of demoscopic images for further image processing operation related to CAD. The main concern was to evaluate the distortion on the host image by the median filtering attack using the WPSNR measure. The experiment results show the improved performance of the proposed scheme against a 3×3 median filtering attack in comparison with a 5×5 median filtering attack.

5. References
[1] Kankanhalli M S, Rajmohan and Ramakrishnan K R 1998 Proc. Int. Conf. on Multimedia (Bristol, UK) p 61
[2] F A Damian, S Moldovanu, N Dey , A S Ashour and L Moraru 2020 Computation 8 41
[3] Zhu S and Liu J 2009 Proc. 5th Int. Conf. ISPEC vol 5451 (Xi’an, China) p136
[4] Seshadrinathan K, Pappas T N, Safranek R, Chen J, Wang Z, Sheikh H R and Bovik A C 2009 Image Quality Assessment 2nd edn (Austin, Texas: Elsevier).
[5] Tsai M J 2009 J. Vis. Commun. Image R. 20 323
[6] Gunjal B L and Manthalkar R R 2010 JETCIS 2(1) 37
[7] Dey N, Samanta S and Roy A B 2011 IJCAT 2(6) 1970
[8] Lai C C and Tsai C C 2010 IEEE Trans. Instrum. Meas. 59(11) 3060
[9] Santhi V and Arulmozhivarman P 2016 Int. J. Adv. Media Commun. 5(4) 260
[10] Tsai M J, Liu J and Yin J S 2014 Multimedia Tools and Appl. 72(2) 1311
[11] Rangel-Espinoza K, Fragoso-Navarro E, Cruz-Ramos C and Nakano-Miyatake M, Cedillo-Hernandez M, Perez-Meana H 2004 Proc. Int. 7th International Workshop on Biometrics and Forensics (IWBFI) (Cancun, Mexico) pp 1
[12] Levicky D and Foris P 2004 Radioengineering 13(4) 38
[13] Hoshyar A N, Al-Jumaily A and Hoshyar A N Procedia Comput. Sci. 42 32
[14] Voloshynovskiy S, Herrigely A, Baumgartenr Y and Punz T 1999 Proc. Int. 3rd International Workshop Information Hiding (Dresden, Germany: Springer) p 211
[15] Abdel-Aziz B and Chouinard J Y 2003 Proc. Int. 2nd International Workshop IWDW Digital Watermarking (Seoul Korea, Heidelberg, Berlin: Springer) p 277
[16] Cox I J, Kilian J, Leighton J F T and Shamoon T 1997 IEEE Trans. Image Process. 6(12) 1673
[17] Yong D 2018 Visual quality assessment for natural and medical image (Berlin: Springer)
[18] Mannos J L and Sakrison D J 974 IEEE Trans. Inf. Theory 20(4) 525