Apple Shape Classification Method Based on Wavelet Moment

* Jiangsheng Gui, Qing Zhang, Li Hao, Xiaoan Bao
College of Information, Zhejiang Sci-Tech University, Hangzhou 310018, China
* E-mail: dewgis@126.com

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Abstract: Shape is not only an important indicator for assessing the grade of the apple, but also the important factors for increasing the value of the apple. In order to improve the apple shape classification accuracy rate, an approach for apple shape sorting based on wavelet moments was proposed, the image was first subjected to a normalization process using its regular moments to obtain scale and translation invariance, the rotation invariant wavelet moment features were then extracted from the scale and translation normalized images and the method of cluster analysis was used for finished the shape classification. This method performs better than traditional approaches such as Fourier descriptors and Zernike moments, because of that Wavelet moments can provide time-domain and frequency domain window, which was verified by experiments. The normal fruit shape, mild deformity and severe deformity classification accuracy is 86.21%, 85.82%, 90.81% by our method.

Keywords: Shape analysis, Fruit grading, Machine vision, Wavelet moment.

1. Introduction

Apple grading is one of the important processes in post harvest handling and marketing. The shape is an important indicator to assess its grade and it is also an important factor to improve its commodity value. Comparing with the traditional classification method by manual, automatic classification method based on machine vision, image processing and intelligent algorithms has pushed forward the progress of fruit grading in nearly two decades [1]. However, due to the impact of natural and other complicating factors during the fruit growth, it is so difficult to uniformly describe the external shape and hard to define clearly like other general industrial products, so there is no perfect solution in fruit shape classification now [2]. At present, five common methods using machine vision technology are applied to describe fruit shape: geometry, wavelet multi-scale method, Fourier descriptors, active shape models and Zernike moments [3]. After extracting fruit shape characteristic parameters by this way, it is need to use multivariate statistical methods, support vector machines and neural networks etc. for mapping fruit Shape grade level. Xianfeng Li regarded geometrical configuration feature as one of the indicators of the multi-feature syncretism apple grading by extracting fruit shape index, geometry characteristic and round shape parameters and so on [4]. Andrew put forward by using the long axis, short axis, shape factor and firmness for grape shape classification [5]. Majid Rashidi used roundness and ellipse features to distinguish normal and abnormal shapes of cantaloupe Kiwifruit [6-7]. Slamet Riyadi extracted the wavelet coefficients of papaya edge, then calculates three statistical properties (wavelet coefficients, variance and mean). Combination each other to form six characteristics as classification of
papaya shape of normal and abnormal basis, and they obtained good results [8]. Abdullah M. Z [9] used Fourier descriptors to assess Carrabolla shape and multilayer neural network was used to classification and the accuracy is from 80 % to 89 %. Ingrid Paulus [10] evaluated six kinds of apple shape by using the top 12 harmonics of the Fourier transform and the coefficient of determination was 0.98. Literature used the top 15 components of the discrete Fourier transform to identify apple shapes and the classification accuracy was above 85 % [11]. Cai Jianrong proposed an apple shape classification method based on active shape models and the classification accuracy was above 85 % [12]. During these methods, geometric parameter method was easier than others so that it was only suitable for certain types of fruit. Active shape model method required manual demarcating point so that it did not unfit for shape automatic classification. Fourier descriptors had the ability to reconstruct a complete shape, but it had no ability to describe the local details of the fruit shapes. Invariant moments, especially Zernike moments is the entire image space so that it could lead to the accumulation of errors and decreasing classification effects [16]. Therefore, this research presents an apple shape classification method based on wavelet moment. This method has the ability to reconstruct a complete shape, but it did not unfit for shape automatic classification. Fourier descriptors could describe shape information very well. But the calculation range of Zernike moments is the entire image space so that it could lead to the accumulation of errors and decreasing classification effects [16]. Therefore, this research presents an apple shape classification method based on wavelet moment. This method has translational stretching and rotational invariance which is necessary for the shape classification and due to the wavelet moments can provide the time-domain and frequency-domain window at the same time, the classification results are superior to the Fourier descriptors and Zernike moments method which are common used now.

2. Description of Image’s Wavelet Moment

Assuming \( f(x,y) \) is the gray-distribution function of the image. Its \((p+q)\) order generalized moment \( M_{pq} \) under Cartesian coordinate system is defined as:

\[
M_{pq} = \iint_{\mathbb{R}^2} f(x,y)\phi_{pq}(x,y)dxdy
\]

where \( \phi_{pq}(x,y) \) is the core function of the transform above. If \( \phi_{pq}(x,y) = \phi^p \phi^q \), it was geometric moments of \((p+q)\) order. In order to obtain a normalized image, the translational and retractable normalization method in literature [17] can be used. Moving the origin of coordinate to the center of the target by conversion and conversion.

\[
f_T(x,y) = f((x - \bar{x})/a, (y - \bar{y})/a)
\]

\( f_s(x,y) \) has invariance of translation and scaling. Where \( \bar{x} = \frac{m_{10}}{m_{00}} \) and \( \bar{y} = \frac{m_{01}}{m_{00}} \), \( m_{ij} \) is \((i+j)\) order geometric moments of \( f(x,y) \). \( a = \sqrt{\beta/m_{00}} \), and \( \beta \) is a predefined constant. \( f_s(x,y) \) was transformed into the polar coordinates and was represented by \( f_s(r,\theta) \), \( M_{pq} \) in polar coordinates is defined as:

\[
M_{pq} = \iint f_s(r,\theta)\phi_{pq}(r,\theta)rdrd\theta
\]

where \( p, q = 0, 1, 2, ... \)

If the two dimensional kernel function \( \phi_{pq}(r, \theta) \) is a variable separable function. \( \phi_{pq}(r, \theta) = g_p(r)e^{iq\theta} \), where \( g_p(r) \) is one-dimensional radial kernel function. \( e^{iq\theta} \) is an angular component of transformed nucleus. The formula (2) can be rewritten as:

\[
M_{pq} = \iint f_s(r,\theta)g_p(r)e^{-iq\theta}rdrd\theta
\]

It can be proved that Characteristic value of mould \( ||M_{pq}|| \) can remain the same after image rotated. Assuming \( ||M_{pq}^1|| \) and \( ||M_{pq}^2|| \) are two eigenvalues of similar fruits respectively; the following relationship exists between them:

\[
||M_{pq}^1|| = ||M_{pq}^2|| + \Delta_{pq}
\]

Assuming the presence of noise, then the above equation is rewritten as:

\[
||M_{pq}^1|| = ||M_{pq}^2|| + \Delta_{pq} + \eta_{pq}
\]

Because the two fruits are similar, \( \Delta_{pq} \) is relatively small. Since the invariant moment and Zernike moments are calculated in the whole image space, \( \eta_{pq} \) is relatively large. If \( \eta_{pq} \) is bigger than \( \Delta_{pq} \), a classified error will occurred. If \( g_p(r) \) is defined in the local space of the image, \( \eta_{pq} \) will decrease significantly, and then it would improve the classification accuracy. Wavelet transform can provide a window time-domain and frequency-domain in the meantime, this characteristic is very suitable to extract local feature of images. So you can consider that the wavelet function set as follows:

\[
\psi_{a,b}(r) = \frac{1}{\sqrt{a}}\psi(r - b/a)
\]

where \( a \in R^+ \) is the scale factor, and \( b \in R \) is the displacement factor. Formula (6) instead of \( g_p(r) \) of equation (3) can obtain wavelet invariant moments of

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images. In digital image processing, a and b can only take discrete values, due to the limited of the image’s size $0 \leq r \leq 1$, then in our research, we choose

$$a = 0.5^n, b = 0.5m \cdot 0.5^n,$$

$$m = 0,1,2,...,n = 0,1,2,...,2^{m+1}$$

The wavelet functions’ set is as follows:

$$\psi_{m,n}(r) = 2^{m/2} \psi(2^m r - 0.5n),$$

(7)

So we can get global and local features of images with different m and n. Then it can be define wavelet invariant moments of the normalized image as:

$$||W_{m,n,q}|| = \int_0 \int_0 f_N(r, \theta) e^{-i\theta q} \psi_{m,n}(r) r dr d\theta$$

$$q = 0,1,2,...,$$

(8)

In the formula (8) above, for a fixed r, stands for the $q^{th}$ feature of the normalized image $f(r, \theta)$ in the phase-space $[0, 2\pi]$.

$$S_q(r) = \int f_N(r, \theta) e^{-i\theta q} d\theta$$

And using different scale factor m and displacement factor n, $\psi_{m,n}(r)$ can throughout the radial space $[0, 1]$, by this way $f_N(r, \theta)$ characteristics at different levels of scale provided by the wavelet invariants moment $||W_{m,n,q}||$ can be used to describe the shape.

3. Experimental Results and Analysis

However, it can be seen from the formula (8) that we get different wavelet moments from different kinds of wavelet functions. The main types of wavelet are spline wavelet, orthogonal wavelet, biorthogonal wavelet and so on. While the large amount of computation and reconstruction boundary error will accumulate in the use of B-spline wavelet transform, this will affect the classification results obviously. Coiflets wavelets possess regularity, biorthogonality and approximate symmetry, so we choose Coiflets wavelet as the basic function of formula (8).

For the fixed value m in formula (8), when we choose different translation parameters n, wavelet invariant moments reflect very local information of an image, which will be easily corrupted by noise [18]. So in this experiment, for a fixed m, we should get the sum of the different n which means we only study two parameters m and q. Then we have found a balance between the local features and global features. The combinations of different m and n have many characters, and it is quite difficult to choose the appropriate feature. We have tried a variety of combinations and carry out the following four categories as the basis of classification:

$$m = 2, q = 3; m = 2, q = 4;$$

$$m = 3, q = 3; m = 4, q = 4,$$

(9)

In following experiments, we investigated the plane geometry transformation invariance of the wavelet moment method. Likewise, we extract four wavelet moment characteristics from a set of images in Fig. 1, which listed in the Table 1.

![Fig. 1. Normal shape.](image)

| Table 1. Confusion matrices for the classification correct ratio by wavelet moments based on cluster. |
|----------------------------------|------------------|------------------|------------------|
| Normal shape                    | Slight abnormal shape | Serious abnormal shape |
| Normal shape                    | 75.18 %           | 22.07 %           | 2.77 %           |
| Slight abnormal shape           | 8.93 %            | 70.89 %           | 20.18 %           |
| Serious abnormal shape          | 29.76 %           | 16.67 %           | 53.57 %           |

It can be found that the wavelet eigenvalues after translating (picture e, f), rotating (image c, d) and stretching (image b) are a little different with the original image a. So the wavelet moment characteristics have good plane geometry invariance. In order to further verify the performance of the wavelet moment as a shape descriptor, we use 659 apple color images (size $640 \times 48$) as a sample. According to the laboratory 5 staffs who have many years of experience in agro-processing, 659 apple images are divided into three categories: normal fruit shape, mild deformity, and severe deformity in Fig. 1, Fig. 2 and Fig. 3.
Since cluster analysis classification is based on the level of similarity of the unclassified analysis model. Similar one is classified as a class, dissimilar one is typed as another. In the category, it’s no need to study and train with training samples. C-means algorithm was commonly used in this experiment (because it is the three categories, so take c = 3), and the basic idea of this algorithm is to take a given class c and select c initial cluster centers.

![Fig. 2. Slight abnormal shape.](image)

![Fig. 3. Serious abnormal shape.](image)

According to the principle of the minimum distance, we distribute the mode into a certain class of c class, then it is need to constantly calculate the center of one class and adjust the categories of each model, eventually we should minimize the sum of square distance of each mode to its judgment categories. In order to compare it with the traditional Fourier descriptors and Zernike moments, in this experiment, we extracted the former 25 coefficients of the Fourier descriptors, 9 features of Zernike moments in literature [8] (|A_{20}|, |A_{22}|, |A_{31}|, |A_{33}|, |A_{40}|, |A_{42}|, |A_{44}|, |A_{51}|, |A_{53}|) and pattern characteristic vectors composed by 4 characters of Coiflets wavelet moment from 659 apple images, and then composed them into vectors of model feature. And then the C-means clustering algorithm was applied to cluster, the results shown in Fig. 4. From Fig. 4 (a), it can be seen that the results of feature cluster of Fourier descriptors are relatively poor. It is not effective to distinguish them with three mixed types. The cluster result of Zernike moments features in Fig. 4 (b) is much better, while it is likely to cause misclassification when the center of the green area closes to the red area. From Fig. 4 (c), it was observed that the cluster results of wavelet moment characteristics are best, the regional boundaries of the three categories are obvious and the distance between centers is larger.

![Fig. 4. Cluster results of Fourier descriptors, Zernike moments and wavelet moments.](image)
In order to verify the actual results of the clustering classification method, we select three categories of typical 9 apple images (shown in Table 1) to make up a contrast set, which is used to determine the centers of each cluster corresponding to the shape category.

So we can get the hybrid matrix, the classification accuracy confusion matrix of Zernike Moments features and wavelet moment features (Fourier descriptors characteristic cluster ineffective, here is not to do further analysis), as shown in Table 1 and Table 2.

Table 2. Confusion matrices for the classification correct ratio by wavelet moments based on cluster.

<table>
<thead>
<tr>
<th></th>
<th>Normal shape</th>
<th>Slight abnormal shape</th>
<th>Serious abnormal shape</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal shape</td>
<td>86.21 %</td>
<td>13.45 %</td>
<td>0.34 %</td>
</tr>
<tr>
<td>Slight abnormal shape</td>
<td>12.44 %</td>
<td>85.82 %</td>
<td>1.74 %</td>
</tr>
<tr>
<td>Serious abnormal shape</td>
<td>0 %</td>
<td>9.19 %</td>
<td>90.81 %</td>
</tr>
</tbody>
</table>

Table 1 shows that as far as is concerned Zernike moment characteristics, the classification accuracy of serious abnormal shape is on the low side of only 53.57, the classification accuracy of slight abnormal shape is only 70.89 %. The reason is that the calculation range of Zernike moments is the entire image space; the error will accumulate and result in the distribution of many slight abnormal shapes closing to the core of severe deformity. In Fig. 4 (b), the middle of the red area (slight abnormal shape) nearby the edge of the blue area (serious abnormal shape) is closer to the blue central region, and some distributions of serious abnormal shapes were closer to the core of the normal shape. So over 20 % of slight abnormal shapes were mistaken into serious abnormal shape, and more than 29 % of serious abnormal shapes were mistaken into normal fruit shape.

To the wavelet moment, when the sample is divided into three categories, the classification precision of normal shape and slight abnormal shape is more than 85 %, and the classification precision of serious abnormal shape was over 90 %, and none were divided into normal fruit shape. These results of classification and cluster are fully consistent, the blue area and the green area are far from each other (as shown in Fig. 4 (c)). These results indicated that the classification features of the wavelet moment are more suitable for fruit grading, but the speed of this method is slower than Fourier descriptors, and how to increase the speed is the direction of future research.

4. Conclusion

This research use the wavelet moments as classification features to classify the apple shape and it achieves satisfactory results. First, we normalize fruit image with standard moment so that the image has translation invariance and scale invariance. And then we extracted wavelet moment characteristics from the normalized image, which have rotation invariance. Cluster analysis is applied to classify fruit shape in the meantime. Coiflets wavelet possesses regularity, biorthogonality and approximate symmetry respectively, so we choose coiflets wavelet as the basic function of the wavelet moment feature extraction. The results show that this method performs better than traditional approaches such as Fourier descriptors and Zernike moments.

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