Abstract

Inspecting what sort of starch in commercial starch-noodles is important to international trade, food safety and protecting consumer benefit. At present, the inspection of components of starches in starch-noodle mainly relies on sensory perception, and which is fallibility or trustless. Because the microstructure pattern of starches in starch-noodles depends mainly on a kind or blend of starches from which the starch-noodle was made, this paper presents an approach to classify the starch-noodles by using computer system automatically based on recognizing the microstructure pattern of the starches and components in starch-noodle. The method consists of three step: 1) take the micrograph of starch-noodles with scanning electron microscopy and preprocessing. 2) extract features of fractal geometry and Gray-Level Co-Occurrence from micrograph. 3) distinguish a sort of starch-noodles by using these combined features as input vector of artificial neural networks. The experiments has been conducted with starch-noodles of mungbean blending pachyrhizus, and the experimental results show that the method is practicable and effective.

1. Introduction

Starch noodle, as a traditional Chinese food, is popular in many countries now. There are various starches of crop can be used as a raw material in starch noodle making, such as mungbean, potato, pachyrhizus, corn, pea and the blends of above starches. Starch noodle made from different starch or proportion of ingredient has different qualities, and among them the noodle made from pure mungbean starch is the best in edible qualities, favorite in market but the high in price[1][2][3]. Consequently, inspecting the ingredient of commercial starch noodle and identifying fake starch noodle productions are necessary to international trade, safety and so on. Traditionally, the work has been done by Bureau of Entry-Exit Inspection and Quarantine of Quality Food and Technical Supervision according to the physical qualities of starch-noodle by sensory evaluation such as colour, transparent, pliability and uniformity of starch-noodle. This method is subjective and fallibility, especially to being similar in sensory feels but far not in edible qualities.

The inbeing structure in starch noodle is the Gelatinization and Retrogradation of starch which formed at the heating and cooling processes of starch. The different type of starches in starch noodle has distinction in microstructure, and the microstructure image can be obtained by Light or Scanning Electron Microscopy[4]. This paper proposed a method to identify the types of different starch and proportions in starch noodle made from different starches automatically by computer. The process consists of obtaining tissue micrograph of starch noodle with scanning electron, extracting features from micrograph, and classifying by using artificial neural networks. The experiments in which the starch noodles are made from pure mungbean and mixture of mungbean with pachyrhizus starch shows that it is practicable and effective.

2. Obtaining micrograph and analyzing features

2.1. Micrographs of starch noodles

The experimental samples of starch noodles that have been made by traditional processing technique of Longkou starch noodle manufactory are provided by YanTai Entry-Exit Inspection and Quarantine Bureau. For it is evidence in colour and transparent that the quantities of pachyrhizus exceed 25% in starch noodle, so the starch noodles of pure mungbean starch, mungbean starch with 10% pachyrhizus starch, 15% pachyrhizus starch and 20% pachyrhizus are selected for specimens. The starch noodles were cut vertically or horizontally into seemly piece using a blade, mounted on brass specimen holders, and plunged into liquid nitrogen slush. After specimens were sputter-coated for 12 min, it were transferred to Model-1000B scanning electron microscopy (AMRAY, USA), and examined and shot at a voltage of 10 kilovolt (kv).

2.2. Features of micrograph
The making starch noodles mainly utilizes the short-time retrogradation properties of pasting starch [5]. When the raw dough strand of starch flowed into hot water and were heated, the starch granules imbibe many times their weight of water; swell to much larger sizes than their original; the hydrogen-bond disconnects in crystal and uncrystal phase of starch granules and molecular structure destroys; and, at the same time, the partial amylase leaches out of the granules. When cooling through cooling water, the pasted dough strands become the starch noodles or the starch gels in process of which the leached amylase and some amylopectin starch forms partial junction zones or matrix, the swollen granules become the gelatinized starch granules by reconstructing, and both of the gelatinized starch granules and junction zones make up of microstructure map of starch noodle. At the same making condition, the microstructure maps of dissimilar kinds of starch noodles are different. Figure 1 was the scanning electron micrographs of some starch noodles: (A) pure mungbean starch, (B) mungbean starch with 10% pachyrhizus starch, (C) 15% pachyrhizus starch and (D) 20% pachyrhizus starch. Obviously, these images possess the specific characteristic of texture and fractal in intensity [6] and show the obvious difference. The main reasons are: 1) The pasting degree of different starch is different at the same making condition. 2) The quantities of soluble amylase and amylopectin starch differ from each other.

3. The extraction of image feature

Accord to the characteristics of micrographs of starch noodles and experiments, the features derived from the fractal geometry and Gray-Level Co-Occurrence Matrix in experimental images were selected to be used as the feature vectors for pattern classification through artificial neural network system.

3.1. The extraction of fractal feature

The fractal dimension is an important characteristic of fractals because it contains information about their geometric structure. There are many definitions for the fractal dimensions of a fractal set [7], such as cover dimension, information dimension, box dimension, and etc. Box dimension or box computing dimension is one of the most widely used dimensions. Its popularity is largely due to its relative ease of mathematical calculation and empirical estimation. In this study, the box dimension values were calculated from images of starch noodles. Suppose \( F \) is a non-empty and bounded subset of \( R^n \), \( N_\delta (F) \) is the smallest number of subsets which cover the set \( F \), and their diameters are not greater than \( \delta \), the upper and lower bounds of the box computing dimension of \( F \) can be defined by the following formulas:

\[
\text{Dim}_F = \lim_{\delta \to 0} \frac{\log N_\delta (F)}{-\log \delta}, \quad \text{Dim}_F = \lim_{\delta \to 0} \frac{\log N_\delta (F)}{-\log \delta}
\]  

(1)

Where Times New Roman the overline stands for the upper bound of dimension while the underline for lower bound. If both the upper bound and lower bound are equal, the common value is called box computing dimension or box dimension of \( F \), namely:

\[
\text{Dim}_F = \lim_{\delta \to 0} \frac{\log N_\delta (F)}{-\log \delta}
\]  

(2)

The calculation of a box dimension adopts the way proposed by Sarkar and Chaudhuri in [7]. A gray image can be regarded as a curved surface in three-dimension, i.e. \( Z = f(x, y) \), \( (x, y) \) is the coordinates of pixel, and \( Z \) denotes corresponding gray-value. Suppose the ranges of a image is \( M \times M \) pixels, and the \( x \)-\( y \) coordinate plane of the image is divided as grids of \( \delta \times \delta \) (\( \delta \leq M/2 \)), if the maximal and minimal gray-values in the grid of \( (i, j) \)th are \( a_\delta (i, j) \) and \( b_\delta (i, j) \), the difference of both is defined as: \( d_\delta (i, j) = a_\delta (i, j) - b_\delta (i, j) \). The calculational formula of the sums of non-empty box at \( \delta \) length is expressed:

\[
N_\delta = \sum_y d_\delta (i, j) / \delta
\]  

(3)
According to the formula (3), a set of points, \((\delta, N_\delta), i = 1, 2, \ldots, m\), can be obtained by changing the value of \(\delta\). Further, the \(\log N_\delta\) and \(\log \delta\) can be calculated, and the slope of the beeline which was made from the set of points \((\log N_\delta, \log \delta)\) through linear regression of Least squares is the estimated box dimension corresponding to image. In experiments, the window \((M)\) of sub-images was taken as 32 pixels, and the range of scale from 2 to 16 pixels.

3.2. Features derived from Gray Level Co-occurrence Matrix

The Grey Level Co-occurrence Matrix (GLCM), a square matrix of side equal to the number of grey levels in the image, is constructed from the image by estimating the pairwise statistics of pixel intensity, and a popular statistical technique for extracting textural features from different types of images [8]. Each normalized element \(m_{hk}(h, k)\) of the matrix represents an estimate of the probability that two pixels with a specified separation have grey levels \(h\) and \(k\). The separation is usually specified by a displacement, \(d\) and an angle, \(\theta\). Such matrices are a function of the angular relationship and distance between the neighboring pixels. Features (contrast, entropy, correlation, angular second moment) derived from GLCMs and used in this paper are defined as follows:

\[
CON = \sum_h \sum_k (h-k)^2 m_{hk}, \quad ASM = \sum_h \sum_k m_{hk}^2 \tag{4}
\]

\[
ENT = -\sum_h \sum_k m_{hk} \log m_{hk}, \quad COR = \frac{\sum_h \sum_k hkm_{hk} - u_x u_y}{\sigma_x \sigma_y} \tag{5}
\]

Where, \(m_h = \sum_k m_{hk}\) denotes the sum of elements in a row while \(m_k = \sum_k m_{hk}\) in a column; \(\mu_x, \mu_y, \sigma_x, \sigma_y\) represent the mean and standard deviation of \(m_h\) and \(m_k\) respectively. In our experiments, the window of images were 32x32 pixels, the quantization levels 4 in this window, the displacement \(d=1, 2, 3\) \((d=1\text{ was optimal for classification }\), the orientations \(0^\circ, 45^\circ, 90^\circ, \text{and } 135^\circ\), and the average value of GLCM for the four angles was used as a feature vector, i.e.,

\[
\overline{CON} = \frac{1}{4} \sum CON, \quad \overline{ASM} = \frac{1}{4} \sum ASM \tag{6}
\]

\[
\overline{ENT} = \frac{1}{4} \sum ENT, \quad \overline{COR} = \frac{1}{4} \sum COR \tag{7}
\]

4. Networks and experiments

Artificial Neural Networks are developed to simulate some of the organizational principles found in the human brain, and consist of processing elements that can consist of many nodes. Each node can receive many inputs and computes a single output. These processing elements are arranged in layers. Within a processing element, each input is multiplied by a corresponding weight. The products are summed and the processing elements output is computed from the sum via a transfer function. The output is available as an input to any or all of the processing elements in the next layer.

4.1. Configuration of Neural network

The three layers of feed-forward Networks can approach any non-linear function at any precision [9]. In this study, one hidden layer was used in the network which contains 5 processing elements in input and output layers corresponding to dimensions of inputting feature vectors and classes of starch noodles, 10 processing elements in hidden layer through comparison, and Figure 2 shows the network architecture. If using \(X_j = [x_1, \ldots, x_4]^T\) denotes inputting feature vectors and \(W_j = [\omega_{j1}, \omega_{j2}, \ldots, \omega_{ji}, \ldots, \omega_{jn}]\) denotes weight vectors of \(j\)th processing element in hidden or output layer (\(\omega_{ji}\) express processing element \(j\) received input of \(i\) processing element), the sum of all input received by \(j\)th processing element is:

\[
s_j = \sum_{i=1}^n \omega_{ji} x_i + \theta_j = W_j X_j + \theta_j \quad \tag{8}
\]

The function \(f(s_j) = \frac{1}{1 + e^{-s_j}}\) was adopted as transfer function, and output of \(j\)th processing element is:

\[
y_j = f(s_j) = [1 + \exp(-W_j X_j + \theta_j)]^{-1} \quad \tag{9}
\]

![Fig.2 Structure map of Neural Networks](image)

4.2. Training neural network

During training, the ANN output is compared to a target (expectable) output and an error calculated. The error is propagated backward from the output processing element to the input processing element. Weights at each processing element are adjusted to minimize the error. The training cycle
is repeated until the network error is acceptably low. Here the error is defined as:

$$E_p = \frac{1}{2} \sum_{j=1}^{m} (d_{jp} - y_{jp})^2$$  \hspace{1cm} (10)

Where $d_{jp}$ and $y_{jp}$ are the actual and expectable output respectively. The arithmetic of Levenberg-Marguardt is used for learning rule, and basic iterative formula [10] is:

$$\omega(k+1) = \omega(k) - (J^T J + \mu I)^{-1} g$$  \hspace{1cm} (11)

Where $g$ is the grads of $E_p$ to $W_j$, $J$ Jacobian matrix, $I$ identity matrix, and $\mu$ adjustable non-negative.

4.3. Configuration of Neural network

In experiments, the basic learning rate used for training was 0.01, the momentum used in training was 0.1, and the training error was 0.001. The 35 events of each class of starch noodle was used for training, and 15 for inspection. The recognition rates obtained in the 100 Sample-micrographs of starch noodles using our system is all above 80% in Table 1.

<table>
<thead>
<tr>
<th>Classes of starch noodle</th>
<th>Recognition rates</th>
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<tbody>
<tr>
<td>mung bean</td>
<td>93%</td>
</tr>
<tr>
<td>mung bean/ pachyrhizus</td>
<td>9:1 80%</td>
</tr>
<tr>
<td>mung bean/ pachyrhizus</td>
<td>8.5:1.5 86%</td>
</tr>
<tr>
<td>mung bean/pachyrhizus</td>
<td>8:2 93%</td>
</tr>
</tbody>
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5. Summary

There are difference in molecular structure, weight and ingredient of raw starches, so each starch forms special microstructure in starch noodle under the same processing condition. In this paper, the features of image of starch noodles were extracted by using fractal geometry and Gray-Level Co-Occurrence Matrix, the suited artificial neural networks was designed for inspecting raw starch and proportion in starch noodle, and the results of experiments shows that presented method was practicable and effective, but the recognition rate was comparatively lower at the small quantities of pachyrhizus starch.

6. References