Feature Extraction of Tea Leaf Images using Dual-Tree Complex Wavelet Transform and Gray Level Co-occurrence Matrix

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Abstract. Feature extraction is a very important part of machine learning to analyze and find relationships between objects of different categories. This paper aims to analyze the feature vectors of the tea leaf image produced by using a combination of dual-tree complex wavelet transform and gray level co-occurrence matrix techniques. The tea leaf image consists of four different categories, each representing different phases of tea growth and were acquired using a visible camera from eight different orientations. Feature extraction using Principle Component Analysis (PCA) shows that the texture features can identify a different category of the leaf images without being significantly affected by the difference in scale and orientation of the images.

1. Introduction
Nowaday, computer vision technology is being studied intensively and widely used in the field of agricultural automation [1]. In tea farming, this technology is studied among others, for the recognition of tea category and quality [2], detection of leaf diseases [3] leaf classification [4], identification of leaf infections [5], and assessment of leaf lesions and abnormalities [6]. This technology is also a solution to overcome the weaknesses of the human visual system [7] [8].

Computer vision technology uses cameras and computers instead of the human eye to identify, track and measure targets for further image processing [1]. This technology aims to develop an autonomous system that is able to automatically recognize objects based on images with capabilities similar to the human visual system [9]. In its implementation, computer vision tasks include a series of processes, starting from image data acquisition, preprocessing, feature extraction, and image recognition to produce numerical or symbolic information in the form of decisions. So that in this context the image recognition can be seen as a symbolic information transformation of image data with the help of machine learning algorithms, geometry, physics, and statistics [10].

In general, there are two approaches in developing a computer vision-based image recognition system. The first approach is based on the texture and color characteristics of the image, and the second is using threading and clustering techniques. In the first approach, texture, characteristics are generated through feature extraction, then feature data is used to build the machine learning-based prediction models. Some of the popular prediction models are artificial neural networks (ANN) [11], support vector machines (SVM) [2], and k-nearest neighbors (kNN) [12]. To obtain texture characteristics, a number of methods have been proposed in the literature for different purposes, for example graylevel co-occurrence matrix [13], local binary pattern [14], 2 level wavelet transform [12], convolution neural net (CNN), DSIFT and BOVW [15], generalized eigenvalues proximal SVM [2], Bayesian discriminant.
principle [16], texture statistical histogram [17], and combination method of dual-tree complex wavelet transform and gray level co-occurrence matrix, denoted as DTCWT+GLCM [18].

The combination method of the dual-tree complex wavelet transform and the gray level co-occurrence matrix is interesting to investigate to solve the problem of image recognition, especially images with different scale and object orientation. Therefore, the texture features generated by DTCWT+GLCM will be analyzed. The leaf image samples consist of different growth phases. Images were acquired using a digital visible camera from eight different orientation angles and different scale. The feature data will be analyzed using the principal component analysis (PCA).

2. Method
2.1. Data preparation
In this study, the image of fresh tea leaves was taken from a tea plantation using a Canon 4000D camera to identify the growth phase of tea leaves. For this study, 160 tea leaf image samples are used to evaluate the performance of the DTCWT+GLCM method. Leaf images were taken after 3 days of tea growth, then continued every next three days to 12 days of growth. So that the collected tea leaf images consist of four categories (C1, C2, C3, and C4) which represent the tea growth phase after 3, 6, 9, and 12 days. Each category is represented by 40 image samples. Each leaf was taken from eight different camera angles, multiples of 45 degrees.

2.2. DTCWT+GLCM
The dual-tree complex wavelet transform (DTCWT) and the gray level co-occurrence matrix (GLCM), denoted as DTCWT+GLCM proposed by Yang & Yang [18] to overcome pattern recognition problems, especially for scaling and rotated objects. In the method, 1-level two-dimensional dual-tree complex wavelet transform is first implemented to decompose the original image to obtain sub-images at six directions: $\pm \pi/12$, $\pm \pi/4$ and $\pm 5\pi/12$ respectively. Thereafter, a number of texture features may be calculated from the gray level co-occurrence matrix to construct the feature vector. The statistical measures of the gray level co-occurrence matrix are used, e.g. Homogeneity, energy, entropy, correlation, uniformity, contrast, inverse difference, etc. to describe the texture information.

2.3. Feature extraction
A common feature extraction method in machine learning is Principle Component Analysis (PCA). PCA is a technique used to simplify the data, by means of transforming data in a linear manner to form a new coordinate system with variance maximum [19]. PCA also can be used to reduce the number of features by constructing a new variable with a smaller number that captures most of the information found in the original feature. Technically, PCA finds the eigenvector with the highest eigenvalue from the covariance matrix and then uses it to project the data into a new subspace with smaller dimensions. PCA produces principal components, eigenvectors, and eigenvalues. These principal components are the directions in the data that maximize variance when the original data are projected to them; such that the first component explains the most variance in the data. The principal components form the orthogonal basis in the data space. By using these principal components, all high-dimensional feature, data can be projected together into a 2D feature map.

3. Results
Before further processing the original images are converted into a single-channel of 255 grayscale image. Then, the DTCWT+GLCM method is applied to the images. According to the method, the first 1-level two-dimensional DTCWT is implemented to decompose the original image to obtain sub-images at six directions. After that, the gray level co-occurrence matrix of each sub-image is calculated and the corresponding statistical values are used to construct the feature vector. A number of statistical values were calculated for each Metrix as texture features, including parameters as follows: autocorrelation (f1), contrast (f2), correlation (f3), cluster prominence (f4), cluster shade (f5), dissimilarity (f6), energy (f7), entropy (f8), and homogeneity (f9).
The results of principal component analysis are shown in Table 1 and Table 2. From Table 1, the first principal component (PC1) and second principal component (PC2) account for 75.30% and 18.90% of the total variation in the data respectively, or account for about 94.2% of the total variation in the data. Table 2 shows the variables that correlate the most with the first principal component (PC1) are Autocorrelation (38.3%), Contrast (38.2%), Dissimilarity (38.2%), and Entropy (31.6%). The first principal component is positively correlated with all four of these variables. Therefore, increasing values of Autocorrelation ($f_1$), Contrast ($f_2$), Dissimilarity ($f_6$), and Entropy ($f_8$) increase the value of the first principal component. The first three principal components explain 99.8% of the variation in the data.

### Table 1. Eigenanalysis of the feature data

|       | PC1     | PC2     | PC3     | PC4     | PC5     | PC6     | PC7     | PC8     | PC9     |
|-------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| Eigenvalue | 6.7785  | 1.6998  | 0.5051  | 0.0083  | 0.0061  | 0.0022  | 0.0001  | 0       | 0       |
| Proportion | 0.753   | 0.189   | 0.056   | 0.001   | 0.001   | 0       | 0       | 0       | 0       |
| Cumulative | 0.753   | 0.942   | 0.998   | 0.999   | 1       | 1       | 1       | 1       | 1       |

### Table 2. Eigenvectors

|       | PC1  | PC2  | PC3  | PC4  | PC5  | PC6  | PC7  | PC8  | PC9  |
|-------|------|------|------|------|------|------|------|------|------|
| $f_1$ | 0.383| 0.067| -0.016| 0.16 | -0.053| 0.305| -0.176| -0.835| -0.012|
| $f_2$ | 0.382| 0.024| 0.122| 0.028| 0.281| -0.247| -0.633| 0.198| 0.508|
| $f_3$ | -0.371| -0.176| 0.146| -0.191| -0.110| -0.732| -0.122| -0.459| -0.005|
| $f_4$ | -0.291| -0.369| 0.620| -0.113| 0.483| 0.375| -0.034| -0.083| -0.001|
| $f_5$ | -0.303| 0.377| -0.512| -0.271| 0.631| 0.047| -0.069| -0.158| -0.002|
| $f_6$ | 0.382| 0.022| 0.121| 0.02 | 0.307| -0.263| -0.121| 0.100| -0.806|
| $f_7$ | 0.031| 0.715| 0.491| -0.448| -0.207| 0.052| 0.011| 0.006| 0      |
| $f_8$ | 0.316| -0.416| -0.217| -0.806| -0.128| 0.118| -0.001| 0.012| 0.001|
| $f_9$ | -0.382| -0.019| -0.119| -0.009| -0.348| 0.285| -0.73 | 0.108| -0.302|

Projection of all feature data to the first two principal components (PC1 and PC2) can be seen in a score plot as in Figure 1. From the figure, it can be seen that there are four clusters of feature data clearly separated by the first principal component. This shows that the nine statistical measures used in DTCWT+GLCM can be used as texture features to identify the growth phase of tea leaves. Figure 1 (b) shows a loading plot that explains the correlation between the principal components and the original variables. The loading plot indicates that the $f_1$, $f_2$, and $f_6$ variables point to the same direction as the first principal component (PC1). The graph also shows that the second principal component (PC2) is primarily in the direction of the $f_7$ variants, with a small shift towards the direction of the $f_5$ and $f_8$. The second principal component is essentially orthogonal to the $f_1$, $f_2$, $f_6$, and $f_9$ variables. These results provide an indication that there are a number of feature variables that can be reduced, for example, for the set of variables $\{f_1, f_2, f_6\}$, as well as $\{f_3, f_9\}$. This result is also in line with its correlation with the eigenvalues of principal components. From this result, dimension reduction can be done without significantly reducing the essential information of the image.
Figure 1. Score plot (a) and loading plot (b) of the texture features data.

4. Conclusion
In this study, the feature vectors of tea leaf images generated by the combination method of dual-tree complex wavelet transform and gray level co-occurrence matrix (DTCWT-GLCM) were analyzed. From the results of feature extraction using Principal Component Analysis (PCA) it can be explained that the texture feature can identify the growth phase of the tea leaves without being significantly affected by difference scale and orientation of an object in the images. The results of data analysis also found that there were several characteristic features pointing in the same direction as one of the principal components, so that further dimensional reduction is possible.

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