Object Characterization in Outdoor Scene Analysis

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Abstract

This paper presents a novel strategy for object characterization in outdoor scenes. In contrast to the classical approaches used in the general classification problem, where the most suitable subset of features is selected in order to obtain the best ratio, we propose to characterize each object class of interest by a specific subset of features. This new focusing of the feature selection process changes back to a more reliable outdoor vision system, as the experimental results show.

Keywords: Outdoor scenes analysis, Feature evaluation, Feature selection.

1 Introduction

The feature selection and feature evaluation processes have been widely discussed in statistics, pattern recognition, and the machine learning community. Their goal is to select the most suitable subset of features to obtain the best ratio in a general classification problem. In order to do that, most recognition systems require a previous learning or modeling task which enables them to perform the process of obtaining the patterns (represented by a set of d features) which best characterize the objects of interest. A main goal in the whole process is to correctly choose those features which allow pattern vectors belonging to different classes to occupy compact and disjoint regions in a d-dimensional feature space. The problem of choosing these features is known as feature selection, and has been widely analyzed over the last few decades [1, 2]. Jain et al. [3] indicate that it is important to make a distinction between feature selection and feature extraction. The term feature selection is defined as the problem of choosing a small subset of features that is necessary and sufficient to describe target concepts, while methods that create new

Figure 1: Colour images of a tree through the seasons.

features based on transformations or combinations of the original feature set are called feature extraction algorithms.

Our research is focused on object recognition in outdoor scenes, analyzing the learning process and the recognition process. Concerning segmentation and object characterization, outdoor scenes are especially complex to treat in terms of lighting conditions. It is well known that chromatic characteristics of natural elements are not stable [4]. As an example, figure 1 demonstrates how seasons affect an outdoor scene, in which the colour and texture of objects can vary considerably. Identifying suitable instances of general object classes is an extremely difficult problem partly due to the variations among instances of many common object classes (so-called *intraclass variation*), and because the classes differ from each other not only in the values of their features, but also in terms of which features are defined (so-called *interclass variability*).

The main goal of this paper is to propose a novel strategy for object characterization, attending data affected by intraclass and interclass variability. In section 2 the proposed strategy is presented, while in section 3, the new specific criterion function which handles intraclass and interclass variation is explained. Section 4 analyzes some feature selection methods, showing the results obtained with them. A discussion of the results and the conclusions end the paper.

2 Strategy for object characterization

Recognition systems are usually based on a single features subset which allows classification of different object classes, as is shown in figure 2.a. Therefore, feature selection is used with the aim of selecting the most suitable subset of features which permits the best ratio in the classification problem. As was stated in the introduction, identifying instances of general object classes in outdoor scenes is a very difficult problem due to intraclass and interclass variability. For example, `houses` can usually be recognized using some of their shape features and a limited number

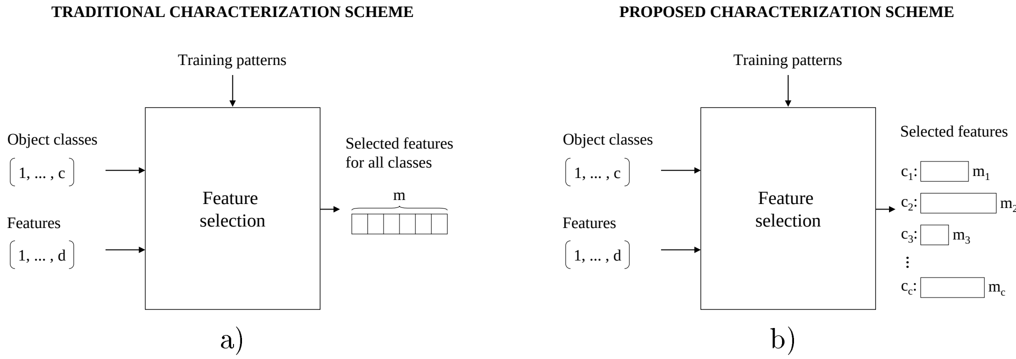

Figure 2: Strategies for object characterization: a) traditional approach, and b) proposed approach.

of well-delineated colours. Other objects, such as `trees` present a very different array of features. It would be difficult and probably meaningless to count the number of distinct colours in a tree. Combined with the texture features associated with `leaves`, `branches` and `crowns`, the colour of a `tree's leaves` produces a characteristic colour variation which is probably the best single feature description for `tree` recognition. Thus both class definitions (i.e., `houses` and `trees`) include colour features, but how those features are represented and matched is obviously quite different.

Therefore, it is necessary to emphasize the fundamental conclusion that not all object classes are defined in terms of the same attributes. Consequently, every single object class can be described by specific features in order to facilitate later recognition processes and improve accuracy classification [5]. Figure 2.b illustrates the proposed scheme for object characterization, in which a specific feature selection process for every object class is performed in order to obtain the best feature subset for every single object class. As previously mentioned, the feature evaluation method is the other important factor and is detailed in the next section.

3 Feature evaluation for intraclass and interclass variability

The goal of feature evaluation is to measure the quality of a subset produced by some generation procedure, Quality should understood in this context as the ability of a feature subset to distinguish different class labels, i.e. the ability to provide compact and maximally distinct descriptions for every class.

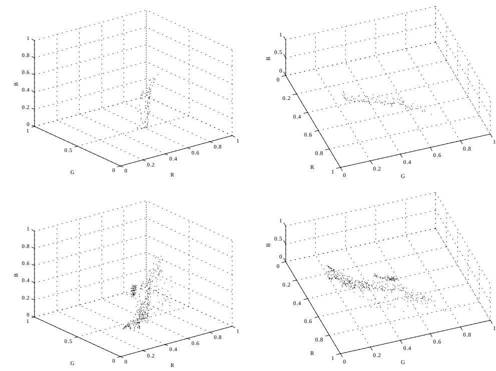

Figure 3: Example of intraclass variation in the object class `tree`. Top: RGB samples of a single image; distribution rotated. Bottom: RGB samples extracted over 10 images; distribution rotated.

Feature evaluation has been studied for many years and different measures have been proposed [1, 6]. Obviously, an optimal subset obtained in the frame of a given criterion function may not be the same as that for a different criterion function. Therefore, the choice of a good evaluation method plays a key role in the process of obtaining the best feature subset for recognition process.

In outdoor image analysis, the data are affected by intraclass variation due to the fact that characteristics of natural elements are not stable, as can be seen in figure 3, where a `tree` class is mapped into the RGB space (notice the differences in its apparent colour in the RGB space obtained from a single image, and the variation over 10 images). In general, the instability of characteristics in outdoor image analysis are inherent and can be caused by changes in lighting conditions, seasons, cloud cover, and other weather conditions. As shown in figure 3, the data distribution does not make a compact cluster, complicating the feature evaluation.

As a way to solve the intraclass and interclass variability in feature evaluation, we propose using only two labels: the analyzed object class and the remaining objects classes. Hence, the goal is to find the best features (or the most appropriate subset) in order to characterize and describe a single object class as distinct from the rest.The used criterion function is based on the multivariate decision trees which provide the misclassification rate for every single label. The basic goal of a multivariate decision tree is to divide the feature space into regions, provided that all the training samples in a given region have the same label. Our proposed methodology is to see that all instances in the current region of the features space have the same label. If so, label the region; if not, find the hyperplane(s) which maximally separates instances of the two labels, divide the feature space into two regions using the obtained hyperplane, and recursively on each region.

4 Feature selection

A common trend in many works related to feature selection is finding a single feature subset in order to characterize all the object classes at the same time, assuming sometimes that the data fit a known distribution. However, in outdoor analysis the object classes differ from each other not only in the values of their features, but also in what the features to define every object class are. Therefore, feature selection will be used in order to select the best features and to characterize and describe every single object class correctly. Consequently, each object class will have its specific feature subset.

Many authors have evaluated the existing feature selection methods [2, 6, 7]. Among them, we have used some generic feature selection methods in order to test our approach. The following methods have been used: SFS, SBS, SFFS, SBFS, and GA. Figure 4 illustrates the results obtained using these methods for one object in a training set with a total of 23 features per pattern, using 1000 patterns for 4 different objects: `tree`, `sky`, `road`, and `ground`. After an exhaustive analysis of these methods in different object classes, and using a different number of features and training sets, the followings guidelines can be stated: the SFS and SBS methods are fast but low in performance, while both methods suffer from nesting problems. In contrast, the SFFS and SBFS methods are very effective when trying to find the subset of a given size which maximizes the criterion value. On the other hand, GA is very useful in handling large-scale problems, because its low computational time allows for a balanced solution between the maximum criterion value and the minimum size subset.

5 Conclusions

In this paper we have proposed a novel strategy to perform object characterization in outdoor scenes. It is based on the fact that not all the object classes are defined in terms of the same attributes. Therefore, every single object class need to have its own specific feature subset in order to facilitate later recognition processes and to improve the accuracy of the classification. The experimental results have demonstrated that the feature evaluation method used in this approach can resolve the intraclass and the interclass variability which unavoidably appear in outdoor scene data. Different feature selection methods have been used in order to choose the best features to characterize and describe object classes. The performance of these methods have been evaluated using some real training tests.

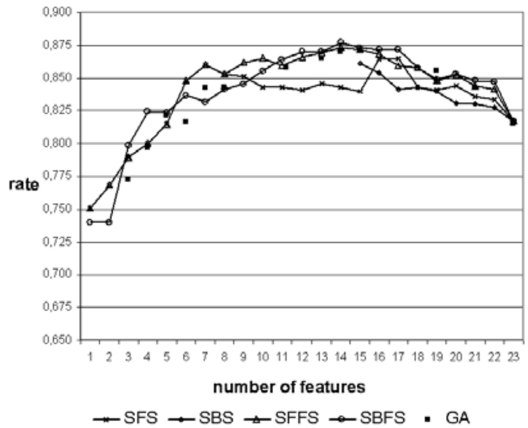

Figure 4: Performance of feature selection methods for the object class `tree`.

References

[1] P. A. Devijver and J. V. Kittler. *Pattern Recognition. A Statistical Approach.* Prentice-Hall, Englewood Cliffs, NJ, 1982.

[2] A.K. Jain and D. Zongker. Feature selection: Evaluation, application, and small sample performace. *IEEE Trans. On Pattern Analysis and Machine Intelligence*, 19(2):153–158, February 1997.

[3] A.K. Jain, R. P.W. Duin, and J. Mao. Statistical pattern recognition: A review. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 22(1):4–37, January 2000.

[4] J. Batlle, A. Casals, J. Freixenet, and J. Martí. A review on strategies for recognizing natural objects in colour images of outdoor scenes. *Image and Vision Computing Journal*, 18(6–7), May 2000.

[5] B. Draper, A. Hanson, and E. Riseman. Knowledge-directed vision: Control, learning, and integration. *Proc. IEEE Signals and Symbols*, 84(11):1625–1637, November 1996.

[6] M. Dash and H. Liu. Feature selection for classification. *Intelligent Data Analysis*, 1(3), 1997.

[7] M. Kudo and J. Sklansky. Comparison of algorithms that select features for pattern classifiers. *Pattern Recognition*, 33(1):25–41, 2000.