Hidden Markov Model Based 2D Shape Classification

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Abstract. In this paper, we propose a novel two step shape classification approach consisting of a description and a discrimination phase. In the description phase, curvature features are extracted from the shape and are utilized to build a Hidden Markov Model (HMM). The HMM provides a robust Maximum Likelihood (ML) description of the shape. In the discrimination phase, a weighted likelihood discriminant function is formulated, which weights the likelihoods of curvature at individual points of shape to minimize the classification error. The weighting scheme emulates feature selection procedure in which features important for classification are selected. A Generalized Probabilistic Descent (GPD) method based method for estimation of the weights is proposed. To demonstrate the accuracy of the proposed method, we present classification results achieved for fighter planes in terms of classification accuracy and discriminant functions.

1 Introduction

Object recognition is classic problem of computer vision. Among others, object recognition based on shape is widely used. First step towards the design of a shape classifier is feature extraction. Shapes can be represented by their contour or region \cite{11}. Curvature, chain codes, Fourier descriptors, etc. are contour based descriptors while medial axis transform, Zernike moments, etc. are region based features. Contour based descriptors are widely used as they preserve the local information which is important in classification of complex shapes.

Feature extraction is followed by shape matching. In recent years, dynamic programming (DP) based shape matching is being increasingly applied \cite{8}, \cite{1}. DP approaches are able to match the shapes part by part rather than point by point, and are robust to deformation and occlusion. HMMs are also being explored as one of the possible shape modeling and classification frameworks \cite{2}, \cite{3}, \cite{5}. Apart from having all the properties of DP based matching, HMM also provides a probabilistic framework for training and classification. HMM based shape classification approaches in \cite{2}, \cite{3}, \cite{5} presented classification results for very dissimilar shapes. However, in practical situations shapes to be classified are generally very similar. To handle such situation modifications to existing approaches is mandatory.

The HMM approaches mentioned above apply maximum likelihood (ML) as their classification criterion. Due to good generalization property of HMM, applying ML criterion to similar shapes does not provide good classification. Also, ML criterion is evaluated using information from only one class and does not take advantage of information from the other classes. Generally shapes can be discriminated using only parts
of the boundaries rather than comparing whole boundary. ML does not provide such mechanism.

To overcome these shortcomings, we propose a weighted likelihood discriminant for shape classification. The weighting scheme emulates comparison of parts of shape rather than the whole shape. The weights are estimated by applying GPD method. Unlike ML criterion, GPD uses information from all the classes to estimate the weights. As GPD method is designed to minimize the classification error, the proposed classifier gives good classification performance with similar shapes.

This paper is organized as follows: The shape description phase of the proposed method is discussed in Section 2 while Section 3 formulates discriminative training with GPD. Experimental results are presented in Section 4 and the paper ends with the conclusions and suggestions for further research in Section 5.

2 Shape Description with HMM

Before we delve into details of the HMM topology used for shape description, we introduce the terminology used.

1. $S$, set of states. $S = \{S_1, S_2, \ldots, S_N\}$, where $N$ is number of states. State of HMM at instance $t$ is denoted by $q_t$.
2. $A$, state transition probability distribution. $A = \{a_{ij}\}$, $a_{ij}$ denotes the probability of changing the state from $S_i$ to $S_j$.
   \[
   a_{ij} = P[q_{t+1} = S_j | q_t = S_i], \quad 1 \leq i, j \leq N. \tag{1}
   \]
3. $B$, observation symbol probability distribution. $B = \{b_j(o)\}$, $b_j(o)$ gives probability of observing the symbol $o$ in state $S_j$ at instance $t$.
   \[
   b_j(o) = P[o \text{ at } t | q_t = S_j], \quad 1 \leq j \leq N. \tag{2}
   \]
4. $\pi$, initial state distribution. $\pi = \{\pi_i\}$, $\pi_i$ gives probability of HMM being in state $S_i$ at instance $t = 1$.
   \[
   \pi_i = P[q_1 = S_i], \quad 1 \leq i \leq N. \tag{3}
   \]

If $C_j$ is $j^{th}$ shape class where $j = 1, 2, \ldots, M$ and $M$ is total number of classes then for convenience, HMM for $C_j$ can be compactly denoted as,

\[
\lambda_j = (A, B, \pi). \tag{4}
\]

An in depth description about HMM can be found in [9].

For the approach proposed in this paper, the description phase employs HMM topology proposed in [2]. The curvature of the shape is used as the descriptor. The shape is filtered with large variance Gaussian filter to reduce the effect of noise in curvature estimation. The filtered shape is normalized to a fixed length to simplify comparison and its major eigen-axis is aligned horizontally to achieve an invariant starting point. Let the aligned shape be indicated by $D = \{D_n\}$ and $D_n = (x_n, y_n)$ for $1 \leq n \leq T$, [9].