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VIRTUAL RICE LEAF COLOR MODEL DRIVEN BY PIGMENT CONTENT

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Abstract

A virtual rice leaf color model based on the relationship between pigment contents in rice leaf and leaf color was established with the aid of machine learning tools and optimization algorithms. The results showed that the accuracy of the obtained training model and prediction model for red (*R*), green (*G*), and blue (*B*) components in leaf color reached 96.9 - 97.6, 98.0 - 98.3 and 83.5 - 84.7%, respectively. The correlation coefficient between the true and predicted values demonstrated that pigment contents were highly related to the *R* and *G* components, whereas the correlation for the *B* component was relatively low. The results of this study verified the effective applications of artificial intelligence and machine learning technologies in science of traditional agriculture.

Introduction

A virtual rice leaf color model that provides information technology support for rice producers is an important component of precision agriculture. With the continuing development of information technology (IT), the integration of information science (IS) and traditional natural sciences has become an effective approach to technological innovation in which IS provides powerful technological methods to support traditional sciences. For instance, such techniques as machine learning, big data, and intelligent optimization algorithms are effective in supporting computer-aided design (CAD) systems. A virtual plant refers to a model established by simulating the growth and development of plants using virtual reality technologies on computer platforms. This model can facilitate the analysis and monitoring of plant growth rhythms, which are important applications of IT in the field of precision agriculture (Room *et al.* 1996, Hanan 1997). According to the sorting and analysis of reported literature, since 1960s, there have been a large number of studies in geometric modeling of virtual plant shapes by various scholars who used various approaches, such as form language (Prusinkiewicz and Lindenmayer 2012, Yang *et al.* 2019), fractal theory based on iterated function systems (IFS) (Barnsley 2014, Balasubramani 2017), cellular automation (Frolov *et al.* 2015, Hordijk and Altenberg 2020), numerical calculation of curves and surfaces (Sousa and Prusinkiewicz 2003, Uyar and Ülker 2017, Liang *et al.* 2018, Oqielat 2019, Wang *et al.* 2020), and half-edge data structures (Gasch *et al.* 2018, Somogy 2018). However, the research on physio-ecological characteristics of virtual plants is still in its early stages. As an important vegetative organ for plants, the leaf may change its color in the process of plant cultivation if the photosynthesis of chlorophyll is directly influenced by improper fertilizer, water supply and pests. Thus, agricultural research staff and producers often adjust for more reasonable cultivation schemes by predicting biomass concentrations in leaves according to the changes in leaf color (Friedman *et al.* 2016, Zhang *et al.* 2019). Visualization of the process of leaf color change in plants can enable large-scale or high-cost agricultural experiments that were not possible or not easy to perform to be conducted on the computer platform. This approach not only helps to save labor and material costs in studies of rules

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of leaf color changes but also predicts trends in leaf color changes. Therefore, the establishment of an accurate computer model that agrees with the rules of leaf color changes of plants in the real world is an issue that urgently needs to be solved in this study field.

At present, studies related to virtual plant leaf color models can be categorized into the following two types: linear and nonlinear regression models. In the linear regression model, the scientific understanding of the physiological mechanisms of leaf color changes is used to identify those biological characteristic variables that influence leaf color changes. Then, the mathematical equations of multiple linear regression are used to establish the relational model between these variables and the RGB components. In the nonlinear regression model, the method of machine learning is utilized to establish the learning model between the physiological or ecological factors of plants and leaf color changes. Studies that belong to the first type of model include the following. The causal model was established between the nitrogen contents in two different varieties of rice leaves and their leaf color changes (Zhang *et al.* 2014). The experimental results obtained by these researchers showed that the proposed model could accurately simulate the actual leaf color change of a certain rice variety. In another study the canopy images of maize growth were collected and the causal model was obtained between the color and the chlorophyll, which could then be applied to chlorophyll concentration predictions in satellite remote sensing images (Nguy-Robertson *et al.* 2015). The relationship was established between pigment contents of leaves with different phyllotaxes and RGB components by the fitting of the curve equation (Yi *et al.* 2018). Leaf images were denoised with image processing techniques and further, the regression model was established between the soil plant analytical development (SPAD) value and the leaf color of tobacco (Chen *et al.* 2020). With the rapid development of artificial intelligence technologies, new opportunities have emerged for traditional agriculture studies that involve leaf color modeling work related to machine learning. For example, the prediction model of external growth environment factors of rice and leaf SPAD values was established via support vector regression (SVR) (Yi *et al.* 2016a). The results demonstrated that SVR solved the regression problem of small samples well. Support vector machines (SVM) and neural networks were adopted to establish the prediction models of rice leaf pigments and leaf color, respectively (Sun *et al.* 2017). The model was built between the SPAD value and RGB in artificial neural network, which they then used in the nondestructive detection of chlorophyll contents in potato leaves (Gupta and Pattanayak 2017). Several other researchers adopted deep learning techniques in the establishment of plant leaf color regression models and the identification of different leaves (VijayaLakshmi and Mohan 2016, Lee *et al.*2017, Zhu *et al.* 2018, Kaur *et al.* 2019).

The factors that have impacts on leaf color changes are complicated. Specifically, the first group of modeling methods is guaranteed by strict linear equations, whose modeling process is easy to implement. However, due to the models' oversimplification, they show a weaker generalization ability. In contrast, the second group of modeling methods is mainly based on machine learning technologies that search for an optimized solution in a hypothetical space. Therefore, the generalization ability of the models for learning is stronger than that of the first group. Pigments of plant leaves mainly consist of chlorophyll a, chlorophyll b, lutein, and carotene with blue-green, yellow-green, and yellow and orange colors, respectively. Without considering the influence from external light, when the contents of chlorophyll a and chlorophyll b exceed those of lutein and carotene by a large margin, the apparent leaf color will be green (Croft and Chen 2017). In view of this finding, machine learning was used in this study to establish a visualization model between the aforementioned four types of pigments and the leaf color. Furthermore, an intelligent algorithm of meta-parameters optimization for SVR was designed to reduce the prediction errors of the proposed model.

Materials and Methods

This study takes the regular "Zhongjiazao 35" rice variety planted in the middle and lower reaches of the Yangtze River in China as the testing material, and models the aforementioned four kinds of biological pigments and the virtual rice leaf color as examples. The detailed research content and methods are shown in Fig. 1.

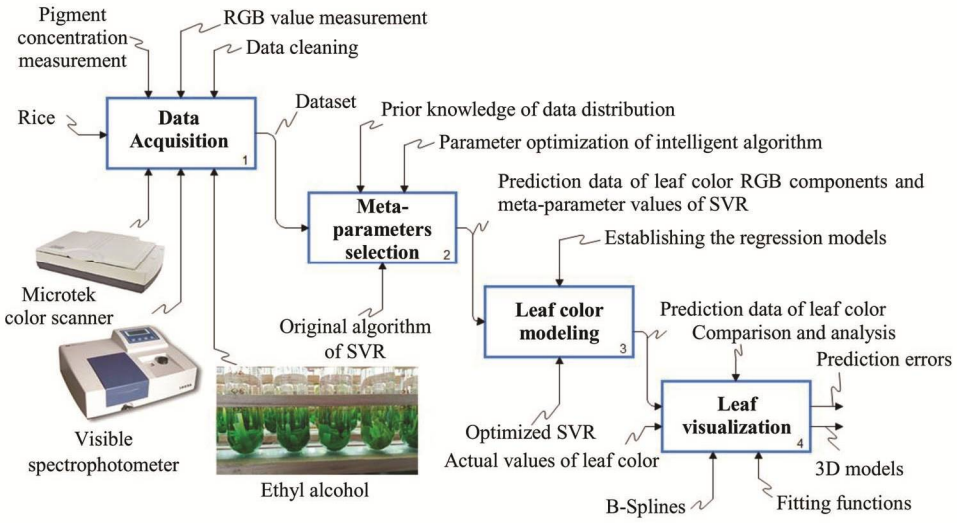

Fig.1. Research methods and technology roadmap.

The rice leaf data related to modeling were provided by the Key Laboratory of Agricultural IT of Colleges and Universities in Jiangxi province, China. The measurement procedure for concentrations of chlorophyll a, chlorophyll b, lutein, and carotene are as follows. At first, holes were punched on leaves with an equal mass for sampling. Afterwards, the samples were soaked in 95% ethyl alcohol of until all the pigments were extracted. The solutions were then measured by a 722(N) visible spectrophotometer for the absorbance of the four pigments at wavelengths of 665, 649, 449 and 446 nm. Furthermore, the equation introduced in Yi *et al.* (2017) and Yi *et al.* (2018) was used to convert the values of absorbance to the concentrations of the four pigments. For leaf RGB, the obtainment process was divided into the following two steps. First, a Microtek color scanner (Model: 1660XL Plus, resolution: 600 dpi) was used to scan the front of the leaf. Second, the image processing toolkit in Matlab R2013a was utilized to remove the image impurities and obtain the RGB values of leaf color.

SVM possesses significant advantages in solving nonlinear classification problems with small samples. To allow SVM to solve regression problems, Vapnik introduced insensitive loss in SVM as $\varepsilon: \left\| f(X^{(i)}) - y^{(i)} \right\|_1 ::= \max\{0, \left\| f(X^{(i)}) - y^{(i)} \right\|_1 - \varepsilon\}$, where ε is the allowed regression error threshold and y is the true sample value (Vapnik 2013). The Eq. 1 presents the predicted value of $f(X)$

$$f(x^{(i)}) = \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^*\right) \kappa(x^{(i)}, x) + b, \tag{1}$$

where, $f(x)$ is the separated hyperplane in the high-dimensional feature space; α_i and α_{i^*} are the Lagrange multipliers; c is the penalty factor introduced when solving for the optimal values of α_i and α_{i^*}; and k is the kernel function that is used to map the inner product among samples in the original feature space into the high-dimensional feature space. The data measurement error in this experiment satisfies the Gaussian distribution, and the Gaussian kernel function is adopted for leaf color modeling, as shown in the Eq. 2 below.

$$\kappa\left(x^{(i)}, x\right) = N(x^{(i)} - x; 0, \delta^2 I), \quad (2)$$

where, N is the standard normal density function and δ signifies the radial radius of the distribution.

The constrained optimization of SVR meta-parameters c, δ and ε can enhance the generalization ability of the regression model. However, research in this regard remains an open-ended question at the moment (Soentpiet 1999). As the value of ε influences the accuracy of task solving, only the first two meta-parameters are optimized and selected in this study as indicated in the Eq. 3.

$$fit(c^*, \delta^*) = \arg\min_{c,\ \delta \geq 0} \left[\frac{1}{n} \sum_{i=1}^{n} \left(f((X^{(i)}) - y^{(i)} \right)^2 \right], \quad (3)$$

where, c^* and δ^* are the values of the meta-parameters after SVR optimization. The solution draws on the lessons from the intelligent algorithm proposed by Pan (2012), which simulated the fruit flies' searching for food via olfaction and vision. According to Liu *et al.* (2006), fruit flies not only have sensing capabilities in olfaction and vision but also olfactory and visual memories. To include the two types of memorizing abilities above and improve the convergence rate and accuracy of the SVR meta-parameter optimization algorithm, two aspects of the fruit fly optimization algorithm (FOA) were modified in the current study. One change is that the estimated value of sample distribution proposed by Cherkassky and Ma (2004) is used as the rough memory of food location for the fruit fly population, i.e., the knowledge learned or the prior knowledge is applied. The corresponding calculation formulas are shown in the Eqs. 4 and 5:

$$c_0^* = \max(\left| \bar{y} + 3\Delta y \right|, \bar{y} - 3\Delta y), \quad (4)$$

$$\delta_0^d \in (0.1 - 0.5) * range(X), \quad (5)$$

where $\bar{y}$ and Δy are the average value and standard deviation of the leaf color RGB components, respectively, and d is the dimension of the input leaf pigment data X, whose value range can be determined by the function of range.

The FOA algorithm adopts the reciprocal of the distance from the fruit fly to the origin of the Cartesian coordinate system as the food concentration smelled by the fly, which then leads to the loss of the fruit fly's original memory for the food odor in the next algorithm iteration. Therefore, in the second modification to the FOA algorithm, the original memory value of the fruit fly is added into the algorithm as indicated by steps 1, 2, and 11 of algorithm 1 shown below.

Through the data acquisition and algorithm design of the SVR meta-parameter optimization, the feature set S of the rice leaf color model is obtained as $S = \{X,Y\}$, in which X consists of concentrations of chlorophyll a, chlorophyll b, lutein and carotene, and Y comprises the R, G, and B components of leaf color. The process of meta-parameter extraction and fitting of leaf color parameters based on SVR is shown in Fig. 2.

Algorithm1: Meta-parameter optimization SVR

Input: S
Output: c^*, δ^*

1. Calculate the value of c_0^* according to the equation 3.
2. Calculate the value of δ_0^* according to the equation 4.
3. Initialize the number of fruit flies: n.
4. Initialize the number of iterations: m.
5. Initialize the locations of the fruit flies: $L_{c,\delta}=(c_0^*, \delta_0^*)$.
6. **While** j **is less than or equal to** m
7. **While** i **is less than or equal to** n
8. Update the fruit flies' location so that they search randomly around themselves: $L_{c,\delta} = L_{c,\delta} + rand(i, 2)$.
9. Calculate the distance from each fruit fly to the origin of the Cartesian coordinate system: $D_i = \left\| l_c^i + l_\delta^i \right\|_2$. Since the convergence of the algorithm is satisfied, the derivative of distance is defined as the concentration of food odor smelled by i-th fruit fly: $smell_i = 1/D_i$.
10. Find a better fruit fly position based on $\min\{smell_i\}$;
11. Correct its position and store it $(c_i, \delta_i) + L_{c,\delta}$;
12. Substitute the position of the better fruit fly into the fitness function: $fit(c^*, \delta^*)$.
13. $i \leftarrow i+1$.
14. $fit_j(c^*, \delta^*) = \min\{fit_j\}$.
15. If fit_j of the current iteration is less than that of the previous generation, replace the best position of the previous iteration with the best position of the fruit fly in this iteration.
16. $j \leftarrow j+1$.

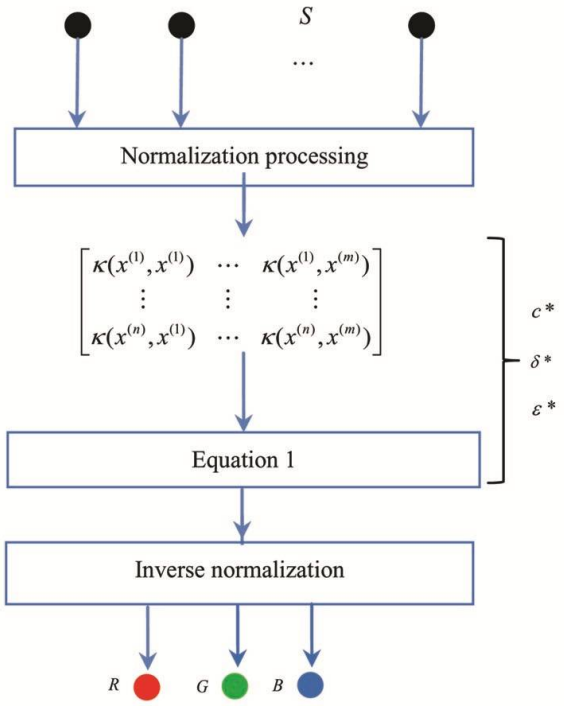

Fig. 2. Meta-parameters selection of SVR.

The shape edge of plant leaves can be plotted as a closed curve. Taking the leaf of rice as an example, its leaf apex only satisfies the C^o continuity property, and the local bending deformation of the leaf can happen under the influence of internal and external forces. As the B-Spline curve defines different basis functions in the range of [0 - 1], its curve of degree n is merely related to $n + 1$ control points. Therefore, the local shape control of this curve is comparatively flexible and the constructed curve satisfies the property of C^0 continuity or above (Cottrell *et al.* 2009). In consideration of this finding, the cubic B-Spline curve was selected in this work and its parametric equation is represented as follows:

$$C(t) = \sum_{i=0}^{n} P_{i+j} N_{i,3}(t), \qquad (6)$$

where, $C(t)$ refers to all the points on the edge of the leaf, $t \in [0, 1]$; P represents the control points of curve deformation, which is defined in the corresponding basis function N; and j is the index of the starting control point influenced by one basis function. In this study, C++, Open Graphics Library (OpenGL) 2.1, and OpenGL Shading Language 330 were adopted in the programming. The point data structure on the edge of the rice leaf is defined as a combined vector: *vector4 <vector3, vector4, vector3, vector2>*, as shown in Fig. 3. The first and third components are the vectors of a point and its normal vector in the spherical coordinates, the second component is the predicted leaf color value, and the last component consists of the texture coordinates.

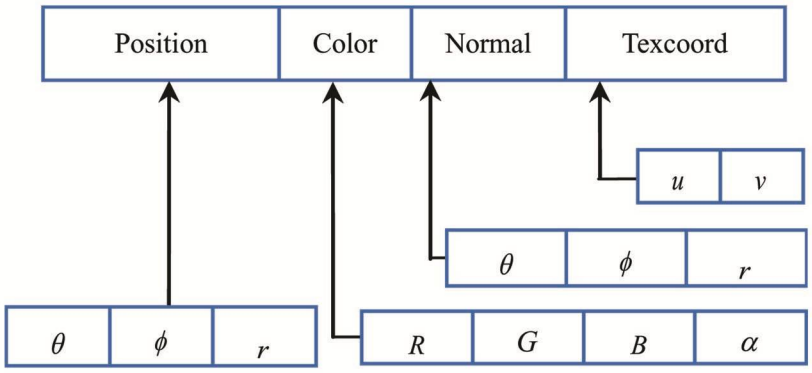

Fig. 3. Data structure of the geometric vertex.

Results and Discussion

The morphological change of plant leaves is a highly complex life process, which finds an outstanding external expression in the rich leaf colors. Pigments are the blending agent for the leaf color, which to a large extent decides the functional performance of biological substances (photosynthesis). To study the leaf color change rules of the virtual plants on the computer platform, accurate data models should be first built. However, samples of eco-physiology data of plants are difficult and costly to collect; therefore, abundant sample data were not collected. Therefore, this study introduced SVR into the data modeling process of virtual rice leaf color. To enhance the training and prediction accuracy of the SVR-based models, the authors improved the artificial intelligence (AI) algorithm of FOA for selecting meta-parameters for SVR and built visual models of rice leaf by the spline function and the OpenGL rendering library. The proposed algorithm and three other algorithms were compared and evaluated (Fig. 4).

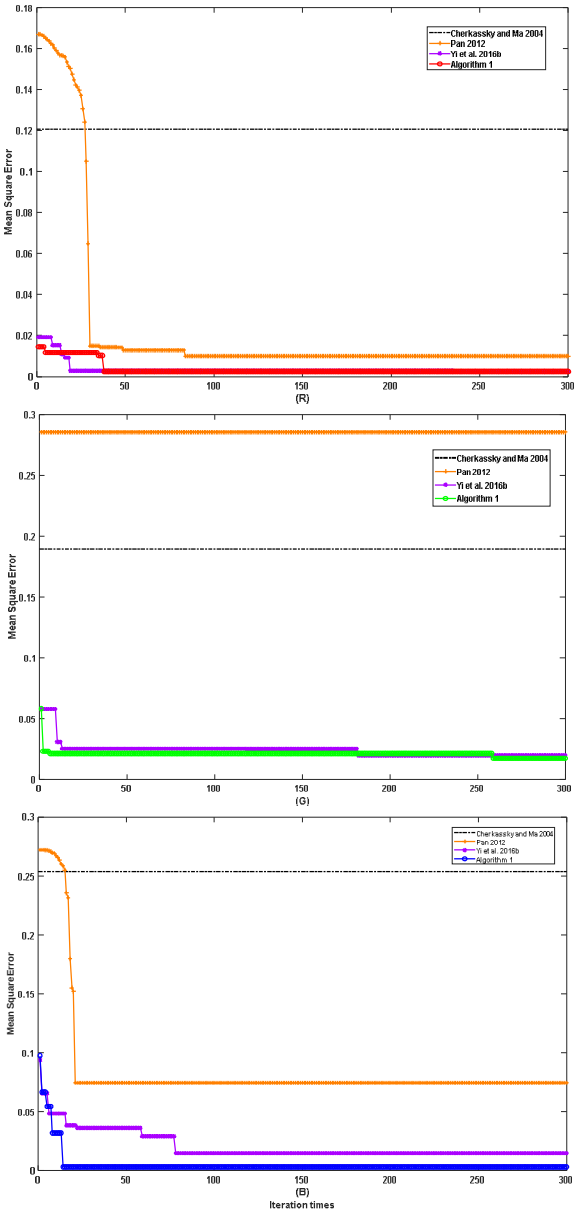

Fig. 4. Comparison of four types of meta-parameter search algorithms for pigments and RGB colors in SVR learning. The horizontal axis is the number of iterations in the algorithm, and the vertical axis is the mean square error of the algorithm, which can be calculated as in the Eq. 3.

In Pan (2012), the initial locations of fruit flies were random, satisfying the diverse characteristic of intelligent algorithms which, however, led to instability in the execution of the algorithm. Yi *et al.* (2016b) adopted the method of Cherkassky and Ma (2004) to estimate the initial locations of the FOA population, which were fixed within a certain range for searching. In the first round of iterations, the fruit fly population was rapidly brought close to the feasible solutions for the SVR meta-parameters. The experimental results showed that the improvement enhanced the searching

accuracy of population parameters which is in accordance with the findings of Yi *et al.* (2016b). For the FOA algorithm to converge, Pan (2012) adopted the reciprocal of distance from the population to the origin of coordinates as the evaluation function. If the algorithm proposed in Yi *et al.* (2016b) failed to converge in the first iteration, the estimated information of the target to be solved would be lost in the second or following iterations. This approach can lead to random searching in a wide range, thereby compromising the convergence rate of parameter optimization for the algorithm. Based on these, the current study was undertaken the parameter estimation approach as in Cherkassky and Ma (2004) for pigments and obtains prior knowledge for the *R*, *G*, and *B* components of leaf color. Furthermore, these sets of knowledge were added in the expression of the evaluation function in the FOA algorithm.

During the process of SVR modeling for 41 training samples and 30 testing samples of pairs of pigments and rice leaf RGB components, the initial population of the optimization algorithm was 30, and the number of iterations was 300. As shown in Table 1, the proposed algorithm performed better in its overall convergence time and error evaluation of SVR meta-parameter optimization during sample training were compared to the first three approaches.

Table 1. Evaluation of the meta-parameter optimization for four algorithms.

Algorithms	Popula-tion	Number of iterations	Convergence time (*epoch*)			Fitting function value/Error evaluation		
			R	G	B	R	G	B
Cherkassky and Ma 2004	-	-	-	-	-	0.1206	0.1893	0.2534
Pan 2012	30	300	84	69	21	0.0099	0.2854	0.0744
Yi *at el.* 2016b	30	300	236	182	78	0.0025	0.0197	0.0147
Algorithm 1	**30**	**300**	**38**	**259**	**14**	**0.0024**	**0.0174**	**0.0031**

The leaf blade is the carrier of leaf color. In this context, the RGB components are obtained by the SVR prediction of biological pigment concentrations. The true and predicted RGB component distributions corresponding to the 30 similar samples with biological pigments are presented in Fig. 5. The results show that the values of the *R* and *G* components were larger than that of the *B* component, which is consistent with the experimental results of Zhang *et al.* (2014) and Yi *et al.* (2018).

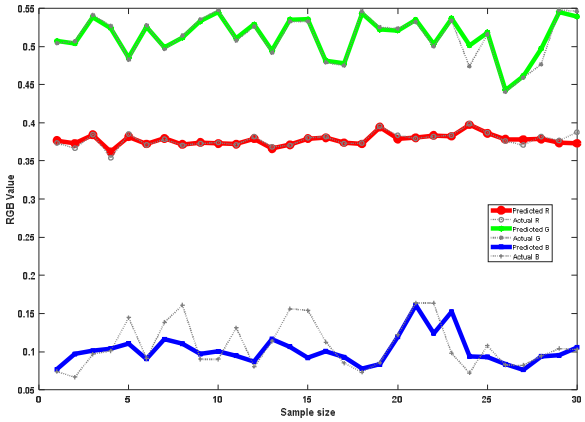

Fig. 5. Distribution of the predicted values of the RGB components. The vertical axis shows the normalized RGB values, respectively. Taking R as an example, the calculation formula is *R*/(*R*+*G*+*B*).

The predicted values of the RGB components from the three sets of pigment samples with chlorophyll a (Ca), chlorophyll b (Cb), lutein (Cc), and carotene (Cd) were selected for leaf color visualization, and the results are presented in Fig. 6. In the growth and development period, rice leaves were green. When concentrations of lutein and carotene were enhanced, the value of the *G* component in leaf color reduced, resulting in a darker leaf color. In terms of object choice in leaf color modeling, two differences between the present study and that of Yi *et al.* (2018) observed. One difference is that the latter only considered the influence of the total concentrations of Ca, Cb, and carotenoid on leaf color. The other difference is that Yi *et al.* (2018) fitted the values of the *R*, *G*, and *B* components, respectively while ignoring their synergy. In the data acquisition of the present study, the three components were normalized, thereby reflecting the relation among the biological pigment concentrations, the leaf color components and the components themselves. In this way, more abundant biological semantic information was expressed.

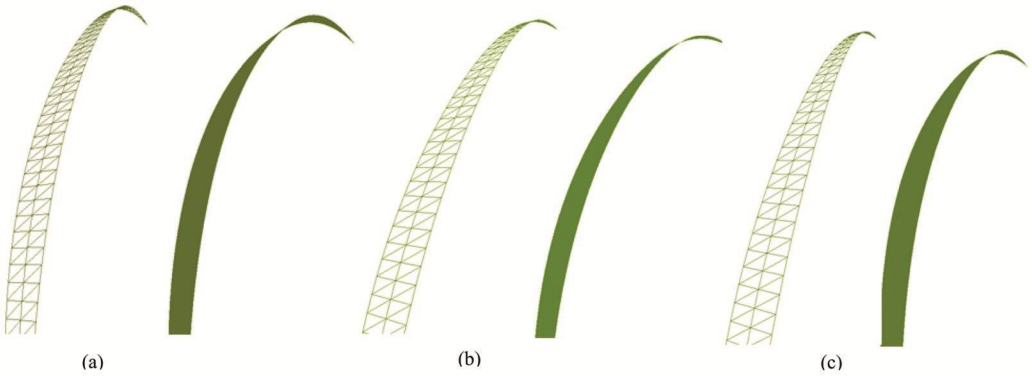

Fig. 6. Simulation results of virtual leaves. The rendered leaf color value corresponding to pigment concentrations: (a) (Ca=0.545, Cb=0.257,Cc=0.746, Cd=0.816) ↦ (R=0.372549, G=0.462745, B=0.164706); (b) (Ca=0.532, Cb=0.227,Cc=0.686, Cd=0.745) ↦ (R=0.378261, G=0.547826, B=0.073913); (c) (Ca=0.367, Cb=0.159,Cc =0.462 , Cd=0.508) ↦ (R=0.371094, G=0.515625, B=0.113281).

To measure the error between the predicted value from the leaf color model and the actual value, the standard root mean square error (RMSE), an internationally applied value, was adopted for validation in this study. The calculation formula is shown in the Eq. 7. The degrees of correlation between the biological pigment concentrations and the *R*, *G*, and *B* components of the leaf color were calculated using the Eq. 8 following Chang and Lin (2011).

$$RMSE = \sqrt{\sum_{i=1}^{n} (y^{(i)} - \hat{y}^{(i)})^2 / n} \ , \tag{7}$$

$$r^2 = \left(n\sum_{i=1}^{n} f(x^{(i)})y^{(i)} - \sum_{i=1}^{n} f(x^{(i)}) \sum_{i=1}^{n} y^{(i)} \right)^2 / \left(n\sum_{i=1}^{n} f(x^{(i)})^2 - \left(\sum_{i=1}^{n} f(x^{(i)}) \right)^2 \right) \left(n\sum_{i=1}^{n} (y^{(i)})^2 - \left(\sum_{i=1}^{n} y^{(i)} \right)^2 \right) \tag{8}$$

where y is the actual value of the *R*, *G*, or *B* in leaf color and the corresponding predicted value is $\hat{y}$, and n is the number of training samples, which is set to be 41 in this study. The experimental condition is shown in Table 2 in which c_i^* and δ_0^* are the estimated results of the biological pigment samples in the SVR meta-parameter optimization, i.e., the samples' prior knowledge, and while c^*

and δ^* are the values at the moment of convergence for the algorithm. In addition, ε is the threshold of allowed regression error, which is set to be 0.01 (Chang and Lin 2011).

Table 2. Model evaluation indicators.

Label	Prior knowledge		SVR meta-parameters			Training stage		Predicting stage	
	c_0^*	δ_0^*	c^*	δ^*	ε	*RMSE*	r^2	*RMSE*	r^2
R	0.403694277	0.531329044	2.1931	5.3362	0.01	0.023975	0.87938	0.031348	0.8048
G	0.596586577	0.575331531	6.2479	18.2575	0.01	0.016542	0.95062	0.020157	0.92732
B	0.201693658	0.441043654	1.0219	1.1858	0.01	0.15295	0.42258	0.16529	0.34164

The training and predicting RMSEs of the leaf color RGB models ranged from 2.4 - 3.1, 1.7 - 2.0 and 15.3 - 16.5%, respectively. Moreover, the correlation between the actual *R*, *G* and *B* components of leaf color and the values predicted from the pigment concentrations were r_R^2 = 87 - 80.5%, r_G^2 = 95.1 - 92.7% and r_B^2 = 42.6 - 34.2%, respectively. As seen, $r_G^2 > r_R^2 \geq 0.8$ holds whether the model is in the training stage or the predicting stage, which means that the relevance between the pigments and the *R* and *G* components is high. For the *B* component, $0.3 \leq r_B^2 < 0.5$, indicated a low correlation. The variation tendency of the experiment above fits those obtained from Zhang *et al.* (2014) and Yi *et al.* (2018). However, the model accuracy and correlation coefficients in this study were higher than those of the latter two models.

Visual modeling of plants refers to the generation of visual models of plants by computer simulation using visual reality (VR) technology, which is one aspect of VR application in precision agriculture. Computer visual modeling of plant growth has two main forms: one considers visual effects alone, while the other embodies the theory of Botany based on plant eco-physiology features. The former has been applied to industrial design, game and movie special effects, art teaching, and other fields; the latter, on the other hand, has been used for plant science research, simulation of the agricultural production process, optimization and prediction of crop yield. In the present study, with the modeling of rice leaf color as an example, SVR based on selecting the meta-parameters algorithm was designed to gain prior knowledge of training samples and memory abilities. The models based-SVR were built to map 4D-vector (chlorophyll a, chlorophyll b, lutein and carotene) onto leaf color RGB components. The algorithm not only improved the SVR training speed but also enhanced the models' predictive accuracy.

To sum up, a complete set of methods, including rice leaf pigments and color data collection, optimization design of data modeling SVR and leaf color visualization, and results of experimental verification were examined in this paper. The modified AI algorithm meta-parameters selection described in this report can significantly improve training and predictive accuracy of the models based-SVR. The obtained virtual rice leaf color models with biological properties (pigments) can enrich the theoretical knowledge of plant leaf color modeling. In future research, the authors would attempt to (1) further improve the accuracy of the virtual rice leaf color model by improving the prior knowledge acquisition ability of the SVR meta-parameter selection algorithm and (2) build leaf color models of human-machine unified perception to make the visualized virtual rice leaf color more realistic.

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