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Affine-invariant contours recognition using an incremental hybrid learning approach ☆

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ABSTRACT

In this paper, a planar shape recognition system is proposed. This proposal is based on a global incremental scheme which combines two learning mechanisms: the Incremental Non-parametric Discriminant Analysis and the mode analysis method. At the feature selection stage, a novel adaptive curvature estimator for shape characterization is presented. This method describes the planar shape using an affine-invariant triangle-area representation obtained from its closed contour. Contrary to previous approaches, the triangle side lengths at each contour point are adapted to the local variations of the shape, removing noise from the contour without missing relevant points. In order to reduce the dimensionality of the shape descriptor, an Incremental Non-parametric Discriminant Analysis is conducted to seek directions for efficient discrimination (incremental eigenspace learning). At the classification stage, the incremental mode analysis is employed to classify feature vectors into a set of spherically-shaped groups (incremental prototype learning). The classification is conducted based on the *k*-nearest neighbor approach whose prototypes are updated by the mode analysis method. This scheme enables a classifier to learn incrementally, on-line, and in one-pass. Experimental results show that the proposed shape recognition system is well suited for shape indexing and retrieval.

1. Introduction

Pattern recognition is an important task in computer vision which plays a crucial role in a large number of applications such as image retrieval or object recognition. Particularly, the increasing number of applications relying on multimedia databases has motivated that object representation and classification will be the subject of much research. Among other image features which are used to achieve this goal, like colour or texture, shape is commonly considered the most promising tool to represent and identify objects (Alajlan et al., 2007). Shape description refers to the process of presenting the shape in a suitable format for storage and matching (Marji and Siy, 2003). One of the most typically used shape descriptors is the shape contour, and different methods for representing it have been proposed (Loncaric, 1998). Among them, this paper is focused on those techniques which attempt to represent shapes using the curvature of their outer boundaries.

Object recognition also constitutes one of the typical examples of real-world applications where a complete set of training samples cannot be usually provided in advance when building a classifier. For instance, there exists a recent interest in the mobile robotics community for using object detection and recognition approaches to provide natural landmarks for the sake of simultaneous robot localization and environment mapping (Asmar et al., 2006). In this framework, objects are detected little by little and the properties of the real scenario where they are acquired could be slightly changed as time passes. Therefore, the learning of a system must be also conducted sequentially in an on-line manner. On the other hand, it is desirable that the human supervisor only provides training samples to the robot when it does not correctly classify autonomously perceived patterns. On-line learning, also termed incremental learning, is primarily focused on processing the data in a sequential way so that in the end *the classifier is no worse than a hypothetical classifier trained on the batch data* (Kuncheva, 2004).

In this paper, we describe a global incremental scheme for shape-based object recognition which can perform without an a priori knowledge about the shape of the classes which compound the feature space where objects will be represented. The proposed approach combines an incremental non-parametric discriminant analysis (Raducanu and Vitrià, 2007) and an incremental, centroid-based version of the mode analysis classifier (Wishart,

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1969) as two learning schemes. As other recognition approaches, our proposal can be split into two main stages: feature selection and classification. In the first stage, the proposed system employs a curvature-based approach. Curvature-based algorithms characterize the contour by computing its curvature at each point. In our case, curvature is estimated using an adaptive scheme which allows to correctly describe the contour details present at different natural scales. To reduce the dimensionality of this shape descriptor, a non-parametric discriminant analysis (NDA) is conducted. NDA is an eigenspace-based method, which is focused on seeking directions for efficient discrimination. Since it does not have embedded assumptions about the structure of the feature space, they can analyze arbitrarily structured feature spaces (Comaniciu and Meer, 2002). In the proposed approach, the incremental NDA (INDA) will be used for eigenspace learning (incremental feature selection). On the other hand, the classification stage combines the incremental mode analysis with a *k*-nearest neighbor algorithm. The incremental mode analysis is a fast one-pass, distance-based clustering algorithm (Bandera et al., 1999), which includes the input feature vector in the most suitable existing cluster, creating a new one if necessary. As other approaches, e.g. the Evolving Clustering Method (ECM) (Kasabov, 2002), it is capable of achieving this goal with no supervision nor previous training. However, contrary to other clustering algorithms, it cannot optimize a classification criterion because it does not memorize information about all samples which were supplied. In our on-line classifier, this algorithm is used to cluster the input patterns into a reduced set of groups and to determine the cluster centers of these groups (*prototypes*). The classification is finally conducted based on the *k*-nearest neighbor algorithm.

Fig. 1 shows an overview of the proposed system. Briefly, the on-line process of classification and learning is conducted sequentially as follows. First, we assume that N training samples are given in advance to form an initial eigenspace model. Then, the incremental mode analysis is used to group the transformed training samples into a set of clusters, which will be only represented by their cluster prototypes. When a query input is presented to the system, the classification is carried out. The classification of the feature vector obtained from the projection of the input shape into the eigenspace is conducted based on a k-nearest neighbor algorithm whose prototypes are provided by the incremental mode analysis. If the training sample is misclassified, this input and its class label are applied to the INDA to update the current eigenspace model. The updated eigenspace model is utilized for transforming the query input into a feature vector, and this vector as well as the updated prototypes are used to train the classifier using the incremental mode analysis. Thus, the proposed on-line classification stage is able to simultaneously perform the feature selection and the classifier learning in one-pass, being training samples presented only once to learn. Finally, it must be noted that one condition is imposed by the proposed approach: the incremental mode analysis must always perform an over-classification of the parameter space, i.e. the number of spherically-shaped groups must be greater than the real one.

This paper is organized as follows. Section 2 describes previous work related to the representation and classification stages of the proposed shape recognition system. Sections 3 and 4 present the two stages of the proposed method. The experimental results revealing the efficacy of the method are described in Section 5. The paper concludes along with discussions and future work in Section 6.

2. Related work

2.1. Curvature-based shape contour descriptors

The literature on planar shape representation is relatively huge (Loncaric, 1998). However, in this section, we only focus on methods that are based on curvature because of their close relation with our work. Besides, these descriptors are very popular. Thus, a curvature-based approach, the *curvature scale space*, has been used in the MPEG-7 standard (Torres et al., 2007).

By definition a curvature function encodes the boundary of a shape in terms of their local curvature or orientation. Let $c(t) = (x(t), y(t))$ be a parametric plane curve. Its curvature function $\kappa(t)$ can be calculated as (Mokhtarian and Mackworth, 1986; Fontoura and Marcondes, 2001)

$$\kappa(t) = \frac{\dot{x}(t)\ddot{y}(t) - \ddot{x}(t)\dot{y}(t)}{(\dot{x}(t)^2 + \dot{y}(t)^2)^{3/2}} \quad (1)$$

This equation implies that estimating the curvature involves the first and second order directional derivatives of the plane curve coordinates, $(\dot{x}, \dot{y})$ and $(\ddot{x}, \ddot{y})$ respectively. This is a problem in the case of computational analysis where the plane curve is represented in a digital form (Fontoura and Marcondes, 2001). In order to solve this problem, two different approaches are typically employed: those that approximate the plane curve coordinates (*interpolation-based curvature estimators*), and those that estimate the curve orientation at each contour point with respect to a reference direction (*angle-based curvature estimators*). However, other methods to estimate the curvature can be found in the literature. Thus, Alajlan et al. (2007) have proposed a shape retrieval approach based on the triangle-area representation (TAR), where the curvature at each contour point is measured using the area of the triangle defined by this point and two equally-separated contour neighbors.

Interpolation-based curvature estimators interpolate the plane curve coordinates and then, they differentiate the interpolation curves. Thus, Mokhtarian and Mackworth (1986) propose to convolve $x[t]$ and $y[t]$ with a one-dimensional Gaussian filter defined by

$$h(t, w) = \frac{1}{\sqrt{2\pi}w} e^{-0.5\cdot(t/w)^2} \quad (2)$$

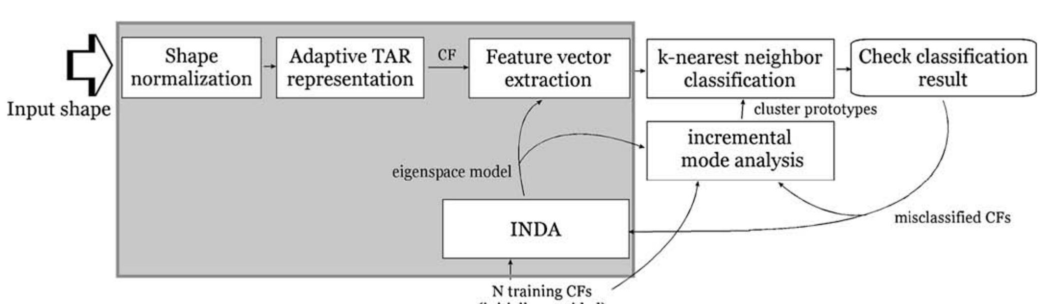

Fig. 1. Overview of the proposed contour-based shape recognition system.