Training Set and Filters Selection for the Efficient Use of Multispectral Acquisition Systems

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Abstract

The quality of the results obtained from a multispectral acquisition system can be affected by several factors, including the training set on which the system characterization model relies and the optical filters that allow acquisition in different bands of the light spectrum.

In this paper, we investigate the joint effect of training set and filter selection on the results of a typical multispectral acquisition system. We evaluate two methods for training set selection and two methods for filter selection, testing all their possible combinations and selecting filter sets and training sets of decreasing numerosity in each case. We then assess the performance of the evaluated methods by comparing the corresponding estimates for the reflectances of a representative target to the values measured using a spectrophotometer.

Introduction

The quality of the results obtained from a multispectral acquisition system can be affected by several factors. Assuming that a proper operational setup has been obtained, including effective correction of hardware noise and discounting of illumination, then the remaining issues are related to the acquisition output data and their processing.

In the typical multispectral acquisition system, the actual multispectral data must be derived from the output of the system using some characterization method,[1] which may in turn rely on a training set. The system output data are obtained using different optical filters (either traditional or tunable filters[2]) that allow acquisition in different bands of the light spectrum. The key issues are then related to the choice of the characterization method, training set, and filters.

In previous papers,[3,4] we investigated different methods for training set and filters selection, with the assumption that a suitable characterization method had been chosen in advance. This is not an uncommon case, as the characterization method is usually dictated by the system response function, so that, for instance, a response function which is linear with respect to reflectance would call for a linear characterization method. The two problems were investigated separately, using a fixed training set when evaluating filter selection strategies and a fixed filter set when evaluating training set selection strategies. With a similar approach, other authors also introduced and tested specific methods for either training set selection[5] or filter selection[6,7] (a review of methods for filter selection can also be found in Hardeberg[8]).

In this paper, we investigate the joint effect of training set and filter selection on the results of a typical multispectral acquisition system. We assume that the colors to be included in the training set are chosen within a large and varied color set (a ‘target’), and the filters used to obtain the system output data are selected among a set of available filters (or tunable filter configurations) whose transmittances cover the visible light spectrum or at least a significant part of it (typically, the interval from 400nm to 700nm).

In particular, we investigate how the quality of reflectance estimation varies when filter sets of decreasing numerosities are chosen, and to which extent this variation is affected by choosing training sets that differ in their composition and in the number of colors included. Although it could be expected that a larger set of properly chosen filters would lead to better results, minimizing the number of filters used is important to reduce operational costs and acquisition time, as well as the amount of data needed to store the acquired spectral images. The numerosities of both filter set and training set also have an impact on the processing time required to obtain reflectance estimates from system output data.

We first report a series of experiments in which we evaluate different strategies for both the choice of filters and training set, testing all their possible combinations and selecting filter sets and training sets of decreasing numerosity in each case. We then assess the performances of single strategies and point out whether some strategy can prove superior to its alternatives independently from other conditions. Last, we repeat some of the previous experiments imposing restrictions that modify the potential effect of training set selection over filter selection.

Training Set and Filter Set Selection Methods

All the methods employed in the following have been introduced in previous papers; here, we briefly explain them and give the corresponding references.

For training set selection, we considered a method by Hardeberg et al.[5] and our Linear Distance Maximization Method (LDMM) method,[3] as these turned out to be the best methods in a previous comparative analysis we had carried out.[3] Both methods adopt an iterative approach in which the training set colors are chosen one by one; the first color is chosen for its characteristics, while each subsequent color is chosen among the remaining target colors because it 'best suits' (in some sense) the set of the colors already chosen.

The method by Hardeberg selects colors based on their reflectances (which must be known, usually through measurements). The color whose reflectance vector has maximum norm among all the target colors (the most reflective color in the target) is chosen as the first color of the training set. At step k, the color $\mathbf{r}$ not already chosen that maximizes the ratio of the smallest to the largest singular value of the matrix $[\ \mathbf{r}_1 \mid \dots \mid \mathbf{r}_{k-1} \mid \mathbf{r}\ ]$, whereby $\mathbf{r}_1, \dots, \mathbf{r}_{k-1}$ indicate those colors already selected, becomes the k-th color in the training set.

The LDMM method selects colors based on their corresponding system output vectors as obtained from an acquisition performed in the chosen operational conditions. The first color of the training set is the color whose associated system output vector has maximum norm among all the target colors (the brightest color in the target for the chosen acquisition conditions). The second selected color is the remaining color that has maximum distance from the first color. At subsequent steps, for each remaining color, the minimum distance from it to the colors already selected is computed, and the remaining color for which such distance is maximum is added to the training set. The distance used is the infinity norm of the difference of the system output vectors corresponding to the colors considered.

For filter selection, we considered the Evenly Spaced Filters (ESF) method and the Filter Vectors Analysis Method (FVAM) as introduced in a previous work of ours.[4] Both methods identify each available filter by the wavelength at which it shows its transmittance peak (see Figure 1).

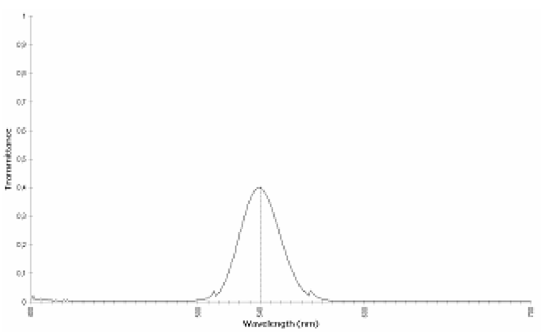

Figure 1. Filters are identified by the wavelength at which they have their transmittance peak.

The ESF method selects a subset of filters of desired numerosity n by choosing n available filters so that their associated wavelengths are as evenly spaced as possible within the spectrum considered. Ideally, the interval between the wavelengths identifying any two 'adjacent' filters should be the same, and the 'first' and 'last' available filters (those whose identifying wavelengths are minimum and maximum) should be included in the selected subset.

The Filter Vectors Analysis Method (FVAM) chooses the filter set based on a statistical analysis of the acquisition of a representive target performed using all the available filters. For every filter, the vector including the output relative to that filter as the target colors vary is considered, and a Principal Component Analysis is then performed on all these filter vectors. Then, for each resulting eigenvector in order of relevance, the filter vector nearest to the eigenvector considered (in the sense of angular distance) is identified, and the corresponding filter is included in the filter set, until the desired numerosity is achieved.

Experimental Setup

To allow comparison between different trials, all the experiments were carried out using the same data and the same characterization method. The data were obtained from a real acquisition; the acquisition system consisted of a 12-bit monochrome digital camera, a VariSpec tunable filter, a high-quality lens, and a cut-off optical filter for infrared and ultraviolet radiations. Each trial was performed employing a linear characterization model built using standard numerical analysis techniques and based on the training set selected for that trial.

In all cases, filters and training set were selected from the same initial available filter set and color target. For the training sets, colors were chosen from the Macbeth ColorChecker DC target (MDC), which contains 177 different colors that show a good variety of colorimetric properties. Filters were instead chosen from among 31 configurations of our tunable filter; these configurations had transmittance peaks that varied from 400nm to 700nm at intervals of 10nm.

To assess the quality of the results, the estimated reflectance values were compared to those measured using a Minolta CM-2002 spectrophotometre. As a measure of the precision of the estimation, we considered the infinity norm of the difference between the measured value and the corresponding estimate. Compared to the customarily employed Root Mean Squared error (RMS), this measure emphasizes greater differences in single components of the reflectance vector rather than smaller differences in several components; also, if the error computed with this measure is small, then the corresponding RMS is small too (while the converse is not necessarily true). To compute errors, we employed the whole MDC target as our test set in all experiments.

Early Experiments

We carried out a first series of experiments in which we tried all four possible combinations of the two methods for training set selection (LDMM / Hardeberg) in conjunction with the two methods for filter selection (ESF / FVAM).

In each of these trials, we estimated reflectance values for the colors in the test set at the same wavelengths at which the employed filters had their transmittance peaks.

This means that, since the chosen filters generally varied from trial to trial, the wavelengths at which reflectance was estimated generally varied too. Also, this means that for the ESF method these wavelengths are evenly spaced.

For each combination of methods, we selected three filter sets of numerosities 16, 11, and 7 respectively. These values were chosen so that the ESF method could space filters across the 400nm-700nm spectrum in a perfectly even manner while including the first and last filters (i.e., those with transmittance peaks at 400nm and 700nm). We combined these filter sets with four training sets which respectively included 31, 16, 11, and 7 sample colors, giving a total of twelve trials for each combination of methods. Results for these experiments are reported in Figure 2 in terms of the maximum error observed on all the colors in the test set.

An analysis of these results shows that, independently from the method employed for filter selection, the LDMM method performs slightly better than Hardeberg's method with more samples in the training set, but its performance degrades much more as the number of samples decreases. This trend, although not always clear and consistent, was confirmed when considering the mean error observed on all the colors in the test set; as an example, in Figure 3 we report the mean error for the combination Hardeberg's method / FVAM method.

Comparing performances between the two filter selection methods, results show that as long as the maximum error is considered, both Hardeberg's method and the LDMM method generally perform better when coupled with the FVAM method. However, if mean error is considered, the LDMM method performs better when coupled with the ESF method. In general, though, trends are again mixed.

As a further reference, we also computed errors using all 31 available filters; as Figure 4 shows, in this case the maximum error clearly increases as the numerosity of the training set decreases, and Hardeberg's method performs better than the LDMM method. The corresponding mean errors generally confirm this observation.

Discussion

Based on the results of these experiments, some remarks can be made. First, choosing only a subset of the 31 available filters generally leads to improved estimates for reflectance; this happens independently from the method chosen for training set selection and, although to a more limited extent, from the training set numerosity as well. This is in accordance with observations made by other authors when working with real systems[9] as opposed to simulations.

Second, none of the two methods for training set selection shows a clear advantage over the other one. On the other hand, decreasing the number of sample colors in the training set generally results in worse estimates, especially when only 7 sample colors are used.

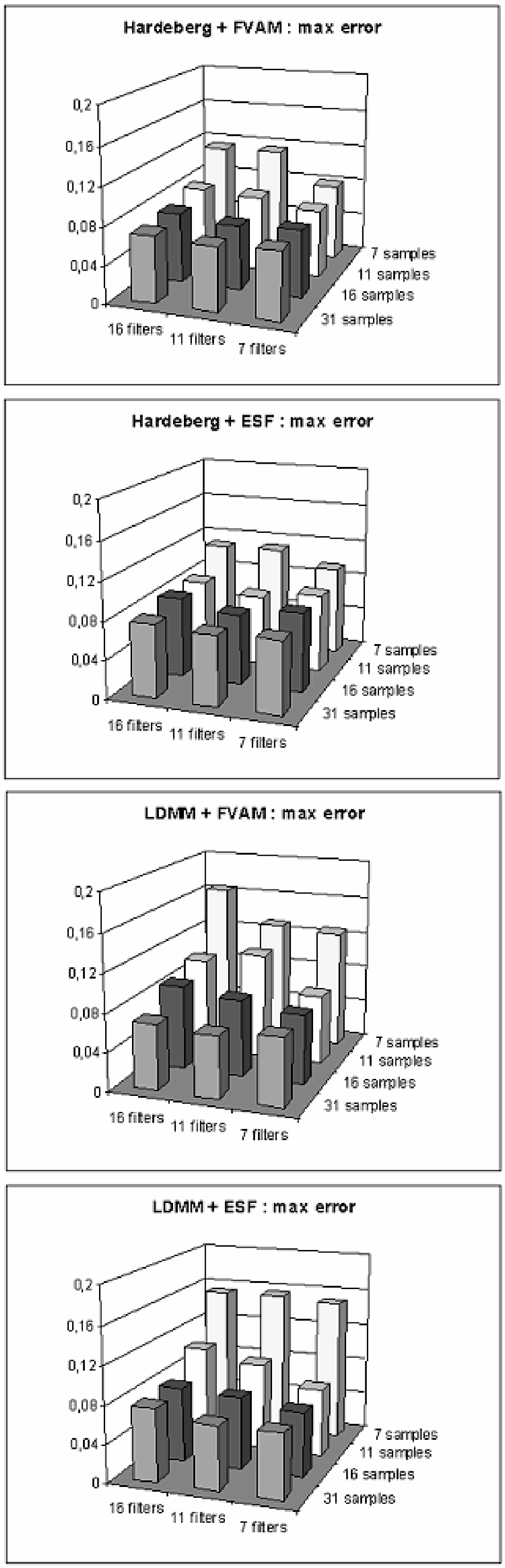

Figure 2. Maximum errors across the whole test set for the four combinations of methods tried.

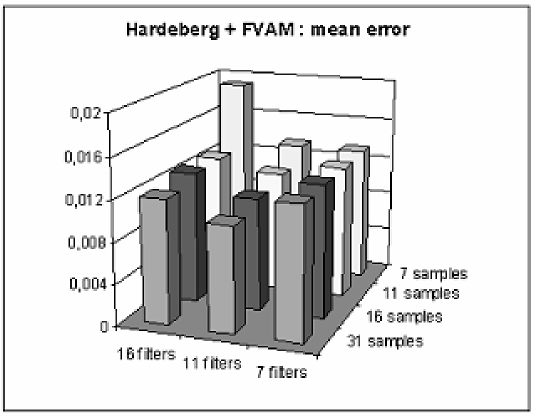

Figure 3. Mean errors across the whole test set for Hardeberg's method in conjuction with the FVAM method.

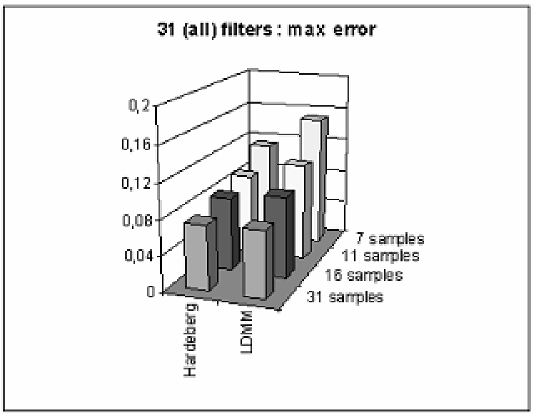

Figure 4. Maximum errors across the whole test set when using all the available filters.

Last, the best estimates are usually obtained when employing 11 filters; however, as far as our results are considered, the little advantage gained with this choice cannot support the claim that 11 filters (or a similar number) can generally be sufficient or necessary. Similarly, the improvements observed in the maximum error when employing the FVAM method over the ESF method are small, and are at least partially offset by opposite indications from the mean error.

Further Experiments

So far, the FVAM method for filter selection was applied considering all the colors in the MDC target; therefore, in all these trials, the choice of the training set only affected the characterization model. In the line of investigating the joint effect of filters and training set selection, a question naturally arises about whether the FVAM method would give different results if it were applied only to the colors selected for the training set.

In order to answer this question, we repeated all the experiments involving the FVAM method, and performed filter selection considering only the system output data relative to the training set colors. However, the results from these trials, which are shown in Figure 5, are not consistently better nor worse than the corresponding results we had obtained in the first series of experiments. The only trend (however faint) that can be identified indicates that choosing filters based on training set colors only generally yields better results with larger training sets, while it performs more poorly with smaller ones. Anyway, this is not sufficient to give any decisive answer.

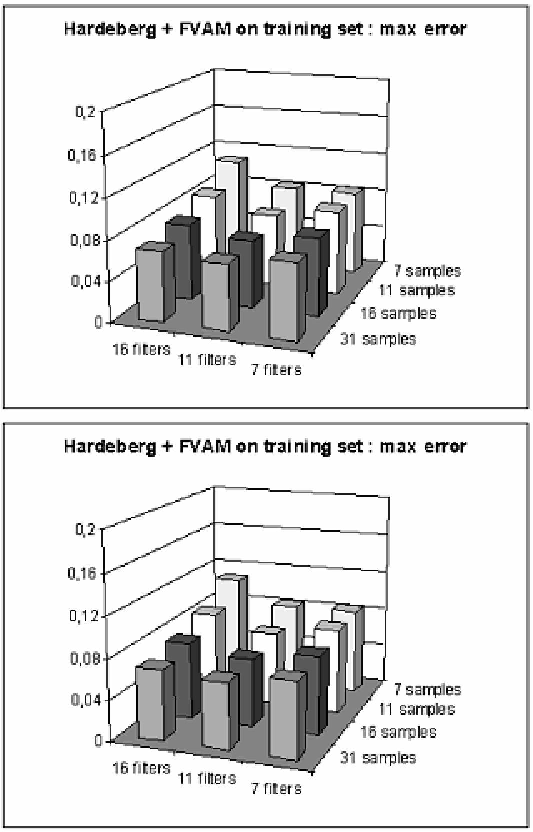

Figure 5. Maximum errors across the whole test set for the two combinations involving the FVAM method with filters chosen considering only the colors in the corresponding training sets.

Conclusions

We investigated the joint effect of training set and filter selection on the results of a typical multispectral acquisition system. We considered two methods for the choice of filters and two methods for the choice of the training set, testing all their possible combinations and selecting filter sets and training sets of decreasing numerosity in each case. The results of our experiments seem to indicate that increasing the number of filters used does not necessarily lead to improved estimates for reflectance, while decreasing the number of sample colors in the training set generally results in worse estimates. However, the estimation errors observed do not show completely consistent trends; in particular, no clear and decisive indication could be obtained in order to conclude that a specific method or combination of methods performs better than the other. For this reason, we feel that the whole analysis should be repeated with different operational setups before any conclusive remarks can be made.

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Biography

Raimondo Schettini is Associate Professor at DISCo, University of Milano Bicocca, where he is in charge of the Imaging and Vision Lab. He has been team leader in several research projects and published more than 140 refereed papers on image processing, analysis and reproduction, and on image content-based indexing and retrieval. He was General Co-Chairman of the First European Conference on Color in Graphics, Imaging and Vision, and of the EI Internet Imaging Conferences (2000-2004). He was guest editor of the special issue Color Image Processing and Analysis (Pattern Recognition Letters, 2003).