CLASSIFIERS SENSITIVITY FOR BOUNDARY CASE TESTING SET IN THE FACE RECOGNITION ALGORITHM BASED ON THE ACTIVE SHAPE MODEL

Andrzej Florek and Maciej Król
Institute of Control and Information Engineering, Automatic Control and Robotics Division
Poznan University of Technology, str. Piotrowo 3A, 60-965 Poznań, Poland

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Abstract: In this paper, experimental results from the face contour classification tests are shown. The presented approach is dedicated to a face recognition algorithm based on the Active Shape Model method. The results were obtained from experiments carried out on the set of 3300 images taken from 100 persons. Automatically fitted contours (as 194 ordered face contour points vector, where the contour consisted of eight components) were classified by Nearest Neighbourhood Classifier and Support Vector Machines classifier, after feature space decomposition, carried out by the Linear Discriminant Analysis method. Feature subspace size reduction and classification sensitivity analysis for boundary case testing set are presented.

1 INTRODUCTION

In this paper, a discussion concerning the choice of a classifier for the face recognition algorithm is presented. We investigate how the classification sensitivity coefficient is influenced by: the feature vector size, the size of the Principal Component Analysis (PCA) used for contours validation procedure, the size of the Linear Discriminant Analysis (LDA), number of classes and boundary case testing set. The presented algorithm for face classification is based on the Active Shape Model method (ASM) introduced by Cootes (Cootes and Taylor, 2001), which is a modification of the Active Contour Model method (ACM), i.e. a snake-based approach to extracting face contour from an image (Kass and Witkin, 1988). The ASM is a two-stage algorithm and it is based on a shape notation, which is defined as an ordered set of points. First, a Point Distribution Model (PDM) is produced, which will be used for validation of a contour shape. Next, a Local Grey Level Model (LGLM) is generated for interactive fitting of the contour points to the local image context. This method is still in progress, where modifications consist of initial contour choice and the new fitting methods (Zao and Li, 2004), (Zuo and de With, 2004). The ASM has been successfully used to extract the facial features of a face image under frontal view. However, its performance degrades when the concerned face is under perspective variations. For this reason, a modified shape model was proposed by Wan and Lam (Wan and Lam, 2005). It can adapt face images from different orientations or facial expressions and represents a face more flexibly.

To obtain PDM and LGLM models, the desirable contour localization on an image of a person has to be known. Thus, placing contours onto images (chosen to create a learning set) has to be performed and this may be done manually or automatically. Arrangement of proper learning set is usually the most important problem of a good classifier choice. A standard approach to classification consists of determining an affiliation of a sample to a class represented by its model. To construct a model of a person, a set of images has to be produced. These images have to be divided into learning and testing sets, for example by simple sampling or multiple sampling with replacement. The classification improvement should be achieved by removing the identified outliers from a training set. Generally, the database is built under surveillance of specialists and

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under determined conditions (distance, light, position, etc.). In practical vision system, the picture of a person (sample) is taken without this surveillance and allows the person a freedom of pose and gesture. Thus, the classification efficiency is in practice lower than it was anticipated. This problem can occur in the situation, when we want to verify if a person from an accidental image is not wanted. In the presented paper, we propose another testing set, which is obtained from images of faces in extreme positions under different perspective variations and facial expressions than in the conventional learning set (boundary cases).

2 CONTOURS

The shape in the ASM method is represented as an ordered set of control points placed on contours describing face elements and it is given by the following vector

$$\mathbf{x} = (x_1, y_1, x_2, y_2,..., x_n , y_n)^T, \quad (1)$$

where x_j and y_j are coordinates of contour control points. In the considered case, for eight chosen components of face contours, n = 194 points have been determined (Fig. 1 and Tab.1) and this implies 388-dimensional shape space.

Table 1: Face contours.

Contour	Number of points
Face outline FO	41
Mouth outer MO	28
Mouth inner MI	28
Right eyelid REL	20
Left eyelid LEL	20
Right eyebrow REB	20
Left eyebrow LEB	20
Nose outline NO	17
TOTAL	194

2.1 Extracting and Calculation of Contours

To obtain normalized learning contours, the initial contour (template – Fig. 1) is placed on the image. Next, it is manually fitted to the correct place that the operator regards as the best localization for the contour points. Subsequently, the derived contours are normalized. Scale coefficient and rotation of contour result from the calculated coordinates of eye centres (pupils). Pupil coordinates are calculated from coordinated contour points located in the eyelid corners. Pupil coordinates determine X-axis; points (-1, 0), (1, 0) are located on right and left pupil, respectively. The symmetrical of this section determines Y-axis and the middle of coordinate system. Next, the contour points are projected on a normalized coordinate system. The normalized contour has to be uniformly sampled (manually extracted contours do not have uniform distances between the adjacent contour control points). The normalized and uniformly sampled contours are presented in Fig. 2.

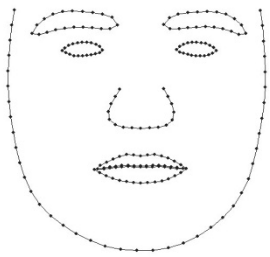

Figure 1: Template contour.

During the normalization procedure, points are ordered in a defined sequence, according to the feature vector definition (1). In the presented approach, the height standardization of face and nose outlines has not been applied.

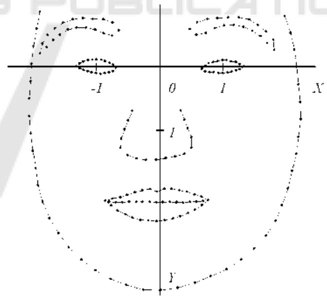

Figure 2: Normalized manually fitted contour.

3 EXPERIMENT

In order to select classifiers for the ASM face recognition algorithm, an experiment consisting of examining a set of face images was undertaken. Colour images of 2048 × 1536 pixels were used. For 100 persons (100 classes) the following images were taken (Fig. 11 and 12):

H – sequence of 30 frames for horizontal head rotation from the right to the left half-profile;

V – sequence of 20 frames for vertical face rotation from slightly risen to hang down head position;
D – frames for different head positions and facial expressions (boundary cases).

The contours were manually positioned on 11 central succeeding images (frames) from *H* and *V* sequences. In presented experiment, 2200 contours were used as the manual learning set (*LSM*) for the ASM algorithm (to determine PDM and LGLM models). Next, the ASM algorithm was performed to generate automatic contours for images from *H* and *V* sequence*s* and additionally from *D*-sequence.

3.1 Set Definitions

The normalized automatic contours were divided into the following sets (see Fig. 11 and 12):

- *LSA* – automatic learning set, 2200 contours, 100 classes, 22 contours for each class (11 central from *H* sequence and 11 central from *V* sequence);
- *A* – learning or testing set, 1100 contours, 100 classes, 11 contours for each class, even frames subset of *LSA;*
- *B* – learning or testing set, 1100 contours, 100 classes, 11 contours for each class, odd frames subset of *LSA*;
- *C100* – testing set, 1100 automatic contours, 100 classes, 11 contours for each person from *H*, *V* (boundary case in relation to *LSA*) and *D*.

The boundary case set *C100* is almost a “regular and balanced set”, i.e. consists of 4 contours from both *H* and *V* sequences, (out of 11 central images) and of 3 contours from *D* sequence. In the goal to examine influence of number of classes on classification sensitivity coefficient, the set *C100* was also divided to subsets *Cnc,* where *nc* is the number of classes, i.e. two *C50*, three *C33*, four *C25* and five *C20*. From analogical reasons, the learning set *LSA* was divided in the equivalent manner too.

Both *A* and *B* sets were used as learning or testing sets alternatively. The normalized contours from testing set *C100* were slightly different for the same person than those from learning sets (Fig. 3).

3.2 Contour fitting

The algorithm of contour fitting utilizes the ASM method (Fig. 4). Firstly, Gaussian pyramid for input image is generated. The initial contour shape is placed at the coarsest level of the pyramid.
Secondly, the initial contour is initialised by placing the mean face shape model (calculated from learning set *LSM*, see Fig. 1) at the position of localized face. Two steps of the ASM algorithm (LGLM and PDM – Fig. 4) are executed in a loop. The LGLM step locates salient features of image along the normal direction of contour control points. Each contour point (x_i, y_i) is shifted along the normal to the best matching position (x_{ij}, y_{ij}). The matching error is defined as minimal Mahalonobis distance d_{ij}

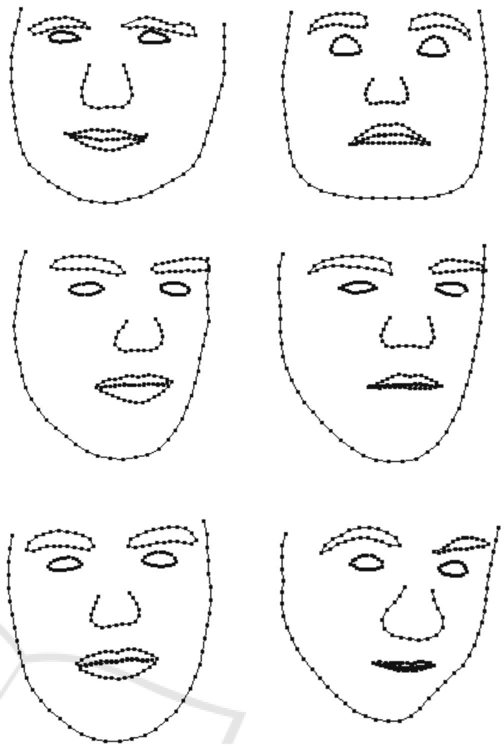

Figure 3: Normalized contours: manual contours from the learning set LSM (left column); automatic contours from the testing set C100 (right column).

$$d_{ij} = \left(\delta_{ij} - \bar{\delta}_i\right)^T \boldsymbol{C}_i^{-1}\left(\delta_{ij} - \bar{\delta}_i\right) \qquad (2)$$

from current LGL profile δ_{ij} to mean profile $\bar{\delta}_i$ for a given contour control point. The mean $\bar{\delta}_i$ and covariance $\boldsymbol{C}_i$ are computed from local grey level around manual contours control points (*LSM*) taken from learning set of images.

In the PDM step, the shape is filtered with forward (3) and inverse (4) transformations

$$b = \boldsymbol{P}^T\left(x - \bar{x}\right) \qquad (3)$$

$$x \approx \bar{x} + \boldsymbol{P}b \qquad (4)$$

to and from the subspace reduced by the PCA. The transformation matrix $\boldsymbol{P}$ is selected as the first *p*-

eigenvectors (p first PCs) of covariance matrix of contours from learning set. In the presented paper, value p=45 were used at 98,8% total variance ratio. The choice of this size is very important because it affects classification efficiency for applied classifier (this will be discussed later in this paper). The iteration ends when shapes stop changing significantly and computation is repeated for finer level of image pyramid until the last level is reached.

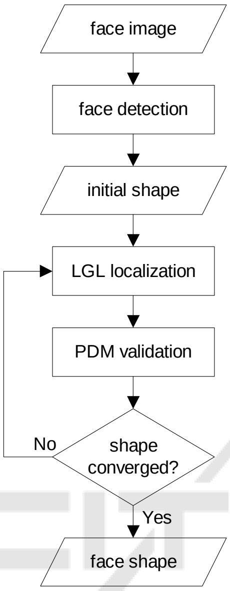

Figure 4: ASM algorithm diagram.

3.3 Classifiers

Three classification methods were tested. The first classifier was the Nearest Neighbourhood Classifier (NNC) in reduced to k-size feature shape subspace, derived from LDA/k decomposition. As a metric, Euclidean distance to a model of class in subspaces for different size k was used (subspaces are not orthogonal). The second method was taken as the SVM method using a Radial Basis Function as kernel and one-to-one voting system with a tie-breaking algorithm. In the presented approach, SVM classifiers were applied in full feature space and in its k-subspaces (the third method), obtained after the LDA/k decomposition in the feature space. As sensitivity measure of classifiers (recognition rate) the coefficient TP/(TP+FN) in percent was chosen, where TP and FN are numbers of True Positive (the person correctly recognized) and False Negative (the person not properly recognized) classifications.
Classification methods are denoted as:

- LDA/k – Euclidean distance in k-size feature space reduced after Linear Discriminant Analysis;
- SVM – SVM classifier in full 388-dimentional feature space;
- LDA/k & SVM – SVM classifier in LDA subspace reduced to k-size.

3.4 Choice of PCA Size for PDM Validation

Determining the dimensionality of the PCA subspace, i.e. the number of PCs to represent face patterns (contours), is an intricate problem. It is usually a trade-off between estimation accuracy and computational efficiency (Motulsky, 1997). Calculated eigenvalues and cumulative variances are presented in Fig. 5 and 6.

The reduction of the feature vector space to around the first p=30 PCs seems to be reasonable (97% of total data variance). Classification results for learning set *LSA* (average from tests where *A* and *B* sets were used as learning or testing sets alternatively) are presented in Fig. 7 and confirm the choice of first 30 PCs. However, results for boundary case testing set *C* suggest that the dimension size p= 45 (98,8% of total variance) will be better for LDA classifier. Small vector size in the PDM validation stage in the ASM algorithm unifies contours and smoothes between-class differences. Large vector size causes relaxation of contour and reduces noise resistance. For the PDM validation procedure in performed ASM algorithm, vector of the first 45 PCs was chosen.

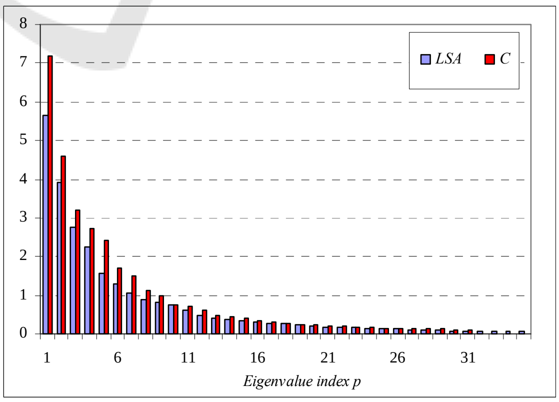

Figure 5: Eigenvalues in the PCA decomposition.

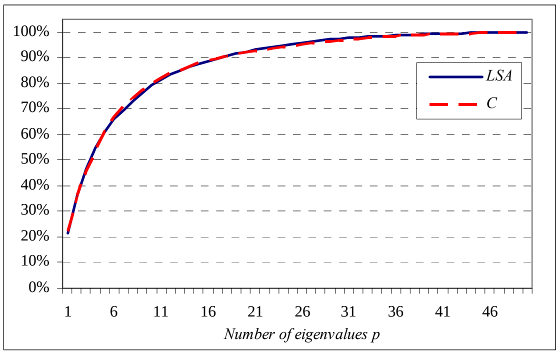

Figure 6: Cumulative variance in the PCA decomposition.

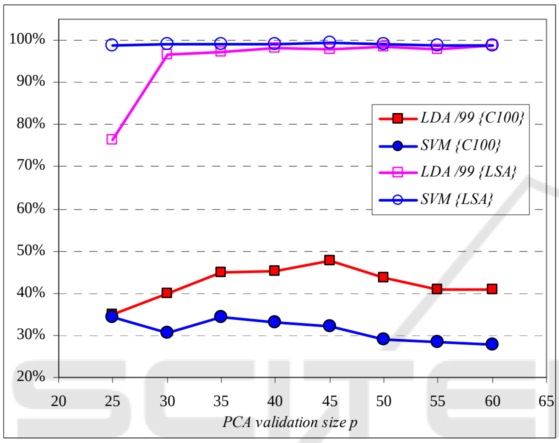

Figure 7: Classification sensitivity for LSA and C100 sets.

3.5 Results and Discussion

The SVM method is commonly used for classification. As we can see in Fig. 7, this method is good for testing samples similar to those from learning set (i.e. when they are close with respect to the face position and gestures). Classification efficiency obtained from *LSA* set was equal (or very close) to 100%. Experimental results demonstrate good property of SVM classifier, however this is the situation where the learning and testing sets were regular subsets of larger learning set *LSA*. For the set *C* as the testing set, the LDA classifier was much better than the SVM classifier in full-dimensional feature space. This suggests that the LDA method is more resistant to diversity of a testing set, because the space transformation function is found in order to maximize the ratio of between-class variance to within-class variance. In subsequent tests we investigated influence of the proposed LDA decomposition on amelioration of classification sensitivity for boundary case set. Results are presented in Fig. 8 We can observe that the LDA decomposition of order higher than PDM model is not necessary for the LDA classifier (for large feature vector size the maximal LDA size is equal to (*nc*-1), where *nc* is the number of classes). On the other hand, LDA feature vector size reduction can ameliorate sensibility of SVM classifier (denoted as LDA /*k* & SVM classifier). Influence of class number on classification sensitivity is presented in Fig. 9 and 10. Results for *nc* classes were averaged, for example for *nc*=25, testing *C100* and learning LSA sets were divided into 4 separate pairs of subsets and partial classifications results were averaged. Results demonstrate that for small number of classes in relation to the size of feature vector (1), the SVM classifier is much better then classifier based on LDA decomposition. This low LDA classification sensitivity mainly comes from ill-conditioned between-classes scatter matrix.

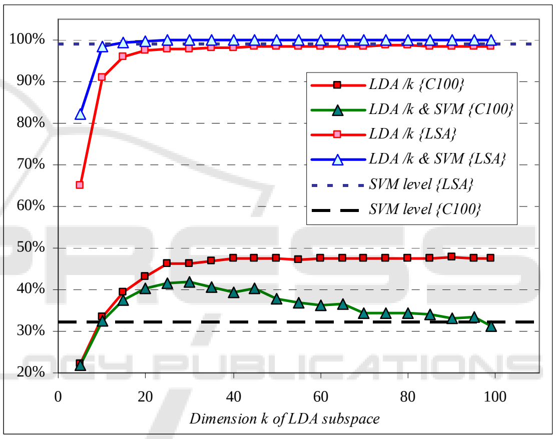

Figure 8: Classification sensitivity for LSA and C100 sets.

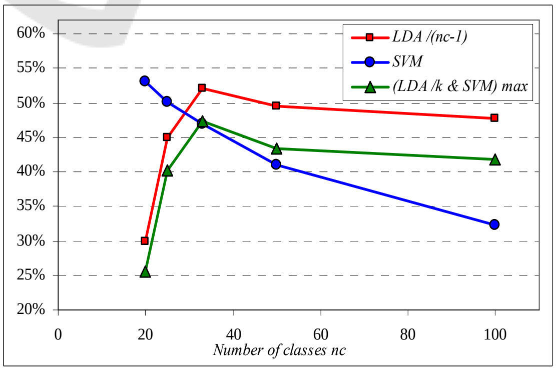

Figure 9: Classification sensitivity for testing sets Cnc.

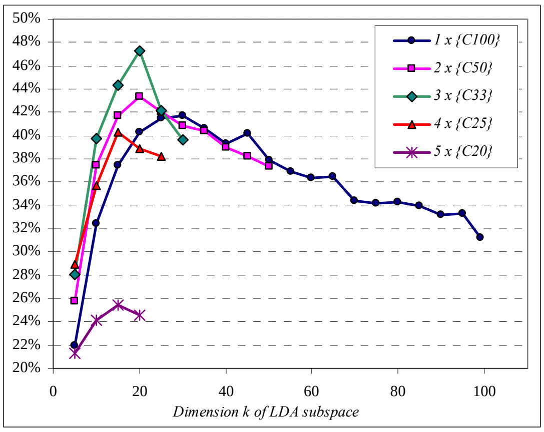

Figure 10: LDA /k & SVM classification sensitivity for testing sets Cnc.

Table 2: LDA /k & SVM classification sensitivity for testing sets Cnc.

No. of classe s *nc*	Classification sensitivity in %			*k* *max*
	LDA /(*nc*-*1*)	SVM	(LDA /*k* & SVM) *max*	
20	29,9	53,2	25,5	15
25	44,9	50,1	40,3	15
33	52,1	46,9	47,3	20
50	49,5	40,9	43,4	20
100	47,6	32,3	41,7	30

4 SUMMARY

The ASM produces reasonably good face contours for our boundary case testing set (Fig. 11 and 12). It is able to handle face images with glasses, beard and long hair. We have found out that ASM has problems with fitting contours to images with non-frontal face orientation.

It is caused by linear nature of Point Distribution Model (PDM), which utilizes the PCA validation procedure (Fig. 4). The PDM validation procedure filters contours according to the first PCs directions in the learning set (3 and 4). This is a significant disadvantage of ASM algorithm which leads to blurring between-classes differences. Authors in (Etamad and Chellapa, 1997) underline that the LDA of faces provides us with a small set of features that carry the most relevant information for classification purposes. For medium-sized databases of human faces, good classification accuracy is achieved using very low-dimensional feature vectors.

In this paper, an experiment consisting of application of boundary case testing set for tuning ASM parameters and for amelioration of SVM classifier sensitivity was presented. It has turned out that same size reduction (according to LDA results) improves the sensitivity of SVM classifier (Fig. 8 and 10). The optimal size of reduced LDA-subspace is lower than PDM validation vector size and much lower than the number of classes *k‹‹(nc-1)*, investigated in the test (Fig. 10 and Tab. 2). This condition for size *k* improves attenuation of disturbances. Those disturbances are understood as

differences between learning and testing sets (extreme face positions under different perspective variations and facial expressions). Generally, for large number of classes, the LDA classifier is better than SVM, but for small number of classes we observe inverse situation (Fig. 9).

It is desirable to examine influence of other contour normalisation procedures. In presented experiments, the height standardisation of face and nose outlines has not been applied. Other normalisation procedures, such as application of initial contour determined by calculated face position (Ge and Yang, 2005) and identified face gestures and head position (Wan and Lam, 2005) will be verified in the future research.

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Figure 11: Images and contours from learning set LSA fitted by the ASM algorithm.

Figure 12: Images and boundary case contours from testing set C100 fitted by the ASM algorithm.