# Learning Techniques in Imaging System Design and Spectral Image Processing

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## Abstract

*Many kinds of color imaging systems have been developed and equipped with an image processing technique. Most accurate imaging systems are implemented if spectral systems and spectral image processing are utilized. In this paper, the machine learning techniques in spectral images that extend traditional image processing methods are considered. Advantages and drawbacks of learning methods in various applications are described and discussed.*

## Introduction

The development of a high quality color imaging system is required in telemedicine, network museum, network shopping, electronic money, digital archives, mobile phones with a digital camera, digital TV, digital copy, digital camera and electronic paper. However, the images acquired by color imaging systems based on three channels are not very accurate, and depend on the illumination and system characteristics. To avoid conventional system problems and to provide high quality imaging systems the spectral imaging systems are introduced. Also, these systems can incorporate the color appearance characteristics of the human visual system [1].

On the other hand, new image acquisition devices and imaging systems require advanced image analysis and image processing algorithms to be used in the applications. In this case, the machine learning algorithms can help to solve the problems arising in different application areas. Recently, many advanced machine learning techniques using neural networks, support vector machines, Bayesian approaches have been introduced and combined in the software libraries that are convenient for the use [2]. Building the image processing methods using the ready-made machine learning algorithms one can get theoretically well-founded algorithms, a unified workflow for current and future studies, and a rich set of methods that provide flexibility for application-oriented research.

Many of the learning methods are density models based on a likelihood that it is important for recognition, and convenient for comparison with other methods. They include regression, clustering and pattern recognition methods. The learning algorithms are easy to use for incorporating the data nonlinearity, when the data dimensionality is reduced or spectral reflectance is estimated, and for data clustering, for example, when a separation of data into the body-reflection and highlight clusters is required. Therefore, the learning techniques are discussed in the following fields

- An imaging system for estimating spectral reflectance of paint.
- A dimensionality reduction technique in spectral images.
- Color mining and colorization.
- Highlight removal in endoscope images.
- Spectral image watermarking using ICA.

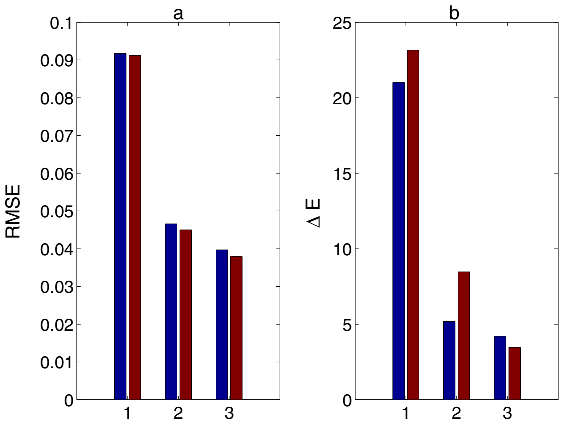
## An Imaging System for Estimating Spectral Reflectance of Paint

Many techniques including learning methods devoted to estimating the spectral reflectance have been proposed [3-7]. The comparison of different methods is useful to provide researchers with guidelines when new applications are developed.

In our previous study, we considered an imaging system for accurately estimating the spectral reflectance of art paintings [8]. We statistically analyzed the reflectance spectra of the color-patch sets of oil and watercolor paintings without noise characteristics, developed three machine-learning based methods and compared them with three traditional methods using a synthetic data set and real color-patch sets. The traditional methods are linear estimators based on low-dimensional principal component analysis (PCA) approximation and Wiener estimation, and a nonlinear estimator based on multiple regression approximation. The machine learning methods extend the traditional methods for estimating a nonlinear data structure. They include: a method based on nonlinear principal component analysis (regressive PCA), a method based on regression analysis (radial basis function (RBF) regression) and a method using a piece-wise linear Wiener estimation. The accuracy of spectral estimation using these methods is evaluated in this study.

For statistical analysis of the spectral reflectance of paintings five sets of color patches of oil or watercolor paint are used as follows: set A, 336 patches of paint (reflectance of paint); set B, 60 patches of paint (Turner acryl gouache); set C, 60 patches of paint (Turner golden acrylics); set D, 91 patches of paint (Kusakabe oil paint) and set E, 18 patches of paint (Kusakabe haiban). All sets were extracted from the standard object color spectral database constructed by the Spectral Characteristic Database Construction Working Group [9]. These sets have a spectral range of 400-700 nm and samples are evenly taken at 10 nm. Set A is used for training the algorithms and sets B-E are used for prediction of the spectral reflectance. The spectral transmittance characteristics are provided by the five separation filters used in a CCD camera. The filters are commercial (BPB-42, SP-9, BPB-50, BPB-55 and BPB-60). Two measurements are utilized for estimation accuracy, spectral color difference and colorimetric color difference (Fig. 1).




*(right bar), 3 is the multiple regression estimation (left bar) and regression estimation (right bar). For each set (A-E) the average RMSE value is measured and then a maximum of these values is given as a bar. For each set (A-E) the maximum CIE ΔE94 value is measured and then a maximum of these values is given as a bar. The learning based methods have slightly smaller RMSE value. The technique based on regression has the best ΔE94 value while the traditional methods have better color differences in two other cases.*

In general, the traditional methods have better average color differences. For example, the overall average ΔE94 measure is 0.42 for the multiple regression method versus 0.6 for the regression method. From this viewpoint these methods seem to be more preferable than the learning methods. This can be explained in the following way. In this study a dimensionality of the subspace is defined by the five given filters. Though the subspace is not optimal (close to optimal) its dimensionality is rather high whereas we can expect that the dimensionality of the nonlinear subspace where the learning methods are most suitable is low. Recently, it was shown that for reflectance spectra the dimensionality of the nonlinear subspace is approximately three [10]. We will consider this problem in our future study.

Thus, we synthesized a spectral color imaging system implementing several estimation methods and analyzed the possibility for accurately estimating the reflectance spectra using the presented techniques.

## A Dimensionality Reduction Technique in Spectral Images

It is very useful in spectral image processing (low- and high-pass filtering, wavelet transforms etc.) to apply a preprocessing step by reducing the dimensionality of an image containing dozens or hundreds of components to several components. In convenient systems the PCA technique is usually utilized for this purpose because it saves computational time and memory. To make this algorithm more efficient a technique that incorporates not only information from the retained principal components but also information from the higher-order (weak) principal components (PCs) without changing the number of principal components is required. The possible solution to the problem is to use a learning technique incorporating the nonlinearity of data.

In our previous paper we analyzed three nonlinear dimensionality reduction techniques and a standard principal component analysis (PCA) technique [11]. The nonlinear techniques included locally linear embedding (LLE), ISOMAP and regressive PCA (RPCA) [12-14]. The LLE and ISOMAP algorithms are modified to provide inverse parametrical mapping (from the subspace to the input space) used in image reconstruction. In this study a number of PCs (or embedded components) is used as a free parameter.

The study is divided into two parts. First, analysis is done for a low-resolution spectral image since the LLE and ISOMAP techniques are computationally demanding and cannot be used for a large data set. The size of the original low-resolution image *fruits and flowers* (taken from the toolbox of the University of Joensuu) is 120x160x81 (the third dimension is spectral). The spectral components are evenly taken in the range 380-780 nm. The image is down sampled to get a size 48x64x81 to make its size appropriate for working with LLE and ISOMAP. The low-resolution test image is shown in Fig. 2.

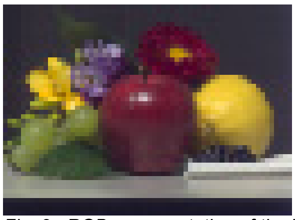


*Fig. 2. RGB-representation of the low-resolution image (fruits and flowers) used in the test.*

The average S-CIELAB ΔE measure [15] for the test image depending on a number of PCs is shown in Fig. 3.

Based on analysis one can conclude that the LLE algorithm lacks in compact representation of spectral images. For the LLE algorithm it is difficult to map the complicated image including several color regions to the proper subspace. The ISOMAP algorithm produces better visual results for the first PC and the first two PCs than PCA while the reconstructed images using PCA for the first three and four PCs are better than the ISOMAP result.

In general, for LLE and ISOMAP the data must be densely populated in the low-dimensional space [16]. The existence of several color regions in the low-resolution image prevents the correct learning of the data structure by LLE and ISOMAP. The PCA method produces a relatively good result because the probability density function (pdf) of the spectral image presented by several color regions is close to the Gaussian pdf according to the Central Limit Theorem. This makes the data structure more linear. The RPCA technique is superior to PCA when one to three principal components are used and is slightly better for four PCs.

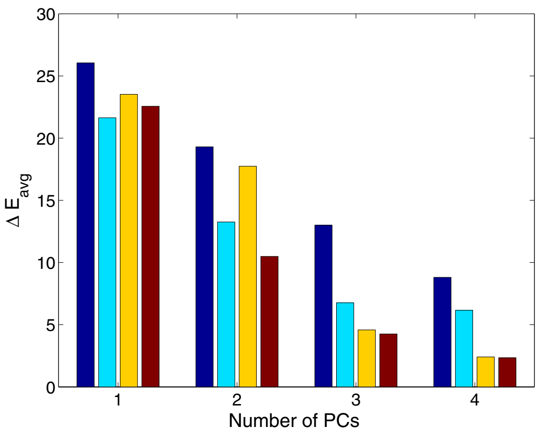



***Fig. 3**. The average S-CIELAB ΔE measure depending on a number of retained PCs. The bars from first to fourth for each number of PCs are given for LLE, ISOMAP, PCA and RPCA, respectively. ISOMAP gives good results for the first and first two components while RPCA is the best in most cases. When the number of used components is increased the difference between PCA and RPCA results is reduced.*

The second experiment is conducted with a set of high-resolution images using standard PCA and regressive PCA. Here we present a part of our study with four images: p1 (*Chart*), p2 (*Japanese Paint*), p3 (*Standard Image*) and p4 (*Fruit*) (taken from the toolbox of the Chiba University). The size of high resolution images acquired with the five-band camera is 508x764. Fig. 4 illustrates RGB-representation of the high-resolution images p1-p4 used in the test.

This study shows that the PCA and RPCA methods are computationally efficient to work with high-resolution images (a computational time when three PCs are used is 3.3 s (PCA) and 135 s (RPCA)). In the case of the high-resolution images the compression ratio for RPCA is close to that for PCA which is 1.66 for three PCs (for the low-resolution image the compression ratio is 26 (PCA) and 23 (RPCA) for three PCs).

RPCA gives visual improvement and better color and spectral difference for high resolution images in comparison with PCA. Examples are given for the spectral difference (Fig. 5), for the color difference (three PCs) (Fig. 6) and for the visual comparison (Fig. 7). The color difference results for PCA and RPCA are comparable in the case of four PCs. In this case the average S-CIELAB ΔE measure is 0.64/0.57 (p1), 0.28/0.28 (p2), 1.03/0.8 (p3) and 0.91/0.95 (p4), where the first value is given for PCA and the second value for RPCA. This means that for the test images a dimensionality of nonlinear subspaces is approximately three.

Based on analysis of low-resolution and high-resolution images we believe that regardless of data linearization, that holds for complicated images, the low-degree residual nonlinearity still exists. RPCA incorporates this nonlinearity by approximating weak PCs. We conclude that the RPCA technique reproduces colors more accurately than PCA, requires approximately the same memory as PCA in applications with high-resolution images and is relatively fast.

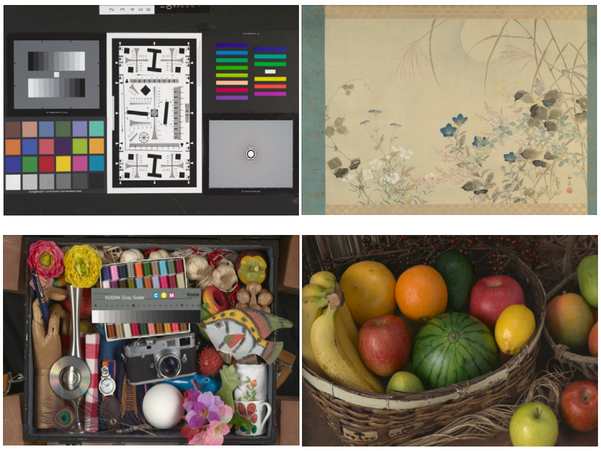


***Fig. 4**. RGB-representation of high-resolution images used in the test: p1 (Chart), p2 (Japanese Paint), p3 (Standard Image) and p4 (Fruit).*

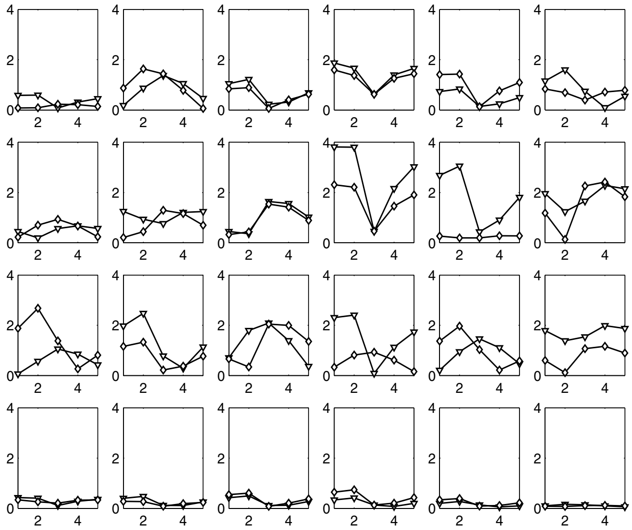


***Fig. 5**. The RMSE for the part of p1 (a colorchecker placed in the left-bottom corner of p1). The curves for PCA and RPCA (three PCs are used) are marked by triangles and diamonds, respectively. The spatial position of each graphic corresponds to the spatial position of the colorchecker patch where the measurement is made. The image component indices (a horizontal coordinate) are consequently located in accordance with the channel spectral characteristics from short wavelengths to long wavelengths. For RPCA a RMSE maximum and RMSE values in most cases are smaller to values given by PCA. Note: the values of a vertical coordinate must be multiplied by the scaling factor $10^{-2}$.*

## Color Mining and Colorization

Colorization is a computerized process where color is added to the gray-level image or movie. Colorization requires human participation that makes colorization very complicated, expensive and time consuming. There are several colorization techniques where color is transferred from the source (color image) to the target (gray-level image) if the intensities (or other achromatic information) of neighboring pixels match between the images. To reduce a computational time only a reduced number of pixels of a color region participate in matching [17-19].

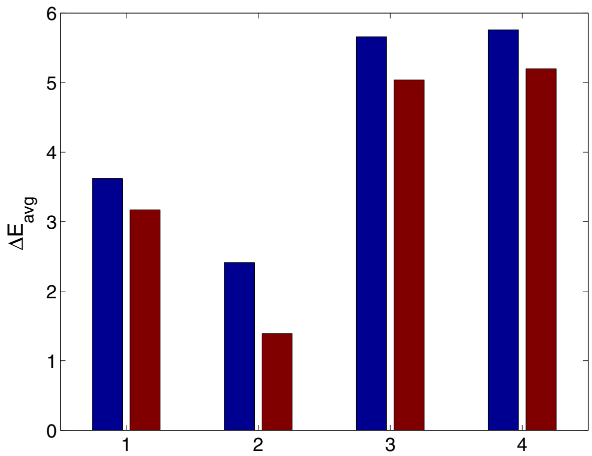



***Fig. 6**. The average S-CIELAB ΔE measure for images p1-p4 corresponding to horizontal coordinate values 1-4, respectively. Three PCs are used. The left bar is given for PCA and the right bar is given for RPCA.*

*Fig. 7. RGB-representation of the scaled image part (p2). PCA reconstruction (left) and RPCA reconstruction (right). The right image has more reddish flowers close to the original. Three PCs are used.*

In our previous paper we introduced nonlinear mapping between the components based on color mining that characterizes the colors of colored objects in spectral images [20]. We propose to pick a set of new colors from the real full-spectral image by reducing the image dimensionality and using nonlinear parametric mapping to the first principal component. Then, the gray level image replacing the first principal component is colored by reconstructing a synthetic full-spectral image. For parametric mapping, two techniques: a mixture of probabilistic principal component analyzers (MPPCA) and regressive PCA (RPCA) are utilized [21], [14].

Fig. 8 and Fig. 9 show an example of color mining for the masked region. The region represents a color object where the dichromatic reflection model is relevant. The first two PCs of the PCA represent the data very accurately. However, the intrinsic dimensionality of the data is less than two. This is discovered by the learning based methods including a mixture of probabilistic PCA and regressive PCA. Fig. 9 shows the S-CIELAB ΔE measure depending on a number of retained PCs.

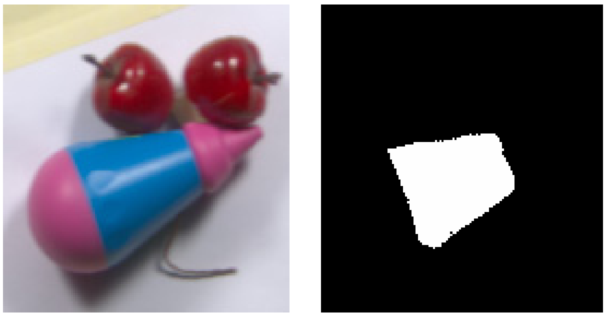


*Fig. 8. RGB-representation of the spectral image and a region mask. The image size is 131x141 pixels with 81 components evenly taken in the range of 380-780 nm.*

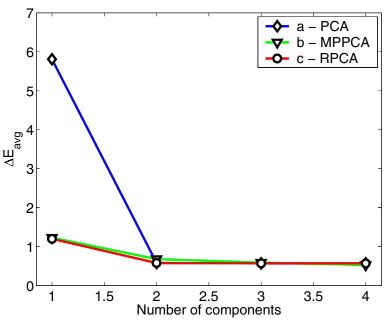



*Fig. 9. The average S-CIELAB ΔE depending on a number of PCs for PCA, MPPCA and RPCA. The PCA technique requires two PCs to represent the region while MPPCA and RPCA show that the data dimensionality is one.*

The colorization procedure reduces the dimensionality of the spectral image and using learnt color information colors a gray-level image. We believe that this study makes the colorization relatively simple providing a good generalization of color because all available pixels of the region are involved in the analysis.

## Highlight Removal in Endoscope images

The highlight removal technique is especially important in medicine for analysis of endoscope images. Highlights are an undesirable factor when medicine images are merged together to obtain a mosaic image.

An efficient algorithm for highlight removal in endoscope images is proposed in the study [22]. According to the analysis the endoscope images are presented by several kinds of regions including a shade surrounding highlight. The dichromatic reflection model is not valid for the whole spectral image because the color of the shade significantly varies in comparison with the background pixels and does not have a smoothed transition with the color of the body-reflection cluster. However it is possible to segment the image using machine learning algorithms and extract only the body-reflection and highlight regions for which the dichromatic reflection model is relevant and then the highlight removal technique is applied.

The algorithm is based on the Gaussian mixture model (GMM) used for fitting the data, clustering and feature analysis to determine the body-reflection and highlight regions. The proposed algorithm removes the highlight in the endoscope image and improves color reproduction of the entire image. Though the algorithm performance depends on data we believe that the considered method can be useful in medical applications where mosaic images are required.

## Spectral Image Watermarking Using ICA

Finally we present continued research on image watermarking. The digital watermark technique has been developed quickly during the last few years and applied to protect the copyright of digital image. The digital watermark is embedded in the source image and should be robust against attacks trying to remove the watermark.

The purpose of this study is to embed the watermark in a spectral image and then to extract it from the image. To enforce the security we introduce also the key image. Three images including a source image, a key image and a watermark are spectral (Fig. 10). The image size is 130x71 pixels with 81 components evenly taken in the range 380-780 nm. For embedding we mix the images with different coefficients and then for extracting the watermark the Fast ICA algorithm is utilized [23]. If the Fast ICA algorithm is used in analysis of the spectral images then a preprocessing procedure should be implemented. The preprocessing procedure involves two steps the dimensionality reduction using PCA and high-pass filtering. PCA is needed to accelerate computing and to avoid overlearning. In general, an overlearning problem prevents finding independent components in the image. Overlearning in ICA relates to a data complexity problem and is observed when the statistical data model has many parameters in respect to the available sample size. The high-pass filtering removes correlation between images and makes the source images more independent. Fig. 10 shows the results on extracting the watermark.

This study seems to be promising because we not only extract the spectral watermark from spectral images but also reproduce its color. The method is robust against attacks including low and high-pass filtering. The used spectral images were acquired from color reproductions and in a future study we will use real spectral images.

## Conclusion

We considered the learning techniques in the following applications: an imaging system for estimating spectral reflectance of paint, a dimensionality reduction technique in spectral images, color mining and colorization, highlight removal in spectral images and spectral image watermarking using ICA. We did not consider the non-negative techniques (non-negative matrix factorization and non-negative independent component analysis) which can be found elsewhere (for example, in Reference [24]).

We think that in practice for estimating spectral reflectance the learning technique can be used without limitations because the size of the training set is usually less than several thousands. For spectral image analysis involving dimensionality reduction the use of the learning technique (except regressive PCA) is usually restricted due to computational time and memory demands.

## Acknowledgements

The authors thank the Academy of Finland for the funding granted to this study.

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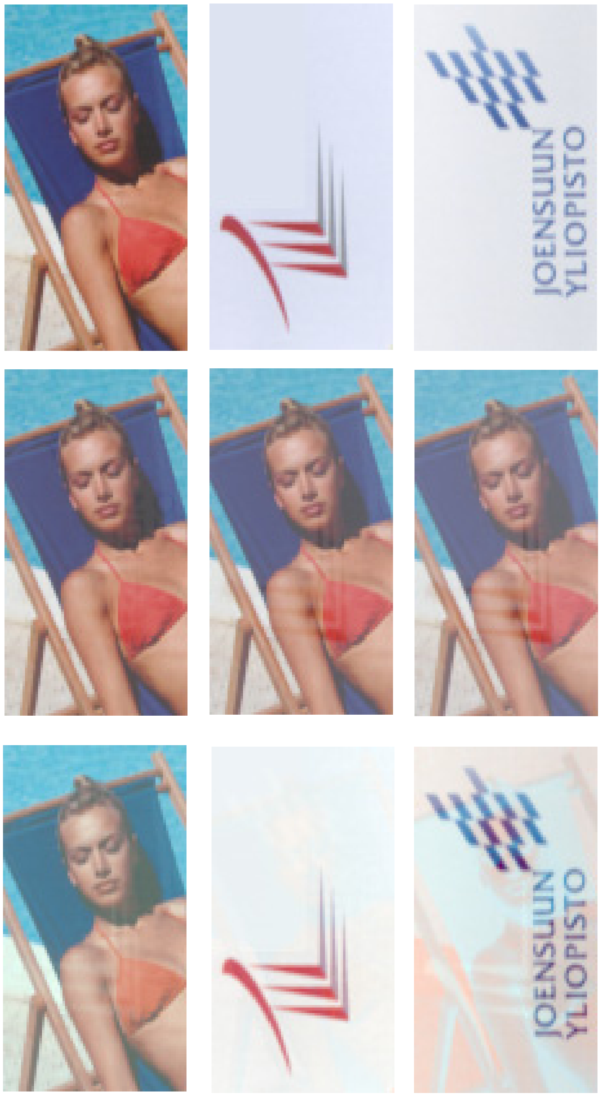


***Fig. 10**. RGB-representation for images used in digital watermarking. The first row (from left to right): the original image, the key image and the watermark. The second row (from left to right): three mixtures obtained by mixing images from the first row. The left image is a watermarked image for which the mixing coefficient values for the watermark and the key image are small (three source images are used). The middle image and the right image are mixtures only of the original image and the key image. The third row shows a result produced by ICA and the right image is the extracted watermark.*

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