

Watermarking Spectral Images with Three-Dimensional Wavelet Transform Subject to Various Illumination Conditions

Arto Kaarna

*Department of Information Technology, Lappeenranta University of Technology, P.O.Box 21, FI-53851 Lappeenranta, Finland
E-mail: arto.kaarna@lut.fi*

Konstantin Krasavin and Jussi Parkkinen

Laboratory of Computer Science, University of Joensuu, P.O.Box 111, FI-80101 Joensuu, Finland

Timo Jaaskelainen

Laboratory of Physics, University of Joensuu, P.O.Box 111, FI-80101 Joensuu, Finland

Ron van Schyndel

School of Computer Science and Information Technology, RMIT University, GPO Box 2476V, Melbourne, Victoria 3001, Australia

Abstract. *Digital imaging continues its expansion into various applications. Spectral images are becoming more popular as one field of digital imaging. At the same time, the economic and security aspects in the utilization of images are finding increased emphasis. In this study, the authors apply a watermarking method for spectral images, whereby embedding is based on the three-dimensional wavelet transform. The authors study the influence of illumination to the watermarked images. The authors also define how to estimate an unknown illuminant. Experiments were performed on a dataset of 13 spectral images. These experiments indicate that the illumination in spectral images should be established before watermarking, owing to the properties of the illuminants. Using the proposed watermarking method, the embedded watermark is also robust towards lossy compression. Guidelines for the parameter selection for watermarking with the proposed approach are given. © 2008 Society for Imaging Science and Technology.
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INTRODUCTION

There are basically two reasons for hiding additional information in captured images. The first considers security issues and the second considers economic issues.¹ Security issues include, e.g., watermarking for integrity control, verification of originality, copyright protection, and steganography. For security, it is very important that the watermark is not visible and that it cannot be detected or extracted easily. The economic issues are related more to the utilization of the images, e.g., copy control, identification, authentication, and annotation. Now the watermark can be visible in images or audible in sound, but still an incorrect or un-

verified extraction process should yield unusable or incorrect information. As such, watermarked images can be freely distributed, and one can develop methods that use these images. The final, reliable results from the methods can be computed as soon as the original information is available. From the viewpoint of the image database provider, the free distribution of images may attract new clients and extend markets for the images. From the viewpoint of the client, methods can be developed and implemented as soon they are ready, and the required original information can be bought from the image database provider. The original information can be transmitted either as full, original images or as secret keys for extracting the watermark from the freely distributed watermarked images. In this approach both the identification and the authorization processes can be maintained through proper watermarking. The secret keys should be designed such that further distribution of the images by the client is, in practice, impossible. A possible strategy would be to include client-dependent information hidden in a robust way within the spectral image.

In this study, we consider the case where a database contains several spectral images which should be watermarked for the economic reasons described above. The watermarking system should embed a robust watermark. It should be difficult to extract the watermark if the embedding process is unknown. If extracted some other way, it would also affect to the original information. Furthermore, clients must be able to utilize various illuminants in the visual range of the spectral images.

From the point of view of the database provider, the data can be also be compressed in a lossy manner. The data transmission and storage then requires less capacity, and still

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the client-side systems can be developed and implemented with this free data. The target of this study is to show and to give guidelines on how to perform watermarking of spectral images with various illuminants and with various lossy compression conditions.

Economic issues are becoming more important as digital imaging becomes dominant over analog modes. Digital presentation allows preservation of the quality of images after image processing operations, copying can be done quickly and easily, and the copy is identical to the original. Digital watermarking offers a possibility for controlling illegal copying or, more generally, access to the original digital information. As a complementary part to cryptography, the watermarking technique protects the data by embedding a watermark in such a way that it does not disturb the image in normal image perception or processing conditions or in the system development. The embedded watermark can then be extracted for the identified, authorized clients.^{1,2}

Color image watermarking has been extensively studied.²⁻¹⁰ Several watermarking techniques have been developed for grayscale and RGB images. Some of the techniques embed the watermark in the spatial domain; some embed the watermark in a transform domain. Color image watermarking has been studied mainly in RGB space or in two-dimensional (2D) transform space.¹¹⁻¹⁵

Spectral color imaging is an imaging method whereby the color of an object is represented more accurately than in traditional three-channel RGB images. Spectral imaging is becoming a practical tool for various applications, e.g., in medical imaging, digital commerce, industrial quality control, and maintenance of cultural heritage in digital museums.¹⁶

Watermarking images is an emerging method for supporting intellectual property in digital media. If the human visual system is used for measuring the embedding quality, then it is easier to define embedding procedures that provide robust watermarking without large visual changes in the image. This approach is most general in watermarking color images. For spectral images the requirements set by the various applications may be very diverse. Again, for visual assessment, watermarking is simpler. In classification applications it is too risky to rely on the results if they are obtained from the modified spectral data, either through watermark embedding or lossy compression. Thus, the original information, or information with very limited loss through noise removal, is needed for classification tasks. Typically, lossless compression of spectral images provides compression ratios from 3 to 5, depending on the image. With lossy methods, compression ratios from 5 to 100 are achieved in practice. Near-lossless methods, which mostly perform limited noise-removal with lossy compression, have been shown to provide compression ratios from 5 to 10.¹⁷ Even though watermarking may modify the original content of the image, the intellectual property rights should be somehow managed. This study defines the requirements for this reality and, as such, provides a practical approach to watermarking spectral images.

Spectral imaging allows separation of the object reflectance and illumination. A reasonable approach for a database provider is to keep the reflectance data and then add the illumination required by the client. This study considers the joint operation of watermarking and illumination. Our purpose is to provide guidelines on how to combine watermarking and illumination.

In comparison to RGB images with three bands, spectral images have many bands. The number of the bands depends on the application. The normal range is from 8 to 256 spectral bands. Thus, spectral images have higher data dimensionality compared to regular RGB images. A watermarking technique especially designed for spectral images can utilize the high dimensionality of spectral images and would, therefore, have advantages over application of RGB or grayscale watermarking techniques to spectral data.^{12,15,18-21} In this study we embed a grayscale watermark in spectral images in the three-dimensional (3D) wavelet transform domain as in Ref. 20, where the approach of using a 2D grayscale watermark in spectral imaging was proposed. We analyze the approach extensively and draw general conclusions. The size of the image database is 13 spectral images.²² Two of the images were remote sensing images and seven were taken under laboratory conditions. The properties of the watermarking on this dataset are studied. The results are usable for spectral image database providers who can watermark and compress their images for general, free distribution. Still they will have full control over the original information, even though method or system development and implementation for the clients is allowed.

The present report is organized as follows. In the following section, we describe the three-dimensional wavelet transform. The next section contains the procedure for embedding and extracting the watermark. The Lossy Compression of Watermarked Images section describes the compression procedure. The section entitled Illuminants for Spectral Image Processing describes the illumination effects. In the Experiments section we report the experiments on the illuminants and on compression. We then have the Discussion section and in the Conclusions section.

THREE-DIMENSIONAL WAVELET TRANSFORM

In the one dimensional case, the wavelet transform $f_w(a, b)$ of a function $f(t)$ can be presented as

$$f_w(a, b) = |a|^{-(1/2)} \int f(t) \psi\left(\frac{t-b}{a}\right) dt, \quad (1)$$

where $\psi(t)$ is a mother wavelet with zero mean.²³ The mother wavelet $\psi(t)$ is defined as a two-parameter function,

$$\psi^{a,b}(t) = |a|^{-(1/2)} \psi\left(\frac{t-b}{a}\right), \quad (2)$$

allowing both scaling with parameter a and translation with parameter b . The original function is recovered by the inverse wavelet transform,

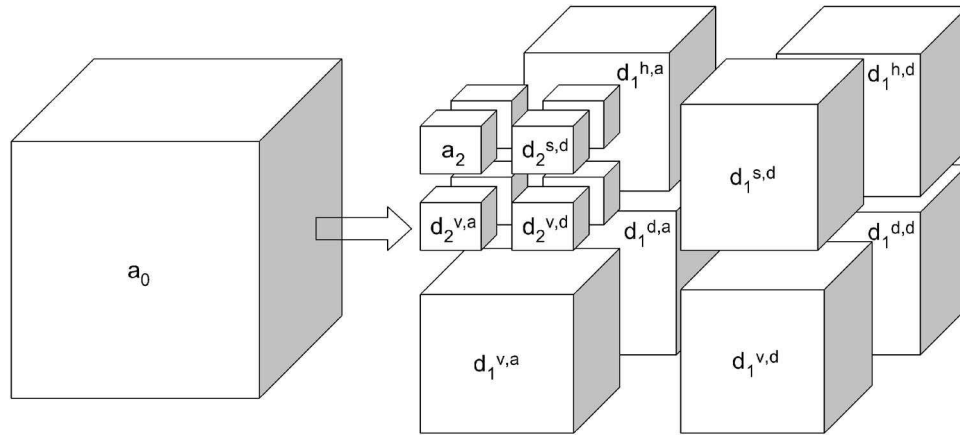


Figure 1. Three-dimensional wavelet transform schema. The coefficients a come from the low pass filtering and the coefficients d from the high pass filtering. The transform is applied with two levels in the multiresolution. The first level and the second level results in horizontal (h), vertical (v), and diagonal (d) dimensions, indicated with their respective subscripts.

$$f(t) = \frac{1}{C_\omega} \iint f_w(a,b) \psi^{a,b}(t) \frac{1}{a^2} da db \quad (3)$$

with the admissibility condition $C_\omega = \int (|\Psi(\omega)|^2 / \omega) d\omega < \infty$ required to ensure that $\Psi(0)=0$, where $\Psi(\omega)$ is the Fourier transform of wavelet function $\psi(t)$.

There exist many families of wavelets. Most popular are orthonormal and biorthogonal wavelets. For discrete signal processing, the continuous wavelets $\psi(t)$ with parameters a and b are discretized and a multiresolution ladder is applied to the signal. For higher dimensional data, the multiresolution is normally extended by separating the dimensions. The wavelet transform carries the perfect reconstruction property as seen from Eqs. (1)–(3). In digital signal processing the continuous functions ($\psi(t), f(t)$) are replaced by discrete values (wavelet filter h , image I) and the filtering is performed using convolution. For the definition of the filter h , the continuous parameters a and b in Eq. (3) are discretized for efficient computation.

Spectral images are three-dimensional signals with two spatial dimensions and one spectral dimension. The spatial dimensions contain the visually seen structures, and the spectral dimension presents the reflectance spectrum connected to each pixel. In the three-dimensional separable case the wavelet is

$$\psi_{j_1,k_1,j_2,k_2,j_3,k_3}(x_1,x_2,x_3) = \psi_{j_1,k_1}(x_1) \psi_{j_2,k_2}(x_2) \psi_{j_3,k_3}(x_3), \quad (4)$$

where $\psi_{j_i,k_i}(x_i)$ is a one-dimensional orthonormal discrete wavelet basis as $\psi_{j,k} = 2^{-j/2} \psi(2^{-j}x - k)$. Each dimension of the image is dilated separately. Thus, the original spectral image of size $N_x \cdot N_y \cdot N_z$ is filtered into octants of size $N_x/2, N_y/2, N_z/2$ (see Figure 1). Here $N_x \cdot N_y$ is the number of pixels in the spatial dimension and N_z is the number of bands in the spectral dimension. In practical applications, the image size is $2^n 2^m 2^b$, where n and m reflect the spatial sizes and b the spectral size. If this requirement is not met, then the image is padded to this size.

EMBEDDING AND EXTRACTING A WATERMARK

The wavelet transform has received increasing popularity in watermarking applications.^{1,14,19,20,24–26} The wavelet transform is a general tool in space-frequency analysis of signals. In addition, it is performed with a multiresolution approach that has correspondence to the human visual system.²³ These profound properties of the wavelet transform also make it a suitable system for watermarking where the robustness and the perception of watermarks must be considered. In the wavelet transform domain it is possible to control the sub-bands where the watermark is embedded providing control over the robustness of the watermark. The strength in embedding can be adjusted to control the visibility of the watermark. The extraction may be blind or nonblind (see the Extraction subsection), depending on the requirements of the application.

In this study, the watermark is a grayscale image. Now the database provider can add this visual watermark, which is easily recognized by humans. Thus, the client is conscious of the watermark but can still develop applications using this freely available watermarked data. On the other hand, the database provider may embed a fragile watermark. Then the purpose is to keep track of the integrity of the images. Now the information or, more exactly, the original information containing a fragile watermark, may be freely available, but the client is not allowed to modify the information in any fashion. Any modification of the information, e.g., low-pass filtering, lossy compression, band manipulation, and cropping, can be detected with a fragile watermark.

The embedding/extraction process in this study considers both of these cases. The embedding will be controlled by a strength parameter and a band-selection to receive the required degree of the robustness.

Embedding

Compared to RGB images, spectral images have higher dimensionality of the spectral data for each spatial location. This gives us more possibilities for watermarking purposes.

The watermark can be a binary image, a grayscale image, or even another spectral image. In this study, we used a 2-bit grayscale image as a watermark. The embedding procedure follows the method described previously.²⁰

- (1) The original spectral image is transformed to 3D wavelet domain.
- (2) The original watermark is transformed to 2D wavelet domain.
- (3) The values of the transformed watermark are added to the values of the transformed spectral image.
- (4) The watermarked spectral image is reconstructed using the inverse 3D wavelet transform.

The watermark is embedded in the 3D wavelet transform domain. First, a three-dimensional wavelet transform I_{wt} of the spectral image I is computed. Then a two dimensional wavelet transform W_{wt} of the watermark W is computed. For both transforms we used a biorthogonal, symmetric wavelet with six and two taps in the analysis phase. The spatial size of the watermark is equal to the spatial size of the transformed approximating sub-band block B_{wt} of the image. This block B_{wt} is composed of the eight blocks a_2 , $d_2^{s,d}$, $d_2^{s,a}$, $d_2^{s,d}$, $d_2^{h,a}$, $d_2^{h,d}$, $d_2^{h,v}$, and $d_2^{d,d}$, as displayed in Fig. 1 for the 3D wavelet transform with two levels. Thus, the size of the spectral image, the size of the watermark, and the number of levels in the transforms should match. The transformed values of the watermark W_{wt} are added to the values of the transformed block B_{wt} of the spectral image, resulting to the watermarked block $B_{wt,wm}$ as

$$B_{wt,wm} = B_{wt} + \alpha \cdot W_{wt}, \quad (5)$$

where α is a weighting coefficient.

For each pixel of the watermark, a suitable band b from the transformed block B_{wt} is selected. The band holding the median of the respective pixels among all the bands in block B_{wt} is selected to store the pixel of watermark. In this way we try to ensure that the watermark is neither stored in a high-energy nor in a low-energy transformed bands of an image. In the previous case, the watermark would be visible or clearly noticeable, and in the latter case, too fragile in compression of the watermarked image. Still, after this definition, it is possible to control the robustness of the watermark. The strength of the watermarking is controlled by a weighting coefficient α , which is calculated as a multiplication of two parameters as

$$\alpha = \alpha_1 \cdot \alpha_2, \quad (6)$$

The first parameter α_1 is selected such that it accounts for the visual response in a band-wise manner. The parameter α_1 depends on the frequency content of the wavelet transformed block B_{wt} ²⁶ and it is calculated with respect to a contrast sensitivity function of the band in order to minimize perceptual error in the watermarked image, as

$$\alpha_1 = \frac{\sqrt{S_b}}{\max_{\forall b} \sqrt{S_b}}, \quad (7)$$

$$S_b = \sum_{\forall u,v} C(u,v) |F_b(u,v)|^2, \quad (8)$$

$$C(u,v) = 5.05 e^{-0.178(u+v)} (e^{0.1(u+v)} - 1), \quad (9)$$

where $C(u,v)$ is the contrast sensitivity matrix with frequencies u and v , $F_b(u,v)$ is the discrete Fourier transform of the band b in the block B_{wt} , and S_b contains the band-wise average values of the sensitivities. The final values for α_1 are received through scaling of the original values S_b .

The parameter α_2 controls the strength of the watermark. The larger the parameter α_2 is, the stronger the embedding may be. The values for this parameter are defined experimentally. In the experiments we studied the influence of α_2 on watermarking. Increasing the value of α_2 makes embedded watermark more robust, but at the same time the difference between the original image and the watermarked image is increasing. Thus, the parameter α_2 acts as a parameter for the database provider to control the strength of the watermark. The first parameter α_1 is defined such that both targets, a robust watermark and a fragile watermark, are still available. The parameter α_1 then controls the embedding strength for each band b in the block B_{wt} , which is needed to maintain automatic control based on the visual content of band b . The parameter value α_2 is then fixed by the user. Even though for a given image the parameter α_2 remains constant, the embedding still respects the band-wise contents of the image.

In the last phase of the embedding procedure, the spectral image now containing the watermark is reconstructed by the inverse 3D discrete wavelet transform (DWT). Since the watermark is embedded in the low frequency sub-band in the transform domain, then in the inverse transform the energy of the watermark is spread over all parts of the reconstructed spectral image due to the energy compaction property of the wavelet transform.

Extraction

There are two ways to extract the watermark. The first approach is non-blind, it requires the original image for detection and extraction. This approach is suitable when a fragile watermark is inserted and the database provider wants to verify that the information is unmodified. Thus, the watermarked image and the original image are available. On the other hand, at purchase of the original spectral image, the client has to download the full image and for her, this type of watermark extraction is not relevant.

Now the watermark extraction is an inverse operation to the embedding procedure. The three-dimensional wavelet transforms I_{wt} and $I_{wt,wm}$ are calculated both for the original image I and for the watermarked image I_{wm} respectively. Then, the difference in the transform domain contains the watermark

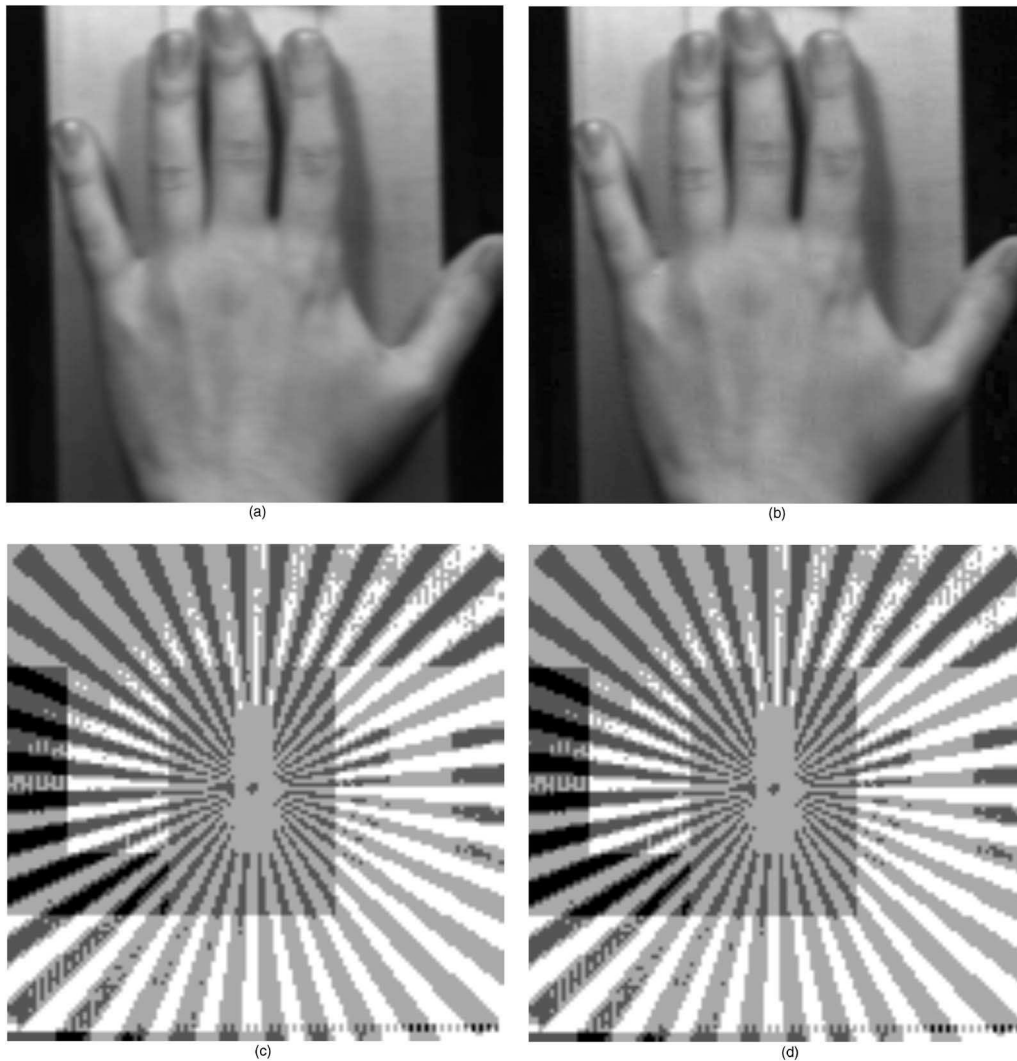


Figure 2. An example of a watermarked image. Value for the parameter: $\alpha_2=1.0$. (a) Original image, RGB reconstructed. (b) Watermarked image, RGB reconstructed. (c) Original watermark. (d) Extracted watermark.

$$B_{wt,wm} = I_{wt,wm} - I_{wt} \quad (10)$$

where $B_{wt,wm}$ is a block containing the watermark. As the database owner knows the bands b of the block $B_{wt,wm}$, where the watermark pixels were embedded, and the strengths α_1 and α_2 , the 2D watermark W_{wt} in the transform domain can be reconstructed by collecting the corresponding values from the known bands b . Then the 2D inverse wavelet transform will finally output the watermark $W_{r,wm}$.

The second approach to watermark extraction is blind. This approach has similarities to the watermarking using pseudo-noise sequences.¹ The database provider sends a secret key to the client and then the client is able to remove the watermark from the watermarked image. The symbolic presentation for watermark extraction derived from Eq. (5) is

$$B_{wt} = B_{wt,wm} - \alpha \cdot W_{wt}. \quad (11)$$

The client has the watermarked image and she can perform the wavelet transform on it receiving the watermarked block $B_{wt,wm}$. Then the secret key contains the information

required for the extraction: the embedding bands b for each pixel of the watermark, their corresponding strengths α_1 and α_2 , and naturally the watermark W_{wt} . With the information given, the client can obtain the original image for further processing. The database provider will get the economic benefit through selling the secret keys. The secret key can be defined such that it totally removes the watermark or, if necessary, the information in the key can be designed such that a fragile watermark or some client-dependent information still remains in the image. With this approach, the client is not able to distribute the information further. If the image was originally compressed in a lossy manner, the secret key can also contain the additional information to reconstruct the original spectral image.

In Figure 2, we show an example of a watermarked spectral image. The original watermark and the extracted watermark are also shown. For the visualization, the corresponding RGB-images from the spectral images were computed. The reconstruction was done using CIE XYZ basis functions with D65 light model. The parameter α_1 was cal-

culated according to Eqs. (7)–(9), the control parameter α_2 was set to unity.

Compared to the original image, the visual quality of watermarked image is good, visual inspection cannot detect any differences between the RGB images. In the embedding, the quality of the watermarked image, measured as the signal-to-noise ratio (SNR; see below), was 35 dB. The extraction process can fully reconstruct the watermark which is why the original watermark and the extracted watermark appear similar.

The watermark in this study is a visual watermark. It contains information derived from the database provider. There are two purposes in using this kind of watermark. The first purpose is to embed the watermark with a high strength such that the watermark is visible in the image. The extraction of the watermark would then make the spectral image unusable since incorrect extraction would change the original information. The second purpose is to use it as a fragile watermark where the changes can be easily visually detected.

LOSSY COMPRESSION OF WATERMARKED IMAGES

The database provider may compress the original spectral images for various purposes: to maintain the capacity of the

watermarked image is measured using the signal-to-noise ratio SNR_{img} defined as

$$\text{SNR}_{\text{img}} = 10 \log_{10} \frac{\sum_{k=0}^{N_z} \sum_{j=0}^{N_y} \sum_{i=0}^{N_x} I_{wm}^2(i,j,k)}{\sum_{k=0}^{N_z} \sum_{j=0}^{N_y} \sum_{i=0}^{N_x} (I_{wm}(i,j,k) - I(i,j,k))^2}, \quad (12)$$

where $I_{wm}(i,j,k)$ is the value of a pixel with spatial coordinates (i,j) of the band k of the watermarked image, and $I(i,j,k)$ is the value of a pixel with the same coordinates of the original image. SNR was selected since it is a common measure in image compression; it describes the quality in the sense of energy preservation. The visual quality of a watermarked spectral image would be of interest, but visualization of a spectral image is not straightforward. One approach is to compute band-wise visual measures and average them over all bands, but then the band-wise qualities are lost and the overall result incurs similar problems to SNR.

The watermark in this study is visual. Due to the lack of the correspondence between SNR and the human visual system, the correlation coefficient (cc) was computed as a quality measure between the original watermark and the extracted watermark defined as

$$\text{cc} = \frac{\sum_{i=1}^m \sum_{j=1}^n (W_{wm}(i,j) - \bar{W}_{wm})(W_{rwm}(i,j) - \bar{W}_{rwm})}{\sqrt{\sum_{i=1}^m \sum_{j=1}^n (W_{wm}(i,j) - \bar{W}_{wm})^2} \sqrt{\sum_{i=1}^m \sum_{j=1}^n (W_{rwm}(i,j) - \bar{W}_{rwm})^2}}, \quad (13)$$

communications channel for free download, to provide a larger selection of images in a limited storage capacity, or even to perform noise removal with the lossy compression approach.

One purpose of this study is to define a reasonable range for parameter α_2 . To find this range, we study the robustness of the embedded watermark with a lossy image compression procedure. A standard approach for the lossy compression of spectral images is based on PCA-wavelet compression.²⁷ To reduce the spectral dimension, principal component analysis (PCA) is applied to the spectra of the images. Compression is achieved by selecting only a limited number of principal components. The selection is based on the importance of the components. The resulting principal images are compressed with a two-dimensional wavelet-based method, in this study we used the implementation called Kakadu.^{28,29} The spectral images are then reconstructed by multiplying the restored principal images by the corresponding principal vectors. The original spectral images were watermarked and, thus, the watermarked spectral images were compressed with PCA-wavelet approach in a lossy manner.

The following measures were used to evaluate the quality of the reconstruction.²⁰ The quality of the reconstructed

where W_{wm} is the original watermark and W_{rwm} is the extracted watermark, \bar{W}_{wm} and \bar{W}_{rwm} are the respective means calculated over all pixels. SNR acts as an energy measure between the two images and cc shows the statistical similarity between them.

ILLUMINANTS FOR SPECTRAL IMAGE PROCESSING

The database provider stores the reflectance or radiance spectra of the images. Depending on the client's requirements, the effects from illumination can be added to the spectra, i.e., the viewing conditions change the perceived color of the spectrum. External illumination can be compensated through convoluting the spectra of the image with the spectrum of the illuminant.

In the preliminary tests, a set of standard light sources are used with the spectral images.³⁰ The characteristics of the standard light sources are shown in Figure 3. The length of each spectrum was 32 channels. For further experiments the light sources "A", "D65," and "F11" were selected. Light sources "A" and "D65" represent typical illumination conditions for incandescent light and daylight, respectively. The spectral characteristics for "A" emphasize red and limit blue colors; "D65" emphasizes greenish colors. In general, they have smooth transitions from one wavelength to another.

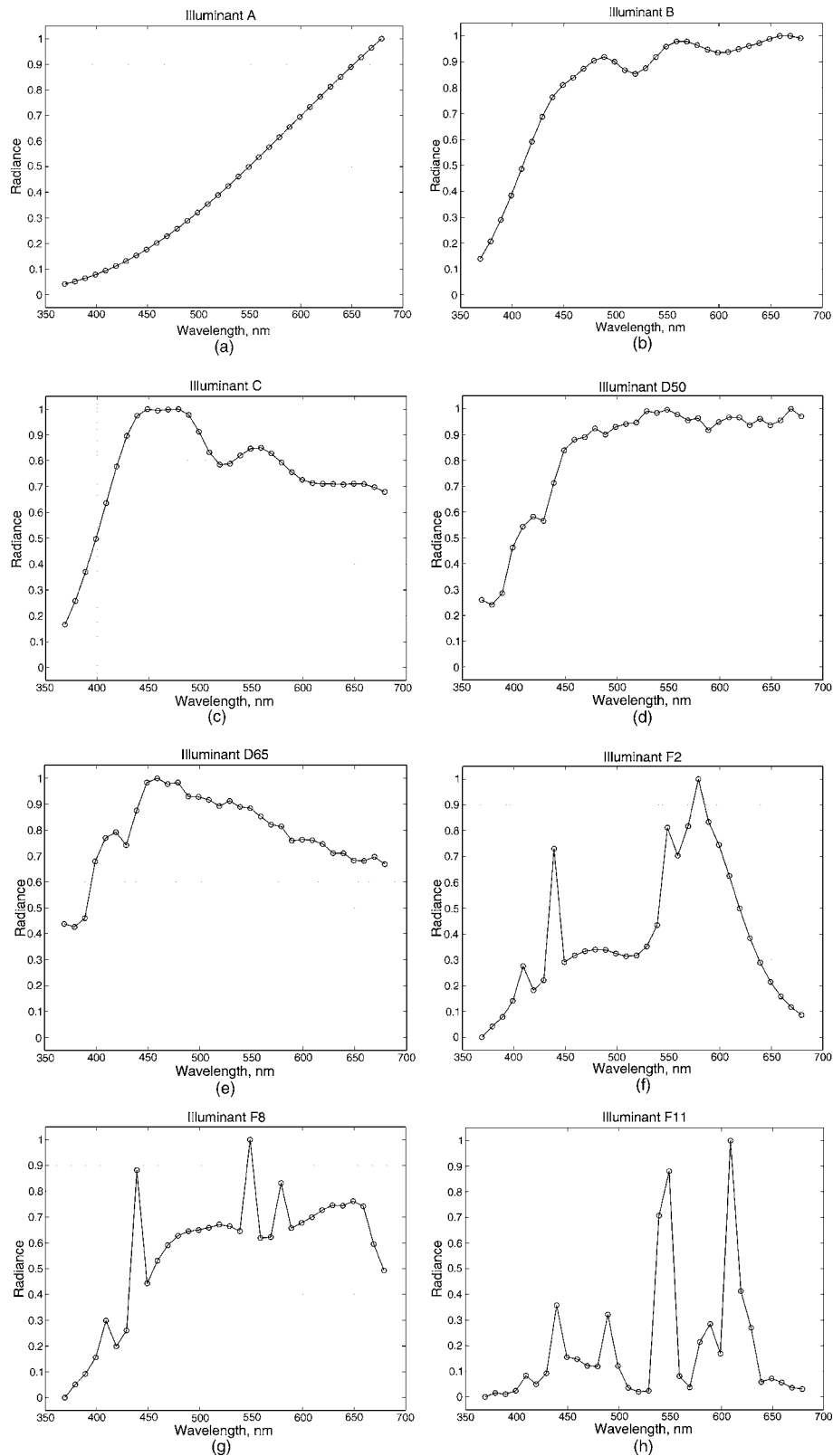


Figure 3. Relative spectral radiance factors of the standard light sources for different visible light wavelengths.

Similar characteristics can be seen also with illuminants “B”, “C,” “D50.” The F-series represent fluorescent lamps, typical illuminants in office conditions. They have sharp peaks at predefined wavelengths thus providing totally different

illumination compared to illuminants “A” and “D65.” We selected illuminant “F11” to represent this family of illuminants.

EXPERIMENTS

Three scenarios for the illumination and watermarking were evaluated. In the first two scenarios the illumination was added by the database provider. The third case is different from the previous two: the illumination is added by the client, and now the database provider is not aware of the light model used by the client. The client has the watermarked image available and she can modify it through illumination for her applications.

We had two basic approaches. In the first approach, the illumination was added before the watermarking and, in the second, the illumination was added after the watermarking. Details of all the practical scenarios are

- (a) Scenario 1. Illumination before watermarking by the database provider: the original spectral image I is multiplied by the illuminant L , and then the resulting image I_L is watermarked to become image $I_{L,WM}$. Then lossy compression is performed on the watermarked image $I_{L,WM}$ to output the image $I_{L,WM,CIRC}$. The watermark WM_e is extracted from the image $I_{L,WM,CIRC}$ and compared to the original watermark WM .
- (b) Scenario 2. Illumination after watermarking by the database provider: the original spectral image I is watermarked to become image I_{WM} and then multiplied by the illuminant L ; the output is $I_{WM,L}$. The resulting image $I_{WM,L}$ is lossy compressed and reconstructed to image $I_{WM,L,CIRC}$. The watermark WM_e is extracted from the reconstructed image $I_{WM,L,CIRC}$ and compared to the original watermark WM .
- (c) Scenario 3. Illumination after watermarking by the client: the original spectral image I is watermarked to become image I_{WM} by the database provider. Then the watermarked image I_{WM} is compressed in a lossy manner to image $I_{WM,CIRC}$. That image can be downloaded from the database provider. The client may apply illuminants L , depending on her applications; the resulted image is $I_{WM,CIRC,L}$. The database provider can extract the watermark WM_e from the image, but the model for the illuminant is unknown. The estimated illuminant L_e can be defined using the original image I and the watermarked, compressed, and illumination multiplied image $I_{WM,CIRC,L}$.

The proposed embedding procedure was applied to watermarking. In the experiments, 13 spectral images were watermarked and then compressed with different bit rates. The embedded watermark was extracted from the reconstructed watermarked images. The SNR was calculated between the original image and the watermarked image. Quality of compression was also calculated as SNR. For the extracted watermark, the correlation coefficients between the original and extracted watermark were calculated.

The original spectral images had different numbers of bands and different spatial sizes. We normalized all the im-

Table I. Compression parameters: number of principal components in spectral domain, bit-rate in spatial wavelet compression as bits/pixel/band and the actual compression ratio.

PCA components	Bitrate in wavelet comp.	Compression ratio (CR)
18	5	5.7
14	3.03	12.0
10	2.03	25.1
6	1.68	50.3
4	1.25	100.6

ages before watermarking in order to have a constant spatial size and a constant number of bands. The spatial size of the normalized spectral images was 256×256 pixels. The number of bands was 32. As a watermark, we used a grayscale image with a spatial size of 128×128 pixels; see Fig. 2(c). All images, both the original spectral images and the watermark, were normalized to range $[0,1]$. All computations were performed using floating point values. In the wavelet compression the data was quantized to 16-bit resolution.

The compression procedure described in the Lossy Compression of Watermarked Images section was applied to the watermarked images. The number of principal components for the spectral domain of the image varied for different compression ratios. In the spatial domain, the lossy wavelet transform compression with various bit rates was used. In Table I we have collected the compression parameters. These values reflect a typical selection of compression parameters between the PCA compression and the wavelet compression.²⁷

As the first task, a reasonable range for the watermark's strength controller α_2 should be found. A large value would mean strong embedding and, thus, it would yield a visible watermark in the image. A small value would result in weak embedding and, thus, fragile watermarking. As such, robust watermarking would mean relatively strong embedding without visible or otherwise annoying errors in the watermarked image. In this experiment we used a relatively large set of spectral images, but the results were averaged to define only one common value of α_2 for all images.

Scenario 1. Illumination Before Watermarking by the Database Provider

This experiment was described as Scenario 1. Various values for α_2 were applied to embedding, and the compression ratios as described in Table I were applied.

The results are shown in Figures 4–6 as a function of the strength control parameter α_2 . The results are averaged over 13 spectral images. The embedding quality is shown in Fig. 4. The quality of embedding as the signal-to-noise ratio was calculated between the two spectral images, namely, between the illuminated image I_L and the watermarked image $I_{L,WM}$. Figure 5 contains the compression quality in the left column, and the extraction quality in the right column. The former was calculated using the images $I_{L,WM}$ and $I_{L,WM,CIRC}$ and the latter with watermarks WM_e and WM . In

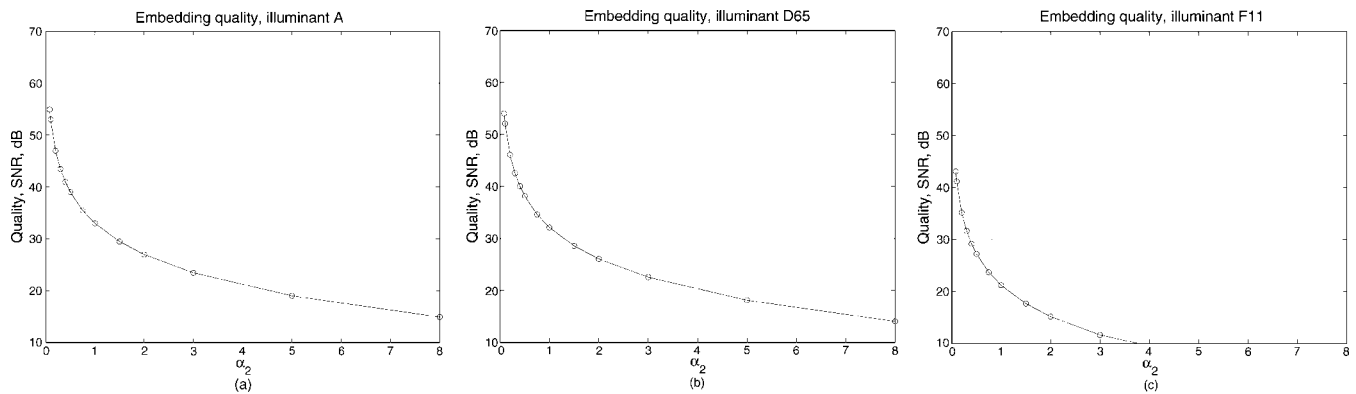


Figure 4. Quality in watermark embedding as SNR as a function of α_2 . SNR is less than 15 dB for illuminant F11 for $\alpha_2 > 2.5$.

Fig. 6 we show an example of visual reconstruction quality. An RGB image was computed from the spectral image using CIE XYZ basis functions with light model “D65”. The RGB image is in the left column and the extracted watermark is in the right column.

According to the computations, the reasonable range for α_2 would be $0.5 < \alpha_2 < 2.0$. With smaller values the embedding is too weak against compression and the quality of the extracted watermark is too low for registration. Values larger than $\alpha_2 > 2.0$ would output an image with visible evidence of the watermark. The RGB images in Fig. 6 do not show visible degradation due to watermarking. The band-wise inspection of the spectral image reveals that with $\alpha_2 > 2.0$ there is a watermark embedded. At higher compression ratios, the extraction quality of the watermark deteriorates as is evident from Fig. 5. The choice of the watermark strength α_2 is illumination dependent. In general, high quality of a watermarked image is achieved with $\text{SNR} > 35$ dB. The correlation coefficient of the extracted watermark should be at least $cc=0.6$ for reliable watermark extraction, either visually or computationally. Based on these requirements we found that for the illuminants “A” and “D65” a watermark strength close to $\alpha_2=1.0$, and for the illuminant “F11” a watermark strength close to $\alpha_2=0.5$ gave results where these orthogonal requirements are both met with sufficient quality. At the same time the compression ratio CR should be kept reasonable, i.e., $CR < 25$.

Scenario 2. Illumination After Watermarking by the Database Provider

This experiment was described as Scenario 2. The strength parameter α_2 was varied and the results are shown in Figures 7–9 as a function of the parameter α_2 . The results are averaged over the 13 spectral images. The embedding quality is shown in Fig. 7 for all illuminants, “A”, “D65”, and “F11”. Now the embedding does not depend on the illuminant. The quality of embedding as SNR was calculated between the images I and I_{WM} . Figure 8 contains the compression quality in the left column and the extraction quality in the right column. The former was calculated using the images I_{WML} and $I_{WM,L,CR}$ and the latter with watermarks WM_e and WM . In Fig. 9 an example of visual reconstruction quality is

shown. An RGB image was computed from the spectral image. The RGB image is in the left column and the extracted watermark is in the right column.

As seen from Fig. 7, the illumination has a stronger effect on the watermarked image than does either the compression or the control parameter α_2 . The effect of compression is larger than in the previous case’ (see Fig. 8). The extraction quality of the watermark is not as high as in the previous case (see Fig. 8 and 9). The quality of the RGB image is still good. Visual changes are not present at low values of α_2 ; with $\alpha_2=2.0$, there are visible errors in yellow, red, purple, and green rectangles, in the center of the image as shown in Fig. 9.

In Figure 10 the bandwise images from one test image are shown. The band numbers are 4, 9, and 32, representing blue, blue-green, and red wavelengths. There are visible defects in the spectral bands. In this experiment we set $\alpha_2=2.0$, and the compression ratio was $CR=12.0$.

In band 4, the error appears as blurring; it is spread in larger areas inside the patches, especially in the mid-gray patches. In band 9, the rays of the watermark can be seen in the light patches, e.g., see the second patch on the second row of band 9. In band 32, the errors exist as individual errors from incorrect wavelet coefficients. There are both abrupt contrast changes and changes in the uniformity of the patch gray level. The changes in Fig. 10 are visible but they are not too large for application development. The client can get nearly reliable results, but at the same time she is aware of the manipulated values in the images. From the database owner’s point of view, she has full control over the data, and she is able to remove the effect of the illumination before watermark extraction. Thus, the extracted watermarks are of high quality (see Fig. 8). The compression affects the extraction quality more heavily, and the compression ratio should be kept limited, i.e., $CR < 12$.

Scenario 3. Illumination After Watermarking by the Client

This experiment was described according to Scenario 3. The strength parameter α_2 was varied and the results are shown in Figures 11–14 as a function of the parameter α_2 . The results are averaged over 13 spectral images. The embedding

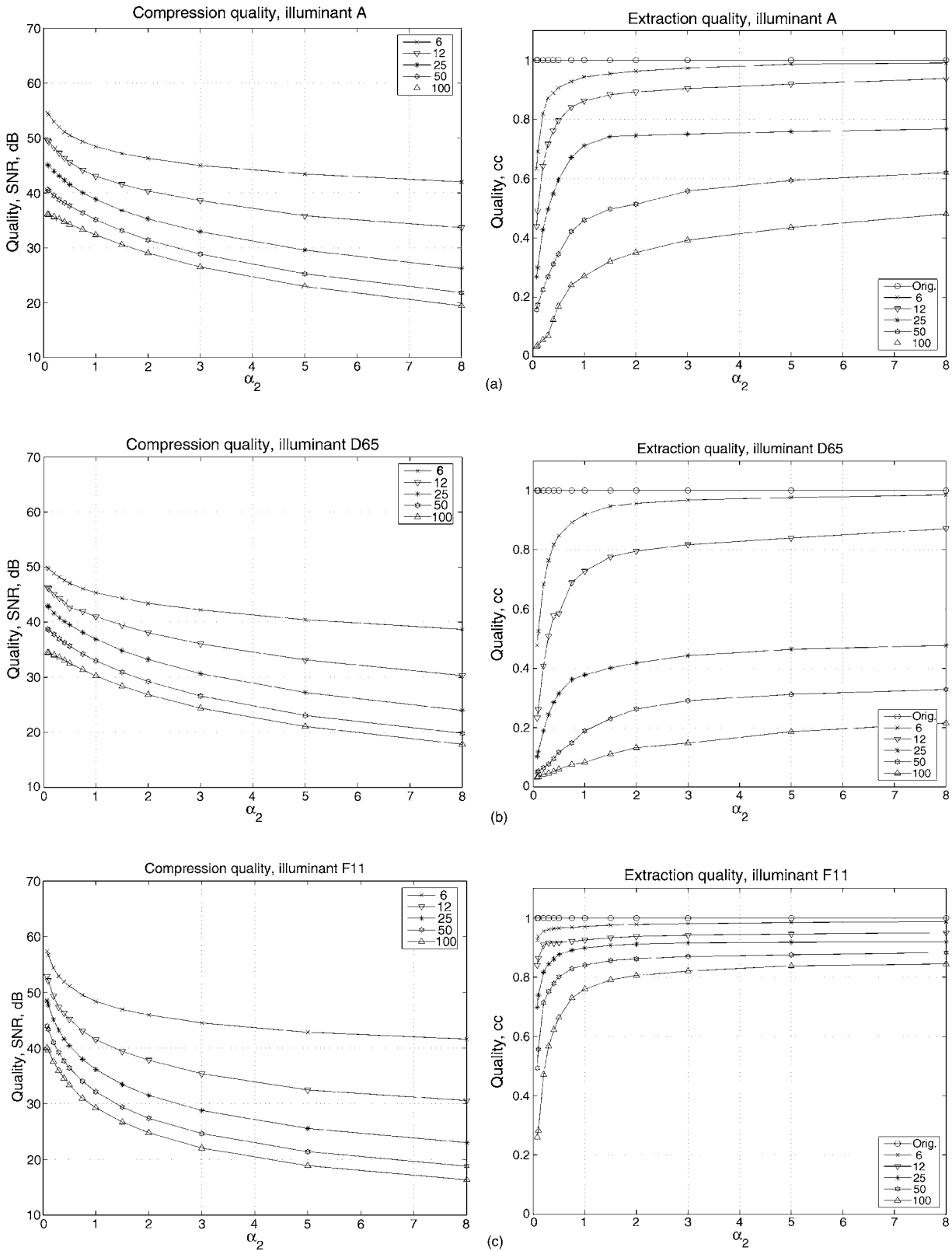


Figure 5. Quality dependence on α_2 . Left column: SNR for the compression of the image. Right column: correlation coefficient, cc, for the extracted watermark. See text for the images in quality computation. (a) Illuminant A. (b) Illuminant D65. (c) Illuminant F11.

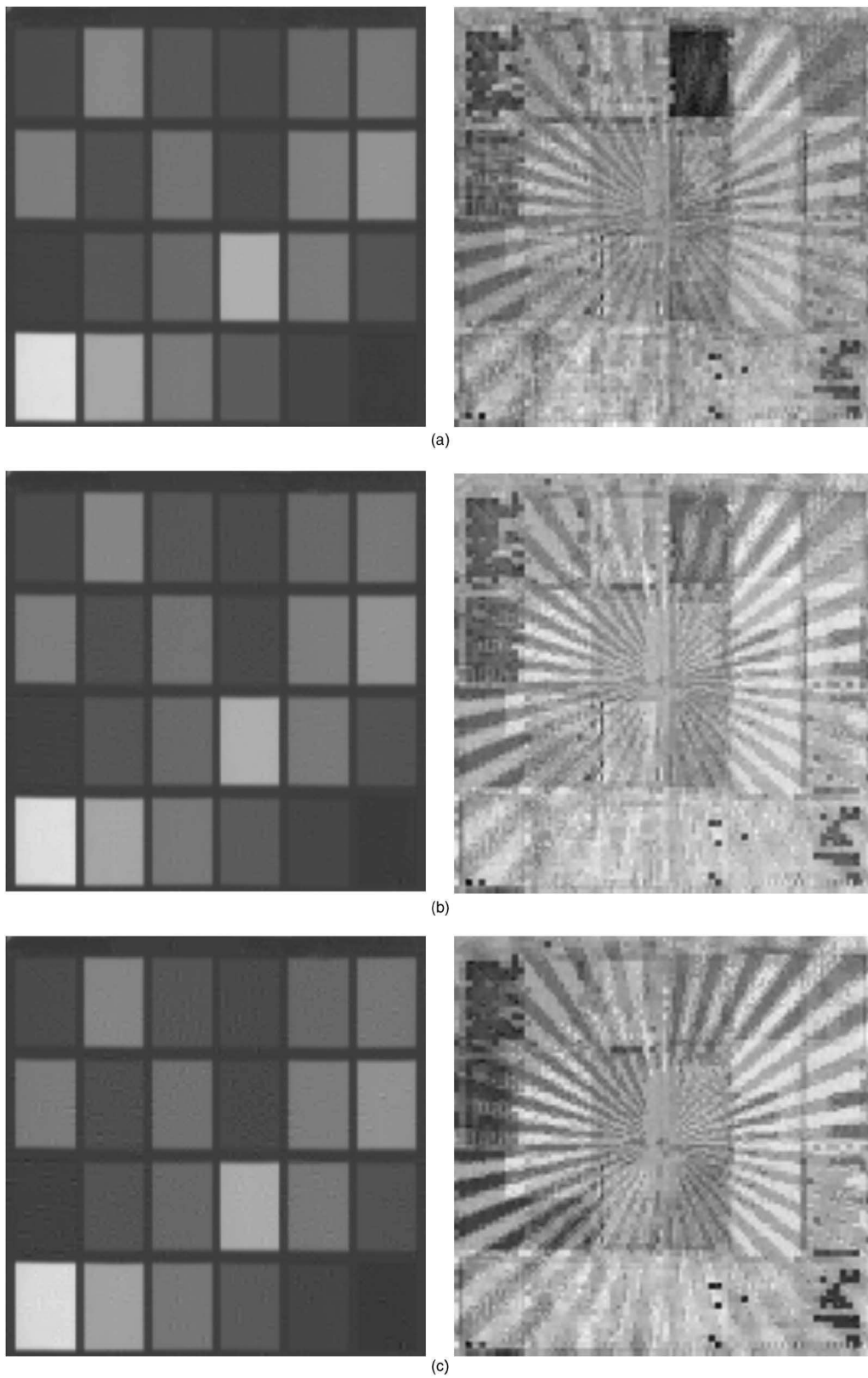


Figure 6. Example of embedding and extraction. Illuminant "D65". The lossy compression ratio was CR=12.0. (a) $\alpha_2=0.5$, cc=0.531. (b) $\alpha_2=1.0$, cc=0.661. (c) $\alpha_2=2.0$, cc=0.754

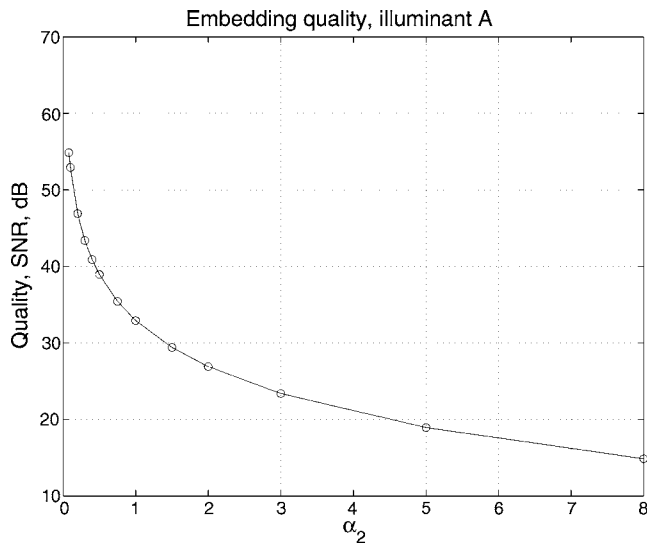


Figure 7. Quality in watermark embedding as SNR as a function of α_2 .

quality is shown in Fig. 11 the embedding is illuminant independent. The quality of embedding as SNR was calculated between the images I and I_{WM} . An estimate L_e for the illuminant L is needed. In this case, L_e was calculated from the band-wise ratios between the original image I and the image $I_{WM,C/RC,L}$. In Fig. 12, there is an example of the quality of the estimated illuminant L_e . Two cases are shown. In Fig. 12(a), the embedding parameter was $\alpha_2=1.0$ and $CR=5.6$. In Fig. 12(b) the value of the embedding parameter was $\alpha_2=8.0$ and $CR=100.1$. These values were selected to represent extreme cases of estimation. For lower values of α_2 , the estimation would be even more exact.

As soon as the estimated L_e is available, this scenario returns to the case where the illumination effect is not present. Thus, the compression quality and extraction quality remain similar for all illuminants. In Fig. 13 the compression quality is shown in (a) and extraction quality in (b). The former was calculated using the images I_{WM} and $I_{WM,C/RC}$, and the latter with watermarks WM_e and WM . To be precise, the image $I_{WM,C/RC}$ is not only the watermarked and the compressed image, but it also contains some error from the estimated L_e . As seen from Fig. 12, this error is very small compared to the error from compression. In Fig. 14, an example of visual reconstruction quality is shown. An RGB image was computed from the spectral image. The RGB image is in the left column and the extracted watermark is in the right column.

This scenario illustrates the case where the database owner allows free download of the watermarked and lossy compressed spectral images. The images are close to the original, but there are differences due to manipulation through watermarking and lossy compression. Using the proposed approach for illuminant estimation, the database owner can still verify the contents of the images. The experiments give guidelines for parameter selection. For the estimated illuminant, even high compression ratios are allowed with strong embedding. The watermark becomes visible (i.e., $SNR > 35$ dB) when $\alpha_2 > 1.0$. Larger values allow em-

bedding of a visible watermark. Smaller values result in a fragile watermark. The change in extraction quality towards the lower values of α_2 is rapid (see Fig. 13). Again, the compression should be kept limited, $CR < 12$.

DISCUSSION

We considered a technique for embedding a watermark into a spectral image. The quality of the watermarked image and the quality of the extracted watermark is controlled by parameter α_2 .

In this study we considered the effect of the illumination of the watermarked images. We considered three scenarios: illumination before watermarking, illumination after watermarking performed by the database owner, and watermarking before illumination by the client. Based on the experimental results for 13 spectral images, we find reasonable ranges for the embedding strength α_2 for different illuminants. We also studied whether the illumination affects the watermarking and vice versa.

In the first scenario, a spectral image was multiplied by the illuminant, then watermarked. The watermark is extracted from the reconstructed image and compared to the original one. According to the experiment the reasonable range for α_2 would be $0.5 < \alpha_2 < 2.0$. With smaller values, the embedding is too weak against compression and the quality of the extracted watermark is too low for registration. For the values larger than $\alpha_2 > 2.0$, the watermark becomes visible in the spectral image. As can be seen in Fig. 5, the choice of the watermark strength α_2 is slightly illumination dependent. We found that for the smooth illuminants “A” and “D65” watermark strength $0.5 < \alpha_2 < 2.0$, and for the peaky illuminant “F11” the watermark strength, α_2 should not be larger than unity. Even with this value the quality of embedding is very low. The compression has greater impact with smooth illuminants “A”, “D65” than with “F11”, which is due to the watermarking approach. For “F11” the watermark is in the same coefficients as the energy of the image. For smooth illuminants, the watermark is spread among various coefficients and they gradually vanish in lossy compression. This similarly applied to the embedding. Since the strength becomes larger, then the effect of the watermark also becomes larger for these wavelet coefficients. Thus for “F11”, the quality of the embedding degrades faster with compression.

In the second scenario, a spectral image was first watermarked, then illuminated, and finally compressed. The watermark is extracted from the reconstructed image and compared to the original. The results show that the quality of the watermarked image and the quality of the extracted watermark depends more on the illumination than on the parameter α_2 or the compression. For the illuminants “A” and “D65”, the visual quality of the extracted watermark is good for α_2 in the range $[0.5, 2]$. For the illuminant “F11”, the extracted watermark is not visible for $\alpha_2 < 2.0$. For values lower than $\alpha_2 < 1.0$, compression heavily affects extraction. Thus, for “F11” a reasonable range would be $1.0 < \alpha_2 < 2.0$.

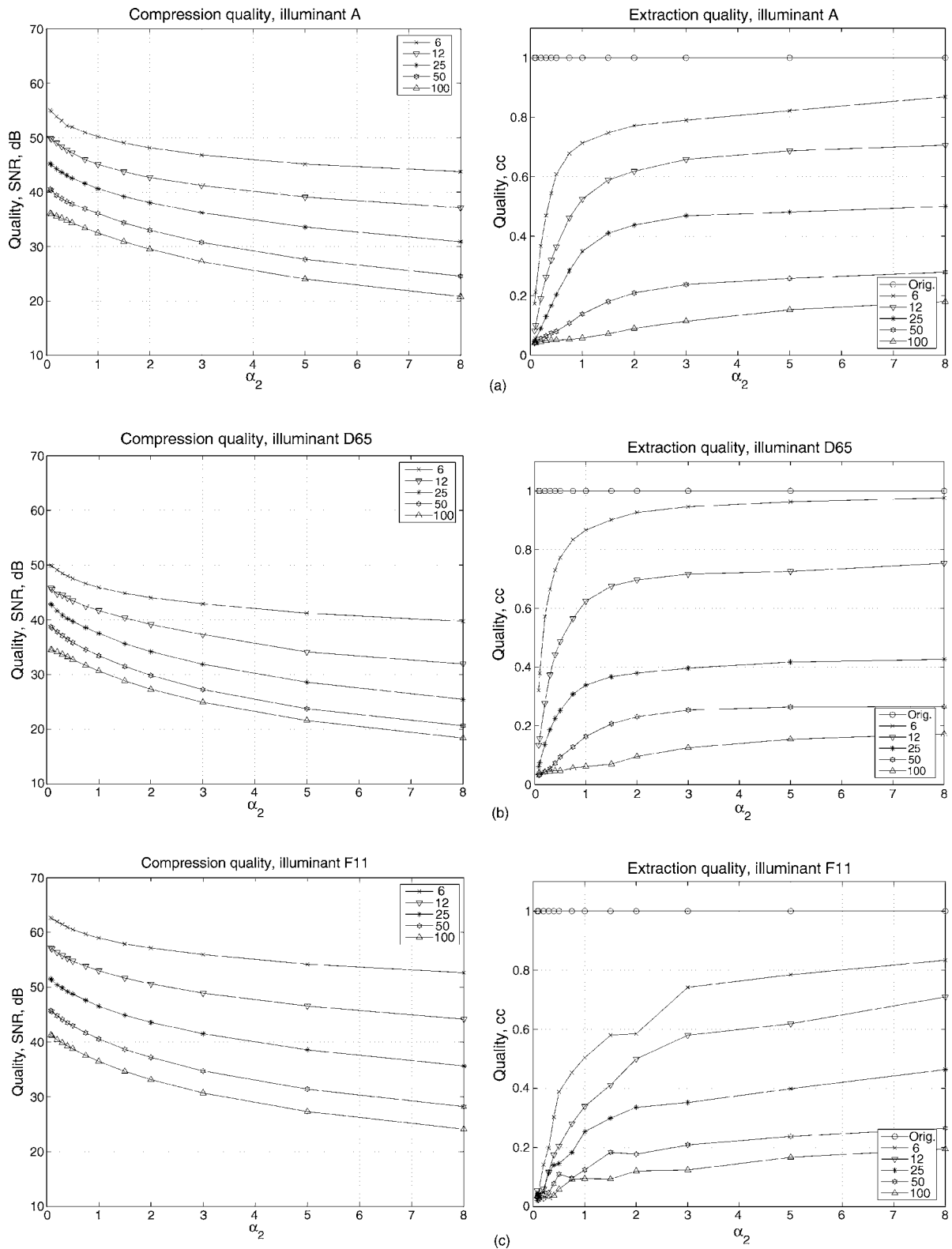


Figure 8. Quality dependence on α_2 . Left column: SNR for the compression of the image. Right column: correlation coefficient, cc , for the extracted watermark. See text for the images in quality computation. (a) Illuminant A. (b) Illuminant D65. (c) Illuminant F11.

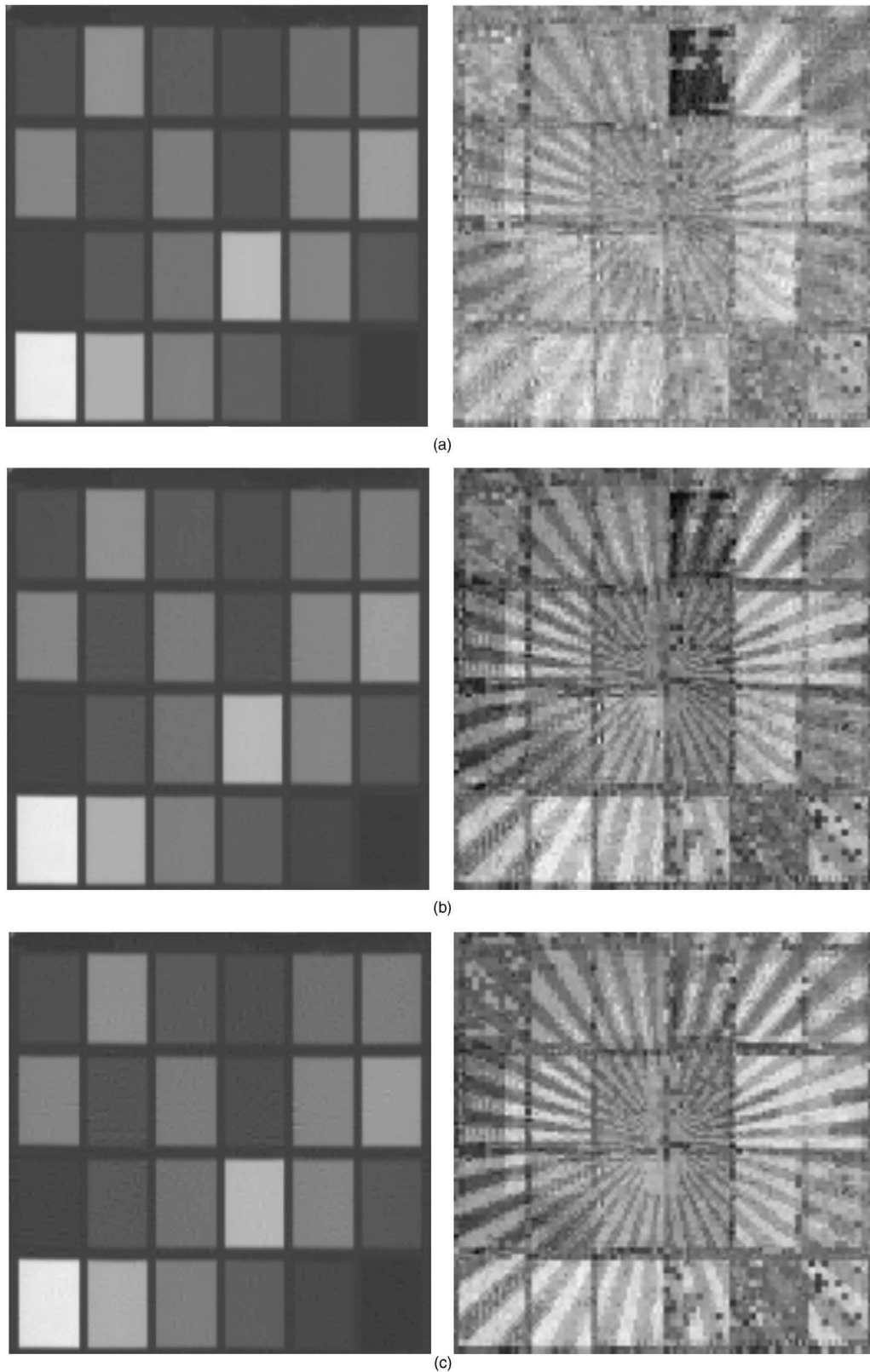


Figure 9. Example of embedding and extraction. Illuminant "D65". The lossy compression ratio was $CR=12.0$. (a) $\alpha_2=0.5$, $cc=0.439$. (b) $\alpha_2=1.0$, $cc=0.589$. (c) $\alpha_2=2.0$, $cc=0.643$.

In the third scenario, the image was watermarked and compressed in a lossy manner. Then the client added the illuminants she needed in her applications. As such, the illuminants were unknown to the database owner. For this

case, we estimated the illuminant; the proposed estimation is simple and of high quality. In this case the extraction returns to the case when the watermark is extracted from the compressed image with some error from the estimated il-

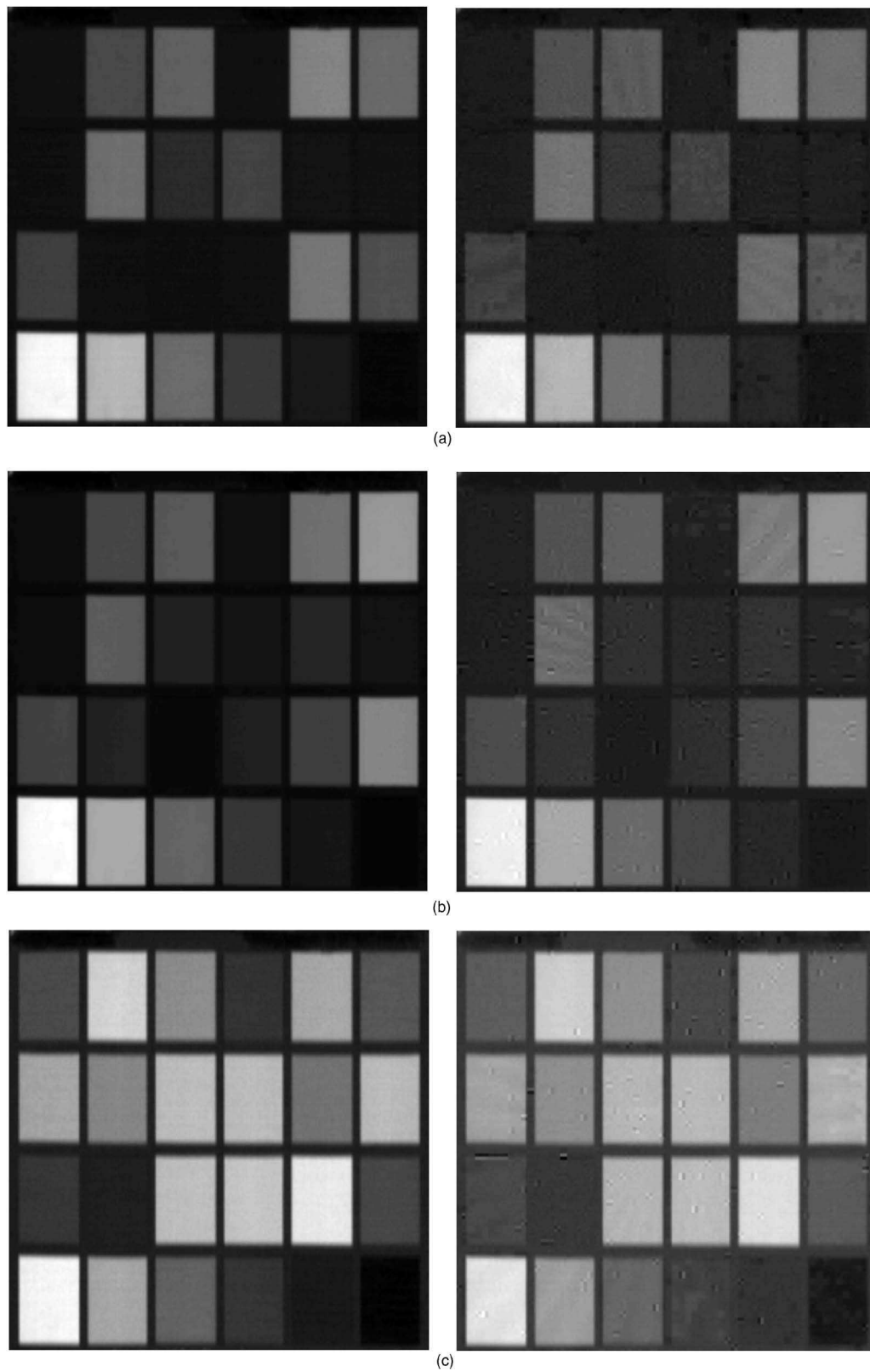


Figure 10. Bandwise images. Left column: bands from the original image. Right column: bands from the watermarked image. (a) Band 4. (b) Band 9. (c) Band (32).

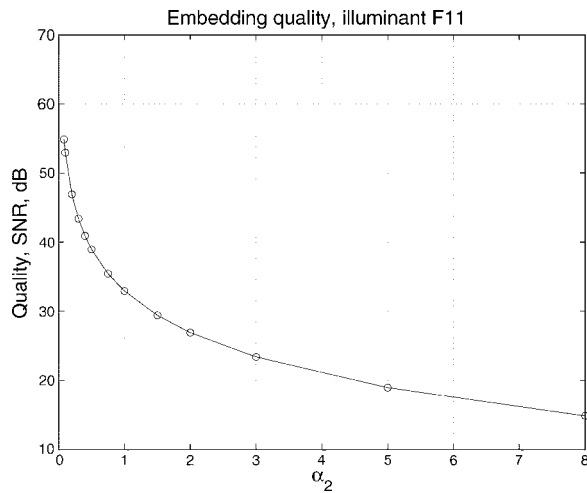


Figure 11. Quality in watermark embedding as SNR as a function of α_2 .

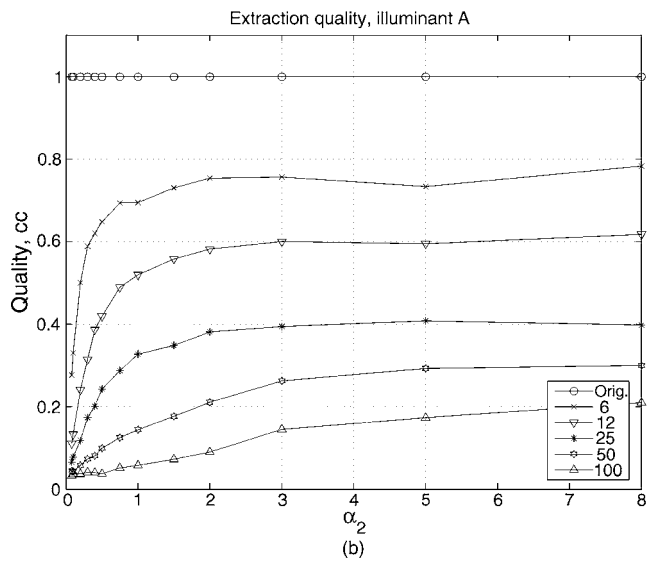
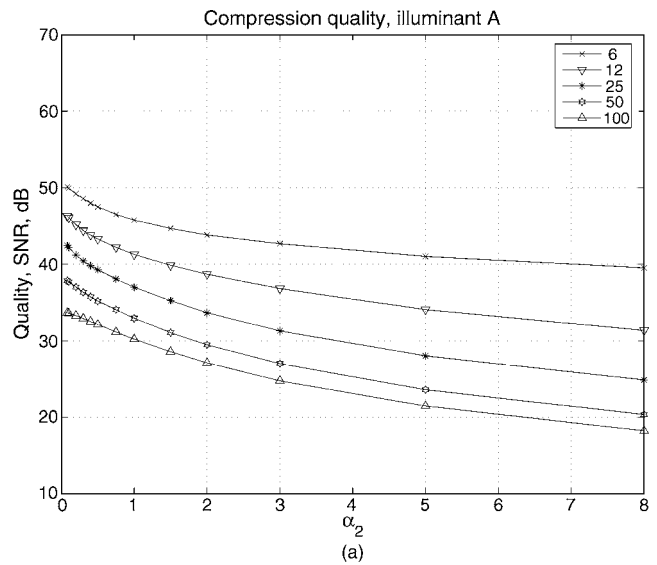


Figure 13. Quality dependence on α_2 . (a) SNR for the compression of the image. (b) Correlation coefficient for the extracted watermark. See text for the images in quality computation.

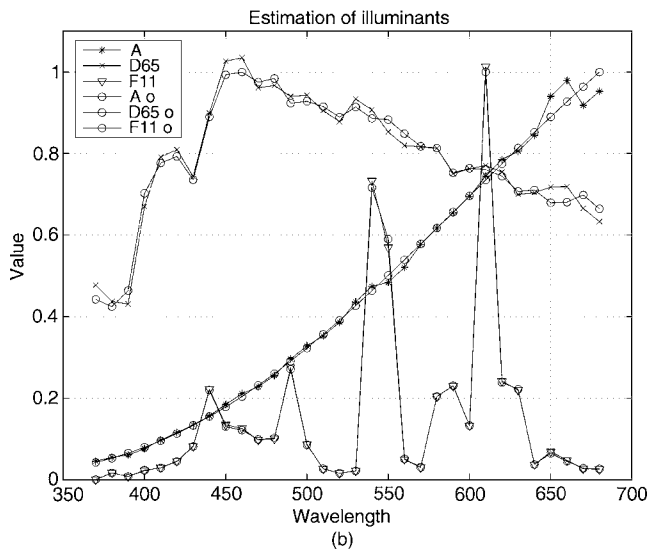
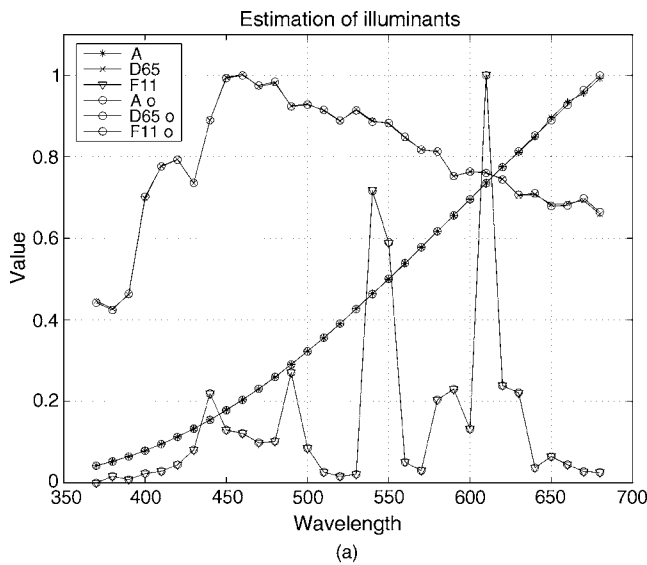


Figure 12. Estimation of illuminants for different visible light wavelengths. Symbol 'o' in 'A o', 'D65 o', and 'F11 o' refers to the original spectrum of the illuminant.

luminant: In that sense, the error of the estimated illuminant is very small and the extraction is accurate. The error comes mostly from artifacts due to lossy compression.

In the experiments the comparisons between the images were considered. It is not reasonable to compare the original image and the image with the illuminant added. In this case the error measured as SNR or measured as a visual difference is large. In principle, the error is proportional to the distance from the illuminant to white. This error dominates over the error contributions from watermarking or from lossy compression.

The current approach to watermarking also is suitable when the watermark can be visually detected. Even then, the watermarked image can be used for application development and implementation purposes.

CONCLUSIONS

Spectral color imaging is becoming a practical tool in many applications. In this study we embedded a grayscale water-

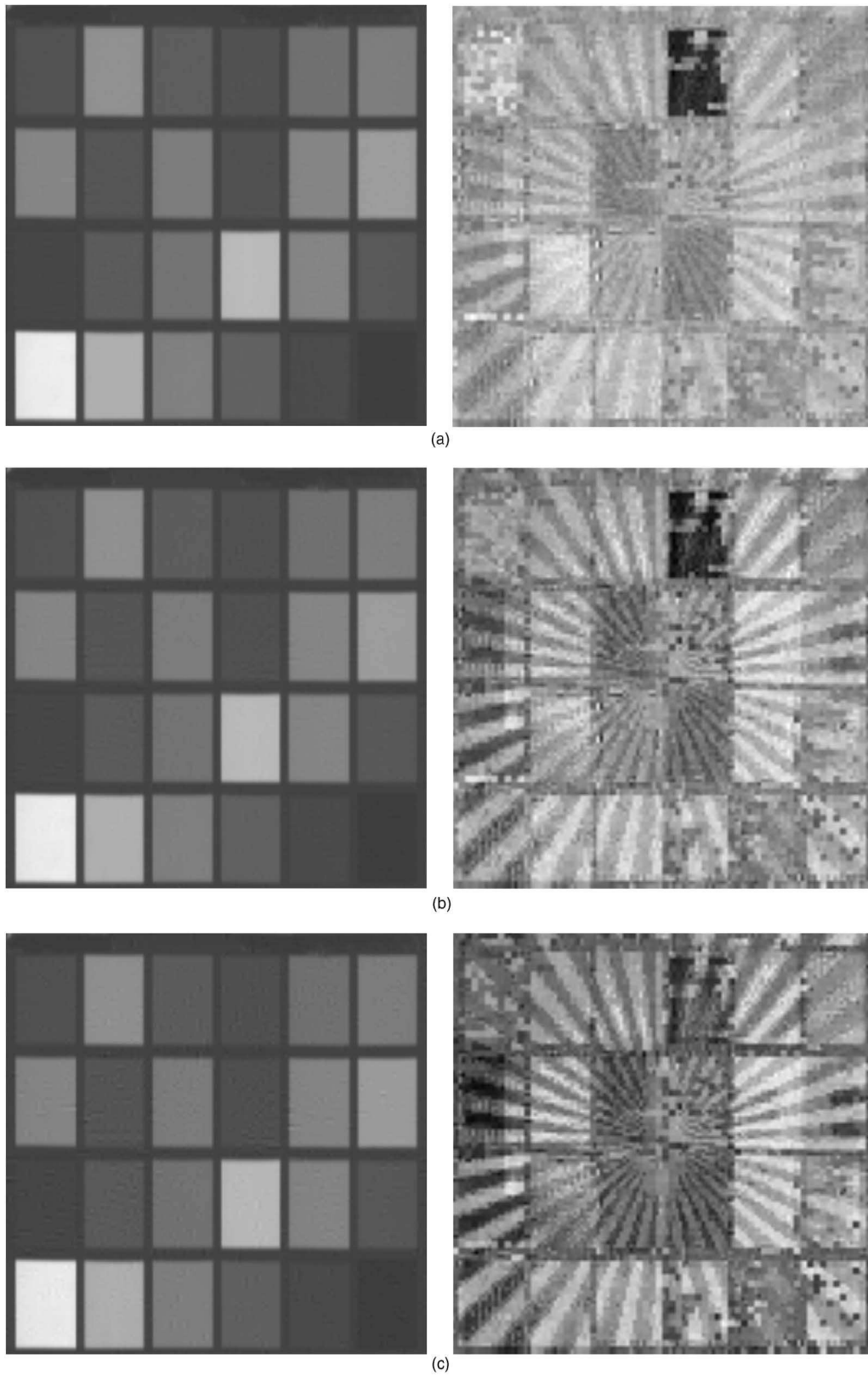


Figure 14. Example of embedding and extraction. Illuminant "D65". The lossy compression ratio was CR=12.0. (a) $\alpha_2=0.5$, $cc=0.394$. (b) $\alpha_2=1.0$, $cc=0.583$. (c) $\alpha_2=2.0$, $cc=0.643$.

mark in a spectral image in the three-dimensional wavelet transform domain. The properties of the watermarking on a set of spectral images were studied. We studied especially the robustness of the embedded watermark to different illumination conditions. Also, the compression of the watermarked images was studied.

We considered three scenarios of illumination of the watermarked image. For all cases an applicable range of embedding strength was defined. This strength range provides adequate visual quality of the extracted watermark, while the quality of the watermarked spectral image is still high. The proposed approach normalized both the image and the watermark before embedding. Use of SNR as a quality measure for spectral images under different illumination conditions is not totally reliable due to significant changes in image spectrum: average changes are still small, but there may be large changes present in specific color channels which are visually annoying. Methods for evaluating the quality of the image with respect to the changes in color will be considered in the future, to find a better alternative.

Illumination has a large effect on the content of the image. The computational results confirm that the database provider should add the effect of illumination before embedding the watermark in the image. The qualities of both the watermarked image and the extracted watermark are higher. This is further emphasized as compression is applied to these images. If the database owner will add only the watermark, then the proposed approach can be used successfully to estimate the illuminant.

This study considered only the illumination and the lossy compression as attacks against the watermarked images. A normal operation with spectral images that is not present with RGB images is bandwise cropping. The approach in this study detects band cropping in the extraction process using the size information of the image. If there are not a required number of bands, the extraction process will not output the watermark. Thus, bandwise manipulations, like changing, mixing, and ordering, cannot be noticed with this approach. The solution for this problem lies in more heuristics in the embedding and extraction processes or in more intelligent watermarking. Other attacks include secret key-based extraction and reverse engineering. With RGB images, it is reasonable to include an invisible, client-based, light-weight watermark, which is appropriate owing to the application of the images; they are mostly viewed by humans. With spectral images the computational approaches are more regular and the manipulation of the images can be detected in computational applications. For spectral images, the computational invisibility should be established, and the watermarking of spectral images should be designed for the appropriate quality metric.

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