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Prediction of Chemical Composition in Tea Based on Image Processing Technology

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The most prevalent method used for tea production makes it difficult to guarantee the tea quality due to the fact that the natural environment is bad and artificial technology level is poor. There is a pressing need to find a feasible way that can estimate tea production schedule and quality. Against this backdrop, this paper introduces the image processing technology into the quality judgment in the tea production to predict chemical constituent changes in tea such that the most appropriate production model will be available. In this study, image processing technology extracts the tea color information in the production process. PCA (principal component analysis) simulates the relationship between the color change information and the chemical composition, based on which to train the BP neural network, and also successfully predict the contents of sugars, starch, total nitrogen, alkalis, and other principal chemical components in the phases of the tea production process. This study provides a reference for tea quality judgment.

1. Introduction

Since the entry of the 21st century, China has made enormous strides in tea production industry by virtue of a traditional model. The tea production process has entered an advanced stage of scale- and technology-based production with a variety of specialized equipment, greatly reducing the cost of tea production and processing and improving the tea production efficiency and benefit. However, due to the widespread distribution of tea production areas in China, there are obvious differentiations in the natural environment, and even more general equipment fail to well control the tea quality in the production process.

In order to fill the above gap, some standards that have been issued by relevant authorities in China strictly specify the tea production equipment and processes. However, these standards cannot still completely eliminate poor tea quality caused by disparities in the natural environment. It is also difficult to guarantee that the workers involved will be unable to produce the tea in full accordance with standards and processes as specified. For this reason, we are in dire need of developing a set of models that are not confined by the natural environment for industrial production and processing and have no stringent requirements on the workers to guarantee the quality of tea production with good judgement. The most frequently-used method is to control the production schedule by tea color according to more traditional tea production process since the tea color has also been regarded as one of the indicators for judging whether it is made successfully and qualifiedly. Based on the above proposition, this paper introduces the IPT into modern tea production and inspection process, explores how it help control a good effect in the tea production process, and provides an idea to solve the problems that has long plagued us in the tea production process using modern equipment.

2. Background

From the perspective of chemical principles, whether the tea is ultimately made successfully or whether the quality well fit the bill has a great bearing on chemical components contained in the tea (Meyer, 1998). In qualified tea leaves, the sugar, starch, total nitrogen, alkali and other ingredients as percentages of the total mass should fall within a specified range. However, in practice, how can we make clear the proportions of various chemical components in tea, and then judge the quality of tea production?

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2.1 Relationship between tea quality and chemical components

Up to now, many scholars have made extensive studies on this issue and agreed with a universe conclusion about it. As most scholars believe, the high-quality tea should satisfy the least two basic conditions (Singh, 2013): First, the raw materials for making tea are better, neither to pick unripe and overripe materials; second, it is the process of making tea that must operate as specified and be well controlled. Otherwise, tea will not be better even if it picks good raw materials. After a clearer understanding of the tea quality, we find that the major chemical components as percentages of high-quality tea are indeed relatively constant. Take the famous Tieguanyin tea in China as an example, the sugars, starch, total nitrogen and alkali in a good tea produced are 2:1:1:1.5. For many black teas, the content of alkaline in well-made teas is higher, which is one of the important reasons why there is difference in taste between black and green teas.

2.2 Judgement method for chemical components of tea

According to the more traditional viewpoints, the tea quality should be judged by professional tea tasters depending on many elements such as tea color, shape, taste and aroma, etc. However, this traditional approach is more subjective and pertains to highly specialized skill, so that it often gets tricky in the face of mass production of tea (Xiao et al., 2009). In this context, some scholars have discovered that it is feasible to judge the tea quality by the color of tea leaves. Some also stated that the tea color can be based to roughly determine the tea production phase, that is, whether the tea is well made can be judged by the change in tea color (Elfaki, 2000). Correspondingly, the IPT is to extract image information from objective things by simulating the human visual system, and it has unparalleled advantages in this respect (Wu, 1999; Ali and Machado, 1981). The above results reveal that, in theory, it is feasible to determine the tea color gradient in production process using IPT, and further judge the tea quality by estimating the chemical composition of tea.

3. Relationship between tea color and chemical composition

In order to hit the mark, we should first determine what the relationship between different colors and chemical composition of tea is in the production process. For this purpose, we adopt the PCA for study.
The color feature of tea leaves can be expressed in RGB color palette, the most basic color model, which, based on the most basic colors such as red, green, and blue colors, can produce any other color by combining these three (Tsai et al., 2003; Calderara et al., 2011; Hasegawa and Kanade, 2005; Mueller,1992). Conversely, any color can also be decomposed into red, green and blue (Suh et al., 2004; Suzuki et al.,2009). Therefore, to accurately express the tea color, we should decompose the color into three dimensions, i.e. red, green and blue.

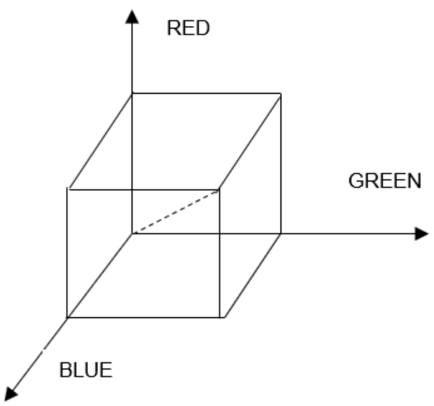

Figure 1: RGB Space

To predict the chemical composition of tea, we should first determine how different color signature and chemical content correlate to each other. Here it should be noted that since this paper bases all studies on the Tieguanyin tea, for each kind of tea, there is the relationship between the color and chemical composition quite different from others, so that it needs to be studied separately. This paper uses the IPT to acquire the color information from Tieguanyin tea production process, as well as corresponding continents as percentages of Tieguanyin tea in different phases. And more, the PCA helps analyze the color signature and study the matchup between the three color dimensions, i.e. red, green, and blue, and the four chemical components, i.e. carbohydrates, starch, total nitrogen, and alkalis. The study results are shown below:

Table 1: RGB Space and Chemical Component of Tea

	Saccharides	*Starch*	*Total Nitrogen*	*Alkali*
RED	0.81*	-0.11	0.19	-0.51**
GREEN	-0.27	0.06***	-0.39	0.46**
BLUE	0.35**	0.54*	0.01*	-0.91***

In the above table, *, **, and **** represent the significance levels at 10%, 5%, and 1%, respectively. When concerning the results in the above table, we should mainly focus on the symbols in front of the figures, where + sign denotes positive effects and - sign does negative effects. Take the figures in the line 2 and column 2 as an example, 0.81* indicates that the sugar content in Tieguanyin tea increases as the shade of red color get strong, and this result is statistically significant. Using the IPT and PCA, we can obtain the congruent relationship between the massive RGB color palette and the chemical composition of tea as the important basis for chemical composition prediction using tea color in the later stage.
The other thing we also need to make clear is that there is a one-to-one correspondence among "tea quality - chemical content - color", because only in this way can we accurately predict the tea quality. In other words, we should determine whether the relationship between chemical content and color is monotonous or linear, provided that the fact the tea quality is subjected to change with different chemical contents is known. With this in mind, we conduct a function test on the correspondence between the chemical content and color dimension of tea, and found that these relations all meet the requirements, and any quadratic or above function relation not significant. The table below shows the results from the function test, for example, a quadratic function relationship test. These results are not significant at the 10%, 5%, and 1% levels.

Table 2: Functional Relation Test

	Saccharides^2	Starch^2	Total Nitrogen^2	Alkali^2
RED	0.05	0.21	0.87	0.01
GREEN	0.11	0.91	1.25	1.15
BLUE	0.24	0.13	0.43	2.14

4. Prediction of chemical composition in tea production process

This section mainly predicts the chemical composition of tea in the production process based on the IPT, BP neural network algorithm, and testifies whether the predicted results are applicable.

4.1 Training of BP neural network

The chemical composition prediction used in this paper is a BP neural network algorithm. In 1943, the neural network algorithm was first proposed (Lópezgranados, 2011; Boopathi and Thiagarasu, 2018). The neural network algorithm is actually inspired by studies of human brain. In essence, it is such a process that imitates the structure of human brain neurons and the function of human brain for self-training, inference and prediction (Deweese, 1996). It first needs to obtain initial data from external world, then imitates the data processing mode of human brain to learn and train, and infers or predicts the change of data after a certain period of time as required (Radwan and Oldham ,1987). There are typical auto-regression approach and sliding average methods, etc., for data prediction using neural network algorithms. This paper adopts the sliding average method as the principal model for prediction. Before formal predictions, we should train the neural network, that is to say, we input the congruent relationship between several colors and chemical composition of the tea obtained in the previous section into the neural network to allow it form recognition on the relationship between tea color and chemical composition by the self-learning process.

4.2 Treatment of tea image signature

The tea image signature treatment process is to extracts the first-hand information about tea color in tea production process, and decomposes these pieces of color information into three basic dimensions, i.e. red, green and blue. Before processing image signature, we will preprocess the image, including three main procedures, image denoising, edge detection, and image segmentation. After the pretreatment, the IPT can clearly and accurately extract the color information of tea leaves. The following figure gives the color information of tea that we extracted at a certain production point. These pieces of information have already been decomposed into three basic color dimensions: red, green, and blue.

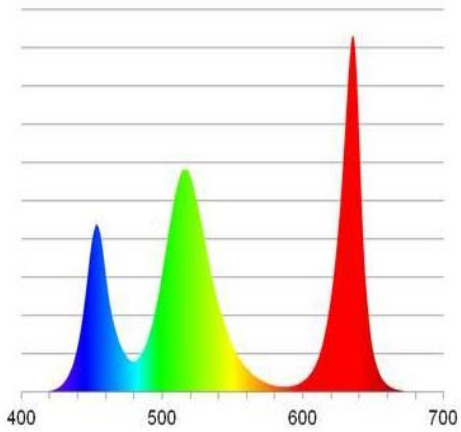

Figure 2: RGB Example of a Tea Leaf

4.3 Chemical composition prediction of tea

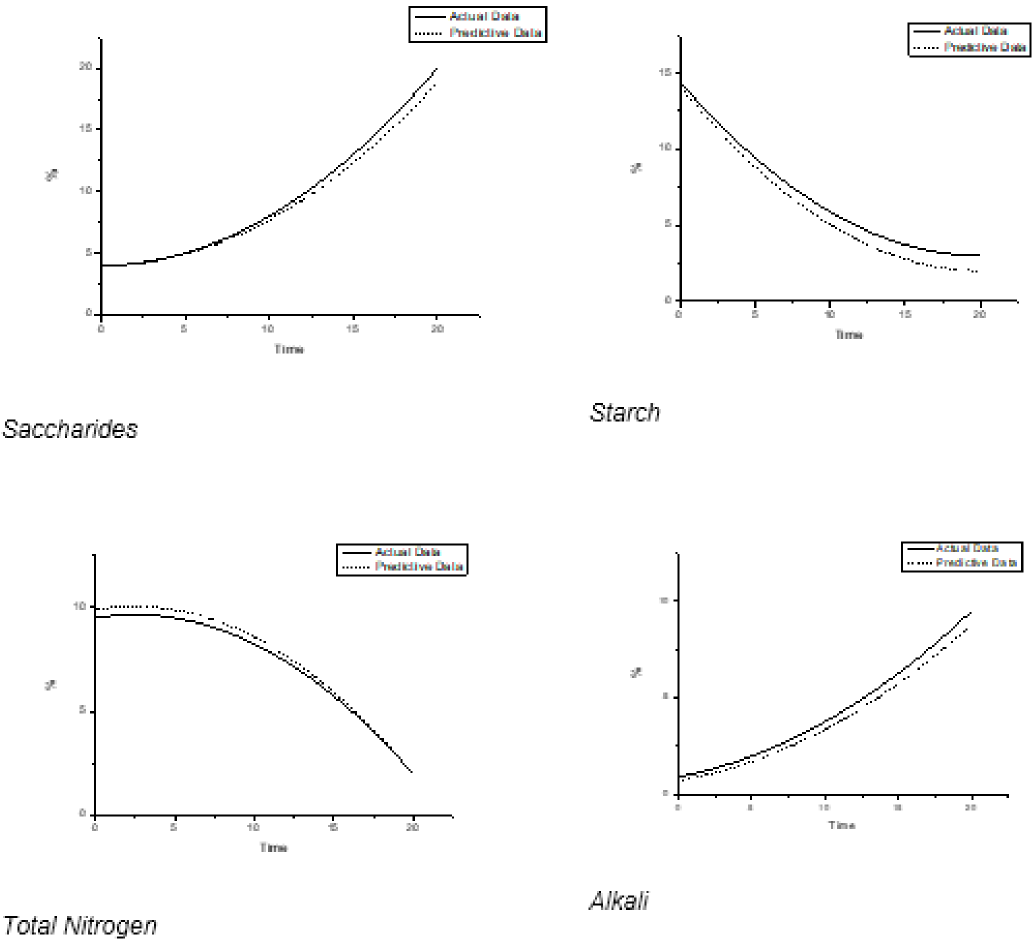

Figure 3: RGB Example of a Tea Leaf

After training the BP neural network, we can predict the chemical components in the tea using tea color information extracted in Section 4.2. As shown in the figures below, the changes in the actual contents of sugars, starch, total nitrogen, and alkalis during the tea production process and their predicted contents are given.

As shown in the figures above, the solid line shows that along with the progression of the production process, the actual contents of sugar and alkali substances in tea has shown an upward trend, the starch and total nitrogen present a downward trend; the dashed line represents the predicted values of major chemical components of the BP neural network algorithm. We can see that the predicted values of sugar, starch, total nitrogen, and alkali substances basically coincide with the actual values, which suggests that it has a good prediction effect. In this sense, it is feasible to judge how the tea quality seems by predicting chemical composition of tea.

5. Conclusions

This paper mainly explores the predication on how the chemical composition of tea changes based on the IPT, and further judge the quality of tea production. It provides an idea to deal with the challenge that tea production quality is difficult to control. The findings are given as follows:

5.1 IPT can accurately decompose the color information of tea into three basic dimensions: red, green, and blue. This provides a basis for us to infer how the chemical composition of tea changes in the production process using color information.

5.2 The results from PCA show that there is a congruent relationship between the color information and the chemical composition in the tea production process.

5.3 The BP neural network algorithm with data training can predict how the chemical composition of tea changes in the production process, and with a better effect, the purpose that chemical composition will help judge the quality of tea production can be achieved.

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