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SUPPORT VECTOR MACHINE IN GENDER RECOGNITION

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In the paper, Support Vector Machine (SVM) methods are discussed. The SVM algorithm is a very strong classification tool. Its capability in gender recognition in comparison with the other methods is presented here. Different sets of face features derived from the frontal facial image such as eye corners, nostrils, mouth corners etc. are taken into account. The efficiency of different sets of facial features in gender recognition using SVM method is examined.

Keywords: face identification, gender classification, face authentication, biometrics, SVM, mobile applications

1. Introduction

Support Vector Machine (SVM) is one of the strongest classification methods [36-38]. One of the features that can be examined with the help of SVM is gender [11, 15-18, 24-27]. There are various gender classifications methods and they can be divided into two groups: feature-based and appearance-based methods [32]. They are briefly discussed in Section 2. The methods of gender recognition use different approaches but usually they are trained and tested on the subsets from the same database. When they are tested on the same e.g. FERET database [31] they show accuracy around 90%. When the testing and training databases are different, the methods' accuracy drops to 60-70%.

In the previous papers [1, 2, [33] we concentrated on the skin color classification as well as the general approach to the gender recognition. Finding skin color pixel is important in face detection. On finding a face at the picture, e.g. [3], one can examine the face to extract its features. After that we examined several classification methods of the gender of the face. We derived a conclusion that using SVM can provide very good result [33]. Our assumption is also based on a strong bibliography research [11, 15-18, 24-27].

It must be taken into account that computer designed methods and applications are also suitable for mobile devices. The mobile apps can have the same functionality as the desktop ones, but mobile devices have often worse hardware specification.

Many authors have presented works using SVM in the context of facial recognition [11, 16-18, 24-27, 39, 40]. However, there are no works showing the possibility of using facial geometry features in the SVM classification [45]. The authors used the appearance-based methods. There are also no works focused on the problem of choosing a minimum set of features that can give satisfactory results. This problem can be important in mobile devices. In this paper, we want to show that it is possible to use only two geometric facial features to construct a classifier that gives satisfactory (though not always optimal) results.

The paper is organized as follows. Section 2 presents a brief description of gender classification methods including various face recognition aspects. In Section 3, Support Vector Machine (SVM) method is presented. Section 4 presents Alex Martinez face database and the sets of features we derived from it for the research presented in the paper. A brief description of face databases like the FERET one is also provided here. Section 5 presents the method of facial features extraction from the images from AR database [43]. Next, we show the results of using different subsets of the whole set of the facial features using SVM method to find the best results of the gender classification. Section 6 contains the discussion and conclusions regarding the use of the presented classification methods in mobile applications, too.

2. Gender classification methods

Gender determination is often the first step in the automatic recognition/authentication process. This process have to start with finding face area on the image. It can be done by skin color pixels detecting. Then the area of the skin color pixels is checked whether it can be classified as a face e.g. using template matching methods. The several approaches to the skin color classification were presented in our previous papers [1, 2]. Nowadays, there is a method very popular and helpful in face detection that was presented by Viola and Jones [3]. On finding a face at the picture, e.g. [3], one can examine the face to extract their feature for future processing.

The second step in the process of gender recognition is feature extraction. In the gender recognition task, we can distinguish two methods of feature extraction: geometric based and appearance based. The first one requires finding the facial characteristic points as nose, mouth, eyes, ears or hair, called fiducial points. The geometric relation between these points (fiducial distances) are used as a feature vector in the classification process. The importance of these distances in the gender discrimination tasks is confirmed by the psychophysical studies [4, 14, 28-30].

Appearance based methods works on the pixel values of images that were previously transformed on the local or global level. At the local level, the image can be divided e.g. into lower windows or specific face regions such as mouth, nose or eyes. This approach preserves natural geometric relationships which can be used as naïve features. This approach can be very computationally demanding because of a very large number of features because each pixel is treated as a feature. In our research we decided to use geometric facial features.

The third step in the gender recognition process it is choosing the proper classification method. In the gender recognition task various classification methods are used: neural network [7, 8], hyper basis function networks [4], radial basis function networks [5], Gabor wavelets [6, 9], Adaboost [10, 12, 13], Support Vector Machines (SVM) [11], linear discriminant analysis (LDA) [11], Self Organizing Maps (SOM) [13], Bayesian classifiers [11] etc. In Table 1 we show the selected works that use different classification methods. It can be seen that the most popular classifier is SVM.

The best results were reported by Zheng et al. [26] - for CAS-PEAL database– 99.8%, and for FERET database 99.1%. However, Zheng et al. selected only frontal face images from the datasets. Based on the results presented in Tab. 1 the best classification efficiency was obtained with the SVM algorithm that is why we also use it in our research.

Table 2 presents the results for the FERET database and the Web testing databases conducted by Makinen and Raisamo [32]. These authors compared the selected gender recognition methods using the same preprocessing and testing methods as original authors. In the first case separate sets of the FERET images were used for training. In the second case all FERET datasets were used for training.

Table 1. Comparison of the selected gender classification methods

	Author	Classifier	Training data	Test data	Efficiency [%]
1	Moghaddam (2002) [15]	SVM-RBF	FERET	cross validation	96.62
2	Shakhnarovich (2002) [10]	Adaboost	Web images	cross validation video seq.	79.00 90.00
3	Sun (2002) [11]	SVM	UNR	cross validation	95.30
4	Castrillon (2003) [16]	SVM+ temporal fusion	Video frames		98.57
5	Buchala (2005) [17]	SVM –RBF	Mix (FERET, AR, BioID)	cross validation	92.25
6	Jain (2005) [18]	SVM	FERET	FERET	95.67
7	Baluja (2006) [19]	Adaboost	FERET	cross validation	94.30
8	Fok (2006) [20]	Convolutional neural net.	FERET	cross validation	97.20
9	Aghajanian (2009) [21]	Bayesian	Web images	Web images	89.00
10	Demirkus (2010) [22]	Bayesian	FERET	Video seqs.	90.00
11	Wang (2010) [23]	Adaboost	Mix (FERET, CAS-EAL , Yale)	cross validation	~97.00
12	Alexandre (2010) [24]	SVM-linear	FERET	FERET	99.07
13	Li (2011) [25]	SVM	FERET	FERET	95.80
14	Zheng (2011) [26]	SVMAC	FERET CAS-PEAL	FERET CAS-PEAL	99.10 99.80
15	Shan (2012) [27]	SVM-RBF	LFW	cross validation	94.80

Table 2. Results for the FERET images

	FERET images without hair	Web images without hair
Method	Classification rate [%]	Classification rate [%]
Neural network	92.22	65.95
SVM	88.89	66.48
Threshold Adaboost	86.67	66.29
LUT Adaboost	88.89	66.19
Mean Adaboost	88.33	66.14
LBP + SVM	80.56	67.25

Source: based on the Mäkinen E., Raisamo R. [32]

It can be seen that the results obtained for the FERET testing set are significantly better than the results obtained for the web images. It can be a result of a greater similarity of the training and testing sets when FERET set are used in both cases. The other reason is that the web images used as a testing set have more quality variations, so they are more difficult to be classified correctly.

3. Support Vector Machine in gender classification

In the SVM algorithm data is divided into two groups using the decision function specified by a subset of training samples called Support Vectors [36-38]. Support vectors are the data points that lie in the closest distance to the decision surface and using them the hyperplane margin can be maximized. . Optimal separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class.. If the original feature space is not well-conditioned (dataset is not linearly separable) it can be mapped to a higher dimensional feature space where the training set is likely separable. The SVM provides non-linear function approximations by mapping the input vectors into a high dimensional feature space where a linear hyperplane can be constructed. Although there is no guarantee that a linear hyperplane will always exist in the higher dimensional feature space. In practice it is quite possible to construct a linear SVM in the projected space. The optimal hyperplane is in the form of:

$$f(x) = \sum_{i=1}^{l} y_i \alpha_i k(x, x_i) + b, \tag{1}$$

where k is the kernel function, while $f(x)$ determines the category of x. Constructing an optimal hyperplane is equivalent to determining nonzero α_i. Any vector x_i that corresponds to a nonzero α_i is a supported vector of the optimal hyperplane. The number of support vectors is usually small and it allows producing a compact classifier.

Choosing the most appropriate kernel function depends highly on the problem at hand and fine tuning its parameters can easily become a tedious and cumbersome task. The motivation behind the choice of a particular kernel can be very intuitive and straightforward depending on what kind of information we are expecting to extract from the data. The kernel function needs to be a scalar product in some feature space. A sufficient condition is that the kernel matrix is positive. Some common kernel functions that fulfill this condition are e.g.:

- the polynomial kernel

$$k(x, y) = (ax^T y + c)^d \tag{2}$$

- Gaussian kernel or Gaussian Radial Basis Function (RBF)

$$k(x,y) = \exp\left(-\frac{\|x-y\|^2}{2a^2}\right) \tag{3}$$

- exponential kernel

$$k(x,y) = \exp\left(-\frac{\|x-y\|}{2a^2}\right) \tag{4}$$

In our experiments Gaussian kernel function has been used because of the best results it gave.

SVMs can be used to solve various problems. Experimental results show that SVMs achieve significantly higher search accuracy than traditional query refinement schemes. Gender classification can be carried out with the use of different methods, like LDA or Fisher's Algorithm. In Fisher's Algorithm we have to calculate the Eigen vectors and its value for training data which can be skipped in SVM. SVM is very often used in the gender recognition problem as one of the algorithms, which provides the best results [26, 39-42].

4. Facial databases

The FERET database [31] is the most often used as a training set for gender classifiers. The classification efficiency is the ratio of correctly classified test examples to the total number of test examples. The most popular method of results testing is cross validation, but many authors report also that they train and test results on the different datasets [32].

The comparison of various facial recognition methods based on their classification efficiency is very difficult, because researchers use different datasets and parameters for their methods evaluation. Even if authors use the same FERET database, they don't have to use the whole of it. They can select the different subsets of images which are more or less difficult to classify. In our experiments, we used a part of AR face database [43] containing frontal facial images without expressions. The AR face database was created by Aleix Martinez and Robert Benavente in the Computer Vision Center (CVC) at the U.A.B. It contains over 4,000 color images corresponding to 126 people's faces (70 men and 56 women). Images show frontal view faces with different facial expressions, illumination conditions, and occlusions (sun glasses and scarfs). The pictures were taken at the CVC under strictly controlled conditions. Images are of 768×576 pixel resolution and of 24 bits of depth.

We used a subset containing 92 frontal face images: 49 women and 43 men.

5. Results of classification using Support Vector Machine

In our research we have taken into account 11 facial characteristic points (Fig.1): *RO* - right eye outer, *RI* – right eye inner, *LI* - left eye inner, *LO* - left eye outer, , *RS* and *LS* – right and left extreme face point at eye level, *MF*- forehead point, *M* – nose bottom point, *MM* – mouth central point, *MC* – chin point and *Oec*, the anthropological face point has coordinates derived as an arithmetical mean value of the points *RI* and *LI*. The points were marked on each image manually. These features were described in [30], 34, [34] and are only a part of facial geometric features described in [14]. The coordinates are bounded with *Oec* point and their values are recalculated in *Muld* units [30], [34], where

$$1\,Muld = 10 \pm 0.5\ mm \tag{5}$$

Muld is equal to a diameter of the person iris and it is constant for each person from 4-5 year of his/her life [44]. For each picture *Muld* unit was measured separately and all coordinates and distances are also denoted in that unit. Hence, the face is scaled in the person own *Muld* unit [34][35].

The chosen points allowed to define 7 distances which are used as a features in the classification process:

1. Distance between anthropological point and mouth center, further referred shortly as MM.
2. Distance between anthropological point and chin point (MC)
3. Chin/jaw height (MC-MM).
4. Distance between nose-end point and chin point (MC-M).
5. Face width at eye level (RSLS).
6. Distance between outer eye corners (ROLO).
7. Face height (MF-MC).

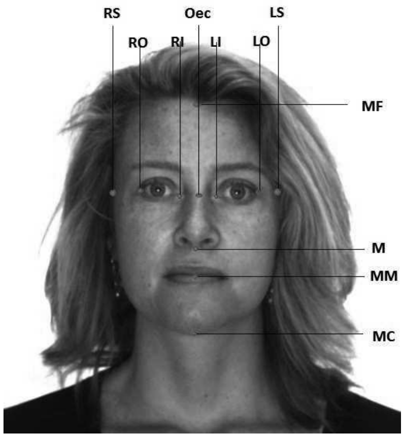

Figure1. Face characteristic points [34, [34], image from [43]

It is important to create mobile classification applications but mobile devices have very various hardware and OS specifications. That is why our aim has been to build classifiers as simple as possible. In our research, from the set of features described and derived above we have taken subsets and test classification efficiency using that subsets. We want to choose a minimal feature subset or subsets that will give the best classification results.

The results of the experiments presented in Table 3 have shown that the classification error is smaller than in the methods shown in Table 2. It means that 2 features are sufficient to obtain satisfactory classification results. The best results are shown in Table 3.

Cross validation method was used to verified the classification results. Eight sets of 10 objects (5 women and 5 men) were used. The best results we obtained using 2 features: distance between eye outers and distance from anthropological point to the chin point. For this pair error rate is 17,5 %.

Table 3. Results for all sets of 2 features

Features	**1 MM**	**2 MC**	**3 MC-MM**	**4 MC-M**	**5 RSLS**	**6 ROLO**	**7 MF-MC**
1MM	X	72,5%	76,3%	72,5%	76,3%	73,8%	70,0%
2 MC		X	72,5%	75,0%	76,25%	82,5%	70,0%
3 MC-MM			X	67,5%	71,3%	53,8%	70,0%
4MC-M				X	77,5%	77,5%	73,8%
5RSLS					X	68,8%	73,8%
6 ROLO						X	65,0%

6. Discussion and conclusions

In our research, we choose from the set of features described and derived in Sec. 4 subsets having 2 features. The classification efficiency of the SVM algorithm was evaluated by using that subsets. We wanted to show that such a minimal feature subset (2-elements) can also give satisfactory classification results. It has appeared that one feature connected with the height and one connected with the width of the face can give the classification rate around 82%.

In the paper, we focused on gender classification using SVM method and testing it in the mobile applications. Because of the mobile hardware variety and different OS specifications we built classifier as simple as possible. The results of classification presented in Table 3 vary from the results shown in Table 2 for web images even if we used only 2 features to the classification. Nonetheless, that classification based on 2 features is very easy to implement and utilize in mobile applications.

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