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Research Article

Plant Leaf Recognition through Local Discriminative Tangent Space Alignment

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Manifold learning based dimensionality reduction algorithms have been payed much attention in plant leaf recognition as the algorithms can select a subset of effective and efficient discriminative features in the leaf images. In this paper, a dimensionality reduction method based on local discriminative tangent space alignment (LDTSA) is introduced for plant leaf recognition based on leaf images. The proposed method can embrace part optimization and whole alignment and encapsulate the geometric and discriminative information into a local patch. The experiments on two plant leaf databases, ICL and Swedish plant leaf datasets, demonstrate the effectiveness and feasibility of the proposed method.

1. Introduction

Plant recognition based on leaf images plays an important role in agricultural informatization, ecological protection, and automatic plant recognition system. One of the most important steps in the image based plant recognition is to validly extract classifying features. Currently, the commonly employed classifying features for plant recognition based on leaf image could be categorized into color, shape, and texture features [1–3]. Plant leaf classification is a challenging problem due to its high dimensionality data, complexity, and irregular shape of plant leaf images [4–6]. Traditional dimensionality reduction methods typically have a smaller data space from linear combinations of the original data. The most common example is principal component analysis (PCA), which seeks a low-dimensional linear subspace spanned by the eigenvectors which correspond to the largest eigenvalues of the covariance matrix of all the samples. However, for plant leaf images, the assumption of global linearity is a severe constraint because the leaf images are quite sensitive to seasonality, location, and illumination conditions. Thus, it is not reasonable to believe that the leaf image data could be linearly separable from each other.

Manifold learning has been utilized in many applications such as pattern recognition, visualization, and classification tasks. In the last ten years, many manifold learning nonlinear algorithms have been introduced with an assumption that the processed data lies on or close to some low-dimensional manifolds which are embedded in a high-dimensional unorganized Euclidean space. In these manifold learning algorithms, the most representative ones are isometric feature mapping (ISOMAP) in [7], locally linear embedding (LLE) in [8], Laplacian eigenmaps (LE) in [9], Hessian-based locally linear embedding (HLLE) in [10], maximum variance unfolding (MVU) in [11], local tangent space alignment (LTSA) in [12], local spline embedding (LSE) in [13], and local discriminative tangent space alignment (LDTSA) in [14]. One of the most important advantages of manifold learning [7–14] compared with conventional methods is how the data are treated mathematically. Manifold learning methods allow the data to be related nonlinearly, which leads to the fact that manifold learning methods can much more accurately capture the proper structures among the data, thus allowing for accurate recognition. For every manifold learning algorithm, it tries to preserve a different geometrical property of the underlying manifold. Local methods such as LLE, HLLE, LE, LTSA,

and LSE try to preserve the neighborhood structure in the data, while global methods like ISOMAP aim to preserve the metrics at all scales. Thanks to their nonlinear nature, geometric intuition, and computational feasibility, these nonlinear methods have promising results on some artificial and real-world datasets. In [15] a framework, which is called patch alignment, was proposed and it consists of two stages: part optimization and whole alignment. In this paper, we take an alternative view of the framework to introduce an efficient method based on local discriminative tangent space alignment (LDTSA) for plant leaf recognition. Compared with current plant leaf recognition methods, the proposed one can avoid the small sample size problem, preserves the discriminative capability, and detects the intrinsic structure from the plant leaf image data.

The paper is organized as follows: Section 2 briefly describes the dimensionality reduction algorithm based on local discriminative tangent space alignment and its procedures. Experiments on plant leaf database are offered in Section 3 and the paper is ended with some conclusions in Section 4.

2. Local Discriminative Tangent Space Alignment Algorithm

Suppose n original labeled data points $X = [x_1, \ldots, x_n]$, including all the samples $x_i \in R^m$, $i = 1, 2, \ldots, n$. The objective of a dimensionality reduction algorithm is to compute the corresponding low-dimensional representations of X $Y = [y_1, \ldots, y_n]$, $y_i \in R^d$, $i = 1, 2, \ldots, n$, where $d \ll m$. For the linear dimensionality reduction, it is necessary to find projection matrix A, such that $Y = A^T X$. For the nonlinear dimensionality reduction, it is usually difficult to provide an explicit mapping to transform data from a high-dimensional space to a low-dimensional subspace. For classification task, in part optimization stage we always hope to project the high-dimensional data into a low-dimensional feature space, in which the projection is characterized by within-class compactness and between-class separability [15]. Assume that there is an interaction force between any pairwise points in the ambient space; the mutual force can be distinguished as within-class attraction or between-class repulsion between any pairwise points from the same or different class, respectively (see Figure 1) [16].

In the reduced subspace, in order to achieve within-class attraction for data point y_i, the following objective function is defined as

$$\arg\min \sum_{j=1}^{k_1} \left\| y_i - y_{i^j} \right\|^2, \tag{1}$$

where k_1 is the number of the nearest neighbors with respect to x_i from data points in the same class as x_i.

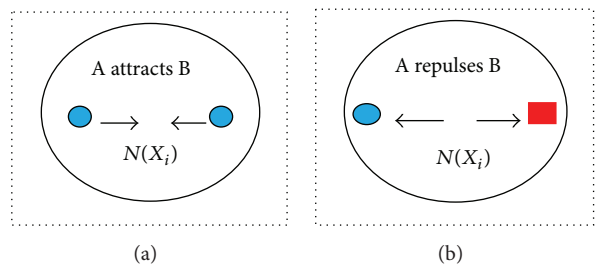

Figure 1: An intuitive demonstration of within-class attraction and between-class repulsion between pairwise points, where the circle denotes k nearest neighbors $N(X_i)$ of X_i; (a) A and B belong to the same class; (b) A and B belong to different classes.

In order to achieve between-class separability purpose for the data point y_i, the following objective function is defined as

$$\arg\max \sum_{p-1}^{k_2} \left\| y_i - y_{i_p} \right\|^2. \tag{2}$$

LTSA uses tangent coordinates to indicate the local geometry. Assume that there is an affine projection matrix, which projects tangent coordinates to the low-dimensional coordinates in a local patch which contains neighbors from both the same and different classes. To obtain the optimal tangent coordinates, we have the following objective function on each patch:

$$\arg\min \left\| Y_i R_{k+1} - T_i \Theta_i \right\|^2, \tag{3}$$

where $R_{k+1} = I_{k+1} - e_{k+1} e_{k+1}^T / (k+1)$ denotes the centralization matrix; $e_{k+1} = [1, \ldots, 1]^T \in R^{k+1}$; I_{k+1} is $(k+1) \times (k+1)$ identity matrix; and $\Theta_i \in R^{d\lambda(k+1)}$ is the tangent coordinates corresponding to an orthonormal basis matrix of the tangent space.

Since the patch formed by the local neighborhood can be considered approximately linear, we write the part discriminator by using the linear manipulation as follows:

$$\begin{aligned} \underset{y_i}{\operatorname{argmin}} \Bigg(& \sum_{j-1}^{k_i} \left\| y_i - y_{i^j} \right\|^2 \\ & - \alpha \sum_{p-1}^{k_2} \left\| y_i - y_{i_p} \right\|^2 + \beta \left\| Y_i R_{k+1} - T_i \Theta_i \right\|^2 \Bigg), \end{aligned} \tag{4}$$

where α and β are scaling factors to unify different data points of the within-class distance and the between-class distance and they are selected based on experiments.

Then objective function (4) can be rewritten by patch alignment:

$$\begin{aligned} \underset{Y_i}{\operatorname{argmin}} \sum_{j=1}^{l} \Big[& \operatorname{tr}\left(Y_i L_{i_{w1}} Y_i^T \right) + \beta \operatorname{tr}\left(Y_i L_{i_{w2}} Y_i^T \right) \\ & - \alpha \operatorname{tr}\left(Y_i L_{i_b} Y_i^T \right) \Big], \end{aligned} \tag{5}$$

where

$$L_{i_{w1}} = \begin{bmatrix} \sum_{j=1}^{k_1} (\omega_i)_j & -\omega_i^T \\ -\omega_i & \operatorname{diag}(\omega_i) \end{bmatrix},$$
$$L_{i_{w2}} = R_{k_1+1} - V_i V_i^T, \tag{6}$$
$$L_{i_b} = \begin{bmatrix} \sum_{j=1}^{k_2} (\omega_i)_j & -\omega_i^T \\ -\omega_i & \operatorname{diag}(\omega_i) \end{bmatrix},$$

where V_i denotes the matrix of d right singular vectors of $X_i R_{k+1}$ corresponding to its d largest values; and $\omega = [\overbrace{1, \ldots, 1}^{k_1}, \overbrace{-\beta, \ldots, -\beta}^{k_2}]^T$ is a coefficient vector.

In (5), the first two parts only involve the data points belonging to within-class neighbors and they share the same selection matrix S_w. The third part concerns the between-class neighbors and uses selection matrix S_b.

Then (5) can be reformed to the following:

$$\begin{aligned} &\underset{Y_i}{\operatorname{argmin}} \sum_{i-1}^{l} \left[\operatorname{tr}\left(Y_L S_w L_{i_w} (Y_L S_w)^T\right) + \alpha \operatorname{tr}(Y_L S_b)^T \right] \\ &= \arg \min_{Y_i} \operatorname{tr}\left(Y_L L Y_L^T\right), \end{aligned} \tag{7}$$

where S_w and S_b are selection matrix and

$$\begin{aligned} L_{i_w} &= L_{i_{w1}} + \beta L_{i_{w2}}, \\ L &= \sum_{i=1}^{l} \left(S_w L_{i_w} S_w^T + \alpha S_b L_b S_b^T \right). \end{aligned} \tag{8}$$

In summary, the main procedure of the proposed algorithm for the plant leaf image classification task can be described as follows.

Step 1. Select representative labeled plant leaf image samples to which the following dimensionality reduction will be done.

Step 2. For each point x_i, find its within-class neighborhood set $N_w(x_i)$ with k_1 elements and between-class neighborhood set $N_w(x_i)$ with k_2 elements.

Step 3. Generate two vectors $X_w = [x_{i_1}, \ldots, x_{i_{k_1}}]$ and $X_b = [x_{i_1}, \ldots, x_{i_{k_2}}]$, with their elements from $N_w(x_i)$ and $N_w(x_i)$, respectively.

Step 4. Construct $L_{i_{w1}}$ with k_1 within-class neighbors, then centralize the neighbors and compute the top-d eigenvector from the autocorrection matrix, and then construct $L_{i_{w2}}$ and record the selection matrix S_w.

Step 5. Construct L_{i_b} with k_2 between-class neighbors, and record the selection matrix S_b.

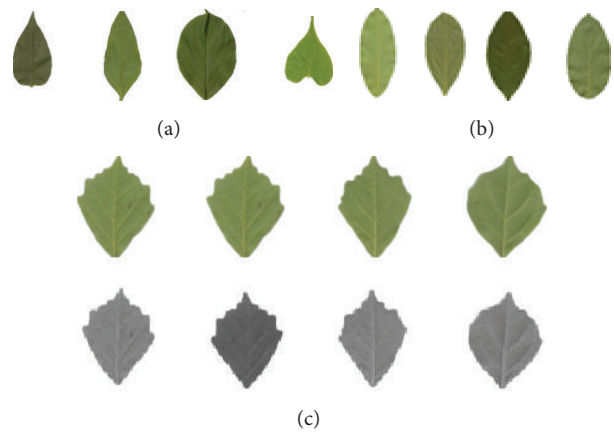

Figure 2: Typical leaves of the leaf database ICL.

Step 6. Generate global L with patch alignment through respective selection matrix.

Step 7. Perform eigendecomposition on XLX^T and the eigenvectors form projection matrix U.

Step 8. Final reduced dimensionality results are $Y_L = U^T X$.

3. Experiment Results

3.1. Experiment Results on ICL Dataset. ICL leaf database has 17032 plant leaf images of 220 species and image number of each class is unequal [17]. In order to verify the effectiveness of the proposed method in this paper, we construct one leaf image subset from the ICL leaf dataset, which has 15 species with 11 samples per species, and all classes are carefully chosen so that the shapes could be distinguished easily by human eyes or the shapes are similar but still can be identified [16]. Some typical example images are demonstrated in Figures 2(a), 2(b), and 2(c). Preprocessing is performed to crop all leaf images from two databases. The illuminations keep the same condition and the backgrounds are white, and the size of each cropped leaf image in experiments is 64×64 pixels, with gray level of 256 gray levels per pixel in preprocessing step, as demonstrated in Figure 2(c) of one species.

Then, every image is represented in a 4096-dimensional vector in the image space. By prereducing by PCA, 98 percent image energy is kept and all principal components are selected corresponding to the nonzero eigenvalues for each method. The 1-NN classifier is employed to classify leaf images for its simplicity. The distance measure is Euclidean distance.

The leaf image dataset is randomly separated into two subsets: one part is for training (sizes are 30, 45, 60, 75, 105, and 120) and the other is for testing purpose. The training sets are used to obtain the low-dimensional subspace with a projection matrix. The testing sets are utilized to test the final

Table 1: Average classification rates (%) and standard deviations ICL plant leaf database.

Train samples	LSDA	LLTSA	LDTSA
30	86.26 ± 3.52	73.3 ± 3.48	86.56 ± 3.62
45	88.83 ± 3.63	78.33 ± 3.39	89.33 ± 3.04
60	91.81 ± 2.29	82.19 ± 2.22	92.71 ± 2.38
75	91.61 ± 2.76	81.39 ± 2.56	92.93 ± 2.63
105	93.25 ± 2.62	82.83 ± 2.76	94.08 ± 2.78
120	94.12 ± 2.54	80.67 ± 3.26	94.56 ± 3.78

Table 2: Average classification rates (%) and standard deviations Swedish plant leaf database.

Train samples	LSDA	LLTSA	LDTSA
300	82.35 ± 3.45	71.3 ± 3.62	84.59 ± 3.34
600	84.73 ± 3.58	75.39 ± 3.76	87.38 ± 3.21
900	89.67 ± 3.31	80.49 ± 2.89	91.91 ± 2.73

classification accuracy. Each time the test is repeated 20 times and the accuracy rate is calculated each time, as follows:

$$\text{Accuracy} = \frac{\text{Num}(R)}{\text{Num}(T)} \cdot 100\%, \tag{9}$$

where Num(R) is the right sample number detected and Num(T) is the total sample number tested.

Table 1 shows the average classification rates and standard deviations of three algorithms in our experiments on the selected datasets which are locality sensitive discriminant analysis (LSDA), linear local tangent space alignment (LLTSA), and the proposed LDTSA. It can be seen that the proposed method obtains better accuracy.

3.2. Experiment Results on Swedish Dataset. Swedish leaf dataset [18] has 1125 images from 15 different plant species, with 75 leaf images per species. The preprocess of the leaf image is the same as ICL dataset [16]. For each method, random subsets with 20, 40, and 60 images per species are selected for training, the rest for testing. Such experiment with a specific number is independently performed 20 times, and then the best average classification results are recoded. Table 2 shows the maximal average classification accuracy with different size of training sets and test sets. It could be found that the proposed method outperforms the other algorithms in all the cases.

4. Conclusions

Plant recognition based on leaf images has been an important and difficult research topic, especially for leaves with different and complicated shapes. Although there are many existing algorithms for plant leaf recognition, the recognition rates are still low due to the complexity of plant leaf. Manifold learning based dimensionality reduction algorithms are promising alternatives to traditional plant leaf recognition methods. A dimensionality reduction method based on local discriminative tangent space alignment (LDTSA) is proposed for plant leaf recognition task in this paper, and it embraces part optimization and whole alignment and encapsulates the geometric and discriminative information into a local patch. The experiment performed on two plant leaf databases shows the effectiveness and feasibility of the proposed method in this paper.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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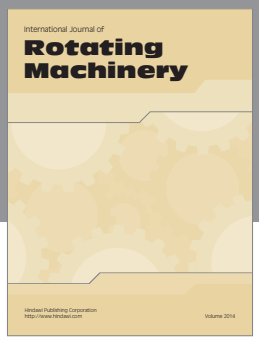

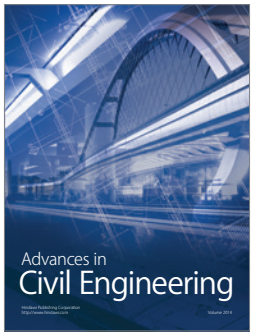

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