Single and Multiple Illuminant Estimation Using Convolutional Neural Networks

Simone Bianco, Claudio Cusano, and Raimondo Schettini

Abstract—In this paper we present a method for the estimation of the color of the illuminant in RAW images. The method includes a Convolutional Neural Network that has been specially designed to produce multiple local estimates. A multiple illuminant detector determines whether or not the local outputs of the network must be aggregated into a single estimate. We evaluated our method on standard datasets with single and multiple illuminants, obtaining lower estimation errors with respect to those obtained by other general purpose methods in the state of the art.

Index Terms—Color constancy, illuminant estimation, convolutional neural networks.

1 INTRODUCTION

Many computer vision problems in both still images and videos can make use of color constancy processing as a pre-processing step to make sure that the recorded color of the objects in the scene does not change under different illumination conditions. The observed color of the objects in the scene depends on the intrinsic color of the object (i.e. the surface spectral reflectance), on the illumination, and on their relative positions.

In general there are two methodologies to obtain reliable color description from image data: computational color constancy and color invariance [1]. Computational color constancy is a two-stage operation: the former is specialized on estimating the color of the scene from the image data, the latter corrects the image on the basis of this estimate to generate a new image of the scene as if it was taken under a reference light source. Color invariance methods instead represent images by features which remain unchanged with respect to specific imaging condition.

In this work we focus on illuminant estimation. Our method is based on supervised learning and includes a Convolutional Neural Network (CNN) specially designed for the local estimation of the illuminant color. Recently, deep neural networks have gained the attention of numerous researchers outperforming state-of-the-art approaches on various computer vision tasks [2], [3]. One of CNNs advantages is that it can take raw images as input and incorporate feature learning into the training process. With a deep structure, CNN can learn complicated mappings while requiring minimal domain knowledge. In our method the outputs of the CNN provide a spatially varying estimate of the illuminant that can optionally be aggregated into a single global estimate by a local-to-global regressor based on non-linear Support Vector Regression (SVR). To make a final decision between the local and the global optionaly be aggregated into a single global estimate by a local-to-global regressor based on non-linear Support Vector Regression (SVR). To make a final decision between the local and the global operation: the former is specialized on estimating the color of the scene, the latter corrects the image on the basis of this estimate to generate a new image of the scene as if it was taken under a reference light source. Color invariance methods instead represent images by features which remain unchanged with respect to specific imaging condition.

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Preliminary findings reported in this paper appeared in [4], where we presented the basic architecture of the CNN and where we evaluated its performance in the single illuminant scenario. This paper extends the previous one in several ways:

- since one of the assumptions that is often violated in color constancy is the presence of a uniform illumination in the scene, we have extended the applicability of the proposed algorithm to the case of non-uniform illumination. The method is adaptive, being able to distinguish and process in different ways images of scenes taken under a uniform and those acquired under non-uniform illumination.
- In the case of uniform illumination, the multiple local estimates must be aggregated in a single global estimate. To do so we designed a new local-to-global regression method that replaces the per-channel median operator used in [4] with a non-linear mapping based on a RBF kernel over local statistics of the CNN estimates. The parameters of the mapping are obtained by applying a regression procedure that minimizes the median angular error on the training set.
- Preliminary results reported in [4] included only images having a single color target in the scene, thus allowing only the comparisons with global illuminant estimation methods. We present a much more detailed experimental evaluation using both a multiple illuminant synthetic dataset and a dataset of RAW images containing at least two known color target for benchmarking.

We show experimentally that the proposed method advances the state-of-the-art on standard datasets of RAW images for both the cases of single and multiple illuminants. In addition to the superior overall performance, we also show quantitative and qualitative results that demonstrate its accuracy in estimating single and multiple illuminants.

The rest of the paper is organized as follows: Section 2 formalizes the problem of illuminant estimation and reviews the main approaches in the state of the art. Section 3 illustrates in detail the proposed method. Section 4 describes the data and the algorithms used in the experimentation, while Section 5 discusses the results obtained. Finally, Section 6 summarizes the findings.

- S. Bianco and R. Schettini are with the Department of Informatics, Systems and Communication, University of Milano Bicocca, Italy. E-mail: {simone.bianco, raimondo.schettini}@disco.unimib.it
- C. Cusano is with the Department of Electrical, Computer and Biomedical Engineering of the University of Pavia, Italy. E-mail: claudio.cusano@unipv.it

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of our experimentation and proposes new directions for future research in this field.

2 Problem formulation and related works

The image values for a Lambertian surface located at the pixel with coordinates \((x, y)\) can be seen as a function \(\rho(x, y)\), mainly dependent on three physical factors: the illuminant spectral power distribution \(I(x, y, \lambda)\), the surface spectral reflectance \(S(x, y, \lambda)\) and the sensor spectral sensitivities \(C(\lambda)\). Using this notation \(\rho(x, y)\) can be expressed as

\[
\rho(x, y) = \int I(x, y, \lambda)S(x, y, \lambda)C(\lambda)d\lambda,
\]

where \(\lambda\) is the wavelength, \(\rho\) and \(C(\lambda)\) are three-component vectors and the integration is performed over the visible spectrum. The goal of color constancy is to estimate the color \(I(x, y)\) of the scene illuminant, i.e. the projection of \(I(x, y, \lambda)\) on the sensor spectral sensitivities \(C(\lambda)\):

\[
I(x, y) = \int I(x, y, \lambda)C(\lambda)d\lambda.
\]

Usually the illuminant color is estimated up to a scale factor as it is more important to estimate the chromaticity of the scene illuminant than its overall intensity \([5]\). Thus, the error metric usually considered, as suggested by Hordley and Finlayson \([5]\), is the angle between the RGB triplet of estimated illuminant \((I(x, y))\) and the RGB triplet of the measured ground truth illuminant \((\hat{I}(x, y))\):

\[
e_{\text{ANG}}(x, y) = \arccos \left( \frac{\hat{I}(x, y)\cdot I(x, y)}{\|\hat{I}(x, y)\|\|I(x, y)\|} \right).
\]

Since the only information available are the sensor responses \(\rho\) across the image, color constancy is an under-determined problem \([6]\) and thus further assumptions and/or knowledge are needed to solve it. Several computational color constancy algorithms have been proposed, each based on different assumptions. The most common assumption is that the color of the light source is uniform \([5]\) — generated by setting \((n, p, \sigma) = (0, 1, 0)\) — is based on the assumption that the average color in the image is gray and that the illuminant color can be estimated as the shift from gray of the averages in the image color channels; the White Patch algorithm \([9]\) — generated by setting \((n, p, \sigma) = (0, \infty, 0)\) — is based on the assumption that the maximum response is caused by a perfect reflectance: a surface with perfect reflectance properties will reflect the full range of light that it captures and consequently, the color of this perfect reflectance is exactly the color of the light source. In practice, the assumption of perfect reflectance is alleviated by considering the color channels separately, resulting in the maxRGB algorithm. The Gray Edge algorithm \([7]\) — generated by setting for example \((n, p, \sigma) = (1, 0, 0)\) — is based on the assumption that the average color of the edges is gray and that the illuminant color can be estimated as the shift from gray of the averages of the edges in the image color channels.

The Gamut Mapping method does not follows \([4]\) and assumes that, for a given illuminant, one observes only a limited gamut of colors \([10]\). It has a preliminary phase in which a canonical illuminant is chosen and the canonical gamut is computed observing as many surfaces under the canonical illuminant as possible. Given an input image with an unknown illuminant, its gamut is computed and the illuminant is estimated as the mapping that can be applied to the gamut of the input image, resulting in a gamut that lies completely within the canonical gamut and produces the most colorful scene. If the spectral sensitivity functions of the camera are known, the Color by Correlation approach could be also used \([11]\).

2.2 Learning-based algorithms

The learning-based illuminant estimation algorithms, that estimate the scene illuminant using a model that is learned on training data, can be subdivided into two main subcategories: probabilistic methods and fusion/selection based methods.

One of the first learning-based algorithms is \([12]\), where a Neural Network was trained on binarized chromaticity histograms: input neurons are set either to zero indicating that a chromaticity is not present in the image, or to one indicating that it is present. Bayesian approaches \([13]\) model the variability of reflectance and of illuminant as random variables, and then estimate illuminant from the posterior distribution conditioned on image intensity data.

Given a set illuminant estimation algorithms, in \([14]\) an image classifier is trained to classify the images as indoor and outdoor, and different experimental frameworks are proposed to exploit this information in order to select the best performing algorithm for each class. In \([15]\) it has been shown how intrinsic, low level properties of the images can be used to drive the selection of the best algorithm (or the best combination of algorithms) for a given image. The algorithm selection and combination is made by a decision forest composed of several trees on the basis of the values of a set of heterogeneous features. In \([16]\) the Weibull parametrization has been used to train a maximum likelihood classifier based on mixture of Gaussians to select the best performing illuminant estimation method for a certain image.

In \([17]\) a statistical model for the spatial distribution of colors in white balanced images is developed, and then used to infer illumination parameters as those being most likely under their
model. High level visual information has been used to select the best illuminant out of a set of possible illuminants [18]. This is achieved by restating the problem in terms of semantic interpretability of the image. Several illuminant estimation methods are applied to generate a set of illuminant hypotheses. For each illuminant hypothesis, they correct the image, evaluate the likelihood of the semantic content of the corrected image, and select the most likely illuminant color. In [19], [20] the use of automatically detected objects having intrinsic color is investigated. In particular, they show how illuminant estimation can be performed exploiting the color statistics extracted from the faces automatically detected in the image. When no faces are detected in the image, any other algorithm in the state-of-the-art can be used. In [21], [22] the surfaces in the image are exploited and the illuminant estimation problem is addresses by unsupervised learning of an appropriate model for each training surface in training images. The model for each surface is defined using both texture features and color features. In a test image the nearest neighbor model is found for each surface and its illumination is estimated by comparing the statistics of pixels belonging to nearest neighbor surfaces and the target surface. The final illumination estimation results from combining these estimated illuminants over surfaces to generate a unique estimate.

In [23] it was showed how simple moment based algorithms can, with the addition of a simple correction step deliver much improved illuminant estimation performance. The approach employs first, second and higher moments of color and color derivatives and linearly corrects them to give an illuminant estimate.

In [24] four simple image features are used for training an ensemble of decision trees. Each of these trees is computed from samples in the training data that are biased to a local region in chromaticity space of the ground truth illuminations. The final estimate is made by finding consensus among the different features trees estimations.

In [4] two different approaches using CNNs were investigated: in the first one an ad-hoc CNN for the color constancy problem was trained; in the second one a pre-trained one was used by extracting a 4096-dimensional feature vector from each image using the Caffe [25] implementation of the deep CNN described by Krizhevsky et al. [3]. Features were computed by forward propagation of a mean-subtracted $227 \times 227$ RGB RAW image through five convolutional layers and two fully connected layers. More details about the network architecture can be found in [3], [25]. The CNN was discriminatively trained on a large dataset (ILSVRC 2012) with image-level annotations to classify images into 1000 different classes. Features are obtained by extracting activation values of the last hidden layer. The extracted features were then used as input to a linear Support Vector Regression (SVR) [26] to estimate the illuminant color for each image.

In [27] illuminant color is predicted from luminance-to-chromaticity based on a conditional likelihood function for the true chromaticity of a pixel, given its luminance. Two approaches have been proposed to learn this function. The first was based purely on empirical pixel statistics, while the second was based on maximizing accuracy of the final illuminant estimate.

2.3 Multiple illuminant estimation

The great majority of state-of-the-art illuminant estimation methods assumes that a uniform illumination is present in the scene. This assumption is often violated in real-world images. It is not trivial to extend the existing illuminant estimation algorithms to work locally instead of globally, since the spatial support on which they accumulate the statistics is reduced, and the final local estimate could be biased by local image properties. One of the first methods following this strategy is Retinex [9], which is able to deal with non-uniform illumination assuming that an abrupt change in chromaticity is caused by a change in reflectance properties. This implies that the illuminant smoothly varies across the image and does not change between adjacent or nearby locations. Ebner [28] proposed a method that assumes that the illuminant transition is smooth. The method uses the local space average color for local estimation of the illuminant by convolving the image with a Gaussian kernel function. Bleier et al. [29] investigated whether existing color constancy methods, originally developed assuming uniform illumination, can be adapted to local illuminant color estimation using image sub-regions. Multiple independent estimations are then combined through regression to obtain a more robust final estimate. Gijsenij et al. [30] proposed a method that makes use of local image patches, which can be selected by any sampling method. After sampling of the patches, illuminant estimation techniques are applied to obtain local illuminant estimates, and these estimates are combined into more robust estimations, since it is assumed that the number of different lights is less than the number of patches. This combination of local estimates is done with two different approaches: clustering if the number of lights is known, segmentation otherwise. Recently Bianco and Schettini [20], and Jozef and Drew [22] respectively extended the face-based and exemplar-based color constancy algorithms to deal with multiple illuminations. A different class of algorithms is based on user guidance to deal with the case of two [31] and multiple lights [32].

3 THE PROPOSED APPROACH

In the last years deep learning techniques allowed to obtain significant improvements in the solution of several computer vision problems. Their success often depends on the availability of a large amount of annotated training data. Compared to other image-related problems, in illuminant estimation annotated data is scarce. Therefore, the straightforward procedure of learning the most probable illuminant color directly from the image pixels needs some major adjustments.

We propose a three-stage method: the first stage is patch based, that is, a CNN is trained to predict the illuminant color from a small square portion of the input image. A large training set of patches can be obtained even from a relatively small data set, making it possible the use of deep learning techniques. This first stage allows to obtain multiple local estimates of the illuminant across the input image.

The second stage determines whether or not there are multiple illuminants in the scene. This decision is taken on the basis of a statistical analysis of the local estimates produced by the first stage. When multiple illuminants are detected, the local estimates can be directly used as the final output of the whole method.

The optional third stage is applied when the second one determines that the scene has been taken under a single illuminant. In this case it is better to aggregate the noisy local estimates into a single prediction. For this purpose, in our previous work we experimented with the mean and the per-channel median operators. In this work we propose a local-to-global aggregation procedure based on supervised learning. More in detail, statistical
features are extracted from the local estimates, and then fed to a non-linear mapping whose output is the final global estimate of the color of the illuminant. Differently from the first stage, this stage is image based. Therefore, its complexity is limited by the small number of annotated images. For this reason, instead of using a deep learning approach, we adopted a “shallow” non-linear regression scheme. Figure 1 shows a schematic view of the proposed method.

3.1 CNN architecture

In the first stage a convolutional neural network produces local estimates of the illuminant. The network, described in greater detail in [4], takes as input non-overlapping patches that have been previously subjected to a stretching of the histogram so that the output estimate is invariant with respect to the local contrast. The network has been designed taking inspiration from LeNet [33] since its input was of similar size. After a large number of experiments in which we adjusted the architecture of the net we selected the following sequence of layers (see also Figure 2 for a graphical representation):

- input RGB patches of size $32 \times 32 \times 3$;
- a bank of 240 convolutional $1 \times 1 \times 3$ filters producing an output of size $32 \times 32 \times 240$;
- downsampling via an $8 \times 8$ max pooling layer to a size of $4 \times 4 \times 240$, followed;
- reshaping of the result of pooling into a 3840-dimensional vector;
- a linear $3840 \times 40$ layer producing a 40-dimensional feature vector;
- a ReLU activation function;
- a linear $40 \times 3$ layer producing the output RGB estimate.

Taking into account all the linear coefficients and the biases, the network include a total of 154,723 parameters that have been learned by applying the standard back propagation algorithm to minimize the cosine loss without any improvement). The size of the network is limited, and any attempt to include additional layers was not successful. Beside its size, compared to the networks used for scene and object recognition we notice two major differences: (i) $1 \times 1$ convolutional filters that basically perform punctual transformations of the color space, and (ii) the large $8 \times 8$ pooling. These two elements both suggest that the local spatial structure is mostly ignored by the network. This fact can be explained by considering that with respect to object/scene recognition, illuminant estimation is a dual problem: instead of trying to identify the content of the image regardless the illuminant, here we need to estimate the illuminant regardless the content of the image. From the color constancy point of view, these choices confirm the finding of Cheng et al. [34], where they showed that spatial information does not provide any additional information that cannot be obtained directly from the color distributions.

3.2 Detection of multiple illuminants

Since our CNN is applied to each patch independently, it can be easily used to predict local illuminants. However, local estimates tend to be noisy and sometimes (when there is a single illuminant, or when the color of all the light sources is very similar) it is better to replace them with a single global estimate. What we need is an automatic rule to switch between the two modalities. In order to decide if the image contains single or multiple illuminants, the per patch illuminant estimates are normalized and projected onto the normalized chromaticity plane. Then, an efficient 2D kernel density estimation (KDE) [35] is applied. The modes $(R_i, B_i)$, $i = 1, \ldots, n$, i.e. the red/blue chromaticities (the green channel is scaled to one) with the highest densities are identified using a scale-space filtering [36]. Only the modes with a value higher than $t$ times the maximum are retained:

$$J = \left\{ j \in \{1, \ldots, m\} : \frac{\text{density}(R_j, B_j)}{\max_{i=1,\ldots,n} \text{density}(R_i, B_i)} \geq t \right\}. $$

The angular difference between each pair of the retained modes $((R_j, 1, B_j), j \in J)$ is computed. If the maximum difference
Fig. 2. The architecture of the CNN that produces the local estimates.

exceeds a set threshold then the scene is considered as taken under multiple illuminants. Otherwise, we proceed by assuming the presence of a single illuminant. Following [20], [37] we set the threshold to 3°, since it has been judged to be a noticeable but acceptable difference.

3.3 Local to global aggregation of the estimates

In our previous work [4] we generated a single illuminant estimation per image by pooling the predicted illuminants on the image patches. By taking image patches as input, we have a much larger number of training samples compared to using the whole image on a given dataset, which particularly meets the needs of CNNs, but we loose the information that certain patches belong to the same image. Thus, we fine-tuned the learned net by adding knowledge about the way local estimates are pooled to generate a single global estimate for each image.

In this work we extend the per-channel average and median pooling operators used in [4] with a non-linear mapping based on a RBF kernel over local statistics of the CNN estimates. The parameters of the mapping are obtained by applying a regression procedure that minimizes the median angular error on the training set. Given as input the map of the per-patch illuminant estimates having a size of \( w \times h \), the first step in this module is the smoothing via convolution with a \( 5 \times 5 \) Gaussian filter. The response is then independently pooled in three different ways: average pooling and standard deviation pooling both with size \( w/3 \times h/3 \) (i.e. on a subdivision in nine rectangular regions), and median pooling with size \( w \times h \) (i.e. on the whole image). These values are reshaped and given as input to a SVR (with RBF kernel) which predicts the global illuminant by minimizing the median angular error over the training set. The architecture of this module is reported in Figure 3.

In Figure 4 the output of each stage of the proposed illuminant estimation method is showed in the case of multiple and single illuminants.

4 EXPERIMENTAL SETUP

The aim of this section is to investigate if the proposed algorithm can outperform state-of-the-art algorithms in the single and multiple illuminant estimation on standard datasets of RAW images.

4.1 Image Datasets and Evaluation Procedure

To test the performance of the proposed algorithm for the global illuminant estimation, a standard dataset of RAW camera images having a known color target are used. Images have been captured using high-quality digital SLR cameras in RAW format, and are therefore free of any color correction. The dataset was originally available in sRGB-format, but Shi and Funt [38] reprocessed the raw data to obtain linear images with a higher dynamic range (14 bits as opposed to standard 8 bits). The dataset has been acquired using a Canon 5D and a Canon 1D DSLR cameras and consists of a total of 568 images. The Macbeth ColorChecker (MCC) chart is included in every scene, and this allows to accurately estimate the actual illuminant of each acquired image. Examples of images within the Gehler-Shi dataset are reported in Figure 5.

To test the performance of the proposed algorithm for the multiple illuminant estimation, two different datasets have been used. The first one is synthetically generated from the Gehler-Shi dataset: each image is relighted using two, three and four random illuminants taken from the same datasets. This synthetic dataset thus contains a total of 1704 images. The second dataset used is a subset of the Milan portrait dataset [20]. It has been acquired using four different DSLR cameras: Canon 40D, Canon 350D, Canon 400D, and Nikon D700. The dataset is the union of different subsets that have been acquired in three different world locations: Italy, Taiwan, and Japan. The dataset includes portraits of a single person with a single MCC up to multiple persons with multiple MCCs. In this work we used the subset containing multiple MCCs, for a total of 197 images. Some examples of images within the Milan portrait dataset are reported in Figure 6.

4.1.1 Relighted Gehler-Shi dataset

We synthetically generated a relighted version of the Gehler-Shi dataset: each image is balanced using the corresponding ground truth illuminant and relighted using two, three and four random illuminants taken from the original dataset. Their position in the image was set randomly with the constraint of being at least \( \min\{w, h\}/3 \) apart, with \( w \) and \( h \) being image width and height respectively. The ground truth for each image has been generated by nearest-neighbor assignment followed by Gaussian smoothing to simulate illuminant mixing. This synthetic dataset thus contain
Fig. 3. The architecture of our local-to-global regressor.

Fig. 4. Output of each stage of the proposed illuminant estimation method is showed in the case of multiple (top row) and single illuminants (bottom row). From left to right: input image, subdivision in patches, local illuminant estimate, output of KDE where it is possible to see the peaks of the different illuminants found: two for the first image and one for the second one; final illuminant estimate: local illuminant estimate for the first image (since the number of peaks found by KDE is greater than one), global illuminant estimate for the second one (since only one peak is found by KDE); corrected images.

Fig. 5. Example of images within the Gehler-Shi dataset.

Fig. 6. Example of images containing multiple MCCs within the Milan portrait dataset.

Fig. 7. Cumulative histograms of the maximum angular distance among the illuminants in each image of the synthetically relighted Gehler-Shi dataset.

A total of 1704 images. The average maximum angular distance among the illuminants in each image are $8.6^\circ$, $12.2^\circ$, $14.8^\circ$ for the subsets relighted with two, three, and four illuminants respectively. The cumulative histograms of the maximum angular distances are reported in Figure 7.
4.2 Benchmark algorithms

Different benchmarking algorithms for color constancy are considered. Since each image of the dataset contains only one MCC, only global color constancy algorithms based on the assumption of uniform illumination can be compared. Six of them are generated varying the three variables \((n, p, \sigma)\) in Equation 4 and correspond to well known and widely used illuminant estimation algorithms. The values chosen for \((n, p, \sigma)\) are reported in Table 1 and set as in [39]. The algorithms are used in the original authors’ implementation which is freely available online (http://lear.inrialpes.fr/people/vandeweijer/code/ColorConstancy.zip). The seventh algorithm is the pixel-based Gamut Mapping [40]. The value chosen for \(\sigma\) is also reported in Table 1. The other algorithms considered are: (i) the BAY estimation chromaticity via Support Vector Regression (SVR) [41]; the Bayesian (BAY [13]); the Natural Image Statistics (NIS [16]); the High Level Visual Information (HLVI [18]; bottom-up (HLVI BU), top-down (HLVI TD), and their combination (HLVI BU&TD); the Spatio-Spectral statistics [17]; with Maximum Likelihood estimation (SS ML), and with General Priors (SS GP); the Automatic color constancy Algorithm Selection (AAS) [15] and the Automatic Algorithm Combination (AAC) [15]; the Exemplar-Based color constancy (EB) [21]; the Face-Based (FB) color constancy algorithm [19] using GM or SS ML when no faces are detected; the CNN-based algorithms [4] and the AlexNet fine-tuned with a linear Support Vector Regression (SVR) [26] to estimate the illuminant color for each image [4] (AlexNet+SVR); the ensemble of regression trees applied to simple color features [24] (SF); the corrected-moment illuminant estimation [23] (CM) and the one predicting chromaticity from pixel luminance (PCL) [27].

| Algorithm            | \(n\) | \(p\) | \(\sigma\) |
|----------------------|-------|-------|-------|
| Gray World (GW)      | 0     | 1     | 0     |
| White Patch (WP)     | 0     | \(\infty\) | 0     |
| Shades of Gray (SoG) | 0     | 4     | 0     |
| general Gray World (gGW) | 0     | 9     | 9     |
| 1st-order Gray Edge (GE1) | 1     | 1     | 6     |
| 2nd-order Gray Edge (GE2) | 2     | 1     | 1     |
| Gamut Mapping (GM)   | 0     | 0     | 4     |

The last algorithm considered is the Do Nothing (DN) algorithm which gives the same estimation for the color of the illuminant \((I = [1 1 1])\) for every image, i.e. it assumes that the image is already correctly balanced.

4.3 Learning of the main modules

We train our CNN on \(32 \times 32\) patches randomly taken from training images of the Gehler-Shi dataset in RAW format (patches including portions of the reference MCC are excluded from training). Images have been resized to \(\max(w, h) = 1200\) pixels. The net is learned using a three-fold cross validation on the folds provided with the dataset: for each run one is used for training, one for validation and the remaining one for test. For training, we assign each patch with the illuminant ground truth associated to the image to which it belongs. At testing time, we generate a single illuminant estimation per image by pooling the the predicted patch illuminants. By taking image patches as input, we have a much larger number of training samples compared to using the whole image on a given dataset, which particularly meets the needs of CNNs. Net parameters have been learned using Caffe [25] with Euclidean loss.

The learned net is then applied to each whole image in the training set by masking the MCC to obtain an illuminant estimation map. The pooled features computed from these maps are the input to our local-to-global regressor to give a single global illuminant estimate for each image. We train our regressor using the same three-fold cross validation as before using an \(\epsilon\)-SVR [26] with RBF kernel in which we used a modified cost function to minimize the median angular distance between illuminate estimates and ground-truths. The regressor is able to give a more accurate global estimate than a simple average or median pooling for two reasons: (i) it is learning-based and is able to leverage the different local estimates coming from the patches belonging to the same image; (ii) it is trained by explicitly minimizing the error metric using in the evaluation of illuminant estimation methods.

5 RESULTS AND DISCUSSION

We evaluated the proposed method in both single and multi-illuminant estimation.

5.1 Global illuminant estimation

In Table 2 the minimum, the \(10^{th}\)-percentile, the median, the average, the \(90^{th}\)-percentile, and the maximum of the angular errors obtained by the considered state-of-the-art algorithms and the proposed approach on the Gehler-Shi dataset are reported. The table is divided into three blocks and for each of them the best result for each statistic is reported in bold. The first block includes statistic-based algorithms, the second one learning-based algorithms, and the third one the different variants of the proposed approach.

From the results it is possible to see that the deep CNN pre-trained on ILSVRC 2012 [3] coupled with SVR (i.e. AlexNet+SVR) is already able to outperform most statistic-based algorithms and some learning-based ones. The CNN introduced in our previous work [4] in its various instantiations allowed to obtain a median angular error below 2 degrees which is better than almost all the other methods considered. Even better results have been obtained with the recent method by Cheng et al. [17] for which the median error is 1.65 degrees. The method proposed here obtained the lowest error (1.44 degrees if we consider the median). The ranking of the algorithms does not change if we consider the mean error instead of the median; the best maximum error, instead has been obtained by the fine-tuned CNN [4].

Note that for this experiment we did not apply the multiple illuminant detection module and we always performed the local-to-global aggregation. This last step brings a significant improvement. In fact, without it the median error raises by more than one degree, reaching the 2.69 degrees corresponding to the “CNN per patch” result. It is also a significant improvement with respect to the other aggregation methods considered in our previous work: average pooling, median pooling and fine tuning, that obtained median errors of 2.44, 2.32 and 1.98, respectively. Figure 5 shows the distribution of the angular errors obtained with and without the local-to-global regressor. It is possible to see how the introduction of the aggregation module pushes the angular error distribution towards zero.
TABLE 2
Angular error statistics obtained by the state-of-the-art algorithms considered on the Gehler-Shi dataset.

| Algorithm       | Min  | $10^{\text{th}}$ prc | Med  | Avg  | $90^{\text{th}}$ prc | Max  |
|-----------------|------|----------------------|------|------|----------------------|------|
| DN              | 3.72 | 13.55                | 13.62| 16.45| 27.37                |      |
| GW              | 0.18 | 1.88                 | 6.30 | 6.27 | 10.12                | 24.84|
| WP              | 0.08 | 1.38                 | 5.61 | 7.46 | 15.68                | 40.59|
| SoG             | 0.18 | 1.04                 | 4.04 | 4.85 | 9.71                 | 19.93|
| gGW             | 0.03 | 0.82                 | 3.45 | 4.60 | 9.68                 | 22.21|
| GE1             | 0.16 | 1.82                 | 4.55 | 5.21 | 9.78                 | 19.69|
| GE2             | 0.26 | 2.06                 | 4.43 | 5.01 | **8.93**             | **16.87**|
| GM [40]         | 0.05 |                      |      |      | **0.40**             | **2.28**|
|                |      |                      |      |      | **4.10**             |      |
|                |      |                      |      |      | 11.08                | 23.18|
| SVR [41]       | 0.66 | 3.36                 | 6.67 | 7.99 | 14.61                | 26.08|
| BAY [15]       | 0.10 | 1.17                 | 3.44 | 4.70 | 10.21                | 24.47|
| NIS [16]       | 0.08 | 0.93                 | 3.13 | 4.09 | 8.57                 | 26.20|
| HLV BU [18]    | 0.06 | 0.75                 | 2.54 | 3.30 | 6.59                 | 17.51|
| HLV TU [18]    | 0.11 | 0.85                 | 2.63 | 3.65 | 7.53                 | 25.24|
| HLV BU & TD [18]| 0.13 | 0.77                 | 2.47 | 3.38 | 6.97                 | 25.24|
| SS ML [17]     | 0.06 | 0.85                 | 2.93 | 3.55 | 7.23                 | 15.25|
| SS GP [17]     | 0.07 | 0.82                 | 2.90 | 3.47 | 7.00                 | 14.80|
| AAS [15]       | **0.03** | 3.16 | 4.18 | 9.15 | 22.21                |      |
| AAC [15]       | 0.05 | 0.90                 | 2.90 | 3.74 | 7.93                 | 14.98|
| EB [21]        | 0.14 | 0.73                 | 2.24 | 2.77 | **5.52**             | 19.44|
| FB + GM [19]   | 0.05 | **0.40**             | 2.01 | 2.67 | 9.80                 | 23.18|
| FB+SS GP [19]  | 0.08 | 0.75                 | 2.57 | 3.18 | 6.67                 | **14.80**|
| CM [23]        | –    | –                    | 2.04 | 2.86 | –                    | –     |
| SF [24]        | –    | –                    | **1.65** | 2.42 | –                    | –     |
| PCL [27]       | –    | –                    | 1.67 | 2.56 | 5.56                 | –     |
| CNN-based      |      |                      |      |      |                      |      |
| AlexNet + SVR [4] | 0.12 | 3.09                 | 4.74 | 11.18| 29.15                |      |
| CNN per patch  | **0.00** | 2.69 | 3.67 | 7.79 | 30.93                |      |
| CNN average-pooling [4] | 0.04 | 2.44 | 3.18 | 6.37 | 14.84                |      |
| CNN median-pooling [4] | 0.06 | 2.32 | 3.07 | 6.15 | 19.01                |      |
| CNN fine-tuned [4] | 0.06 | **0.69** | **1.98** | **2.63** | **5.54** | **14.77** |
| Proposed single estimate | 0.05 | 1.44                 | 2.36 | 5.72 | 16.98                |      |

Fig. 8. Distribution of the angular errors obtained on the Gehler-Shi dataset with (bottom) and without (top) the local-to-global aggregation module. On each distribution, the black lines indicate the quartiles.

Figure 9 reports some examples of images on which the proposed illuminant estimation method makes the largest errors.

Once we have an estimate of the global illuminant color $I$, each pixel in the image is color corrected using the von Kries model [42], i.e.: $\rho_{\text{out}}(x, y) = \text{diag}(\Gamma^{-1})\rho_{\text{in}}(x, y)$.

5.2 Local illuminant estimation

Our CNN predicts the illumination on small image patches, so it can be easily used to predict local illuminants as well as giving a global illuminant estimate for the entire image. Given the performance of the per patch error in Table 2 we expect our CNN to perform well even on local estimation. We perform here a preliminary test by using our learned CNN as-is on the synthetically relighted Gehler-Shi dataset.

Among the algorithms in the state-of-the-art able to deal with non-uniform illumination, e.g. [9], [20], [22], [28], [29], [43] we report as comparison the results of the Multiple Light Sources (MLS) [30] using White Patch (WP) and Gray World (GW) algorithms, grid based sampling, in the clustering version setting the number of clusters equal to the number of lights in the scene. The numerical results are reported in Table 3 while a some examples are given in Figure 10. It is clear that the proposed method obtain significantly better results than all the other methods considered; the second best obtained about twice the median error (5.92 degrees) than the proposed one (2.96 degrees).

Note that this comparison has been made by disabling the detection of multiple illuminant and by always taking the local estimates. In a further experiment we evaluated the performance in a mixed single/multi illuminant scenario. The dataset used is the single illuminant version of the Gehler-Shi and one-third of the synthetically relighted version so that the numbers of images having single and multiple illuminants are equal. The numerical results are reported in Table 4 where the performance of the four variants of the proposed method are reported:

- single illuminant, that always applies the local-to-global
Fig. 9. Examples of images on which the method makes the largest estimation errors, in the case of a single illuminant. Left to right: input RAW image, correction with the ground truth illuminant, correction with the illuminant estimated by the proposed method (with the local-to-global regressor enabled), and correction with the algorithm in the state-of-the-art making the best estimate on the given image.

TABLE 3
Angular error statistics obtained on the synthetic relighted Gehler-Shi dataset with spatially varying illumination.

| Algorithm          | Min  | 10th prc | Med  | Avg  | 90th prc | Max   |
|--------------------|------|----------|------|------|----------|-------|
| DN                 | 3.72 | 11.12    | 13.47| 13.49| 15.53    | 26.75 |
| LSAC [28]          | 1.27 | 4.41     | 8.60 | 9.00 | 13.78    | 32.78 |
| RETINEX [9]        | 1.27 | 4.47     | 8.61 | 9.03 | 13.75    | 32.76 |
| MLS+WP [30]        | 0.64 | 2.63     | 5.92 | 6.90 | 12.55    | 31.09 |
| MLS+GW [30]        | 0.87 | 4.40     | 8.91 | 9.35 | 14.43    | 33.33 |
| Proposed multiple estimate | 0.12 | 1.57 | 2.96 | 3.75 | 6.79     | 23.87 |

regressor;
• multi illuminant, that always keeps the local estimates;
• the fully automatic, that uses the multiple illuminant de-
tector to decide if the local-to-global regressor must be
applied or not;
• the oracle, that applies the local-to-global regressor only
when, according to the ground truth, the image present a
single illuminant.
Fig. 10. Examples of the illuminant estimation on the relighted Gehler-Shi dataset. From left to right: relighted input image, local illuminant estimate, illuminant ground truth, angular error map between estimate and ground truth, corrected image.

### TABLE 4

Angular error statistics obtained by variants of the proposed method on a mixture of the original and the relighted Gehler-Shi dataset.

| Algorithm          | Min  | 10th prc | Med  | Avg  | 90th prc | Max  |
|--------------------|------|----------|------|------|----------|------|
| single illuminant  | 0.05 | 0.63     | 2.73 | 3.54 | 7.62     | 23.61|
| multi illuminant   | 0.46 | 1.51     | 3.08 | 4.10 | 8.23     | 23.42|
| fully automatic    | 0.05 | 0.64     | 2.50 | 3.05 | 5.94     | 20.10|
| oracle             | 0.05 | 0.64     | 2.48 | 3.05 | 5.98     | 20.10|

The results obtained show that the use of the multiple illuminant detector allows to obtain better results with respect to adopting a single strategy. Its performance are very close to those that can be obtained by exploiting the ground truth information about the presence of single or multiple illuminants (i.e. the oracle version).

The last experiment is performed on the subset of the Milan portrait dataset containing multiple MCCs. The numerical results are reported in Table 5, where the performance of the proposed method are reported enabling the multiple illuminant detector to decide if the local-to-global regressor must be applied or not. The results obtained show that the proposed method performs better than all the single illuminant estimation algorithms as well as all the general purpose multiple illuminant estimation ones. The only algorithm able to outperform the one proposed here is the face-based [20], which is specifically designed to leverage skin properties in images containing faces.

An example taken from the Milan portrait dataset is reported in Figure 11.

### 6 Conclusion

In this work we have developed a CNN-based color constancy. Our algorithm combines feature learning and regression as a complete optimization process, which enables us to employ modern training techniques to boost performance. The net has been specially designed to work on image patches in order to estimate the local illuminant color. When our method detects a single illuminant in the image, the local estimate is given as input to a trained local-to-global regressor which is able to predict the global illuminant with a higher accuracy.

The experimental results showed that our algorithm achieves state-of-the-art performance on a standard dataset of RAW images with a single illuminant, outperforming 24 algorithms in the state-of-the-art belonging to both statistic-based and learning-based classes of methods. A second experiment on a synthetically relighted dataset with multiple illuminants showed that our method outperforms all the general purpose local illuminant estimation methods in the state of the art. Results are further confirmed on the Milan portrait dataset, where our method is outperformed only by an illuminant estimation method using faces.

The results obtained suggest that a possible future research direction is that of feeding additional semantic information in the form of scene category or detected objects to further improve illuminant estimation performance. Another possible research direction is that of re-considering combinational methods [44] including most recent methods.

Currently, our method is articulated in three separate steps. In the future we plan to merge them into a single estimation model. In order to allow the end-to-end learning of such a model, we will collect a larger dataset of RAW images with both single and multiple illuminants.

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TABLE 5
Angular error statistics obtained on the Milan portrait dataset (multiple targets).

| Algorithm                | Min  | 10th prc | Med  | Avg  | 90th prc | Max  |
|--------------------------|------|----------|------|------|----------|------|
| DN                       | 10.84| 15.71    | 17.30| 17.53| 19.74    | 28.60|
| WP                       | 0.31 | 1.74     | 12.16| 11.39| 19.08    | 28.60|
| GW                       | 0.20 | 1.18     | 4.26 | 4.86 | 9.26     | 20.04|
| SoG                      | 0.16 | 0.88     | 4.39 | 5.93 | 14.03    | 20.02|
| gGW                      | 0.11 | 0.83     | 5.25 | 6.42 | 15.07    | 20.80|
| GE1                      | 0.19 | 1.52     | 4.59 | 5.08 | 9.50     | 18.22|
| GE2                      | 0.36 | 2.45     | 4.93 | 5.39 | 9.69     | 15.36|
| SS ML                    | 0.09 | 0.67     | 2.94 | 3.72 | 8.03     | 16.28|
| LSAC [28]                | 0.20 | 1.59     | 4.23 | 4.79 | 8.66     | 18.99|
| RETINEX [9]              | 0.12 | 1.56     | 4.28 | 4.83 | 8.39     | 20.54|
| MLS + WP [30]            | 0.15 | 0.99     | 3.21 | 4.04 | 7.55     | 17.19|
| MLS + GW [30]            | 0.11 | 0.92     | 3.33 | 4.18 | 8.82     | 17.97|
| Fusion Grad. Tree Boost. [29] | 0.03 | 1.51     | 4.48 | 5.29 | 9.95     | 31.26|
| Fusion Rand. Forest Regr. [29] | 0.03 | 1.07     | 3.23 | 3.96 | 7.61     | 27.76|
| Face-based [20]          | 0.11 | 0.87     | 2.11 | 2.66 | 5.15     | 11.43|

Proposed (fully automatic) | 0.20 | 0.81     | 2.75 | 3.30 | 6.24     | 15.22|

Input image correction using the ground truth correction using Face-based [20] correct. using the proposed meth.

illuminant ground truth Face-based illuminant estimate our illuminant estimate angular error

![Fig. 11. Example image with multiple illuminants taken from the Milan portrait dataset. Top row: input image, correction using the ground truth, correction using the illuminant estimate from the Face-based method [20], and correction using the estimate of the proposed method: since multiple illuminant were detected in the input image, the method outputs a local illuminant estimate. Bottom row: illuminant ground truth, illuminant estimate from the Face-based method, estimate from the proposed method, and angular error map between our estimate and the ground truth.](image)

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Simone Bianco obtained the BSc and the MSc degree in Mathematics from the University of Milano-Bicocca, Italy, respectively in 2003 and 2006. He received the PhD in Computer Science at Department of Informatics, Systems and Communication of the University of Milano-Bicocca, Italy, in 2010, where he currently a post-doc. His research interests include computer vision, optimization algorithms, machine learning, and color imaging.

Claudio Cusano received the Laurea and PhD degrees from the University of Milano Bicocca in 2002 and 2006, respectively. He has been a researcher with grant at the ITC institute of the Italian National Research Council and then at the Imaging and Vision Laboratory of the University of Milano-Bicocca. Currently, he is assistant professor at the Department of Electrical, Computer and Biomedical Engineering of the University of Pavia. The main topics of his research concern 2D and 3D imaging, with a particular focus on image analysis and classification, and on face recognition.

Raimondo Schettini is a professor at the University of Milano Bicocca (Italy). He is head of Imaging and Vision Lab and Vice-Director of the Department of Informatics, Systems and Communication. He has been associated with Italian National Research Council (CNR) since 1987 where he has leaded the Color Imaging lab from 1990 to 2002. He has been team leader in several research projects and published more than 200 refereed papers and six patents about color reproduction, and image processing, analysis and classification. He has been recently elected Fellow of the International Association of Pattern Recognition (IAPR) for his contributions to pattern recognition research and color image analysis.