Estimating Illumination Chromaticity via Support Vector Regression

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Abstract

The technique of support vector regression is applied to the problem of estimating the chromaticity of the light illuminating a scene from a color histogram of an image of the scene. Illumination estimation is fundamental to white balancing digital color images and to understanding human color constancy. Under controlled experimental conditions, the support vector method is shown to perform better than the neural network and color by correlation methods.

Introduction

Accurate estimation of the spectral properties of the light illuminating an imaged scene by automatic means is an important problem. It could help explain human color constancy and it would be useful for automatic white balancing in digital cameras. Many papers have been published on the topic. Some aim to recover the full spectrum of the illumination, while others aim to recover either a 2-parameter (eg., xy or rg) estimate of its chromaticity[18, 22] or a 3-parameter description of its color (e.g., XYZ or RGB)[10,12].

The new method we propose here is similar to previous work by Funt et. al. [18, 19] and Finlayson et. al. [22] in that it aims to recover the chromaticity of the scene illumination based on the statistical properties of binarized chromaticity histograms; however, the proposed method replaces the neural networks and Bayesian statistics of these previous methods with powerful support vector machine regression.

Vapnik's[1,2] Support Vector Machine theory has been applied successfully to a wide variety of classification problems [3,4,5,6]. Support vector machines have been extended as well to regression problems including financial market forecasts, travel time prediction, power consumption estimation, and highway traffic flow prediction [7,8,9].

Depending on the problem domain support vector machine based regression (SVR) can be superior to traditional statistical methods in many ways. SVR enables inclusion of a minimization criterion into the regression, training can be easier, and it achieves a global rather than local optimum. It also facilitates explicit control of the tradeoff between regression complexity and error. We show how the illumination estimation problem can be formulated in SVR terms and find that, overall, SVR leads to slightly better illumination estimates than the neural net and color by correlation methods.

1. Support Vector Regression

SVR estimates a continuous-valued function that encodes the fundamental interrelation between a given input and its corresponding output in the training data. This function then can be used to predict outputs for given inputs that were not included in the training set. This is similar to a neural network. However, a neural network's solution is based on empirical risk minimization. In contrast, SVR introduces structural risk minimization into the regression and thereby achieves a

To appear: IS&T/SID Twelfth Color Imaging Conference, Nov 2004

global optimization while a neural network achieves only a local minimum [26].

Most classical regression algorithms require knowledge of the expected probability distribution of the data. Unfortunately, in many cases, this distribution is not known accurately. Furthermore, many problems involve uncertainties such that it is insufficient to base a decision on the event probability alone. Consequently, it is important to take into account the potential cost of errors in the approximation. SVR minimizes the risk without prior knowledge of the probabilities. This paper explores the extent to which the relatively new tool of SVR can improve upon the performance of related likelihood estimation illumination estimation algorithms.

Smola and Schölkopf [1] provide an introduction to SVR. Some simple intuition about it can be gained by comparison to least-squares regression in fitting a line in 2-dimensions. Least squares regression minimizes the sum of squares distance between the data points and the line. SVR maximizes the space containing the data points subject to minimization of the distance of the points to the resulting line. The width of the space is called the 'margin'. Points within an 'insensitivity' region are ignored. The technique represents the region defined by the margin by a subset of the initial data points. These data points are called the support vectors. SVR is extended to the fitting of a non-linear function by employing the kernel trick[1] which allows the original non-linear problem to be reformulated in terms of a kernel function. The reformulated problem is linear and can be solved using linear SVR. We used the Chang and Lin [25] SVR implementation.

2. SVR for Illumination Chromaticity Estimation

In this section, we discuss how the SVR technique can be applied to analyze the relationship between the image of a scene and the chromaticity of the illumination chromaticity incident upon it.

As introduced in the neural network method[19], we will first use binarized 2D chromaticity space histograms to represent the input image data. Later, we extend these histograms to 3D to include intensity as well as chromaticity. Chromaticity histograms have the potential advantage that they discard intensity shading which varies with the surface geometry and viewing direction, but is most likely unrelated to the illumination's spectral properties.

The training set consists of histograms of many images along with the measured chromaticities of the corresponding scene illuminants. Each image's binarized chromaticity histogram forms an SVR binary input vector in which each component corresponds to a histogram bin. A '1' or '0' indicates that the presence or absence of the corresponding chromaticity in the input image. Partitioning the chromaticity space equally along each component into N equal parts yields N × N bins. The resulting SVR binary input vector is of size N^2. We experimented with various alternative choices for N and eventually settled on N=50. All the results reported below are based on this choice. With N = 50 the chromaticity step size is 0.02. With $0 \leq r, g \leq 1$ only half these bins can ever be filled, so a sparse matrix representation was used. Support vector regression then finds the function mapping from image histograms to illuminant chromaticities.

Since some other illumination estimation methods [12,15] (gamut mapping and color by correlation) benefit from the inclusion of intensity data, it is natural to consider it in the SVR case as well. The neural network method has thus far not been applied to 3D data (chromaticity plus intensity) because the number of input nodes becomes too large and the space too sparse for successful training, given the relatively small size of the available training sets.

Support vector regression handles sparse data reasonably well, so we experimented with 3D binarized histograms in the training set. Intensity, defined as $L = R + G + B$, becomes the third histogram dimension along with the r and g chromaticity. We quantized L into 25 equal steps,

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so the 3D histograms consist of 62,500 (25x50x50) bins.

2.1 Histogram Construction

To increase the reliability of the histograms, the images are preprocessed to reduce the effects of noise and pixels straddling color boundaries. We have chosen to follow the region-growing segmentation approach described by Barnard et. al. [15] This also facilitates comparison of the SVR method to the other color constancy methods he tested. The region-growing method is good because the borders it finds are perfectly thin and connected. Membership in a region is based on chromaticity and intensity. A region is only considered to be meaningful if it has a significant area. For the sake of easy comparison we used the same thresholds as [15]; namely, to be in the same region, the r and g chromaticities at a pixel must not differ from their respective averages for the region containing the pixel by more than 0.5% or its intensity by 10%. Also, regions that result in an area of fewer than 5 pixels are discarded. The RGB's of all pixels within each separate region are then averaged, converted to L, r, g and then histogrammed.

2.2 *K*-Fold Cross Validation for SVR Parameters

The performance of SVR is known to depend on its insensitivity parameter ε, the choice of kernel function associated parameters. Different kernel functions work better on some problem domains than others. Four of the commonly used kernel functions are listed in Table 1. From a practical and empirical standpoint, the bigger the insensitivity parameter ε, the fewer the support vectors, and the higher the error in estimating the illumination. After much experimentation with different ε, we fixed its value to be 0.0001.

In the case of SVR for illumination estimation, the best choice of kernel function and its parameters may depend on the training set. We eliminated the Sigmoid kernel function from further consideration since it is invalid for some values of the parameter r and focus instead on the RBF and polynomial kernel functions.

.Name	Definition	Param.
Linear	$K(x_i,x_j) = (x_i)^T x_j$	---
Polynomial	$K(x_i,x_j) = [(x_i)^T x_j+1]^d$	d
Radial Basis Function (RBF)	$K(x_i,x_j) = e^{-\gamma\|x_i-x_j\|^2}$	γ
Sigmoid*	$K(x_i,x_j)=tanh[(x_i)^T x_j+r]$	r

(*: For some r values, the kernel function is invalid)

Table 1 Admissible Kernel Functions

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This leaves the choice of either the RBF or polynomial kernel functions and for each of these kernels the parameters: penalty C and width γ for the RBF kernel function; or penalty C and exponential degree d for polynomial kernel function. The parameters γ and d control the corresponding kernel function's shape. The kernel choice and parameter settings are made during the training phase by k-fold cross validation, which involves running the training using several different parameter choices and then selecting the choice that works best for that particular training set. This is described in more detail below.

For the KBF kernel function, we allow the penalty parameter to be chosen from 4 different values $C \in \{0.01, 0.1, 1, 10\}$ and the width value from $\gamma \in \{0.025, 0.05, 0.1, 0.2\}$. For the polynomial kernel function, we used the same 4 penalty candidates and selected the best degree d from the set {2 3 4 5}. Thus for each training data set, 32 test cases (2 kernel choices with 16 pairs of parameter settings each) will be tested to find the best choice.

Among the algorithms generally used to find the best parameters for support vector regression, we chose *k*-fold cross validation because it does not depend on a priori knowledge or user expertise and it handles the possibility of outliers in the training data. The disadvantage of the *k*-fold method is that it is computationally intensive.

In *k*-fold cross validation, the whole training set is divided evenly into *k* distinct subsets. Every kernel function and each of its related parameters forms a candidate parameter setting. For any candidate parameter setting, we conduct the same process k times during which (k-1) of the subsets are used to form a training set and the remaining subset is taken as the test set. The RMS chromaticity distance errors (see section 3.1 for definition) from k trials are averaged to represent the error for that candidate parameter setting. The parameter setting leading to the minimum error is then chosen and the final SVR training is done using the entire training set based on the chosen parameter setting.

3. Experiments

We tested the proposed SVR-based illumination estimation method on both synthetic and real images. The implementation is based on the SVR implementation by Chang and Lin [25]. To this we added a Matlab interface which reads data files representing the image histograms and associated illumination chromaticities. Each row in the training data file represents one training image and consists of two parts: the true illumination chromaticity followed by the bin number for each non-zero histogram bin.

Barnard et. al. [14,15] reported tests of several illumination estimation methods, including neural-network based and color by correlation. We have tried to follow their experimental procedure as closely as possible and used the same image data so that SVR can be compared fairly to these other methods.

3.1 Error Measures

There are two basic error measures we use. The first is the distance between the actual (r_a,g_a) and estimated chromaticity of the illuminant. (r_e,g_e) as:

$$E_{i-dist} = \sqrt{(r_a - r_e)^2 + (g_a - g_e)^2} \qquad (1)$$

We also compute the root mean square (RMS) error over a set of N test images as:

$$RMS_{dist} = \frac{1}{N}\sqrt{\sum_{i=1}^{N} E_{i-dist}^{2}} \qquad (2)$$

The second error measure is the angular error between the chromaticity 3-vectors when the b-chromaticity component is included. Given r and g, $b = 1 - r - g$. Thus, we can view the real illumination and estimated illumination as two <r,g,b> vectors in 3D chromaticity space and calculate the angle between them. The angular error represented in degrees is:

$$E_{i-angular} = COS^{-1}[\frac{(r_a, g_a, b_a) \circ (r_e, g_e, b_e)}{\sqrt{r_a^2 + g_a^2 + b_a^2} \times \sqrt{r_e^2 + g_e^2 + b_e^2}}] \times \frac{2\pi}{360} \quad (3)$$

We also compute the RMS angular error over a set of images.

3.2 Synthetic Data Training, Real Data Testing

The first tests are based on training with synthesized image data constructed using the 102 illuminant spectra and 1995 reflectances described by Barnard [14] along with the sensor sensitivity functions of the calibrated SONY DXC-930 CCD[13]. Testing is based on Barnard's[15] 321 real images taken with the SONY DXC-930 of 30 scenes under 11 different light sources. These images are linear (a gamma of 1.0) with respect to scene intensity. This data is available on-line from the Simon Fraser University color database[24].

The number of distinct synthesized training 'scenes' was varied from 8 to 1024 in order to study the effect of training size on performance. Each synthetic scene was 'lit' by each of the 102 illuminants in turn to create 102 images of each scene. The synthesized camera RGB values, their corresponding chromaticities and the illuminant chromaticity are mapped to 2D and 3D binary vectors for input to SVR.

Table 2 shows that the parameters vary with the training set as expected. Although the basis function type was allowed to vary during the cross-validation, the RBF was eventually selected in all cases.

To test on real data, Barnard's calibrated 321 SONY images were first segmented and histogrammed according to the 'generic pre-processing' strategy[15]. Illumination estimation by SVR compares favorably to the methods Barnard tested [15] as shown below in Table 3. The RMS errors for Color By Correlation with Binary Histogram (CC01), Color By Correlation with Maximum

Likelihood (CCMAP), Color By Correlation with Mean Likelihood (CCMMSE), Color By Correlation (CCMLM) and the Neural Network(NN) are from Table II, page 992 of [15].

Training Set Size /102	Histogram Dimension	Kernel Selected	C	γ
8	2D	RBF	0.01	0.2
	3D	RBF	0.01	0.2
16	2D	RBF	1	0.1
	3D	RBF	1	0.05
32	2D	RBF	0.1	0.05
	3D	RBF	0.1	0.025
64	2D	RBF	1	0.05
	3D	RBF	0.1	0.1
128	2D	RBF	0.01	0.025
	3D	RBF	1	0.2
256	2D	RBF	0.01	0.1
	3D	RBF	0.1	0.05
512	2D	RBF	0.01	0.1
	3D	RBF	10	0.025
1024	2D	RBF	0.01	0.05
	3D	RBF	1	0.2

Table 2 Results of k-fold kernel and parameter selection as a function of the histogram type and the number of training set images.

Method	RMS Dist	RMS Angle
2D SVR.	0.080	10.1
3D SVR	0.067	8.1
CC01	0.081	10.9
CCMAP	0.071	9.9
CCMMSE	0.072	9.9
CCMLM	0.072	9.9
Neural Network	0.070	9.5

Table 3 Comparison of competing illumination estimation methods. All methods are trained on synthetic images constructed from the same reflectance and illuminant spectra and then tested on the same SONY DXC930 [15] camera images with identical pre-processing.

Figure 1 shows how the SVR performance initially improves as the size of the synthetic training set increases.

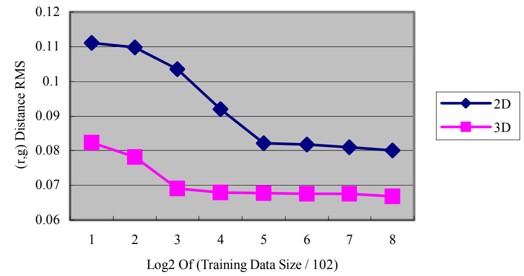

Figure 1 RMS error in illumination chromaticity as a function of increasing training set size.

3.3 Real Image Data Training, Real Data Testing

Training on synthetic image data is convenient because large training sets can be calculated from existing databases of illuminant and reflectance spectra. The disadvantage of synthetic data is that it requires an accurate model of the camera and imaging process. On the other hand, creating a training set of real images is difficult because for each image the scene illumination must be measured.

Our testing with real data is based on three image data sets. To begin, we train and test on Barnard's [15] set of 321 SONY images and find that training with real data is in fact better than training with synthetic data. Then on Cardei's[18] set of 900 images from assorted cameras we find that SVR performs better on this data set than the methods on which he reports. Finally, we train using the 11,346 image set that Ciurea et. al. [20] built using a digital video camera. This very large, real data training set improves overall performance.

The training images are pre-processed, segmented and histogrammed in the same way as described above for the test images. The SVR kernel and parameters were selected based on the '1024' row of Table 2; namely, for 3-D, radial basis function kernel with shape parameter

γ= 0.2 and penalty value C = 1, while in 2-D, these two parameters are set to 0.05 and 0.01 respectively.

Since it would be biased to train and test on the same set of images, we evaluate the illumination error using leave-one-out cross validation procedure[26]. In the leave-one-out procedure, one image is selected for testing and the remaining 320 images are used for training. This is repeated 321 times, leaving a different image out of the training set each time, and the RMS of the 321 resulting illumination estimation errors is calculated. The errors are significantly lower than those obtained with synthetic training data.

Hist. Type	Max Angle	RMS Angle	Max Dist ($\times 10^2$)	RMS Dist ($\times 10^2$)
2D	22.99	10.06	16.41	7.5
3D	24.66	8.069	16.03	6.3

Table 4 Leave-one-out cross validation evaluation of SVR based on real data training and real data testing on 321 SONY images reported in terms of the RMS chromaticity angular and distance error measures.

We next consider Cardei's[18] set of 900 uncalibrated images taken using a variety of different digital cameras from Kodak, Olympus, HP, Fuji Polaroid, PDC, Canon, Ricoh and Toshiba. A gray card was placed in each scene and its RGB value is used as the measure of the scene illumination.

As for the previous image set, histogram subsampling was used to create a training set of 45,000 histograms. The SVR was based on a polynomial kernel function of degree 3 and 0.1 penalty. Leave-one-out SVR performance is compared in Table 5 with the performance reported by Cardei[18] for Color by Correlation and the Neural Network.

Method	Type	Mean($\times 10^2$)	RMS($\times 10^2$)
SVR	2D	2.40	3.27
	3D	2.09	2.94
C-by-C	2D	2.92	3.89
NN	2D	2.26	2.76

Table 5 Comparison of SVR performance to that of Color by Correlation and the Neural Network using leave-one-out cross validation on 900 uncalibrated images. The entries for C-by-C and NN are from Table 7 page 2385[18]

Since a training set of 900 histograms is not very large, we would like to have used the histogram sampling strategy proposed by Cardei[18] in the context of neural network training to increase the training set size. He observed that each a histogram in the original training set could be used to generate many new training histograms by random sampling of its non-zero bins. Each sampling yields a new histogram of an 'image' with the same illuminant chromaticity as the original. The number of possible subsamplings is large, which makes it possible to build a large training set based on real data, but extracted from a small number of images.

We have used this method to construct a set of 45,000 training histograms from the original 900 and used it for SVR. Unfortunately, the training for this sized set takes several hours. Normally, lengthy training time would not matter since it is only done once; however, leave-1-out testing requires 900 separate trainings. As a result, we have not been able to do a leave-1-out based on the enhanced training set. Instead, the leave-1-out results in Table 5 are based on the raw training set of 900 histograms. This puts the SVR method at a disadvantage in comparison to the neural network in terms of leave-1-out error, since the network was trained on an enhanced training set.

Our final test with real data is based on the 11,346 real images extracted from over 2 hours of digital video acquired with a SONY VX-2000. Ciurea et. al.[20] built the database by partially automating the measurement of the illumination's RGB. Their setup consisted of a matte gray ball connected by a rod attached to the camera. In this way, the gray ball was made to appear at a fixed location at the edge of each video frame. The ball's pixels were thus easy to locate in each frame, and hence the chromaticity of the dominant illumination hitting the ball was easily measured as the average chromaticity of the pixels located in the ball's brightest region. The images include a wide variety of indoor and outdoor scenes including many with people in them.

Based on some initial experimentation, for all subsequent tests with the Ciurea database, SVR was trained using the RBF kernel function with 0.1 as the penalty parameter and 0.025 as the width parameter.

The size of the database means that leave-one-out validation is not feasible, although leave-N-out for a reasonable choice of N would be possible. In any case, it would not necessarily be a fair test because of the inherent regularities in the database. Since the database was constructed from a 3-frame-per-second sampling of video clips, neighboring images in the database tend to be similar. Hence, to ensure that SVR that the training and testing sets would be truly distinct we partitioned the database into two sets in two different ways.

The first partitioning is based on geographical location. We take as the test set the 541 indoor and outdoor images taken exclusively in Scottsdale Arizona. The training set is the 10,805 images in the remainder of the database, none of which is from Scottsdale. The estimation errors are listed in Table 6.

The second partitioning divides the entire database into two parts of similar size. Subset A includes 5343 images, and subset B includes 6003. Subset A contains images from Apache Trail, Burnaby Mountain, Camelback Mountain, CIC 2002 and Deer Lake. Subset B contains images from different locations: False Creek, Granville Island Market, Marine, Metrotown shopping center, Scottsdale, Simon Fraser University and Whiteclyff Park. We then used A for training and B testing and vice versa. The results are again listed in Table 6.

Training	Testing	Angular		Distance $(\times 10^2)$	
		Max	RMS	Max	RMS
All-but-Scottsdale	Scottsdale	11.6	3.4	7.05	2.263
Subset A	Subset B	14.9	3.7	12.24	2.625
Subset B	Subset A	16.8	3.6	15.00	2.611

Table 6 SVR (3D) illumination estimation errors for different training and test sets

4. Conclusion

Many previous methods of estimating the chromaticity of the scene illumination have been based in one way or another on statistics of the RGB colors arising in an image, independent of their spatial location or frequency of occurrence in the image. Support vector regression is a relatively new tool developed primarily for machine learning that can be applied in a similar way. We have tried it here, with good results, to the problem of learning the association between color histograms and illumination chromaticity. Under almost the same experimentation conditions as those used by Barnard [14,15] in rigorous testing of the neural network and color by correlation methods, SVR performance is as good or better.

Using Cuirea's[20] large image database, SVR performance is shown, furthermore, to improve as the training set size is increased.

Acknowledgement

Funding was provided by the Natural Sciences and Research Council of Canada.

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To appear: IS&T/SID Twelfth Color Imaging Conference, Nov 2004