Швидка Класифікація Статі Використовуючи Геометричні Характеристики і SVM

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Fast Gender Classification Using Geometrical Features and SVM

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Abstract— In the paper, we have concentrated on the problem of fast gender classification using SVM method for mobile applications. The mobile applications can have the same functionality as the desktop ones, but mobile devices have various hardware and OS specification. Often this specification is worse than for the desktop ones, so we were looking for the possibly simplest classifier giving satisfactory classification efficiency. Many authors have used SVM in the facial classification and recognition problem, but there are not many works using the facial geometry features in the SVM classification. Almost all works are based on the appearance-based methods. Choosing a minimum set of features, that can give satisfactory results, it is important problem too. The minimum set of features can simplified classification process to make it useful for the mobile applications. In the paper, we show that the classifier construct on the base of only two geometric facial features can give satisfactory (though not always optimal) results.

Анотація—розглянуть проблеми швидкої гендерної класифікації з використанням методу SVM для мобільних додатків. Мобільні додатки можуть мати таку ж функціональність як настільні ПК, але мобільні пристрої мають різні апаратні і технічні характеристики ОС. В роботі показано, що класифікатор конструкція на базі тільки двох геометричних рис осіб може дати задовільні (хоча і не завжди оптимальні) результати.

Keywords—face identification, biometrics, gender classification, Support Vector Machine, mobile applications.

Ключові слова—ідентифікації особи, біометрія, гендерна класифікація, підтримка векторних машин, мобільні додатки.

I. INTRODUCTION

The first step in the gender determination process it is finding face area on the image. Skin color pixels detecting can be used in this task. 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]. When the face area is finding we can decide about method of the gender detection.

There are many gender classifications methods, which can be used in the recognition process. They can be divided into two groups: feature-based and appearance-based methods [3][26].

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. Importance of these distances in the gender discrimination task is confirmed by the psychophysical studies [4][10][22-24].

Appearance based methods are based on the values of image pixels that were previously transformed on the local or global level, e.g. at the local level, the image can be divided 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 very large number of features (each pixel is treated as a feature).

In our research, we decided to use geometric face features to limit computational complexity.

II. Gender Recognition Approaches

The other important element in the gender recognition process is the choice of the proper classification method. In this task many different classification methods are used, e.g.:

neural network [7],

radial basis function networks [5],

Gabor wavelets [6],

Adaboost [8],

Support Vector Machines (SVM) [9],

Bayesian classifiers [9].

Support Vector Machine (SVM) is one of the most popular classification method, often used by authors, because of good classification results [3][26]. SVM is one of the strongest classification methods useful in many applications [19-21]. This approach can be helpful also in the process of gender classification. Many authors reports very good efficiency of this method [9][15-18].

The SVM algorithm is based on subset of training samples called Support Vectors, which are used to construct the decision function [19-21]. Support Vectors are the data points that lie closest to the decision surface, which are using to maximize hyperplane margin. If the dataset in the original feature space is not linearly separable it can be mapped to a higher dimensional feature space where the same dataset is likely separable.

The SVM provides non-linear kernel function approximations by mapping the input vectors into a high dimensional feature space where a linear hyperplane can be constructed. In our research we were using Gaussian kernel as the one gives best results.

III. Facial Databases

To train a classifier we always need a set of object examples. We can prepare this dataset ourselves or use existing database. For the gender recognition problem we need the dataset of the face photos. There are several publicly available database that have been used for experiments. The most popular is the FERET database [25]. Publicly available datasets examples are AR, BioID, CAS-PEAL-R1, MORPH-2, LFW.

In our research we decided to use a part of AR face database [12] containing frontal facial images without expressions. The AR face database was prepared by Aleix Martinez and Robert Benavente in the Computer Vision Center (CVC) at the U.A.B. It contains:

over 4,000 color images;

126 people's faces of 70 men and 56 women;

images show frontal view faces with different 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 have chosen AR database subset containing 92 frontal face images: 49 women and 43 men.

IV. Results of Classification

In our research we took 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 eyes level,

MF- forehead point – in the direction of facial vertical axis defined as in [13] or in [24], see Fig.2

M – nose bottom point,

MM – mouth central point,

MC – chin point,

Oec, the anthropological face point, that has coordinates derived as an arithmetical mean value of the points RI and LI.

Points were marked on each image manually. These features were described in [24][13][14] and are only a part of facial geometric features described in [10]. The coordinates are bounded with Oec point and their values are recalculated in Muld units [13][24], where

$$1 \text{ Muld} = 10 \pm 0.5 \text{ mm} \quad (1)$$

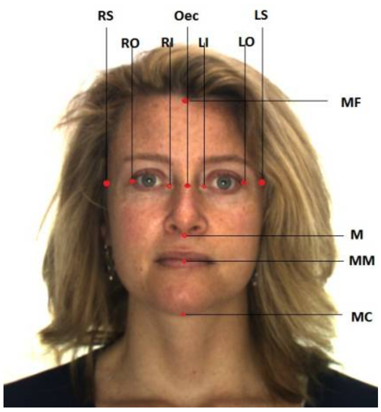

Fig. 1. Face characteristic points [13][14] (image from AR database)

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

MM – distance between anthropological point and mouth center.

MC – distance between anthropological point and chin point.

MC-MM – chin/jaw height.

MC-M – distance between nose-end point and chin point.

RSLS – face width at eye level.

ROLO – distance between outer eye corners.

MF-MC – face height.

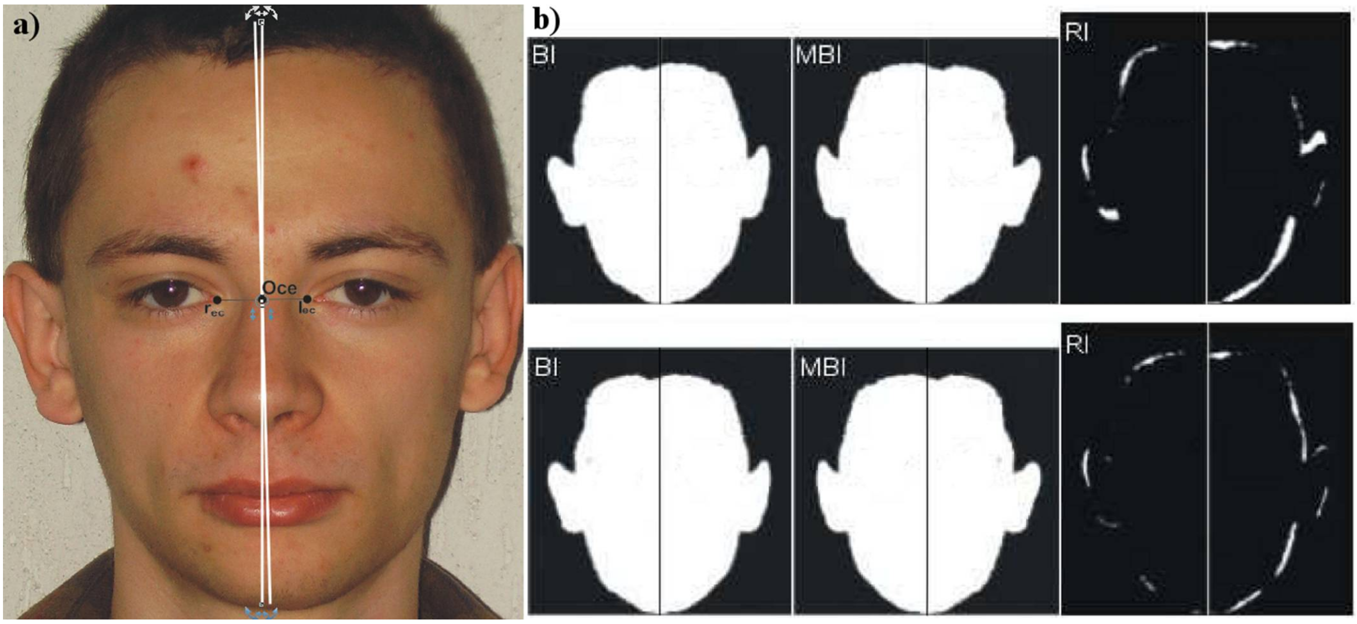

Fig. 2. Example of derivation of vertical projection axis [13]

In our experiments, we test classification efficiency using the subsets taking from the set of features described above. We look for a minimal feature subset that give the best classification results. The classification efficiency is the ratio of correctly classified test examples to the total number of test examples. We can train and test results on the different datasets, but we decided to use cross validation as a method of result testing, because our subset of AR database was not enough big to divide it into two (training and testing) subsets.

TABLE I. RESULTS FOR 2 FEATURE SETS

Features	MC	MC-MM	MC-M	RSLS	ROLO	MF-MC
MM	**72,5%**	**76,3%**	**72,5%**	**76,3%**	**73,8%**	**70,0%**
MC		**72,5%**	**75,0%**	**76,3%**	**82,5%**	**70,0%**
MC-MM			**67,5%**	**71,3%**	**53,8%**	**70,0%**
MC-M				**77,5%**	**77,5%**	**73,8%**
RSLS					**68,8%**	**73,8%**
ROLO						**65,0%**

The results of experiments presented in Table I have shown the classification error. Cross validation method was used to verified the classification results. Eight sets of 10 objects (5 women and 5 men) were used. We have tested all combinations of our 7 features. For large subsets of features we have obtained comparable results as for the best two-element sets. The best results for two-features sets we obtain using distance between eye outers (ROLO) and distance from anthropological point to the chin point (MC). For this pair error rate is 17,5 %.

It was also interesting to find out whether the two genders are evenly recognized, i.e. whether the number of misclassified women is comparable to the number of males who are misclassified. The results are shown in Table II.

We can see that for best feature pair we have visible disproportion between classification error for men and women. Women were classified more efficiently. For different feature pairs we have opposite situation men were misclassified. It suggest that some features can be characteristic for one of the gender.

V. CONCLUSIONS

It the paper, we focused on the use of SVM classifier in the gender recognition application, especially applications dedicated to mobile devices. Mobile applications may have specific requirements, often offering less computing power than desktop applications. Considering that we were looking for a classifier based on the possibly smallest set of features that will be give satisfactory classification results. We showed that it is possible to construct such classifier, using only 2 features. We obtain classification efficiency 82,5%. We showed also that the number of misclassified object depends on gender. In the feature we are going to propose classifier taking into account this relationship.

TABLE II. INDEPENDENT RESULTS FOR MALE AND FEMALE FOR 2 FEATURE SETS

Features	2 MC		3 MC-MM		4 MC-M		5 RSLS		6 ROLO		7 MF-MC	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
1MM	72,5%	72,5%	80,0%	72,5%	80,0%	65,0%	82,5%	70,0%	67,5%	80,0%	52,5%	87,5%
2 MC			85,0%	60,0%	67,5%	82,5%	75,0%	77,5%	75,0%	90,0%	52,5%	87,5%
3 MC-MM					52,5%	82,5%	70,0%	72,5%	90,0%	17,5%	85,0%	55,0%
4MC-M							80%	75%	80,0%	75,0%	80,0%	67,5%
5RSLS									77,5%	60,0%	80,0%	67,5%
6 ROLO											87,5%	42,5%

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