TELKOMNIKA, Vol. 11, No. 10, October 2013, pp. 5530 ~ 5538
ISSN: 2302-4046

Color Calibration Model in Imaging Device Control using Support Vector Regression

Yang Bo*[1], Lei Liang[2], Wang Xue[3]
[1, 2, 3]School of Electrical and Information Engineering,
Chongqing University of Science & Technology (CQUST)
University Town, 401331, Chongqing, P. R. China, Ph./Fax: +8623-65022172
Corresponding author, e-mail: bob_cq@163.com[1], cqlei.l@163.com[2], saltmaker@163.com[3]

Abstract

In the color system of a computer, the nonlinearity of the image acquisition device and the display device may result in the difference between the colors displayed on the screen and the actual color of objects, which requires for color correction. This paper introduced the Support Vector Regression (SVR) to establish a color correction model for the nonlinear imaging system. In the modeling process, the Successive 3σ Filter was used to eliminate the large errors found in the color measurement. Because the SVR model of RBF kernel has two important parameters (C, γ) that need to be determined, this paper applied Least Mean Squared Test Errors Algorithm to optimize the parameters to get the best SVR model. Compared with quadratic polynomial regression, BP neural network and relevance vector machine, SVR has better performance in color correction and generalization.

Keywords: *color reproduction, support vector regression, successive 3σ filter, least mean squared test errors*

1. Introduction

In recent years, ICC (International Color Consortium) color management is gradually being received and adopted. The core of its management is to characterize the behavior of color description of each device in imaging systems, namely, the establishment of a function between RGB or CMYK of device control signal values and the tristimulus values. This function is often described in different ways, such as Look-up Table (LUT) combined with the interpolation [1], multiple regression [2] and neural networks [3, 4], etc.

Under normal circumstances, the Look-up Table method provides a precision higher than other methods, but it requires a lot of calibration samples. To reduce the data dimension of calibration samples, Wang et al used the color correction method for the domain partition of the multi-channel printer color correction [5]. Multiple regression works by means of polynomial approximation to the nonlinear characteristics of device color, featured in a simple conversion relationship and the lower calibration accuracy. Furthermore, the polynomial as a global function may lead to the local distortion to be extended to the whole color space. An effective way is to narrow the range of correction, that is, correction partition [6, 7]. Theoretically, the neural network can approximate any nonlinear relationship, so it has a high applicability when used for color correction. One concern is the difficulty to determine the internal structure of neural networks, such as the hidden layer.

In recent years, support vector machine based on the statistical learning theory has been playing a big role in terms of pattern recognition, image classification, function approximation, etc. And it also finds its way to be applied in the field of color correction [8]. However, research in this area is also relatively less. This paper presented an attempt to introduce a support vector machine model for establishing color correction, with correction of experimental data being used to test the accuracy of the model.

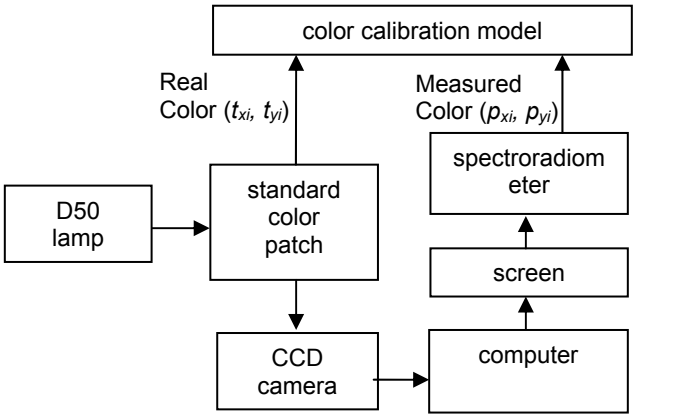
2. Color Correction Program

In the general color system of a computer, as shown in Figure 1, the color of an object was captured by CCD camera in standard lighting conditions (e.g. the D50 light source), and

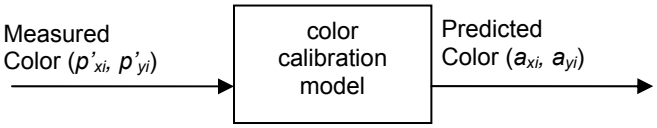
Received March 29, 2013; Revised June 20, 2013; Accepted July 8, 2013

presented on the screen through the computer. ICC is responsible to define color capture and to display the device-independent color space, plus that now there are many acquisition and display devices that support color management, such as gamma correction, color balance, etc. Nonetheless, due to the characteristics of individual equipment, color display on the screen of a computer still have differences in the color system from the actual color, so color correction is needed.

In the color system of a computer, the color correction can be done in two steps, as shown in Figure 1, a), b) below.



a) Constructing the color calibration model



b) Color prediction

Figure 1. Color calibration model

First is the need to create color correction model. In Figure 1a), the actual color on the standard color card was known, and marked with the chromaticity coordinates (t_{xi}, t_{yi}). In the D50 standard illumination conditions, the standard card had the colors displayed on the screen through the camera, and that are usually different from the actual color of the card. Screen showed its colors by the colors using a spectroradiometer, referred to here as the screen colors or measuring colors, marked with the color coordinates (p_{xi}, p_{yi}). The establishment of a color correction model actually means to establish the mapping relationship between measurement color T and the actual color P. As described in section I, this mapping relationship can be established with the help of the look-up table, multiple regression or neural network methods. In this paper, support vector regression was employed to establish the mapping relationship, where the standard color card used to establish color correction model was here known as the training sample.

In color prediction stage, as shown in Figure 1b), the color of the unknown samples could be measured using the spectroradiometer regarding the color displayed via the camera and screen, which was marked with P' (p'_{xi}, p'_{yi}). A well-established model of color correction could be used to obtain the predicted color A (a_{xi}, a_{yi}), which can be used to estimate the actual value T for the unknown color samples. As evidenced later in the experiment, by selecting the appropriate color correction model, the predicted color A, compared to the screen display color P', was able to better estimate the actual color of unknown samples T.

3. Support Vector Regression for Color Calibration based on Least Mean Squared Test Errors Algorithm

a. Support Vector Regression (SVR)

In its present form, the SV machine is a nonlinear generalization of the Generalized Portrait algorithm largely developed at AT&T Bell Laboratories by Vapnik and co-workers [9]. It is firmly grounded in the framework of statistical learning theory, or VC theory [10]. In a nutshell, VC theory characterizes properties of learning machines which enable them to generalize well to unseen data. Due to the industrial context, SV research has up to date had a sound orientation towards real-world applications. In regression applications, excellent performances were obtained [11, 12].

b. Successive 3σ Filter

3σ rule uses the fact that 99.73% of all values of a normally distributed parameter fall within three standard deviations of the average [13]. Although the 3σ rule uses the normal distribution as a basis, the same is true of other distributions [14].

In the acquisition process of the color coordinate measurement value and the actual value, the light, measuring instruments and recording process may be random to the introduction of random error. This study involved the use of the 3σ criterion to filter the original data. Taking into account the sample data with the original dimension of 2, the actual 3σ filtering was based on the distance between measured value and actual value as criterion, used to determine whether the data was in a reasonable range.

Successive 3σ filtering algorithm is as follows:

1) Calculate the color deviation of the original color coordinates data Δx_i, Δy_i

$$\Delta x_i = t_{xi} - p_{xi}, \Delta y_i = t_{yi} - p_{yi} \tag{1}$$

Where, p_{xi}, p_{yi} are chromaticity coordinates of the sample measurements, and t_{xi}, t_{yi} are the chromaticity coordinates of the actual value of samples. In the following formula, the meanings of these symbols are the same;

2) Calculate the raw data pair regarding the color coordinates in the chromaticity diagram Δe_i

$$\Delta e_i = \sqrt{\Delta x_i^2 + \Delta y_i^2} \tag{2}$$

3) Calculate the mean distance $E(\Delta e)$ and the mean square estimate $\hat{\sigma}_{\Delta e}$. MSE is based on the actual standard deviation to estimate

$$E(\Delta e) = \frac{1}{N}\sum_{i=1}^{N} \Delta e_i$$
$$\hat{\sigma}_{\Delta e} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (\Delta e_i - \Delta \bar{e})^2} \tag{3a, b}$$

4) If $\left|\Delta e_i - \Delta \bar{e}\right| > 3\hat{\sigma}_{\Delta e}$, remove No. *i* sample;

5) If a sample is removed, go back to 3), otherwise the algorithm ends.

c. Least Mean Squared Test Errors Algorithm

In the RBF kernel based SVR, two parameters named the penalty parameter C and the kernel parameter γ should be determined first. Different values of these two parameters (C, γ) lead to different results of SVR prediction. To find the best parameters, the experiment data could be divided into two independent sets, one for training, and the other for validating.

Thus, the Least Mean Squared Test Errors algorithm (LMSTE) is used in this paper.

Objective function that received repeated training for optimization was the least mean squared test error, i.e.

$$\min\ mse_{test} = \frac{1}{N_{test}} \sum_{i=1}^{N_{test}} (t_i - a_i)^2 \quad (4)$$

Where a_i is the predictive value of the sample; t_i is the actual value of the sample; N_{test} is the number of test samples, 16.7% of the total sample in this study.

Thus, the algorithm can be modified as follows:

1) Use of successive 3σ filter to preprocess the original data;

2) Data after pretreatment are divided into training samples set, test samples set and prediction samples set, the ratio is: 0.5:0.167:0.333;

3) Data normalized to [-1, 1];

4) Set the training parameters, including the penalty parameter C and the kernel parameter γ with the range C_{min}, C_{max}, γ_{min}, γ_{max} and the growth steps C_{step}, γ_{step}, the initial value of the training parameters (C, γ)=(C_{min}, γ_{min});

5) Use (C, γ) and training samples set to perform the training of the SVR;

6) The test sample is used for this trained SVR to obtain the predicted value, calculate its mse_{test};

7) If mse_{test} is lower than the previous saved value, then save this trained SVR model;

8) (C, γ) = (C + C_{step}, γ + γ_{step});

9) If (C, γ) ≤ (C_{max}, γ_{max}), go back to 5), otherwise the training ends.

4. Experimental Results and Analysis

a. Experimental Data and Compared Methods

Experimental data included 240 groups, where the Successive 3σ Filter was used to process the raw data. Two thirds were taken as training samples and another one third as predicted samples to test the various fitting methods in terms of their generalization performance.

To illustrate the calibration performance of SVR, the comparative experiments were also carried out on several algorithms that are commonly used in color calibration, including polynomial regression[15], BP neural network and relevance vector machine[16].

1) Polynomial regression

Taking into account that the actual color imaging and display is incorporated into a nonlinear system, as shown in Figure 1, P and T are subject to a non-linear function, so the experiments in this paper introduced a quadratic polynomial for comparative experiments, as expressed in the following form.

$$\begin{bmatrix} A_x \\ A_y \end{bmatrix} = \begin{bmatrix} b_{x1} & b_{x2} & \dots & b_{x5} \\ b_{y1} & b_{y2} & \dots & b_{y5} \end{bmatrix} P + \begin{bmatrix} b_{x0} \\ b_{y0} \end{bmatrix} \quad (5a, b)$$

$$P = \begin{bmatrix} P_x & P_y & P_x^2 & P_y^2 & P_x P_y \end{bmatrix}^T$$

2) BP neural network (BP)

BP neural network is widely used. It is a proven fact that three-layer BP network can approximate any complex function. In this paper, three-layer BP neural network was also used in comparative experiments. As far as the BP network of three layers, the hidden nodes need to be elaborated. In order to reflect the performance of BP network in this case, the hidden nodes received a repeated training using the BP network of a variable structure to test the minimum sample MSE, aiming to determine the best hidden nodes[17]. Furthermore, Levenberg-Marquardt (LM) back-propagation with early stopping method was applied to prevent overfitting.

The main parameters are: the transfer function of hidden layer is hyperbolic tangent sigmoid transfer function (*tansig*), and the output is linear transfer function (*purelin*). The training function is LM back-propagation.

It is noteworthy that because the initial weight matrix for each training session was based on random values, a single training in a particular network structure may not be able to get the results that truly reflect the performance of the structure. This paper was designed to

perform the training for 20 times in each network structure, where the best performance (i.e., minimum MSE) was used to express the performance of the network structure. Using this strategy and, ultimately, the best structure of the network was 2*2*2. This paper had the experimental results of the BP network that were all derived in this network structure.

3) Relevance Vector Machine (RVM)

In regression analysis, RVM can get a vector matrix that is sparser than the SVR. Meanwhile, it also has more flexible features including the definition of the kernel function and the probability of output. In recent years, the research activities have become increasingly active on the RVM. So, this paper also involved the use of the Sparse Bayesian Modeling algorithm (version 2.0) (available from http://www.relevancevector.com) provided by Tipping for comparative experiments, where the kernel function was consistent with Gaussian kernel, and its main parameter basis width (bw) also subject to the optimization strategy similar to that in section 3. The final parameters obtained are:

$$[bw_x \; bw_y]^T = [2.82 \; 19.5]^T \tag{6}$$

b. Experiment Contents

1) SVR training

In this paper, Least Mean Squared Test Errors algorithm described in section III was employed to obtain the training parameters of SVR (C, γ). With the help of LIBSVM[18],SVR algorithm was programmed under Matlab R2009a.

The training parameter (C, γ) and *mse* on the parameter space consisting of test samples are as shown in Figure 2. Least Mean Squared Test Errors algorithm looked to get the parameter pair (C, γ) to minimize mse_{test}. In this case, SVR was obtained as the optimal parameters:

$$[C_x \; \gamma_x]^T = [128 \; 0.0625]^T \text{ and } [C_y \; \gamma_y]^T = [32 \; 0.125]^T \tag{7a, b}$$

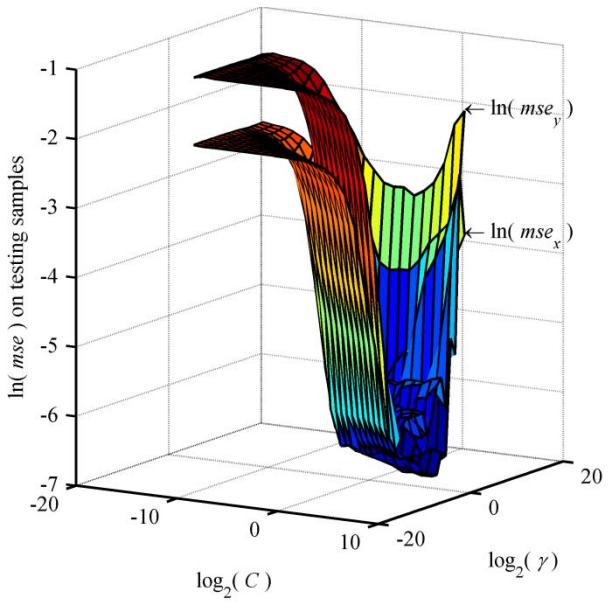


Figure 2. SVR mse variation with different parameters (C, γ)

In Figure 2, SVR has 120 training samples, and 40 test samples, with *mse* to be calculated on the test sample. Subscript x and y denote the CIE 1931 chromaticity coordinates x and y. The Least Mean Squared Test Errors algorithm (LMSTE) was employed to search parameters (C, γ) in the parameter space to minimize *mse*.

In the neural network training, the immediately fixed training samples and network results will also have the different prediction models because of different initial weights of the network, and the randomness of their training may lead to the network to be convergent to local optimum. As for the SVR training parameters, so long as the training samples and training remain the same, the same prediction model is always obtained, with the convergence result always being the global minimum. This is another obvious feature of SVR that is better than the neural network.

2) Performance Evaluation

This experiment also went to the comparison on several other calibration methods that were mentioned in section IV. They presented the calibration results on the color calibration, as shown in Table 1.

Table 1. Performance of different calibration methods

Performance	Uncalibrated	Quadratic polynomial	BP	RVM	SVR
SSE_t	0.14275	0.02699	0.02894	0.02902	0.02734
SSE_p	0.03662	0.00762	0.00945	0.00764	0.00637
$RMSE_t$	0.02987	0.01299	0.01345	0.01347	0.01307
$RMSE_p$	0.02240	0.01022	0.01138	0.01023	0.00934
R^2_t	0.90855	0.98271	0.98146	0.98141	0.98248
R^2_p	0.88695	0.97647	0.97083	0.97641	0.98034
$MEAN(\Delta d_p)$	0.02094	0.00808	0.00958	0.00803	0.00663
std_p	0.00800	0.00629	0.00618	0.00638	0.00662
r_t **	0.98998	0.99157	0.99111	0.99093	0.99146
r_p **	0.98989	0.99064	0.98946	0.98981	0.99167
$MAX(\Delta d_t)$	0.05961	0.06308	0.06469	0.06481	0.06327
$MAX(\Delta d_p)$	0.05329	0.04526	0.04410	0.04279	0.04534
$*NG_p$	0	1	6	5	1

*NG indicated the number of samples with greater Δd than uncalibrated.
**r was defined as Pearson product-moment correlation coefficient[19].

In Table 1, all evaluation indicators were calculated on distance error vectors Δd_i .

$$\Delta d_i = \sqrt{(t_{xi} - a_{xi})^2 + (t_{yi} - a_{yi})^2} \quad (8)$$

In this study, the output variable was two, including chromaticity coordinates x, y. Therefore, the error calculation needs to cover the errors in both directions. a_{xi} is x for the predicted value of the sample, a_{yi}, the coordinate y; Likewise, t_{xi}, t_{yi} indicate x, y for the actual value of the sample.

The subscript t and p identified the calculation on 160 training samples or 73 prediction samples. As seen from the Table 1, although the SVR did have the best correction performance for the training sample, it had the best value for the indicators of all the predicting samples, especially r_p and NG_p (NG, the Number of samples with Greater Δd than uncalibrated.). This shows that the SVR had the optimum generalization ability.

Among the experimental results, the quadratic polynomial and the performance of BP network are similar to results obtained by Liu et al[20]. However, this does not show that the neural network has a performance that is worse than that of the quadratic polynomial, only to find that in this case, as few as 160 samples were used for training, leading to is not fully neural network learning and the decline of its generalization ability. This also shows that in the case of small samples, SVR, based on statistical learning theory, has better generalization ability. RVM failed to show good performance in this case, in spite of the use of Gaussian kernel same as SVR, which used a sparser relevance vector, resulting in the decreased ability of the exact approach and thus underfitting appeared. Therefore, there is a need to find a suitable kernel function for improving the performance of RVM. Quadratic polynomial displayed a good performance in this case, mainly attributed to a high degree of linear correlation of the original sample (r_t=0.98998, r_p=0.98989), and the second polynomial further improved its linear correlation coefficient.

Figure 3 shows the prediction error of various methods in CIE 1931 chromaticity diagram, which includes the size of forecast errors and their directions in the chromaticity diagram. The size of forecast errors can be more clearly seen in figure 4. In Figures 3 and 4, it is clear that no correction of almost all samples are larger than the correction brought by the different correction methods, with only a few values that are only relatively small (the specific number were given by NG_p in Table 1. This shows that the various correction methods can reduce the errors of the original measurements, where the average error corrected by SVR is the smallest, with the best overall performance.

In Figure 3, the abscissa and vertical coordinates are, respectively, the measured values of chromaticity coordinates x, y for prediction samples. Vector diagram stands for the difference between predicted and actual values for a variety of methods. In order to be clearly displayed on the map, the length of the vector has undergone the automatic scaling.

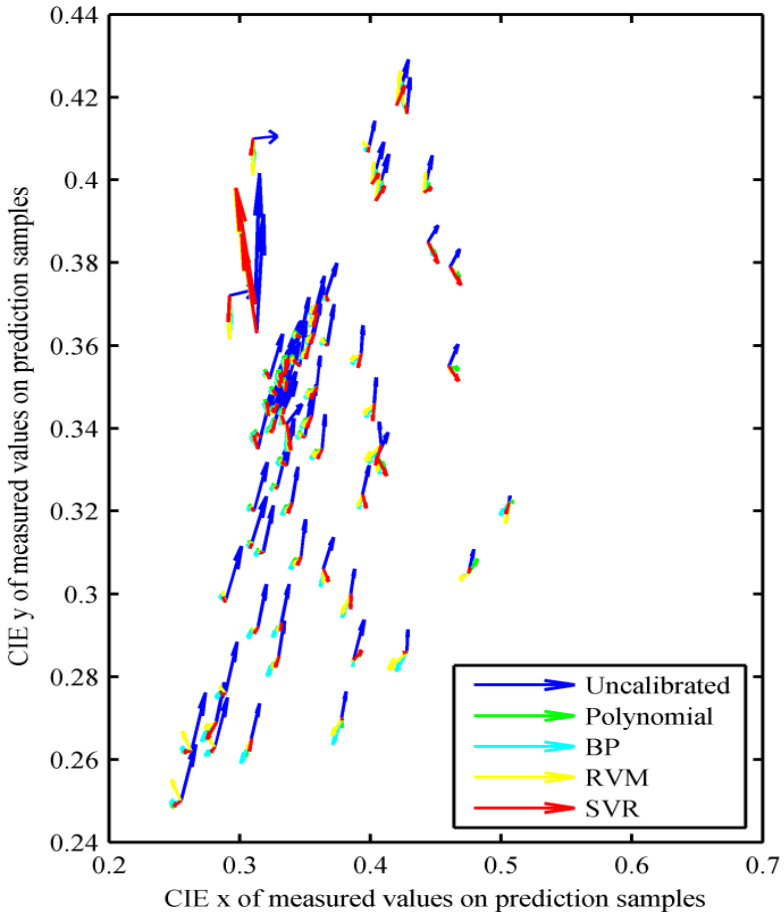


Figure 3. Scaled error vectors on prediction samples

In Figure 4, the abscissa is the number of prediction samples, and in this study, the number of predictive samples is 73. Vertical axis is the distance between the measured and predicted values in the CIE 1931 chromaticity coordinates. The error curve shows the generalization ability of these five methods, the mean error and the standard deviation can be seen in Table 1. In the figure, four kinds of data obtained by the samples were closer to the actual value than the uncorrected data.

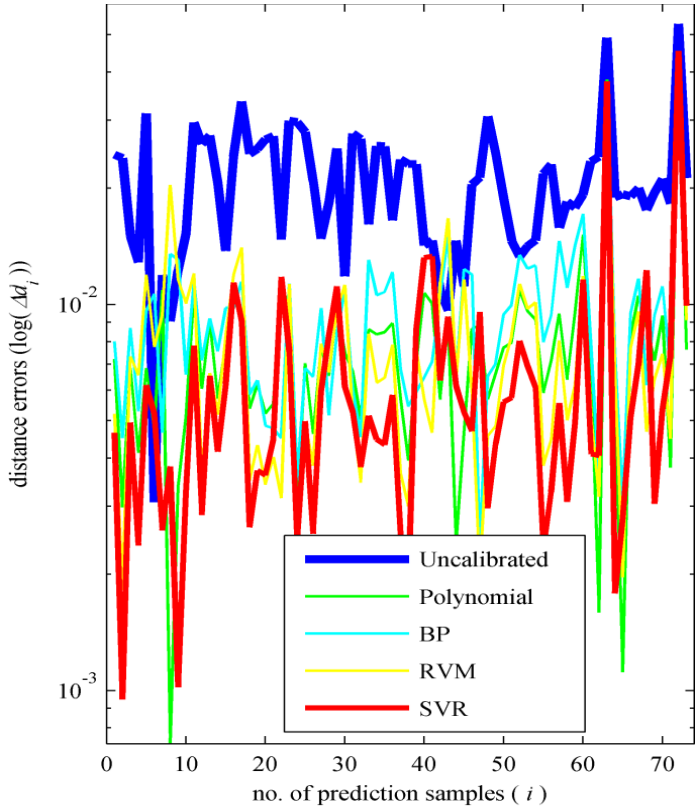


Figure 4. Calibration errors of different methods

5. Conclusion

These above results may lead to the following conclusions:

1) Successive 3σ Filter algorithm can be used to eliminate the larger errors found in the measurement data, and also able to improve the generalization capability of correction algorithm;

2) The Least Mean Squared Test Errors algorithm can be used to optimize the SVR parameters, while reducing the amount of fitting and over fitting;

3) Compared with other methods in color correction, the SVR method presented a more accurate prediction of unknown samples, that is, chromaticity coordinates of its projections showed the more accurate estimation on the actual chromaticity coordinates.

Through the proposed dynamic overmodulation method, a quick dynamic torque control can be achieved by selecting a voltage vector that produces the largest tangential flux component. The proposed method is capable of obtaining the fastest dynamic torque control for any operating conditions including the field weakening region with six-step mode. The proposed dynamic overmodulation resulted in a simple hysteresis-based structure as originally DTC. Only minor modification is needed and no SVM and hence voltage reference are required to be generated. Most of the main components of the basic DTC hysteresis-based structure are retained.

Acknowledgments

This work was supported by the Chunhui Plan sponsored by Ministry of Education (Grant Z2008-1-63019) and the scientific and technological research project by Chongqing Municipal Education Commission (Grant KJ091409). Thanks for the postdoctoral research in department of optics and photonics of National Central University.

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