Boosting Face Identification in Airports

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Abstract

Robust face identification system in complex airport environment, which can identify certain candidates from a crowd of people in real time, is in urgent demand. S-AdaBoost is discussed in this paper as a variant of AdaBoost to handle real world environment. The Face Identification System for Airports (F1SA), based upon S-AdaBoost algorithm, is implemented in an international airport. Comparison of results obtained from FISA with those from other leading face identification approaches based on FISA database clearly demonstrates the effectiveness of FISA in real airport environment.

1 Introduction

When AdaBoost [Freund and Schapire 1996] is used to handle scenarios in complex environment with outliers, its limitations have been pointed out by researchers [Dietterich, 2000]. Some discussions and approaches [Ratsch, et al., 2001] have been proposed to address these limitations.

S-AdaBoost works by dividing the input space into a few sub-spaces and using dedicated classifiers to classify patterns in the sub-spaces. The final classification result is the combination of the outputs of the dedicated classifiers. The S-AdaBoost Machine is made up of an AdaBoost divider, an AdaBoost classifier, a dedicated classifier for outliers, and a non-linear combiner. S-AdaBoost can enhance AdaBoost's capability of handling scenarios in real world complex environment.

2 S-AdaBoost in Classification

S-AdaBoost applies the *Divide and Conquer Principle* through *dividing* the input pattern space S into a few sub-spaces and *conquering* the sub-spaces by finding simple fittings (decision boundaries) to the patterns in the sub-spaces. Input space can be denoted by:

$$\hat{\mathbf{S}} = \{\mathbf{P} = (\mathbf{X}, \mathbf{Y})\}$$

where,

$X = \{x_i\}$ denotes the input patterns.
$Y = \{y_i\}$ denotes the classification results.
$P = \{P_i = \{(x_i, y_i)\}\}$ denotes the input pattern and classification result pairs.

In S-AdaBoost, patterns in S can be divided into a few sub-spaces relative to a classifier $\mathbf{F(x)}$:

$$\hat{\mathbf{S}} = \hat{\mathbf{S}}_{nu} + \hat{\mathbf{S}}_{sp} + \hat{\mathbf{S}}_{ns} + \hat{\mathbf{S}}_{hd} \quad (1)$$

where,

$\hat{\mathbf{S}}_{nu} = \{\mathbf{P}_{no}\}$: Normal Patterns (Patterns can be easily classified by F(x)).
$\hat{\mathbf{S}}_{sp} = \{\mathbf{P}_{sp}\}$: Special Patterns (Patterns can be classified correctly by F(x) with bearable adjustment).
$\hat{\mathbf{S}}_{ns} = \{\mathbf{P}_{ns}\}$: Patterns with Noise (Noisy patterns)
$\hat{\mathbf{S}}_{hd} = \{\mathbf{P}_{hd}\}$: Hard-To-Classify Patterns (Patterns hard to be classified by F(x)).

A typical input pattern space is shown in Figure 1. The first two sub-spaces are further referred to as Ordinary Pattern Space, and the last two are called Outliers in S-AdaBoost:

$$\hat{\mathbf{S}}_{od} = \hat{\mathbf{S}}_{nu} + \hat{\mathbf{S}}_{sp} \quad (2)$$
$$\hat{\mathbf{S}}_{ol} = \hat{\mathbf{S}}_{ns} + \hat{\mathbf{S}}_{hd} \quad (3)$$

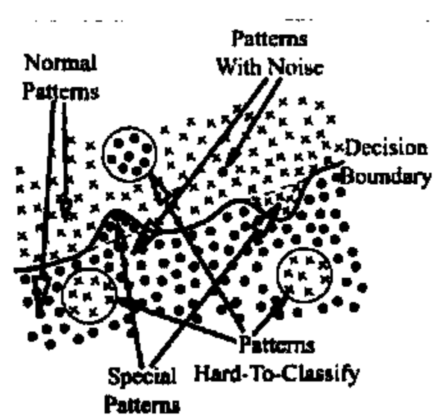

Figure 1: Input Pattern Space

During training, S-AdaBoost uses an AdaBoost $\mathbf{D(t)}$ as a divider to divide the patterns in the original training input space § into two separate sets in $\hat{\mathbf{S}}_{od}$ and $\hat{\mathbf{S}}_{ol}$. One set in $\hat{\mathbf{S}}_{od}$ is used to train the next AdaBoost $\mathbf{F_{od}(x)}$, which has good generalization characteristic; and another set in $\hat{\mathbf{S}}_{ol}$ is used to train a dedicated outlier classifier $\mathbf{IO(x)}$, which has good localization characteristic. The structure of S-AdaBoost is shown in Figure 2. During testing, the divider $\mathbf{D(t)}$ is no longer needed, testing patterns are fed directly to the two classifiers $\mathbf{F_{od}(x)}$ an $\mathbf{IO(x)}$ lowed by the combiner $\mathbf{Ç}$ to obtain the classification results.

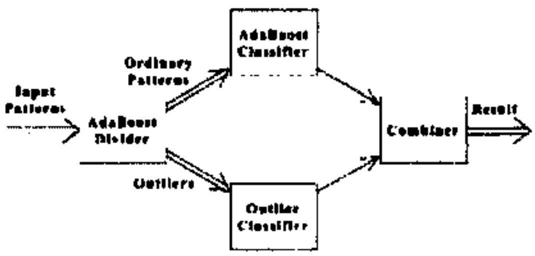

Figure 2: S-AdaBoost Machine

3 FISA

In FISA, 40 candidate's face images are stored in the candidate database. 5000 images with one or multiple face images in an airport environment are collected within 3 months; about 40% of the images contain one or a few candidate faces. 3000 images are randomly selected as the training set and the remaining 2000 images are chosen as the test set.

The pro-processor will detect potential faces and generate constant flow of 20 X 20 segmented potential face images to FISA. Back-Propagation (BP) Neural Network is used as the base learner for AdaBoost $\mathbf{D(t)}$ and $\mathbf{F_{od}(x)}$ in FISA. A three-layer RBF Neural Network with dynamic number of hidden nodes is chosen to implement $\mathbf{IO(x)}$ due to RBF Neural Network's good localization characteristic. The radii of hidden nodes in RBF are also chosen to be very small to enhance RBF network's good local clustering characteristic, which helps to isolate the $\mathbf{P}_{ol}$ from the $\mathbf{P}_{hd}$. A Multi-Layer Perceptron (MLP) Neural Network is used to implement the combiner C in FISA.

To test the effectiveness of S-AdaBoost (S-AB) on face identification in airports, we compared the performance of FISA (when Threshold t was set to $1/(M \times \partial^2)$) with other leading approaches. We implemented the neural network based EBGM (Elastic Bunch Graph Matching) approach [Wyner et al., 2001], the statistical subspace LDA (Linear/Fisher Discriminant Analysis) approach [Friedman et al., 1998], and Probabilistic PCA (Principle Component Analysis) approach [Freund, 1999], PPCA. The False Negative Rate (FNR) and False Positive Rate (FPR) of the four algorithms as well as those of the AdaBoost (AB) algorithm were used in our analysis.

The same training and testing face images (as used in FISA) were used in our experiment to compare the effectiveness of different approaches in real complex airport environment. In FISA testing, the pre-processed data (20 X 20 images) were fed directly to $\mathbf{F_{od}(x)}$ and $\mathbf{IO(x)}$. The testing results obtained from various approaches are listed in Table 1.

%	S-AB	AB	EBGM	LDA	PPCA
FPR	33.4	44.6	40.2	43.3	38.5
FNR	0.1	1.4	0.2	0.6	0.5

Table 1: Comparison of error rates of different approaches on FISA Database

4 Discussion and Conclusions

FISA is introduced as a practical system to handle face identification in real airport environment. S-AdaBoost, which is a variant of AdaBoost and is more effective than the conventional AdaBoost in handling outliers in real world complex environment, is also introduced as the algorithm behind FISA. Experimental results on FISA databases clearly show S-AdaBoost's effectives in handling classification in complex environment and FISA's capability in boosting Face Identification in Airport. Improvements of the algorithm will focus on utilizing more hybrid approaches to improve the overall identification rates of the system.

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