PCA Component Mixing for Watermark Embedding in Spectral Images

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Abstract

This study considers watermark embedding in spectral images. The embedding takes place in a transform space which is obtained through the Principal Component Analysis (PCA). The watermark is embedded in one eigenimage by mixing one eigenimage and the watermark. The watermark is a visual watermark which spreads to all bands of the image after the inverse PCA-transform. This new method is a generalization of an existing method. Our experiments indicate that a suitable set of parameter values allows better embedding than the methods compared.

Introduction

The intellectual rights are becoming more important in the information society due to the easy access to digital information. Watermarking is one way to embed the copyright information in the content. The watermarking procedure should maintain the following properties: the watermark should be undetectable and secret for an unauthorized user, the watermark should be invisible or inaudible in the information carrying signal and finally, the watermark should be robust on the possible attacks [1], [2], [3], [4].

Watermarking techniques have been developed for grayscale and RGB-color images [5]. The watermark can be embedded either in the transform domain of the image [6], [7] or in the original spatial domain [8]. For RGB-color images different color spaces have been considered for watermarking [9].

Spectral images has various applications in remote sensing and nowadays, they are largely applied to solve industrial problems in areas like quality control, exact color measurement, color reproduction. This evolution has been possible due to the development in the spectral imaging systems [10],[11].

In this paper we describe a new watermarking model for spectral images. The parameter space of the model is analyzed and the experiments are performed to show the usability of the method. The paper is organized as follows: first, we define the model, then the results from the experiments are shown. The conclusions and directions for the future work are also included.

Defining the model

In the transform domain the watermark is embedded into one PCA-component as

$$I_n = \alpha_1 I_m + \alpha_2 I_{wm} \tag{1}$$

where I_n is the PCA-component n, I_m is the PCA-component m, α_1 is the weighting coefficient, and α_2 controls the strength of the watermark I_{wm}.

One special case arises if α_2 is replaced by a multiplication of two coefficients as $\alpha_2 = \alpha_{21}\alpha_{22}$. The coefficient α_1 can now be expressed as $\alpha_1 = \alpha_{11}(1 - \alpha_{21})$. Now the mixing of two PCA components and the watermark is more clear as

$$I_n = \alpha_{11}(1 - \alpha_{21}) I_m + \alpha_{21}\alpha_{22} I_{wm} \tag{2}$$

The model presented in Eq.1 includes an earlier model based on the PCA-transform [12]. The selections $n = 10$, $m = 10$, $\alpha_1 = 0$, and $\alpha_2 = 1$ comprises that. If the two-dimensional wavelet transform is applied to the PCA components and to the watermark, the model in Eq.1 enhances also the model presented in [13].

The parameter space consists of the parameters n and m for the PCA components and of the weighting parameters α_1 and α_2.

Optimal solution for the parameter values α_1 and α_2 for each pair (n, m) can be found with the following optimization setup

$$max_{\alpha_1,\alpha_2}\,(\sqrt{q_1 q_2}) \tag{3}$$

where

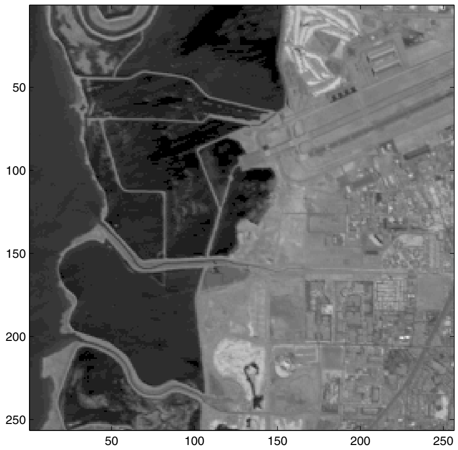
$$q_1 = 10log\frac{E(I^o)}{E(I^o - I^{wm})} \tag{4}$$

$$q_2 = 10log\frac{E(W^o)}{E(W^o - W^{extr})} \tag{5}$$

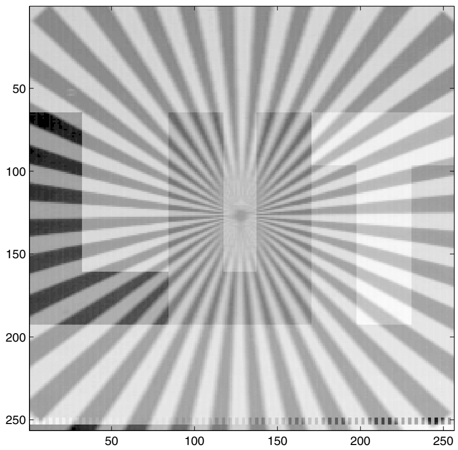
where $E(.)$ means energy of the signal, I^o refers to the original image, I^{wm} refers to the watermarked image, W^o refers to the original watermark, and W^{extr} refers to the extracted watermark.

Experiments

In the experiments we used one AVIRIS image as a base image. The image was of size 256*256*32. The resolution of the measurements was 16 bits [14]. The watermark was a visual watermark containing 256 gray levels and it had 256*256 pixels. In Figure 1 we show the experimental data.



a)



b)

Figure 1. a) Band 11 from the AVIRIS image. b) The visual watermark.

In the experiments we try to find good values for n, m, and α_i as expressed in Eqs. 1 and 2. The first experiment gives guidelines for selection a usable range for n and m. We set $\alpha_1 = 0$ and $\alpha_2 = 1$, and set $n = m$, $1 \leq n, m \leq 20$. The result of the experiment is in Figure 2. The quality measure is the peak-signal-to-noise ratio between the original spectral image and the reconstructed spectral image.

In the second experiment we set $1 \leq n \leq 20$ and $1 \leq m \leq 20$. In addition, $\alpha_1 = 1$ and $\alpha_2 = 0$, thus there was no watermark embedded. The result of the experiment is in Figure 3.

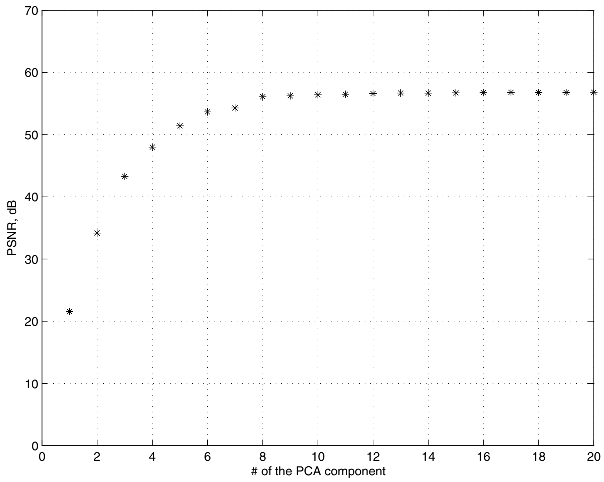


Figure 2. Embedding a watermark in PCA components 1-20.

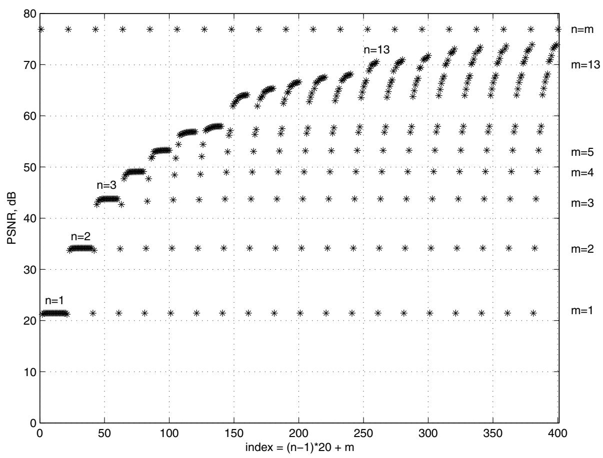


Figure 3. Replacing PCA component n with PCA component m.

These experiments show the behavior of the PCA transform. The first components contain most of the energy of the image and they should not be modified or replaced, see Figures 2 and 3. On the other hand the replacement of the PCA components above $n = m = 13$ cause negligible errors, and thus, the replacement of those components is not expected to change the watermarking process. Thus, a suitable range for n and m is $5 \leq n, m \leq 13$.

In the following experiments we consider the coefficients α_i with varying $5 \leq n, m \leq 13$. In the first experiment $n = m = 5$ and $0.0 \leq \alpha_1 \leq 1.0$, $0.1 \leq \alpha_2 \leq 1.0$. Then we let $n = 5$, $m = 8$ and values are similar to the previous experiment. The results are displayed in Figure 4 and in Figure 5.

From the same experiments the quality of the extracted watermark was calculated. The error measure is PSNR between the original watermark and the extracted water-

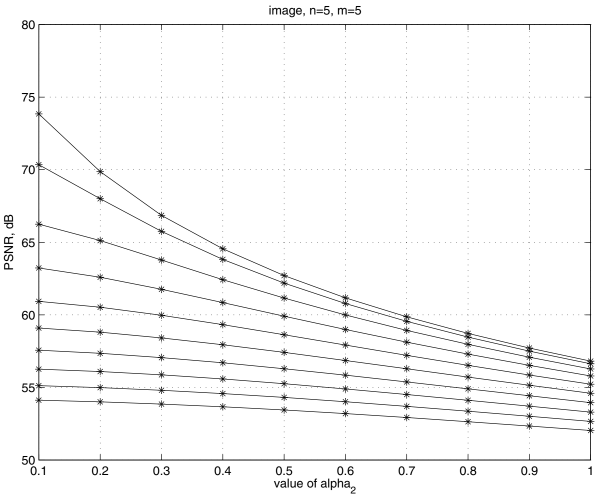


Figure 4. Image, $n = m = 5$, varying $0.0 \leq \alpha_1 \leq 1.0$, $0.1 \leq \alpha_2 \leq 1.0$. The lowest curve has $\alpha_1 = 0$ and the topmost curve has $\alpha_1 = 1$.

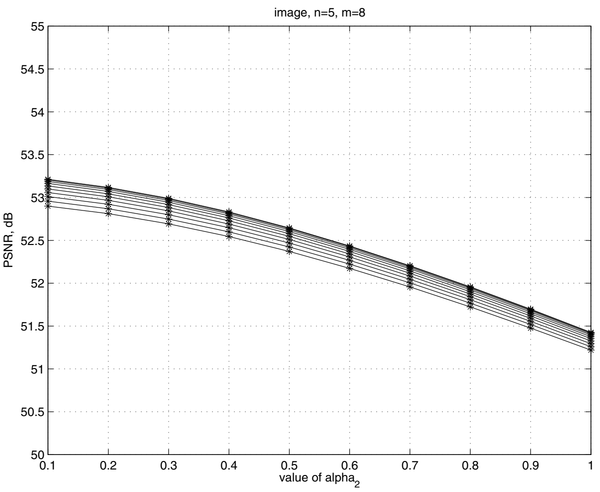


Figure 5. Image, $n = 5$, $m = 8$, varying $0.0 \leq \alpha_1 \leq 1.0$, $0.1 \leq \alpha_2 \leq 1.0$.

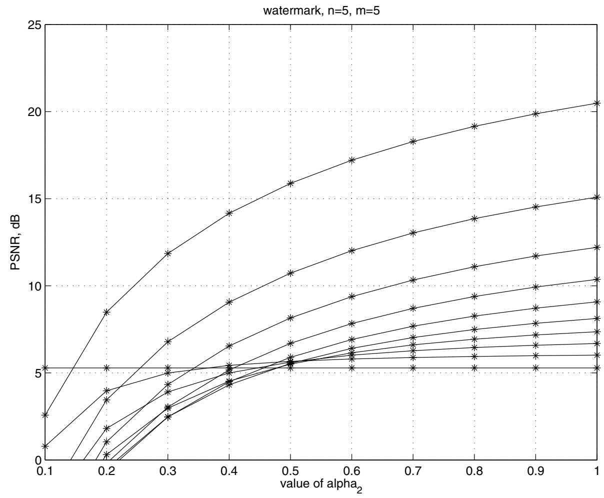


Figure 6. Watermark, $n = 5$, $m = 5$, varying $0.0 \leq \alpha_1 \leq 1.0$, $0.1 \leq \alpha_2 \leq 1.0$.

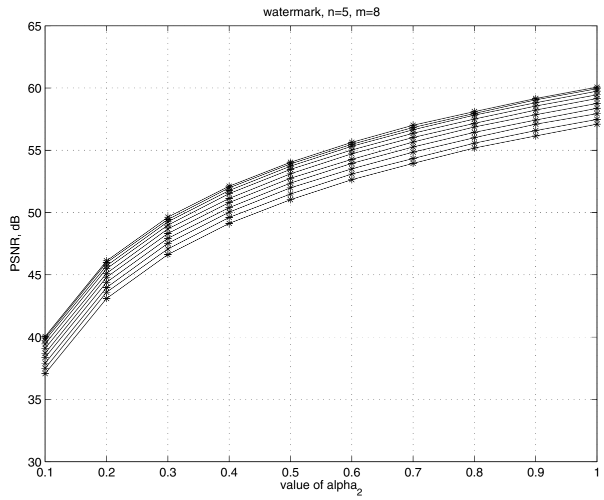


Figure 7. Watermark, $n = 5$, $m = 8$, varying $0.0 \leq \alpha_1 \leq 1.0$, $0.1 \leq \alpha_2 \leq 1.0$.

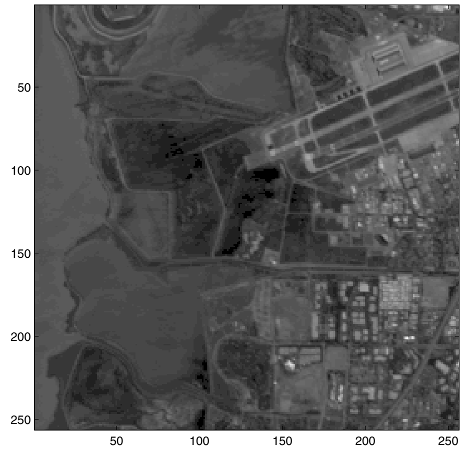
mark. The results are in Figures 6 and 7.

Band 4 from the watermarked image is shown in Figure 8 a). The band 4 has the largest average error after watermark embedding. The extracted watermark is shown in Figure 8 b). The quality of the extracted watermark is $PSNR = 37.5dB$. The parameters have values $n = 5$, $m = 8$, $\alpha_1 = 0.1$, $\alpha_2 = 0.1$.

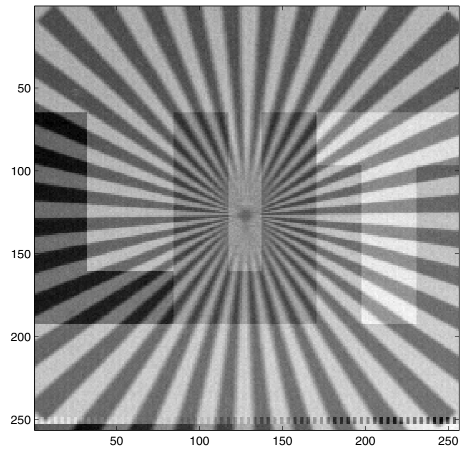
From the results shown the following conclusions can drawn:

- Higher quality in image reconstruction yields to lower quality in watermark extraction.
- a suitable range for PCA component mixing is from 5 to 13.
- mixing is not destroying image reconstruction when the watermark is embedded at the same time. This can be read from Figures 4 and 5 compared to the results in Figure 3.

Finally, we perform the optimization task. The previous experiments have reduced the ranges of the parameters and then, the optimal values within the allowed ranges are found. We let $n = 5...13$ and for each value of n we let $m = 5...13$. Thus, for each pair (n, m), optimal values for α_1 and α_2 are found through maximizing the cost function. The cost function is selected such, that both the

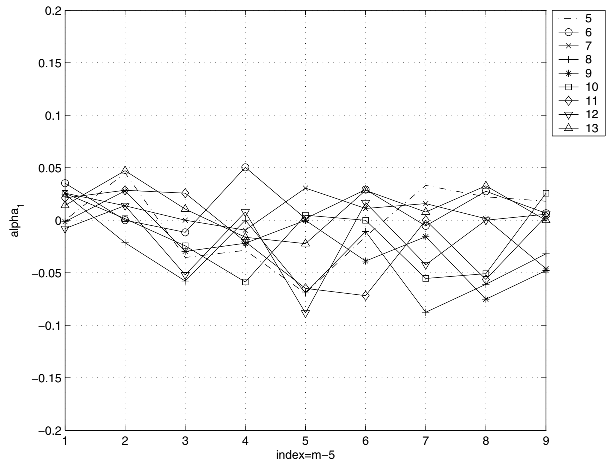


a)

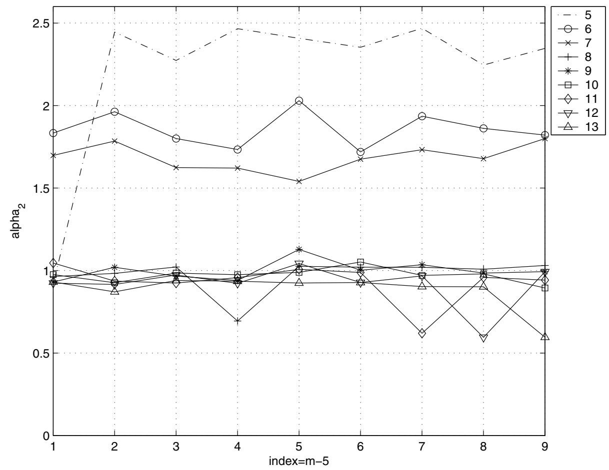


b)

Figure 8. a) Band 4 from the watermarked image. b) Extracted watermark.



a) α_1



b) α_2

Figure 9. a) α_1. b) α_2. Each line has a constant value of n and the horizontal axis is $index = m - 5$.

image reconstruction and the extracted watermark obtain the highest possible quality.

In Figure 9 we illustrate the results from optimization process.

The results shown in the figures indicate, that in most cases it is reasonable to keep α_1 close to zero and vary α_2 in range $1...2.5$. This means, that replacing the PCA component with a watermark gives the best result for embedding.

Conclusions

We have considered a method for embedding a watermark into a spectral image. The embedding happens in the PCA transform space of the image. The watermark is a visual watermark, i.e. the extracted watermark can be visually inspected and certified.

The results indicate, that high quality embedding is received when a PCA component is replaced by a properly weighted watermark. In addition the images shown, we also applied another spectral image and the watermark. The watermark should be scaled such that the range of values for the watermark and for the image are compatible. For the images shown the ratio of the maximum value of the image and the maximum value of the watermark was $19527/255 = 76.6$.

PCA eigenimages with high eigenvalues should not be replaced with other eigenimages. If this replacement was anyhow performed, the optimization resulted to a high quality watermark reconstruction but the watermark was clearly visible in the bands of the image.

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