Colour Camera Characterization of a Computer Vision System Using LS-SVM Regression

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Abstract

The aim of this work is to evaluate the potential of least squares support vector machine (LS-SVM) regression to solve the colour camera characterization problem in computer vision systems (CVS). A laboratory CVS, based on colour digital camera (CDC), was implemented and three LS-SVM models were trained and validated, one for each output variables (L*, a*, and b*) required by this problem, using the RGB signals generated by the CDC as input variables to these models. The colour target-based approach was used to camera characterization and a standard reference target of 242 colour samples was acquired using the CVS and a spectrophotometer. This data set was split in two sets of equal sizes, for training and validating the LS-SVM models. An effective two stage grid search process on the parameters space was performed in MATLAB to tune the regularization parameters γ and the kernel parameters σ^2 of the three LS-SVM models. The LS-SVM models developed in this research allowed to obtain high correlations between L*a*b* data acquired using the spectrophotometer and the corresponding data obtained by transformation of the RGB data acquired by the CVS. In particular, for the validation set, R^2 values equal to 0.999 for all the three chromatic parameters were obtained. The RMSE values were 0.32, 0.32, and 0.27 for L*, a*, and b* respectively, and the average of colour differences ΔE_{ab} was 0.82±0.54 units. Thus, LS-SVM regression seems to be an useful tool to solve the camera characterization problem in the CVS.

Keywords: food, CIELAB colour space, colour measurements

Introduction

In recent years, computer vision systems (CVS) based on colour digital cameras (CDC) have been shown to be a good tool to quantify easily and quickly the colour of any food, using equipment that is readily available at reasonable cost (Mendoza et al., 2006). However, there are some issues that are important to consider for colour measurements, especially where colorimetric precision is important. Specifically, the RGB signals generated by a colour digital camera are device-dependent, and these colour signals are not colorimetric. Therefore, in order to objectively measure colour and detect colour features from food products with accuracy, a colorimetric transformation that defines a mapping between the device-dependent RGB signals and a device-independent colour space, such as the L*a*b* (or CIELAB) colour space, is an essential step in the implementation of any computer vision system (Valous et al., 2009). The transform derivation process is referred as device or camera characterization.

Recently, León et al. (2006) used a multilayer feed-forward neural network (MFNN) with back-propagation to predicts the L*a*b* values from the RGB values generated by a CDC with good results. However, MFNN suffer critical drawbacks including learning stopping at local minima, over-fitting, and selection type depending excessively on experience (Wang et al., 2009).

Support vector machines (SVM), a new learning algorithm based on the statistical learning theory, can model linear and nonlinear mappings without these disadvantages (Vapnik, 2000). Unlike the classical neural networks approach the SVM formulation of the learning problem leads to quadratic programming (QP) with linear constraint. However, the size of matrix involved in the QP problem is directly proportional to the number of training points. Hence, to reduce the complexity of optimization processes, a modified version, called least squares support vector machines (LS-SVM), have proposed (Sukens, Vandewalle, 1999). LS-SVM encompass similar advantage as SVM, but its additional advantage is that it requires solving a set of only linear equations (linear programming) that is much easier and computational more simple.

In this study, after the implementation of a laboratory CVS based on a CDC, the objective is to evaluate the potential of LS-SVM regression to solve the camera characterization problem. For this purpose, three LS-SVM models were trained and validated, one for each output variables (L*, a*, and b*), using the RGB signals generated by the CDC as input variables to these models.

Materials and method

Computer vision system

The implemented CVS has three main components: an illumination source, a colour digital camera (CDC) and an image processing software. The light source consisted of four fluorescent 15 W lamps (Neon OSRAM TLD65-15W, Germany) with a colour temperature of 6500 K, arranged in a square 0.68 m above the sample. To ensure uniform illumination, the four lamps were connected to electronic ballasts and covered with plastic light diffusers.

The colour digital camera was a Canon EOS 400D (Canon, USA) located vertically over the matte black background at a distance of 0.45 m. The camera was connected to the USB port of a PC (Asus, Taiwan) with a Remote Capture Software (version 2.7.2, Canon, USA) to visualize and receive the digitized images directly from the computer.

As standard setting conditions, the viewing/illuminating geometry was about 0/45. Moreover, the sample illuminators and the camera were placed inside a wooden box with black internal surfaces to exclude external light and reflection. A standard white card (X-rite ColourChecher® White balance Card, USA) was used to set manually the white balance of the CDC. Spatial correction was performed in order to minimise the effect of any lack of spatial uniformity in the intensity of the illumination or of the sensitivity of the CDC. The spatial correction method was based on work by Westland et al. (2004). Manual exposure mode and both lens aperture (f = 6.3) and exposure time (1/4) where fixed during the period of image acquisition. In this experimentation, all the image were acquired with resolution of 3888×2592 pixels (corresponding to a field of view of 32.4×21.6 cm^2), and stored in TIFF format. The image processing software was performed using the MATLAB v7.0 (The MathWorks, USA) image processing toolbox.

Reference target

A practical method to camera characterization, referred as to colour target-based approach, was used. The basic idea of colour target-based characterization is to use a reference target that contains a certain number of colour samples of known CIE (Commission Internationale de l'Eclairage) values which are contrasted with the output average signals captured in standard illumination conditions by an imaging sensor (Hong et al., 2001). In this study, the reference target was the Kodak Q-60R2 reflection chart on Kodak Professional paper (Eastman Kodak Company, USA). This chart is manufactured in accordance with ANSI IT8.7/2- 1993 and ISO 12641 standards and it provides 264 colour samples, including a 22 step neutral scale, which cover a large gamut in the CIELAB colour space.

Colour measurements

For colour measurements, the reference target, located in the centre of the camera field view, was imaged to obtain for each colour samples the camera RGB values in the theoretical range 0-255. The camera RGB values for each colour sample were measured using a MATLAB program which computes the average RGB values of 80% of the pixels in the samples, excluding the boundary pixels. Then, the L*a*b* values of each colour samples (D65 illuminant and 2° observer) were measured using a spectrophotometer (KONICA MINOLTA SENSING Inc., CM-2600d, Japan). This instrument measure spectral reflectance from 380-700 nm in 20 nm intervals from a circular area of 3 mm diameter using a silicon photodiode and a diffraction grating device. The specular component included (SCI) mode was set and the white reference was the white calibration plate of the spectrophotometer (L*=99.30, a*=-0.09, b*=-0.17). In total, a data set of 264 RGB measurements and their corresponding L*a*b* measurements were obtained from the CVS and the spectrophotometer respectively. This data set was split in two sets of equal sizes, for training and validating the LS-SVM models.

LS-SVM models

The LS-SVM regression can be expressed as (Liu et al., 2009):

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b$$

where $K(x, x_k)$ is the kernel function, α_k is the Lagrange multiplier called support value, b is the bias term. Currently, there is no systematic methodology for selection of kernel function. However, compared with other feasible kernel functions, radial basis function (RBF) as a non linear function is a more compacted supported function kernel and able to reduce the computational complexity of the training procedure and give good performance under general smoothness assumptions (Liu et al., 2009). Thus, RBF kernel was adopted as the kernel function of the LS-SVM models in this study. It can be expressed as follows:

$$K(x, x_k) = \exp\left(-\left\|x - x_k\right\|^2\right) / \left(2\sigma^2\right)$$

whereas σ^2, the squared variance of the Gaussian function, is the kernel parameter. To achieve high level of performance with LS-SVM models, two parameters have to be tuned, the regularization parameter γ and the kernel parameter σ^2. Choosing an appropriate regularization parameter and the kernel parameter is an important task and mostly depend on the realized application type. The regularization parameter γ determines the trade-off between structural risk minimization principle (SRM) and empirical risk minimization (ERM), and is important to improve the generalization performance of LS-SWM model. The kernel parameter σ^2 controls the value of function regression error, and influences directly the number of initial eigenvalues/eigevectors. Small values of σ^2 yield a large number of regressors and eventually it can lead to over-fitting. On the contrary, a large value of σ^2 can lead to a reduced number of regressors, making the model simpler, but eventually not so accurate.

Therefore, an efficient search strategy is needed to tune γ and σ^2. In this study, we employ a two stage grid search process on the parameters space. For this purpose, a coarse grid search process is firstly employed to narrow down the search region of the parameters space. In coarse search process, the incremental steps of grid are considerable big to obtain an enough search space. For each grid points, the mean square error (MSE) from L-fold cross validation is determined and minimum MSE interval is detected. In L-fold cross-validation, the trained data is randomly split into L roughly equal subsets. An LS-SVM model is trained using (L-1) of those subsets and validated on the subset left out. This procedure is repeated L times with each of the L subsets used as the validation subset in turn. Averaging the validation errors over the L trials gives a prediction of the generalization error. Then the search is tuned to a finer search in the region where the predicted MSE value from the L-fold cross-validation is the lowest in the coarse search. The minimum MSE value indicates the optimum LS-SVM parameters. All the calculations were performed using MATLAB v7.0 (The MathWorks, USA). The free LS-SVM toolbox (LS-SVM v1.5, Sukens, Leuven, Belgium) was applied with MATLAB to develop the LS-SVM models.

Performance evaluation

The statistics used for estimating the performance of the regression models developed by LS-SVM included determination coefficients for the validation set (R^2) and root mean square error for the validation set (RMSE). Moreover the average and standard deviation of colour differences between the L*a*b* values predicted from the measured RGB values and the L*a*b* values measured with the spectrophotometer for the validation set were computed. The colour differences ΔE_{ab} were computed by the following equation:

$$\Delta E_{ab} = \sqrt{\left(\Delta L^*\right)^2 + \left(\Delta a^*\right)^2 + \left(\Delta b^*\right)^2}$$

Results

In this study the kernel parameters were optimised for each output variables with values of γ in the range of 2^6-2^{13} and σ^2 in the range of 2^2-2^6 with adequate increments. These ranges were chosen from previous studies where the magnitude of parameters to be optimised was established. For each combination of γ and σ^2 parameters, the mean square error of 5-fold cross validation was calculated and the optimum parameters were selected when produced smaller MSE.

The optimising process for L*, a*, and b* was shown in Fig.1, 2, and 3 respectively. The grid '.' in the first step is 10×10, and the searching step in the first step is large. The optimum search area is determined by error contour line. The grid '×' in the second step is 10×10, and the searching step in the second step is smaller. The optimal search area is determined based on the first step. The optimal pair of (γ, σ^2) was found at the value of γ = 6098.31 and σ^2= 12.05 for L*, at the value of γ = 15420.61 and σ^2= 7.59 for a*, and at the value of γ = 203377.21 and σ^2= 16.83 for b*.

The high R^2 values, equal to 0.999 for all the three chromatic parameters, with low RMSE values of 0.32, 0.32, and 0.27 for L*, a*, and b* respectively, showed that LS-SVM has strong ability for regression analysis (Fig.4, 5 and 6). Moreover, the low average ΔE_{ab} of 0.82±0.54 units showed that the LS-SVM approach provides consistent and accurate results in camera characterization.

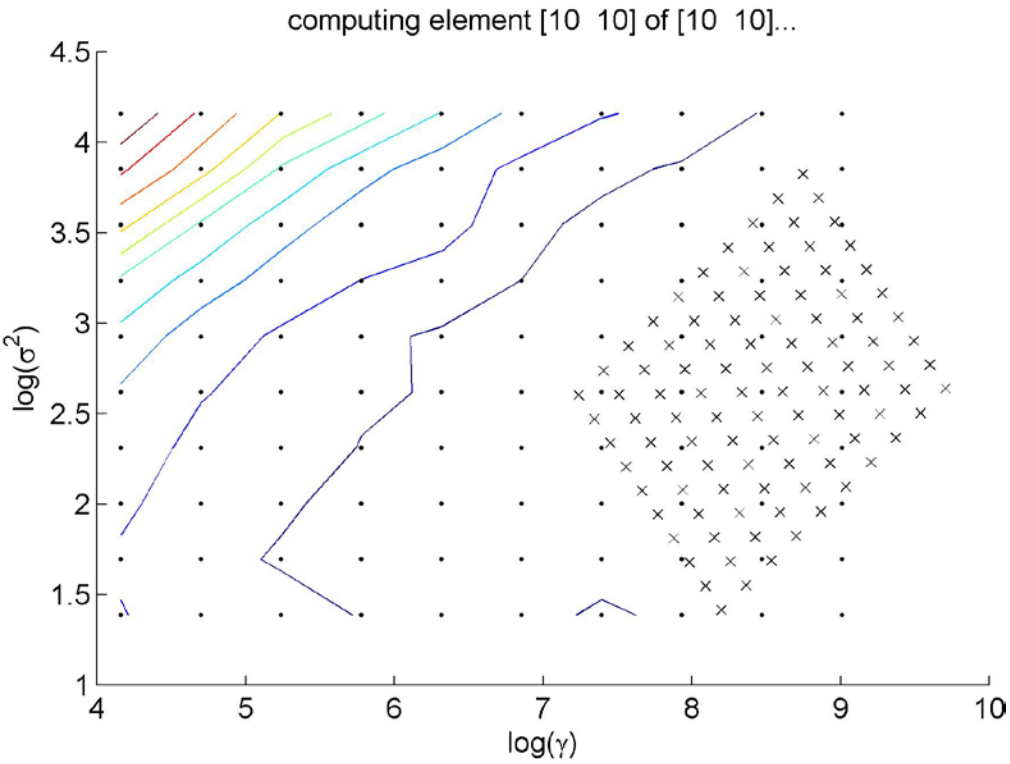

Figure 1. Grid search on γ and σ^2 for the prediction of L* values.

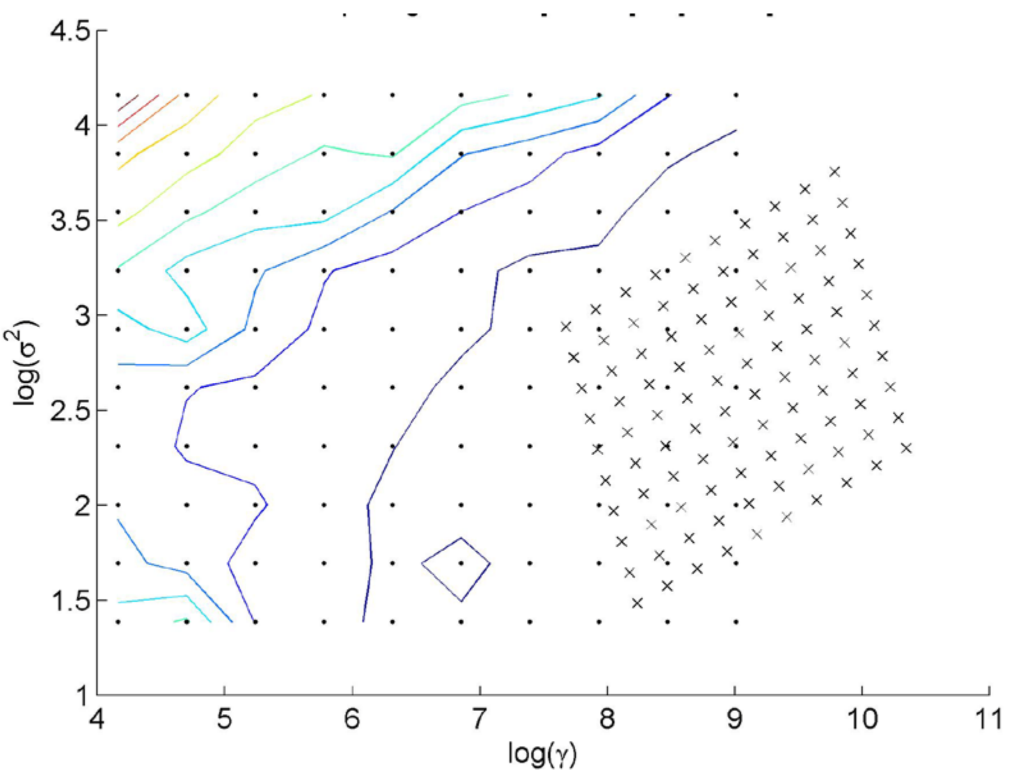

Figure 2. Grid search on γ and σ^2 for the prediction of a*values.

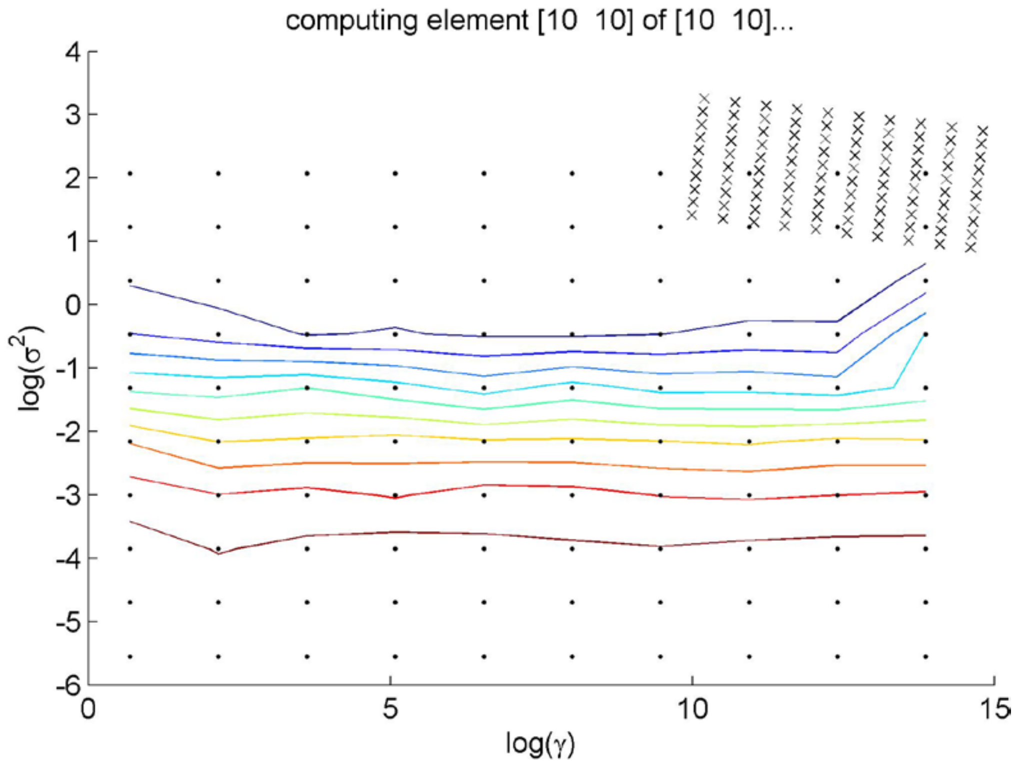

Figure 3. Grid search on γ and σ^2 for the prediction of b* values.

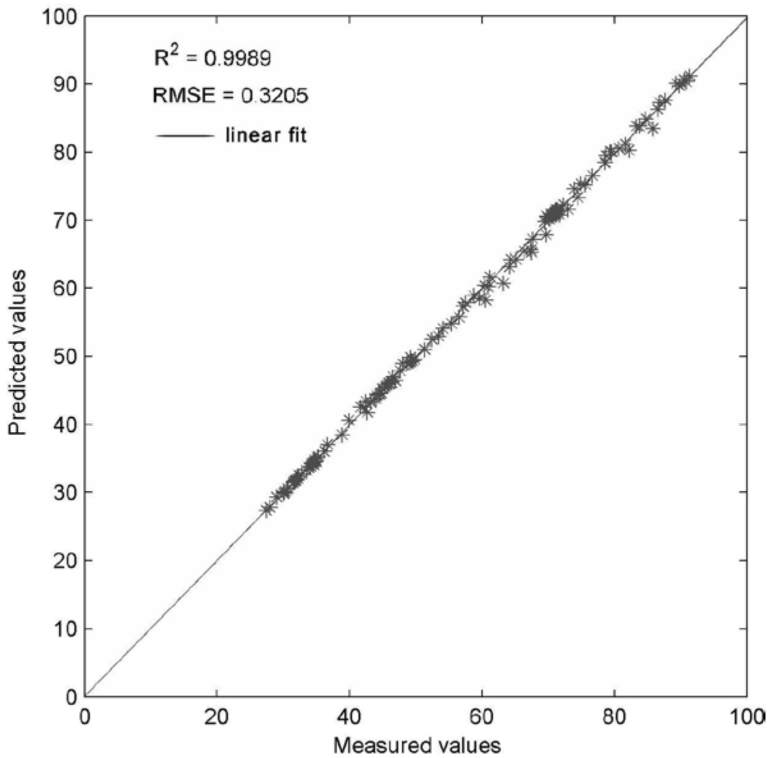

Figure 4. LS-SVM predicted vs. measured values of L* for the validation set.

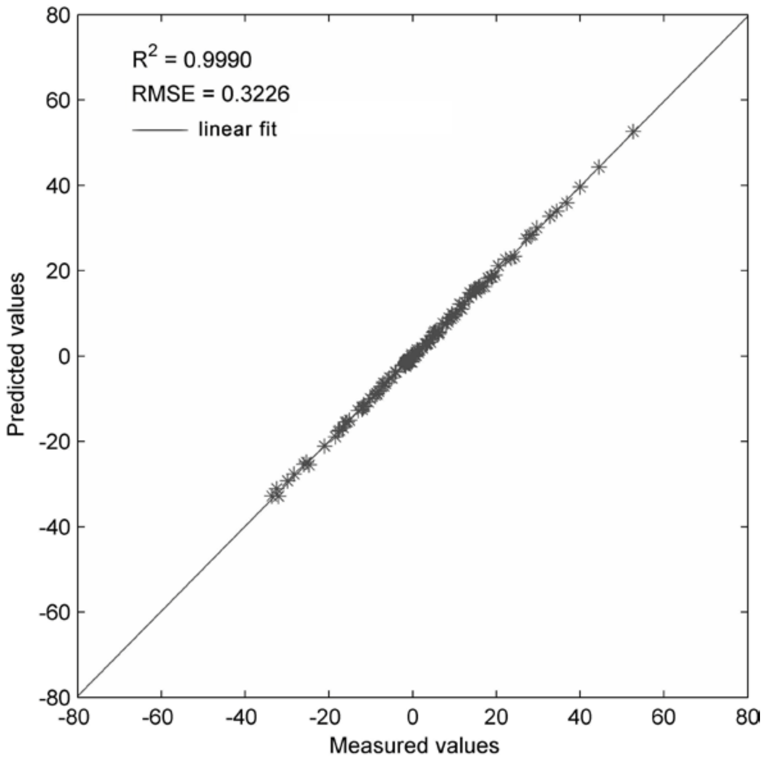

Figure 5. LS-SVM predicted vs. measured values of a*for the validation set.

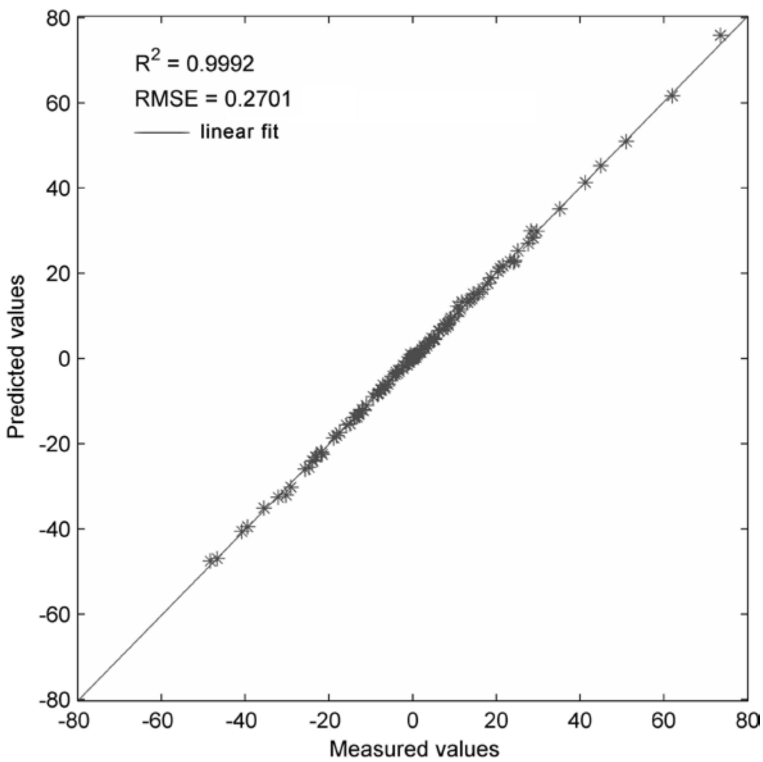

Figure 6. LS-SVM predicted vs. measured values of b* for the validation set.

Conclusions

The objective was to evaluate the potential of LS-SVM regression to solve the colour camera characterization problem in CVS. The results of this study shown that this approach produced high precision and accuracy in predicting the L*a*b*values from the RGB values generated by a CDC. Therefore, LS-SVM regression seems to be an useful tool to solve the camera characterization problem in the CVS and to use these systems for high-resolution L*a*b* colour measurements.

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