Classification of Contour Shapes Using Class Segment Sets

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Abstract

Both example-based and model-based approaches for classifying contour shapes can encounter difficulties when dealing with classes that have large nonlinear variability, especially when the variability is structural or due to articulations. This work proposes a part-based approach to address this problem.

Introduction

The Problem

Shape classes may have a large nonlinear variability of global shape due to structural variation, articulation, or other factors (Figure 1). Existing approaches for shape classification have disadvantages when within-class variability is high.

- Example based approaches that match the target shape to stored example shapes (Laraki 2004; Belongie 2003; Cootes 2003) require a large number of examples to cover the range of variability.
- Model based approaches (Cootes 1991; Davies 2002; Celebrezi 2003) require a large number of parameters.
- Structural approaches (Galadhya 1999; Suhartanto 2002) are computationally expensive.

Our Approach

Allows parts of different examples of a class to contribute to the recognition of an input shape. This is done within a three-level framework of models for contour classes, and the database, connected by Bayesian inference. No models of whole shapes are stored.

Benefits of This Approach

- Both learning and classification are automated.
- Can classify shapes in classes with high variability, as well as partial and occluded shapes.
- Has few parameters.
- Can handle a large number of classes.
- No need to compute a deformation of a shape model or its parts.
- Only parts and not part relationships are explicitly represented.

Overview

Contour segments are extracted from the input shape and compared with the segments in the training database, which are organized by class segment sets. Each result contributes a probability to a class label. The class label with the largest aggregate value is assigned to the input shape.

1. Segments and Representation

- First, keypoint locations on a contour are identified.
- All segments defined by pairs of keypoints on the contour are extracted and normalized by their endpoints (Figure 1).
- Redundancy from the overlapping of segments provides robustness.

2. Class Segment Sets

- The union of all segments from all example contours in a green class is the class segment set of that class of contours.
- Each class is represented by its class segment set.
- Class segment sets allow parts of a query shape to match to parts of different training examples of the same class (Figure 6).

3. Statistical Database Model

- Principle Components Analysis (PCA) is used to compactly represent the parts of the classes and provide a Mahalanobis distance measure between segments.
- This gives an interpretable model of generic segments (Figure 4).

Classification Method

4. Bayesian Classifier

- The contour segments are modeled by an isotropic 2-Dimensional normal density, with scale factor α and centroid vector in the database.
- The class conditional probability density for observing a contour segment belonging to an input shape given that the input shape is in class c is:

\[ P(s|c) = \prod_{i=1}^{M} \frac{1}{\sqrt{2\pi \sigma_i^2}} \exp \left( -\frac{(s_i - \mu_i)^2}{2\sigma_i^2} \right) \]

- The posterior probability for a given segment to belong to an input shape of class c is given by Bayes’ rule:

\[ P(c|s) = \frac{P(s|c)P(c)}{\sum_{c'} P(s|c')P(c')} \]

- The class label assigned to the input shape is found by:

\[ \text{argmax}_c P(c|s) \]

Experimental Results

Classification Accuracy

An MPEG-7 evaluation dataset (Laraki 2000) was used for the classification experiments.

- 70 classes, 20 shapes per class.
- A modified leave-one-out procedure was used. For each one of the 70 classes in the evaluation dataset, one of the 20 shapes in that class was reserved for a test set, and the other 19 shapes in that class were used for training.
- 97% of the test sets were correctly classified, corresponding to 29 errors out of 1400 tests (Figure 7).

Conclusion

This work proposed a method capable of classifying shapes in classes with a high degree of variability. Empirical evaluation of classification accuracy on a large 70-class dataset demonstrated 97% accuracy and robustness to occlusion and clutter.