An overview of Pattern Recognition

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Abstract

Pattern recognition has become more and more popular and important to us and it induces attractive attention coming from wider areas. The general processing steps of pattern recognition are discussed, starting with the preprocessing, then the feature extraction, and finally the classification. Several methods were used for each step of pattern recognition such as segmentation and noise removal in preprocessing, Gabor wavelets transform for feature extraction, Support Vector Machines (SVM) for classification, and so forth. Some pattern recognition methods are presented and their applications are given. The objective of this paper is to summarize and compare some methods for pattern recognition, and future research issues which need to be resolved and investigated further are given along with the new trends and ideas.

Keywords: Pattern recognition, preprocessing, feature extraction, classification.

1 Introduction

Pattern recognition can be seen as a classification process. Its ultimate goal is to optimally extract patterns based on certain conditions and to separate one class from the others. The application of Pattern Recognition can be found everywhere. Examples include disease categorization, prediction of survival rates for patients of specific disease, fingerprint verification, face recognition, iris discrimination, chromosome shape discrimination, optical character recognition, texture discrimination, speech recognition, and etc. The design of a pattern recognition system should consider the application domain. A universally best pattern recognition system has never existed. The basic components of a pattern recognition system are preprocessing, feature extraction, and classification.

Image pre-processing is a desirable step in every pattern recognition system to improve its performance. Its role is to segment the interesting pattern from the background of a given image, plus apply some noise filtering, smoothing and normalization to correct the image from different errors, such as strong variations in lighting direction and intensity. Many methods exist for image preprocessing, such as the Fermi energy-based segmentation method [9].

Feature extraction is a crucial step in invariant pattern recognition. In general, good features must satisfy the following requirements. First, intraclass variance must be small, which means that features derived from different samples of the same class should be close. Secondly, the interclass separation should be large, i.e., features derived from samples of different classes should differ significantly. Also, a major problem associated in pattern recognition is the so-called curse of dimensionality. There are two reasons to explain why the dimension of the feature vector cannot be too large: firstly, the computational complexity would become too large; secondly, an increase of the dimension will ultimately cause a decrease of the performance. For the reduction of the feature space dimensionality, two different approaches exist. One is to discard certain elements of the feature vector and keep the most representative ones. This type of reduction is feature selection. Another one is the feature extraction, in which, the original feature vector is converted to a new one by a special transform and the new features have a much lower dimensions. Furthermore, in a robust pattern recognition system, features should be independent of the size, orientation, and location of the pattern. This independence can be achieved by extracting features that are translation-, rotation-, and scale-invariant. Choosing discriminative and independent features is the key to any pattern recognition method being successful in classification. Examples of features

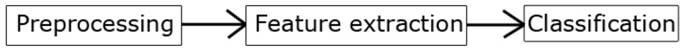

Figure 1: Pattern recognition process.

that can be used: color, shape, size, texture, position, etc. Many methods exist for this step, such as nonlinear principal components analysis (NLPCA)[6], Radon transform [3], dual-tree complex wavelet transform [3][4], Fourier transform [3], Gabor wavelets [10], Curvelet transform [6], skeletonisation [9], rough set theory (RST) [9], Fuzzy invariant vector[7], etc. Some of these methods are reviewed in this paper.

After the feature extraction step, the classification could be done. This step enables us to recognize an object or a pattern by using some characteristics (features) derived from the previous steps. It is the step which attempts to assign each input value of the feature vector to one of a given set of classes. For example, when determining whether a given image contains a face or not, the problem will be a face/non-face classification problem. Classes, or categories, are groups of patterns having feature values similar according to a given metric. Pattern recognition is generally categorized according to the type of learning used to generate the output value in this step. Supervised learning assumes that a set of training data (training set) has been provided, consisting of a set of instances that have been properly labeled by hand with the correct output. It generates a model that attempts to meet two sometimes conflicting objectives: Perform as well as possible on the training data, and generalize as well as possible to new data. Unsupervised learning, on the other hand, assumes training data that has not been hand-labeled, and attempts to find inherent patterns in the data that can then be used to determine the correct output value for new data instances. Classification learning techniques include Support Vector Machine (SVM) [4] [10] [6] [2], Multi-class SVM [12], Neural Networks [5], Logical combinatorial approach [11], Markov random field models (MRF)[1], Fuzzy ART [7], CLAss-Featuring Information Compressing (CLAFIC) [8], K-nearest neighbor [3], rule generation [9], etc. The most important methods are reviewed later in this paper.

The organization of this paper is as follows. Section 2 reviews the pattern recognition process. Section 3 reviews a comparison between some existing classification methods for pattern recognition. Section 4 reviews a small overview about the application of pattern recognition in agriculture. Finally, Section 5 draws the conclusions and gives future work to be done.

2 Pattern recognition process

Pattern recognition has been under constant development for many years. It includes lots of methods impelling the development of numerous applications in different fields. The basic components in pattern recognition are preprocessing, feature extraction, and classification. Once the dataset is acquired, it is preprocessed, so that it becomes suitable for subsequent sub-processes. The next step is feature extraction, in which, the dataset is converted into a set of feature vectors which are supposed to be representative of the original data. These features are used in the classification step to separate the data points into different classes based on the problem. The design of a pattern recognition system is showed in figure 1.

2.1 Preprocessing

As mentioned above, image preprocessing is a desirable step in every pattern recognition system to improve its performance. It is used to reduce variations and produce a more consistent set of data. Preprocessing should include some noise filtering, smoothing and normalization to correct the image from different errors, such as strong variations in lighting direction and intensity. Moreover, image segmentation could also be done in this step; it is typically used to locate objects and boundaries (lines, curves, etc.) in images and it is a way to change the representation of the given image into something more meaningful and easier to analyze. In some applications, segmentation of the interesting pattern of a given image from the background is very important, for example, dealing with diseases detection

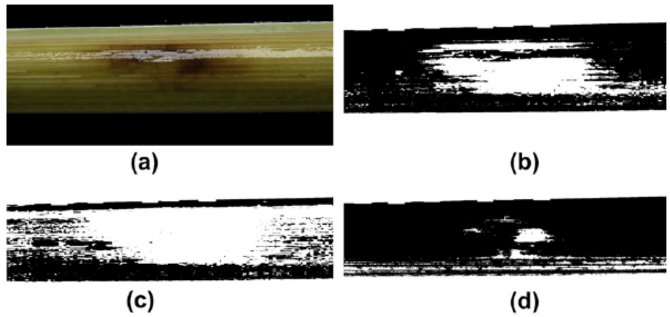

Figure 2: (a) Image infected by sheath rot disease, segmented by, (b) Fermi energy based algorithm; (c) Otsus method and (d) k-means algorithm.

in agriculture applications needs segmentation of the infected region of the diseased plant images. In this example, color image segmentation could extract the spot region image of the leaf since the color of spots is quite different from that of a green leaf as we see in Fig. 2(a). Many methods can be used for image segmentation; Fermi energy-based segmentation method give us the ability to identify special regions using color components of the images, it is designed to capture an object that exhibits high image gradients and shape compatible with the statistical model. Based on this, energy at each pixel position is calculated and compared with the threshold value for segmenting. The results of this method, plus two other segmentation methods (Otsu and k-means), are shown in Fig. 2b-d respectively, while Fig. 2a is the original image before segmentation.

2.2 Feature extraction

As mentioned before, feature extraction is used to overcome the problem of high dimensionality of the input set in pattern recognition. Therefore, the input data will be transformed into a reduced representation set of features, also named feature vector. Only the relevant information from the input data should be extracted in order to perform the desired task using this reduced representation instead of the full size input. Features extracted should be easily computed, robust, rotationally invariant, and insensitive to various distortions and variations in the images. Then optimal features subset than can achieve the highest accuracy results should be selected from the input space. Many methods for feature extraction exist in the literature; some of them are discussed in this section.

2.2.1 Fourier transform

Fourier transform has the ability to analyze a signal for its frequency content. A shift of a 1D or 2D function does not affect the magnitude of its Fourier coefficients (translation property); also a rotation of a function will rotate its Fourier transform with the same angle (rotation property). It is used to eliminate the circular shift effect in the resultant feature domain by taking the spectrum magnitude of the Fourier coefficients and then a rotation-invariant feature vector could be extracted.

2.2.2 Radon transform

Radon transform is a mapping from the Cartesian rectangular coordinates (x,y) to a distance and an angle, also known as polar coordinates. Applying the Radon transform on an image f(x,y) for a given set of angles can be thought of as computing the projection of the image along the given angles. The resulting projection is the sum of the intensities of the pixels in each direction. This transform can effectively capture the directional features in the pattern image by projecting the pattern onto different orientation slices. Also, the radon transform can be performed in the Fourier domain.

2.2.3 Gabor wavelets transform

Gabor wavelets, a wavelet-based transform, could be used for feature extraction. It provides the optimized resolution in both time and frequency domain for time-frequency analysis, plus it has the optimal basis to extract local features for pattern recognition and it has three motivations: biological, mathematical, and empirical. Due to its biological similarity to the human vision system, Gabor wavelets have been widely used in object recognition applications. Given a set of Gabor wavelets going through an initial parameter selection, a common feature extraction approach is to construct a feature vector by concatenating the inner product of an image with each wavelet. Rather than seeking the set of Gabor wavelets, which can approximate an image, we should seek Gabor wavelets that are tuned to discriminate one object from another, this can reduce the computation and memory cost. Boosting algorithms could be used to select only the relevant Gabor wavelets; they have the objective of selecting a number of very simple weak classifiers, to combine them linearly into a single strong classifier.

2.2.4 Fuzzy invariant vector

When an invariant feature vector is extracted, converting it into a fuzzy invariant vector could increase discrimination and reduce the impacts of low-frequency noise. The fuzzy invariant vector is computed using fuzzy numbers. In general, the power spectrum of an input pattern calculated with the Fourier transform has few major frequencies, which gives an impact to distinguish patterns. In a fuzzy-invariant vector, every harmonic of an input pattern has similar distribution, a characteristic which gives better discrimination than the original-invariant vector. Plus, when low-frequency noises are added to an image, some harmonics show higher or lower values than the normal range in the power spectrum of the pattern. With a Fuzzy membership function, the power of each harmonic for an input pattern is mapped identically into fuzzy numbers; these values are mapped to 1 or 0. Therefore, the impacts of low-frequency noise will be reduced.

2.3 Classification

During the classification task, the system uses the features extracted in the previous stage from each of the patterns to recognize them and to associate each one to its appropriate class. Two types of learning procedure are found in the literature. The classifiers that contain the knowledge of each pattern category and also the criterion or metric to discriminate among patterns classes, which belong to the supervised learning. The unsupervised learning in which the system parameters are adapted using only the information of the input, and constrained by prespecified internal rules, it attempts to find inherent patterns in the data that can then be used to determine the correct output value for new data instances. Some classification methods are discussed and reviewed in this section.

2.3.1 Fuzzy ART

Fuzzy ART neural networks can be used as an unsupervised vector classifier. Adaptive Resonance Theory (ART) is compatible with the human brain in processing information, it has the ability to learn and memorize a large number of new concepts in a manner that does not necessarily cause existing ones to be forgotten. ART is able to classify input vectors which resemble each other according to the stored patterns. Also, it can adaptively create a new corresponding to an input pattern, if it is not similar to any existing category. ART1 was the first model of ART; it can stably learn how to categorize binary input patterns presented in an arbitrary order. Plus, Fuzzy sets theory can imitate thinking process of human being widely and deeply. So the Fuzzy ART model, which incorporates computations from fuzzy set theory into the ART1 neural network, is capable of rapid stable learning of recognition categories in response to arbitrary sequences of analog or binary input patterns. Vigilance is a parameter which affects the performance of Fuzzy ART that is evaluated by the recognition rate. The maximal vigilance parameter enables Fuzzy ART to classify input patterns into the highest recognition rate. The combined effects of Fuzzy ART and Fuzzy Invariant Vector (FIV) described above, yields robustness.

2.3.2 Neural networks

The neural approach applies biological concepts to machines to recognize patterns. It is a promising and powerful tool for achieving high performance in pattern recognition. The outcome of this effort is the invention of artificial neural networks which is set up by the elicitation of the physiology knowledge of human brain. Neural networks are composed of a series of different, associate unit. It is about mapping device between an input set and an output set. Since the classification problem is a mapping from the feature space to some set of output classes, we can formalize the neural network, especially two-layer Neural Network as a classifier. While the usual scheme chooses one best network from amongst the set of candidate networks, better approach can be done by keeping multiple networks and running them all with an appropriate collective decision strategy. Multiple neural networks can be combined for higher recognition rate. The basic idea of the multiple networks is to develop N independently trained neural networks with relevant features, and to classify a given input pattern by utilizing combination methods to decide the collective classification. A genetic algorithm is a hybrid method which can be used to combine neural network classifiers. It gives us an effective vehicle to determine the optimal weight parameters that are multiplied by the network output as coefficients. It considers the difference of performance of each network in combining the networks. The neuron having the maximum value is selected as the corresponding class. Two general approaches for combining the multiple neural networks, the fusion technique where the classification of an input is actually based on a set of real value measurements, or the voting technique which considers the result of each network as an expert judgment.

2.3.3 Markov random field

Markov random field (MRF) models are multi-dimensional in nature, for pattern recognition, they combine statistical and structural information. States are used to model the statistical information, and the relationships between states are used to represent the structural information. Only the best set of states should be considered. The global likelihood energy function can be rewritten with two parts, one used to model structural information that is described by the relationships among states, and the second models the statistical information because it is an output probability for the given observation and state. The recognition process is to minimize the likelihood energy function that is the summation of the clique functions. The design of neighborhood systems and cliques is based on connectedness and distance, although neighborhood systems can be of any shapes and sizes in theory where connectedness is about representing some patterns by feature points, and many feature points are not connected directly with others. Therefore, the neighborhood system consisting of the sites within a certain distance is adopted. Neighborhood systems of this kind are particularly suitable for recognizing patterns or retrieving images by critical point or feature point matching, because critical points are not connected.

2.3.4 Support Vector Machine

The Support Vector Machine (SVM) classifier has been proved to be very successful in many applications. The strength of the SVM is its capacity to handle not only linearly separable data, but also non-linearly separable data using kernel functions. The kernel function can map the training examples in input space into a feature space such that the mapped training examples are linearly separable. The frequently used SVM kernels are: polynomial, Gaussian radial basis function, exponential radial basis function, spline, wavelet and autocorrelation wavelet kernel. Theoretically, features with any dimension can be fed into SVM for training, but practically, features with large dimension have computation and memory that cost to the SVM training and classification process, therefore, feature extraction and selection is a crucial step before the SVM classification.

2.3.5 Multi-class SVM

Multi-Classifier System based on SVM for pattern recognition aims to obtain higher classification accuracy than individual classifiers that make them up. Combination of classifiers is able to complement the errors made by the individual classifiers on different parts of the input space. The combination strategy

Classification method	Characteristics
Fuzzy ART	- Capability of rapid stable learning of recognition categories in response to arbitrary sequences of analog or binary input patterns - Strong resistance to noise - Need to find the optimal vigilance level
Neural networks	- Ability to form complex decision regions - Strong points in the discriminative power - Capability to learn and represent implicit knowledge - Capability to combine multiple networks
Markov random field	- Multi-dimensional in nature - Statistical and structural informations are combined
SVM	- Handling non-linearly separable data - Possibility to efficiently deal with a very large number of features - Any local solution is also a global optimum
Multi-class SVM	- Flexible - Good generalization performance while avoiding over-fitting - Higher classification accuracy than individual classifiers - Complementing the errors by the individual classifiers

Table 1: Comparision between the classification methods.

is based on stacked generalization, and it includes a two-level structure: a base-level one, it is a module of N kinds of SVM-based classifiers trained by N features set, and a meta-level one, it is one module of SVM-based decision classifier trained by meta-feature set which are generated through a data fusion mechanism. The main idea of Stacking is to combine classifiers from different learners. Once the classifiers have been generated, they must be combined. For the multi-class classification, many methods can be used, one of them is the one-against-all method, it can be used as multi-class SVM, in other words, when the number of classes is N, this method constructs N SVM classifiers, each to classify one positive (+1) and N1 negative (1) classes. Multi-class SVM can be chosen as a meta-level learner because of its good generalization performance while avoiding over-fitting.

3 Comparison between the classification methods

In this section, a comparison between the classification methods described in this paper is reviewed. In table 1, the caracteristics of Fuzzy ART, Markov random field, neural networks, SVM and multi-class SVM are summarised. As we see, each method has its characteristics and advantages. For each application, a classification method should be efficient and its characteristics should fit the application problem.

4 Pattern recognition application related to agriculture

Nowadays, pattern recognition is a technique used more and more in agriculture, applications could be done for the detection of plant diseases to minimize the loss, and achieve intelligent farming. Plant diseases are one of the most important reasons that lead to the destruction of plants and crops. Detecting those diseases at early stages enables us to overcome and treat them appropriately. The development of an automation system using pattern recognition for classifying diseases of the infected plants is a growing research area in precision agriculture. For the identification of the visual symptoms of plant diseases, texture, color, shape and position of the infected leaf area might be used as discriminator features. Diseased regions such as spots, stains or strikes should be identified, segmented, pre-processed, and a set of features should be extracted from each region. For the classification analyses, the set of features is the input of the classifier, which can be a multi-classifier system, such as the multi-class SVM described above.

5 Conclusion

In this paper we expatiate pattern recognition in the round, including the definition, the composition, the methods of pattern recognition, the comparison of each classification method, plus the application of pattern recognition in agriculture. The developing of pattern recognition is increasing very fast, the related fields and the applications of pattern recognition has become wider and wider. It aims to classify a pattern into one of a number of classes. It appears in various fields like computer vision, agriculture, robotics, biometrics, etc. In this context, a challenge consists of finding some suitable description features since commonly, the pattern to be classified must be represented by a set of features characterizing it. These features must have discriminative properties: efficient features must be affined insensitive transformations. They must be robust against noise and against elastic deformations. The feature extracting method and the classifier should depend on the application itself. Future work will be done by searching for the right methods to develop a pattern recognition system for automatic detection of diseases in the infected plants.

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