Deep Structured-Output Regression Learning for Computational Color Constancy

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Abstract—Computational color constancy that requires estimation of illuminant colors of images is a fundamental yet active problem in computer vision, which can be formulated into a regression problem. To learn a robust regressor for color constancy, obtaining meaningful imagery features and capturing latent correlations across output variables play a vital role. In this work, we introduce a novel deep structured-output regression learning framework to achieve both goals simultaneously. By borrowing the power of deep convolutional neural networks (CNN) originally designed for visual recognition, the proposed framework can automatically discover strong features for white balancing over different illumination conditions and learn a multi-output regressor beyond underlying relationships between features and targets to find the complex interdependence of different dimensions of target variables. Experiments on two public benchmarks demonstrate that our method achieves competitive performance in comparison with the state-of-the-art approaches.

I. INTRODUCTION

Color constancy (auto white balance) works as a key preprocessing step in many computer vision tasks, where intrinsic color of the object is needed for accurate classification, regression, segmentation, and feature extraction [26] as well as scene reproduction using a digital camera. In industrial applications, color distortions due to varying illuminants can cause severe problems, e.g., in mine inspection valuable elements are missed or false detected (Figure 1).

In the words of Hordley [30], the phenomenon of color constancy is how a visual system is able to ensure that the colors it perceives remain stable, regardless of the prevailing illumination. Generally, the mainstream methods approaching color constancy can be categorized into two types of methodology: illumination estimation methodology [11], [3], [44], [13], [18], [2] and color invariant methodology [37], [43], [19], [1]. On one hand, in illuminant estimation methods, illuminant of images under varying lighting conditions is estimated first, then followed by image correction called chromatic adaption [25]. On the other hand, color invariance methods learn illuminant-invariant features, without explicitly estimating the scene illuminant. In other words, these features are learned to keep reflectance characteristics and spatial structure [37].

In this work we focus on the former methodology, of which the first stage of illuminant estimation is critical and is formulated into a discriminative regression problem. Specifically, the problem is to learn a regression mapping between imagery feature representation and continuous illuminate target variables. The first challenge to learn a robust regressor lie in obtaining discriminative feature representation. In this work, we adopt a convolutional neural network (CNN) architecture which has become popular on a number of visual recognition tasks [35], [40], [42]. Our observation from illustrations of the convolution filters of the first convolutional layers to capture low-level visual cues such as edge and high-level visual information [45] encouraged us to apply deep models designed for visual recognition to solves also the color constancy problem. The second challenge is to learn a good regression function for illuminant estimation and to discover latent inter-dimensional correlations between target variables. In the existing frameworks [23], single-output regressors (typically support vector regression and ridge regression) were employed to learn the relationship between observation variables and each color dimension of the target variables independently. Evidently, capturing interdependency across target variables can boost the performance significantly.

In this work, we propose a novel deep structured-output regression learning framework for illuminant color estimation and colors of input (biased) images will be revised using the estimated illuminant parameters. Owing to discriminative CNN features and latent inter-dimensional target correlation, the proposed algorithm can cope with both challenges in a unique framework. Specifically, the novel contributions of this paper are two-fold:

• To our best knowledge, this is the first work to employ convolutional neural networks trained for visual recogni-
tion directly to extract CNN features for illuminant color estimation. More recent and efficient deep networks, e.g., VGG [40] and MRSA-152 [29], can be incorporated into our framework for boosting the performance.

- This work is also the first attempt to jointly learn a unique multi-output regressor to predict color channels of illuminant simultaneously.

We show experimentally that the proposed framework achieves competitive performance over several state-of-the-art methods on two popular color constancy benchmarks.

II. RELATED WORK

In a Lambertian space (diffuse reflection), the image values \( \rho(x, y) \) can be parameterized by three components: the color of light source defined as \( I(x, y, \lambda) \), the visual system sensibility to spectral distribution as \( S(\lambda) \), and the surface reflectance as \( R(x, y, \lambda) \), where \( x, y \) refers to spatial position in the image, \( \lambda \) denotes the wavelength. The aforementioned three items follow image formation notation:

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

which works in a way that RGB value of each pixel is accumulated using \( \int \) along the wavelength in each single channel. In common color constancy tasks, \( \rho \) is given and \( I \) is also available for part of images (data for verifying or learning), while \( R(x, y, \lambda) \) is final target of task. Under this circumstance, there still be some necessary information e.g. camera sensibility \( S(\lambda) \) not available, making this task under-constrained or under-determined [22].

Given \( \rho \) in the testing phase, two types of algorithms based on different assumptions have been proposed and developed. According to their pipeline, methods can be divided into two main groups: illuminant estimation algorithms and illuminant-free algorithms. The former one [5], [6], [11], [12], [25], [33], [44] estimates illuminant \( I(x, y, \lambda) \) first, and then render color constant, while the latter one [17], [43], [19], [11] finds inner characteristic which can, by algebraic manipulation, somehow get rid of the effect of outer illuminant and restore ill-colored images. In this paper we focus on the former one. Moreover, illumination estimation based frameworks can further be categorized into three groups: statistics based [9], [11], [20], [8], [44], [34], [47], gamut based [2] and learning based [24], [25], [13], [33], [23], [6].

One straightforward approach under the naive assumption that the image is always under white light is to use a uniform illumination \( I = \left( \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}} \right) \) across the whole image, which leads to poor performances (termed as DN algorithm in Table I of Section IV-B). To make different assumptions unified, Van de Weijer [44] proposed a formulation, which can cover different algorithms based on exploiting imagery statistics in a single image to estimate the scene illumination as the following:

\[
I(n, \rho, \sigma) = K \sqrt{\int \int \left( \rho(x, y) \otimes G_{\sigma}(x, y) \right)^n dx dy,} \tag{1}
\]

where illuminant \( I \) is decided by the order \( n \) of the derivative, Minkowski-norm \( \rho \), and the scale parameter \( \sigma \) of a Gaussian filter. Operator \( \otimes \) defines convolution between the image \( \rho \) and Gaussian filter \( G \). \( K \) is a constant added to make \( I \) in unit length. As showed in Table [I] by varying \( (n, \rho, \sigma) \) in Eq. (1), a number of existing algorithms can be generated under different assumptions. For instance, GM-pixel [21], GW [11], SoG [17], gGW [44] and WP [12] can be clustered as one group –zero-order statistics based methods, as they are all under the assumption that a part of images (e.g., local regions) has gray average color. In terms of higher order statistics, first-order [44] and second-order based methods [44] respectively adopt the assumption that edges or gradient of edges have gray average color intrinsically. In the light of this, illuminant can be measured by the offset of the average color. Gamut-mapping based methods assume that in real world, part of color spectral distribution of objects can be observed [21], [2]. In other words, the limited set of colors in each biased image is caused by a certain lighting condition, which encourages researchers to introduce a learning based framework to recognize canonical illumination pattern with a sufficient amount of labelled training data.

Beside these statistic-based and gamut-based algorithms, there are a number of alternative algorithms to learn a discriminative object function from imagery feature to illuminate directly. Support Vector Regression is first applied to deal with color constancy task in [23], but the performance is limited by weak explanatory power of color histogram. Bayesians approaches [24] learn probability of illuminant based on presumed normal-distributed reflectance. By unsupervised clustering on texture features and color features, Exemplar [33] estimates illuminant via finding nearest neighbor surfaces of a test image. In [6], CNNs are used to capture low-level visual cues and learn high-level visual information to output illuminant, which is similar to [45]. [5] formulates the color constancy problem as a 2D spatial localization task using CNN which can borrow the recent progress on object detection. [25], [7] apply intermediate parameters like Weibull parameters or face features as criteria to enhance imagery representation in state-of-the-art methods. Employing the CNN pipeline for visual recognition to incorporation of high-level semantic information, our deep model focuses on exploiting latent correlation across target variables, i.e. RGB illuminate, which is missing in the existing frameworks to our best knowledge. Experimental results on two public benchmarks

| Method                        | \( n \) | \( \rho \) | \( \sigma \) |
|-------------------------------|--------|---------|---------|
| Gamut Mapping (GM-pixel)      | 0      | 0       | 4       |
| Gray World (GW)               | 0      | 1       | 0       |
| Shades of Gray (SoG)          | 0      | 4       | 0       |
| general Gray World (gGW)      | 0      | –       | –       |
| White Point (WP)              | 0      | +\infty | 0       |
| first-order Gray Edge (0°GE)  | 1      | –       | –       |
| second-order Gray Edge (1°GE) | 2      | –       | –       |
verify the effectiveness of the proposed framework for color constancy.

III. METHODOLOGY

As shown in Fig. 2, the proposed deep structured-output regression learning framework for computational constancy consists of the following steps in training phrase:

- Given ith training image, we extract imagery feature representation \( x_i \in \mathbb{R}^d, i = 1, 2, \ldots, N \) from the whole image using pre-trained convolutional neural networks on the public ImageNet Challenge 2014 dataset for visual categorization, where \( N \) denotes the total number of training images. With ground truth illuminate \( y_i \in \mathbb{R}^3 \), the training pair consists of \( \{(x, y)\}_i \) for ith image (Refer to Section III-A).
- Given training samples \( \{(x, y)\}_i, i = 1, 2, \ldots, N \), a multi-output regressor (i.e., multi-output support vector regression (MSVR) and multi-output ridge regression (MRR)) is employed to learn both the input-output relationship and latent correlations across output variables jointly (See Section III-B).

During testing, given an unseen image, the CNN features are first extracted and constructed as the model input, and then mapped to the corresponding trained regression model. With the predicted illuminate using trained regressor, image correction can be achieved by linear transformation \([27]\).

A. CNN Feature Extraction

Owing to the observation that semantic information is beneficial for learning a robust regressor \([27]\), we follow the success of recent deep neural networks for object detection tasks \([40], [42]\), we used the 19-layer CNN model following the same network structure in \([40]\) trained on large-scale ILSVRC-2014 ImageNet data. Although CNN provides generic and discriminative features for illuminate estimation, we also tried to fine-tune CNN with the images from benchmarks for color constancy to generate more dataset-specific features in our experiments. However, due to limited training data in the existing benchmarks, the fine-tuned CNN model suffers from over-fitting and therefore we use only the original CNN model without fine-tuning.

Before extracting CNN feature over global region, i.e., the whole image, we first resize the image into the fix-size \((224 \times 224)\). As illustrated in Fig. 2, we use the output of the “fc6” layer in CNN model as our feature in 4096-dimension, which has been verified its superior performance in visual recognition \([16]\). Moreover, to further verify that CNN feature from “fc6” layer can keep its better performance on illuminate estimation, we conduct experiments to illustrate the comparison with features extracted from the “fc7” layer (4096 dimensions) and the “fc8” layer (1000 dimensions), indicating performance gap caused by the hidden fully connected layers.

B. Structured-Output Regression Learning

Now the training pair is represented by \( \{(x, y)\}_i, i = 1, 2, \ldots, N \). The existing learning based works \([23]\) are aimed to learn regression functions independently with the training pair \( \{(x, y')\}_i, i = 1, 2, \ldots, N \), where \( y', l = 1, 2, 3 \) denotes the color (RGB) dimensions. The single-output regression learning can be formulated as the following:

\[
\min \frac{1}{2} ||w||_2^2 + C \sum_{i=1}^{N} \text{loss}(y'_i, f(x_i)),
\]

where \( w \in \mathbb{R}^d \) is the weight vector to be optimized, the trade-off parameter \( C \) is the regularization term and the loss function \( \text{loss}() \), and \( f(x_i) = \phi(x_i)^T W + b \) with \( \phi() \) is the kernel function to project \( x \) to a high dimensional Hilbert space.

In order to cope with structured-output regression learning to simultaneously take the possible correlations between output variables into account, the following formulation can be readily derived:

\[
\min \frac{1}{2} \sum_{l=1}^{3} ||w^l||_2^2 + C \sum_{i=1}^{N} \text{loss}(y_i, F(x_i)),
\]

where \( F(x_i) = \phi(x_i)^T W + b \) with \( W \in \mathbb{R}^{d \times 3} \) and \( b \in \mathbb{R}^3 \). Eq. (3) is the generalized formulation for multi-output regression and can be formulated into a number of regression
frameworks by adopting different loss functions $\text{loss}(\cdot)$. In this paper, we investigate two types popular multi-output regressor: multi-output ridge regression (MRR) and multi-output support vector regression (MSVR).

**Multi-output ridge regression** – For obtaining a closed-form solution, Eq. (3) with a quadratic loss function can be written as multi-output ridge regression (MRR):

$$
\min_{W, b} \frac{1}{2} \sum_{i=1}^{N} \|y_i - (\phi(x_i)^T W + b)\|^2_2 + C \sum_{i=1}^{N} \|y_i - (\phi(x_i)^T W + b)\|^2_2.
$$

which has a closed-form solution based on matrix inversion [8], [14].

**Multi-output support vector regression** – When the loss function $\text{loss}(\cdot)$ is cast as a typical $\epsilon$-sensitive loss function for support vector regression (SVR) [41],

$$
\text{loss}(y_i, f(x_i)) = \begin{cases} 
0, & \text{if } |y_i - f(x_i)| < \epsilon \\
|y_i - f(x_i)| - \epsilon, & \text{if } |y_i - f(x_i)| \geq \epsilon
\end{cases}
$$

then Eq. (3) becomes multi-output support vector regression (SVR) which can approach its approximate optimized solution using cutting-plane strategies [32].

**C. Image Correction**

Given an unseen test image, an estimate of global illuminant can be obtained with trained structured-output regressor in Section III-A. By one more step, we can recover unbiased image with it, which is called chromatic adaptation [46]. Among many chromatic adaptation methods (e.g. Bradford [31] and CIECAT02 [38]), we choose to use the von Kries model [46]: $I = W \times L$ (thus $L = W^{(-1)} \times I$), which is based on the simplified assumption that each channel of color is modified separately to model photometric changes. Despite its simplicity the model is relatively stable in practice [10].

**IV. EXPERIMENT RESULTS**

**A. Datasets and Settings**

To evaluate the proposed framework, two popular benchmarking datasets [4], [24], [39] with linear images are used here. The SFU Color Checker dataset [24], [39] contains 568 14-bits dynamic range images which all include Macbeth Color Checker chart. The SFU Indoor dataset [4] focuses on more synthetic scenes, containing 321 images respectively captured in 11 different light conditions. Examples in two datasets are reported in the first column in Fig. 3.

For fair comparison, we evenly split the whole data into training, validation and testing sets. During training, we train our regressors on training set and use validation set to tune free parameters of regressors. With optimized parameters of regressors, we then use both training and validation sets of images to train regressors to test on the testing sets. We repeat the experiments 30 times and report the average errors.

The direct competitors of multi-output ridge regression (MRR) and multi-output support vector regression (MSVR) are ridge regression (RR) and support vector regression (SVR) with unique CNN features presented in Section III-A. Other free parameters in the aforementioned regressors need to be tuned: penalty parameter $C$, kernel coefficient $\gamma$ for RBF kernel and insensitivity parameter $\epsilon$ in MSVR. For ridge regression, only trade-off parameter $C$ need to be tuned along $C \in \log_{10} (-2 : 1 : 2)$. For our structured-output SVR implementation (i.e., CNN+MSVR), we choose the optimized parameters by searching in grid space where $C \in \log_{10} (-3 : 1:5)$, $\gamma \in \log_{10} (-4:1:4)$ and $\epsilon \in \log_{10} (-4:2:3)$.

In the existing works [4], [15], [24], [39], the true recorded illuminant $I_{gt}$ is provided as ground truth. To measure to the accuracy of illuminate estimation, the angular error $\epsilon$ between estimated illuminant $I$ and $I_{gt}$ is used:

$$
\epsilon_{I, I_{gt}} = \arccos(\frac{I \cdot I_{gt}}{\|I\| \|I_{gt}\|}),
$$

where · means inner product between vectors, $\|\cdot\|$ is Euclidean norm. Although in this paper, we focus on producing color-constant image after correction by pixel-by-pixel spatial prediction, such a performance metric can still reflect the effectiveness of the proposed algorithm.

**B. Results and Discussion**

As shown in Table I, the median, the average, and the maximum of the angular errors of state-of-the-art methods and our methods are evaluated and compared. We categorize these methods into three fold in the table: non-characterized algorithms (top), characterized ones (middle) and learning-based ones (bottom), and the best performance in each metric dimension is marked in bold.

From the Table I, it is evident that even a median-depth CNN [36] coupled with SVR (CNN+SVR) [6] shows better performance than all statistics based algorithms and most of gamut-based and learning based frameworks. Significant improvement on CNN+SVR over its direct competitor SVR can contribute to the introduction of powerful CNN features, which demonstrates our first motivation of adopting CNN features in our framework. Moreover, the last two rows in the table are results obtained by our approaches, which shows our method CNN+MSVR outperforms the best low-level based methods (Grey Pixel) on the SFU color checker and the SFU indoor datasets by decreasing the median angular error with 13.55% and 28.70% respectively. Compared to gamut-based and learning based algorithms, our solution is comparable to
or even much better than state-of-the-arts methods. Different performance on two benchmarks can be explained by the dataset-specific characteristics, i.e., CNN features for the SFU Indoor dataset can be more discriminative to cope with images under the controlled environment. Direct comparison between CNN+SVR and CNN+MSVR can demonstrate our second motivation to capture inter-dimensional target variables by using structured-output models, with CNN+MSVR significantly beating CNN+SVR. Similar situation can be observed for single-output CNN+RR and structural CNN+MRR.

We also investigate the effect of depth of feature extraction layer designed for visual recognition on illuminate estimation. Deep feature has been extracted from three fully-connected layers: “fc6”, “fc7”, “fc8” shown in Fig. 2. Each type of deep feature is fed into MSVR model to compete the estimation performance. In Table III one trend can be discovered: the deeper the CNN layer we adopt, the worse the performance we can achieve. One possible explanation could be that illuminate estimation relies more on low-level information like edges, colors than abstract high-level knowledge for visual understanding as some synthetic examples look fragmented and contain no object or just part of it.

It is known that CNN can work for regression problems directly and we do one more experiments to illustrate the advantages of CNN feature with structured-output regressors over CNN model only. For the aim to expand the amount of training examples massively, two simple cropping or patching strategies are considered. Randomly cropping is to randomly crop $224 \times 224$ clipped image patches using a square sliding window to scan the whole image region. As shown in Table IV this two strategies suffer from over-fitting and cannot achieve competitive performance, compared to deep structured-output regression frameworks.

V. CONCLUSIONS

We adopted structured-output regression frameworks with deep CNN feature and achieved competitive results on two recent and diverse benchmarks on color constancy. In our future work, we will address strong CNN and regression frameworks to provide effective real-time color constancy.

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Fig. 4. Example results of the proposed algorithm applied to several test images. The angular error between corrected images and groundtruth is shown on the right hand side.

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