Deep Separable Convolution Neural Network for Illumination Estimation

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Keywords: Illumination Estimation, Deep Convolution Network, Separable Convolution, Global Average Pooling.

Abstract: Illumination estimation has been studied for a long time. The algorithms to solve the problem can be roughly divided into two categories: statistical-based and learning-based. Statistical-based algorithm has the advantage of fast computing speed but low accuracy. Learning-based algorithm improve the estimation accuracy to some extent, but generally have high computational complexity and storage space. In this paper, a new deep convolution neural network is proposed. We design the network with more layers (11 convolution layers) than the existing methods, remove the “skip connection” and “Global Average Pooling” is used to replace “Fully Connection” layer which is commonly used in the existing methods. We use the separable convolution instead of the standard convolution to reduce the number of parameters. In reprocessed Color Checker Dataset, compared with the present state-of-the-art the proposed method reduces the average angular error by about 60%. At the same time, using separable convolution and “Global Average Pooling” reduces the number of parameters by about 86% compared with do not use them.

1 INTRODUCTION

As we all know, image has three main features: color, texture, and shape. As a global feature, color feature describes the surface properties of the image or image region. However, the extraction of color features needs to be carried out under standard illumination, so the estimation of illumination (you also can call it “color constancy”) in the image becomes the top priority. Although there has been a long history of research on illumination estimation, it is far from achieving the goal of "fast and good", and there are still many problems in practical application.

Currently, illumination estimation algorithms can be roughly divided into two types: statistical-based algorithms and learning-based algorithms. Statistical-based methods estimate parameters based on the statistical attributes of the image and some presuppositions, such as Grey-World (Buchsbaum and Gershon, 1980), Shades-of-Grey (Finlayson et al., 2004), Grey-Edge (Joost et al., 2007), White-Patch (Brainard and Wandell, 1986) and so on. The common advantage of these algorithms is their low computational complexity. But these methods require some illumination estimation experience and do not work well when the scene is complex. Learning-based methods build model with image features to estimate illumination. With the development of machine learning, some techniques have been applied to build models, such as Gamut mapping (Gijsenij et al., 2010), Bayesian (Gehler et al., 2008), SVR (Funt and Xiong, 2006).

They only reduced the error by about 10% compared with the statistical algorithm, but the computational complexity was several times or even tens of times the original.

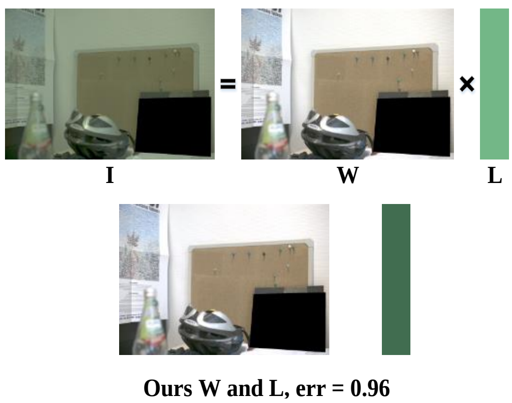

Figure 1: An example of “illumination estimation”: a color-casted image I equals a color-corrected image W multiply the illumination L.

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State-of-the-art methods are associated with convolutional neural networks (CNN). Thanks to the strong fitting ability of CNN, remarkable results have been achieved. Simone Bianco (Bianco S et al., 2017) designed a network with a convolution layer、a pooling layer and a full connection layer. At the same time it use a small patch (32x32) as input to reduce the amount of computation and use the average of local results as the global results. It got the best results of the time, and was very fast. Hu Y (Hu et al., 2017) fine-tuned the Squeeze Net (Iandola et al., 2016) and use a big patch (512x512) as input, because the bigger patch size represents more information and use squeeze module to reduce the number of parameters.

In general, the research and application of illumination estimation still face two main problems: first, whether the accuracy of illumination estimation can be further improved?

Second, whether the storage space and amount of calculation of the algorithm can be further reduced?

To address these problems, we propose a new network with deep separable convolution. First, we use a deeper network structure which has 11 convolution layers to improve the estimation accuracy. Then, we use separable convolution (Chollet, 2017) and "Global Average Pooling" (Lin M et al., 2013) in the network to reduce the number of network parameters.

In reprocessed Color Checker Dataset (Shi, 2010), compared to the state-of-the-art algorithm, the mean angular error has been reduced by about 60%. And after using separable convolution and "Global Average Pooling", the network parameters are reduced by about 86%. The storage space of our method is 0.62MB. So it can be easy used in equipment of "Internet of things" (IoT) or mobile device.

2 RELATED WORK

2.1 Illumination Estimation

The goal of "illumination estimation" is to dislodge the illumination in image. According to Lambertian reflection (Basri, 2001) theory, the color of the image is determined by both the pixel value of the image and the illumination. It can be represented by equation, as in (1).

$$I = W \times L \tag{1}$$

I represents the real image we got. And W represents the white-balanced image and L represents RGB illumination which is shown in Fig. 1.

$$E = \begin{pmatrix} E_R \\ E_G \\ E_B \end{pmatrix} = \begin{pmatrix} MAX(F_R) \\ MAX(F_G) \\ MAX(F_B) \end{pmatrix} \tag{2}$$

"Illumination estimation" is get the image W from image I. We should build a model $f(I)= L$. Then we can get $W = I / L$. At first, people used statistical-based algorithm to build models. White-patch (Brainard and Wandell, 1986) considered that the maximum pixel value of the three channels of RGB reflects the illumination color of the image, as in (2).

$MAX(F_C)$ represents the maximum pixel value of the channel. The advantage of this method is that it is easy to calculate, but because of its assumption that all three channels of RGB should have total reflective surfaces, it is difficult to satisfy in real life. In general, the effect of this method is poor.

Gray-World (Buchsbaum and Gershon, 1980) is a method like White-patch. It considered that the average pixel value of the three channels of RGB reflects the illumination color of the image, as in (3).

$$E = \begin{pmatrix} E_R \\ E_G \\ E_B \end{pmatrix} = \begin{pmatrix} MEAN(F_R) \\ MEAN(F_G) \\ MEAN(F_B) \end{pmatrix} \tag{3}$$

Compared with White-patch, this method has the advantage of low computational cost, but the error of recovery is larger.

In addition to the two methods mentioned above, there are many similar statistical-based algorithms, such as Shades-of-Gray (Finlayson et al., 2004), Gray-Edge (Van De et al., 2007). Because the data set in the study had a single light intensity and many of the parameters in these models is built by experience and reasonable hypothesis, the result of these models was poor and they have no extensive applicability.

In recent years, learning-based algorithms have become popular. Gamut mapping (Gijsenij et al., 2010) calculates a regular gamut of color. For the image of unknown light source, the mapping between the gamut of color and the standard gamut of color is calculated, and the illumination is obtained. Bayesian (Gehler et al., 2008) and SVR (Funt and Xiong, 2006) mode the key features such as brightness and chromaticity distribution of image pixels to estimate illumination. NIS (Gijsenij and Gevers, 2011) trains a maximum likelihood classifier to choose method to estimate illumination. EB (Joze and Drew, 2014) trains the model by unsupervised learning a model for each training surface in training images.

These methods are relatively stable and have a wide range of applications compared to statistical-based algorithms, and the results are better.

Now, convolution neural network has been used to solve this problem. CCC (Barron, 2015) extracted the chromaticity histogram of the image as input and train the model by a small convolution neural network. Convolution neural network is introduced to solve the illumination estimation problem for the first time, and the results are better than before. However, because of the simplicity of the network, the effect is not very good. CNN (Bianco et al., 2017) combined support vector regression with convolution neural network. This method solves the problem of multiple illumination, but because of the simplicity of network structure, it also does not obtain very good results. Cheng (Cheng et al., 2014) used principal component analysis to estimate the illumination in spatial domain. DS-Net (Shi, 2016) trained a two-branch structure network and chooses an estimate from among the hypotheses. Oh (Oh, 2017) transformed illumination estimation into a classification problem. Fc4 (Hu, 2017) fine-tuned the Squeeze Net (Iandola, 2016) with confidence-weighted pooling and up to now got the best result. They all get a good result by using convolution neural network, but some layers such as "Fully Connection" in these networks lead to a waste of storage space.

2.2 Separable Convolution

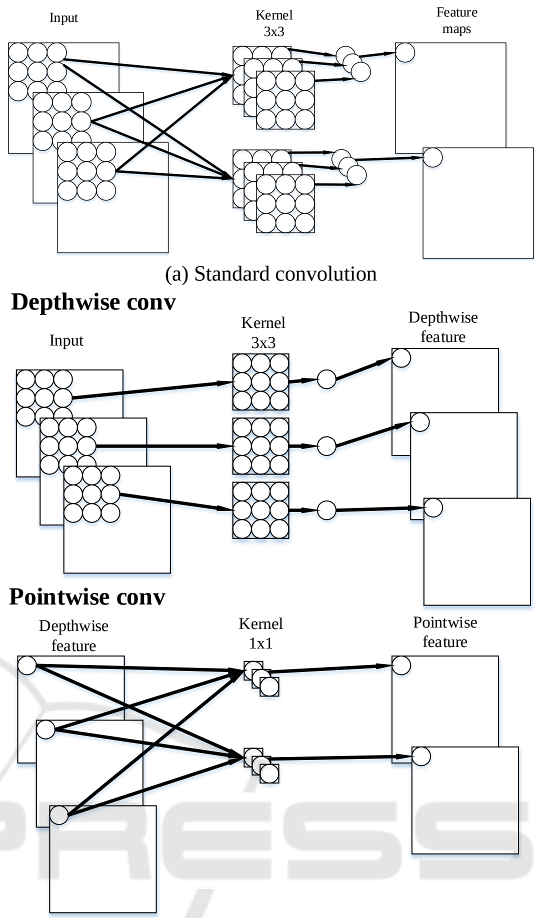
Convolution layer is the core of convolution neural network. The traditional way of convolution is well known, and the study of it has never stopped. AlexNet (Krizhevsky, 2012) used "group convolution" to reduce the computation of network. ResNet (He, 2016) used "skip connection" to make it possible for deep networks to be trained. However, these networks all use standard convolution which is shown in Fig. 2(a).

We can see that the correlation between the channel and the space of the feature map is considered at the same time. There is a question why we consider them at the same time? So, separable convolution (Chollet, 2017) which is shown in Fig. 2(b) is designed to solve it. In Fig. 2, we can see that the number of parameters are reduced about 50% when use separable convolution.

In (4), there are feature maps which have size $H*W*N$ and the kernel is $K*K$ and the channel of output is M.

$$\frac{Separable}{conv} = \frac{\left(K^2+M\right)HWN}{K^2MHWN} = \frac{1}{M} + \frac{1}{K^2} \tag{4}$$

In network, the computation of network can be reduced about $\frac{1}{M}+\frac{1}{K^2}$ when use separable convolution.

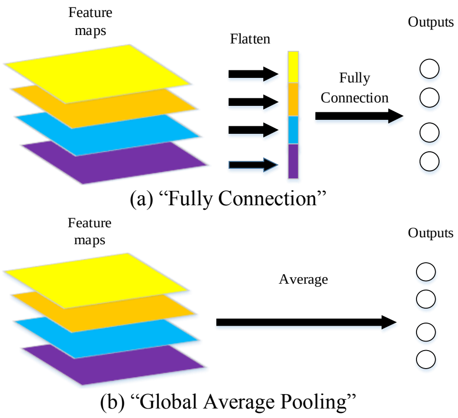


(b) Separable convolution

Figure 2: The difference between standard convolution and separable convolution.

2.3 "Global Average Pooling"

In NIN (Network in Network) (Lin, 2013), authors came up with a lot of interesting ideas. One of them is the correlation analysis of replacing "Fully Connection" with "Global Average Pooling". In the classification task, we all know that using the "Fully Connection" layer can improve the network performance to some extent, but it has a huge disadvantage that the number of parameters is too large. Large amount of parameters will lead to a waste of time and storage space in training and testing, and there will be over-fitting problem. "Global Average Pooling" uses the average of features map to replace them as output. This not only reduces the number of parameters, but also gives practical meaning to each channel. The details about "Fully Connection" and "Global Average Pooling" are shown in Fig. 3.



(a) "Fully Connection"

(b) "Global Average Pooling"

Figure 3: The difference between "Fully Connection" and "Global Average Pooling".

3 PROPOSED METHOD

In training, we transform all images into patches and the size of them is 64x64. The label of them is the same as the label of image which they belong to. Then we randomly choose 20,000 of them as training set to train the model.

In testing, test image is transformed into patched which have the same as training set. And all of them are put into the model and get a result to build a local illumination map. Then we get the median of the map as the estimated illumination of the image. The procedure is shown in Fig. 4.

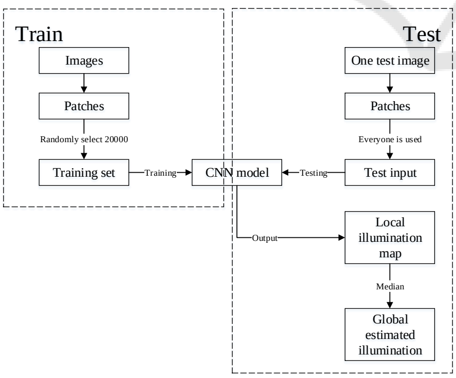


Figure 4: The procedure of proposed method.

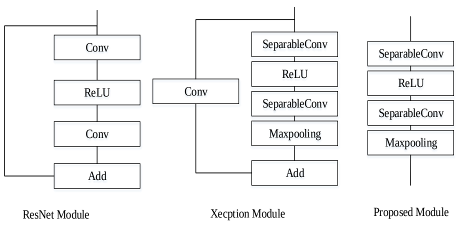


Figure 5: The difference between our modules.

3.1 Network Structure

3.1.1 Basic Module

We use basic convolution module as the basic unit of network structure such as ResNet module (He, 2016), Xecption module (Chollet, 2017). In designing the structure of module, we refer to the above two structures. But compared with them, we use separable convolution instead of standard convolution and remove "skip connection" from module. Because "skip connection" not only transmits useful information, but also becomes the bridge of noise transmission. And we've proved through experiments that with skip connection, the effect is very bad. The corresponding experimental results are shown in Table 3. Using separable convolution can reduce number of parameters. The difference between our modules is shown in Fig. 5. The corresponding experimental results are shown in Table 4.

3.1.2 Network

We design a convolution neural network which has 11 convolution layer (contain 4 modules). At the architectural level, we mainly draw on two important ideas of VGG [24]. The first is to replace the large convolution kernel with the small convolution kernel. The second is to increase the number of feature maps while reducing the size of feature maps. In tiny networks, it is important to have enough number of channels to process the information (Zhang, 2017). Some details of the network structure are shown in Table 1 and Fig. 6.

In the network, we get a patch with size (64x64x3) as input. Then we use two standard convolution layers followed by four basic modules. At the end of network, we use a standard convolution layer to change the channel of output into three. We use GAP (Global Average Pooling) to replace the Flatten and "Fully Connection" layer.

This kind of network structure design is a result that we get the best performance after a lot of experiments. According to the hardware equipment and the actual pursuit of the effect can be adjusted appropriately. The corresponding experimental results are shown in Fig. 7.

3.1.3 Difference from Other Methods of using CNN

Compared with the other methods of using CNN (convolution neural network) to solve the illumination estimation problem the network structure we designed has the following difference.

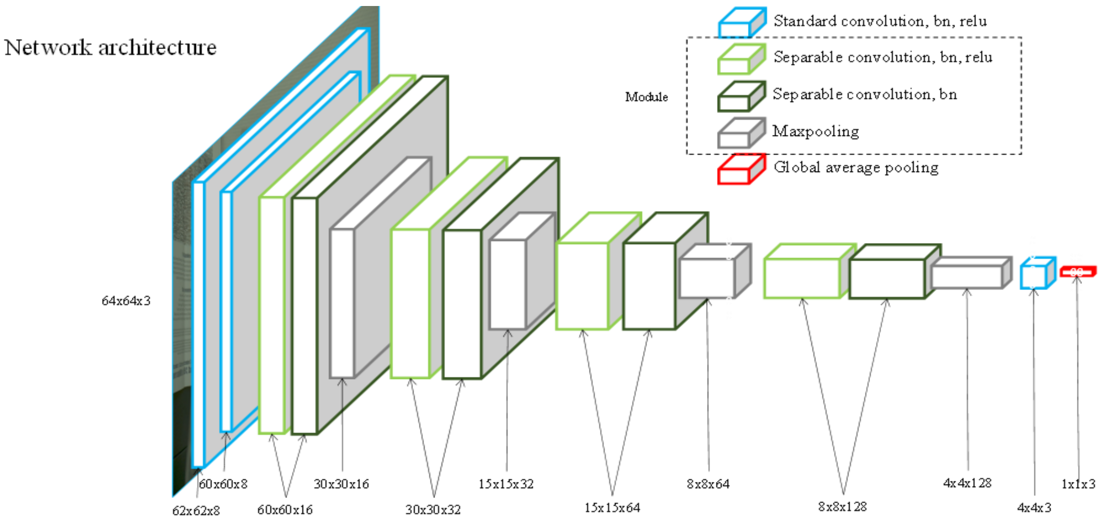


Figure 6: Architecture of our deep separable convolution. We show the different operation by using different color.

Table 1: The details of our network.

	Operation	Output	Parameters
Input	-	64x64 , 3	-
Label	-	1x1 , 3	-
1st layer	3x3 Conv , Bn, Relu	62x62 , 8	248
2st layer	3x3 Conv , Bn, Relu	60x60 , 8	608
1st module	3x3 Separable Conv , Bn, Relu	60x60 , 16	264
	3x3 Separable Conv , Bn	60x60 , 16	464
	Maxpooling	30x30 , 16	-
2st module	3x3 Separable Conv , Bn, Relu	30x30 , 32	784
	3x3 Separable Conv , Bn	30x30 , 32	1,440
	Maxpooling	15x15 , 32	-

	Operation	Output	Parameters
3st module	3x3 Separable Conv , Bn, Relu	15x15 , 64	2,592
	3x3 Separable Conv , Bn	15x15 , 64	4,928
	Maxpooling	8x8 , 64	-
4st module	3x3 Separable Conv , Bn, Relu	8x8 , 128	9,280
	3x3 Separable Conv , Bn	8x8 , 128	18,048
	Maxpooling	4x4 , 128	-
Last layer	3x3 Conv	4x4 , 3	3,459
Output	Global average pooling	1x1 , 3	-

Compared with (Barron, 2015) and (Bianco, 2017), a deeper network is designed. Because we have the experience that more parameters have better fit ability. And in the same number of parameters, a “thin and deep” network works well than a “fat and shallow” network. The reason is a “thin and deep” network can transform the problem into some small problems to solve by modules. And we always want to solve small problems, the network is also.

Compared with (Hu, 2017), the basic module of network is different and (Hu, 2017) uses transfer learning to train network. We train the network by initialization. Of course, another main difference is the comprehension about building a simple network.

3.2 Loss Function

We train the network by minimizing the loss function which can be called angular error. The loss function is shown as in (5). It obtains the angle error between the real illumination vector and the predicted illumination vector.

$$L\left(\hat{P}_g, \hat{P}_p\right) = \frac{180}{\Pi} \arccos\left(\frac{\hat{P}_g \bullet \hat{P}_p}{\left\|\hat{P}_g\right\|\left\|\hat{P}_p\right\|}\right) \quad (5)$$

In the loss function, $\hat{P}_g$ represents the normalized result of the real value and $\hat{P}_p$ represents he normalized result of the output of the network.

Table 2: Compared to the other methods (in degree).

	Mean	Med	Tri	Best 25	Worst 25	95% Quant
GW	6.36	6.28	6.28	2.33	10.58	11.30
WP	7.55	5.68	6.35	1.45	16.12	-
SG	4.93	4.01	4.23	1.14	10.23	11.90
GE	5.13	4.44	4.62	2.11	9.26	-
GM	4.22	2.33	2.91	-	-	-
Bayesian	4.82	3.46	3.88	1.26	10.49	-
SVR	7.99	6.67	-	-	-	14.61
NIS	4.19	3.13	3.45	1.02	9.22	11.7
EB	2.77	2.24	-	-	-	5.52
Cheng	3.52	2.14	2.47	0.50	8.74	-
CCC	1.95	1.22	1.38	0.35	4.76	5.85
CNN	2.36	1.98	-	-	-	-
SqueezeNet-FC4	1.65	1.18	1.27	0.38	3.78	4.73
DS-Net	1.93	1.12	1.33	0.31	4.84	5.99
Oh	2.16	1.47	1.61	0.37	5.12	-
DSCNN	**0.67**	**0.49**	**0.52**	**0.16**	**1.52**	**1.86**

4 EXPERIMENTS AND RESULTS

We have done a lot of experiments to verify the correctness and effectiveness of our method. In addition to verifying the effect of the method, we also verify the setting of some super parameters in the method through experiments.

4.1 Experimental Setting

We built the whole network through the Keras framework. To train the network, we use Adam (Kingma, 2014) to minimize the loss function. All of the parameters are initialized by "glorot_uniform" (Glorot, 2010), and to prevent overfitting, we add L2 regularization to all convolution parameters. We train the network for 200 epochs. In the top 50 epoch, we use a learning rate of 0.001. In 50 to 150 epoch, we use a learning rate of 0.0001. In the last 50 epoch, we use a learning rate of 0.00005.

4.2 Datasets

We use the reprocessed Color Checker Dataset (Shi, 2000) for benchmarking. The dataset has 568 images. These images were got by using two high quality DSLR cameras (Canon 5D and Canon1D) with all settings in auto mode. Using the advice of the authors of the dataset, each image needs to be subtracted from the black level in order to solve the color constancy problem. For the Canon 5D the black level is 129 and for the Canon 1D it is zero. In all images, there is a Macbeth Color Checker (MCC) to show the ground truth illumination color. Because it contains a lot of color information and our network is learning color features, we set these pixels of MCC to zero.

We cut the original image to a patch with the size 64x64. We randomly selected 20, 000 patches as the training set. In training, we selected 2/3 of them for training and the remaining 1/3 for validation. And the size of batch is 128.

4.3 Evaluation Criterion

We use it as an evaluation criterion by calculating the angle between the estimated and real value of the illumination. The same as Hu Y (Hu et al., 2017), we get the error matrix of the 568 images and report the following statistics: mean, median, tri-mean of all the errors, mean of the lowest 25% of errors, mean of the highest 25% of errors and 95% Quant. 95% Quant means 95 percent of the errors is smaller than this value.

4.4 Experiments

4.4.1 Compared to Other Methods

We selected five statistics-based and ten learning-based algorithms as benchmark algorithms. The statistics-based algorithms are: Gray-World (GW), White-Patch (WP), Shades-of-Gray (SG), Gray-Edge (GE). The learning-based algorithms are: Gamut Mapping (GM), Bayesian, SVR, Natural-Image-Statistics (NIS), Exemplar-Based Color Constancy (EB), Cheng et al., (2014), CCC, CNN, FC4, DS-Net, Oh. We show the results in Table 2.

The results show that most of the learning-based methods are better than those based on statistics, which proves that the learning-based method can better extract the color features of images. Moreover, the proposed method is superior to the current optimal algorithm in all evaluation indexes. The average error is reduced by about 60%. There are two reasons why we are able to make such a huge advance. First, compared to most of the CNN-based algorithms, in our algorithm the depth and width of the network are guaranteed. This makes the network strong enough to express feature. Second, compared to the algorithm which have more parameters like Hu Y (Hu et al., 2017), the selection of our network structure and the number of parameters is appropriate. And we do not use transfer learning to train our model. This avoids the impact of other types of data.

4.4.2 Whether "Skip Connection" Is Used or Not

In the design of deep convolution neural network, "skip connection" is a good technique to ensure the convergence of the network. However, "skip connection" is not suitable for all tasks. In illumination estimation, because of the small amount of data, if "skip connection" is introduced, it will propagate noise, which is not good for network training. In Table 3, we experimented with whether to add "skip connection" and found that the results were the same as we had expected.

Table 3: Compare between whether use "skip connection".

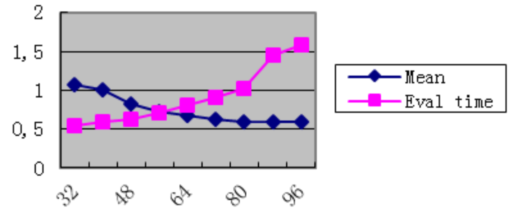
	Mean error
YES	0.74
NO	0.67

4.4.3 Effects of Some Super Parameters

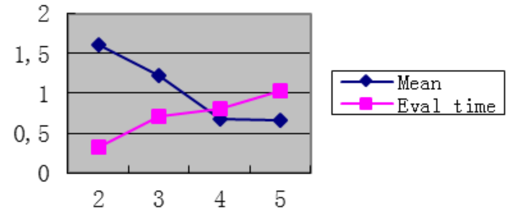
It is very important to set some super parameters in convolutional neural networks. If improper super parameters are selected, the effect of the whole network may be very poor or the network is difficult to converge. Therefore, it is more reliable to determine some of the parameters by experiment than to select them directly from experience.

In Fig. 7(a), we can see that when the size of patch is bigger than 64, there is no significant improvement in performance. And as we all know, the computation of neural network is gradual improvement. So, we choose 64 as our input.

In Fig. 7(b), we can see that when the number of modules is bigger than 4, there is no significant improvement in performance. And as we all know, the computation of neural network is gradual improvement. So, we choose 4 to build network.



(a) Abscissa axis expresses the size of patch. Vertical axis expresses the mean angular error and the evaluation time for one image.



(b) Abscissa axis expresses the number of blocks. Vertical axis expresses the mean angular error and the evaluation time for one image. The size of patch is 64. When use five modules, we remove the pooling layer from the last module.

Figure 7: Results about effects of "size of patch" and "number of modules".

4.4.4 Cost of Storage Space

Compared with the current algorithms, we want to get a better and faster model. So when we design the network, we change the convolution layer and the "Fully Connection" layer, which contain a lot of parameters. We use separable convolution instead of standard convolution and remove the "Fully Connection" layer.

Table 4: Cost of storage space.

	Mean error	Conv layers	Storage space
SqueezeNet-FC4	1.65	26	35.2MB
Proposed(standard)	0.47	11	3.56MB
Proposed(separable)	0.67	11	0.62MB

Because we do not use "Fully Connection" and less convolution layers, the cost of storage space is reduced by about 90%. At the same time, using separable convolution replace standard convolution can reduce storage space by about 86% at the cost of error increased from 0.47 to 0.67.

5 CONCLUSIONS

In this paper, we propose a new algorithm to solve the illumination estimation problem. Due to the shallow network used in the current convolution neural network methods, we design a deeper convolutional neural network and obtain good results. The average angle error on the reprocessed Color Checker Dataset is reduced by about 60%. In addition, we use the separable convolution and "Global Average Pooling" to reduce the computational complexity of the network and the storage space of the network by about 86%. Further improvement of estimation accuracy and estimation of multi-scale illumination will be the focus of our future work.

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