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GENDER CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK

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***Abstract*-- In various biometric applications, face recognition plays to encode the intensity variation among the four basic directions through the central pixel in two bits. This study confirms that ANN classifies the important role. This paper describes how to classify the gender of the image using Artificial Neural Network (ANN) algorithm as it has accuracy and significantly fast speed than conventional speed. Here we use Direction coded Local Binary Pattern (dLBP) for feature extraction to encode the intensity variation among the four basic directions through the central pixel in two bits. This study confirms that ANN classifies the gender of an image with high accuracy**.

Keyword: Artificial neural network; Direction coded local binary pattern; Weber Local Descriptor; Testing; Training; Feature Extraction; Gender Classifications.

INTRODUCTION

It is observable that our behavior and social interaction are greatly influenced by genders of people whom we intend to interact with. Hence a successful gender recognition system could have great impact in improving human computer

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interaction systems in such a way as to make them be more user-friendly and acting more human-like. Moreover, there are a number of applications where gender recognition can play an important role including biometric authentication, high-technology surveillance and security systems, image retrieval, and passive demographical data collections. It is unarguable that face is one the most important feature that characterizes human beings. By only looking ones' faces, we are not only able to tell who they are but also perceive a lot of information such as their emotions, ages and genders. This is why gender recognition by face has received much interest in computer vision research community over past two decades.

One of the early methods for gender classification used a neural network trained on a small set of near-frontal face images. In the combined 3D structure of the head (obtained using a laser scanner) and image intensities were used for classifying gender. SVM classifiers were used by applied directly to image intensities. Rather than using SVM, used AdaBoost for the same purpose, here again, applied to image intensities. Here we use Artificial Neural Network to classify the gender of the image. It is a statistical learning algorithm which are inspired by properties of the biological neural networks they are used for a wide variety of task, from relatively simple classification problems to speech recognition and computer vision.

TECHNICAL PROCESS

Over the past decades, there have been significant advances in facial image processing, especially, in a face detection area where a number of fast and robust algorithms have been proposed for practical applications. There are 2 main steps involved in recognizing genders of humans presented in an image. These are face detection and gender classification, which are applied consecutively. As face detection is one of popular research areas, many algorithms have been proposed for it. Most of them are based on the same idea considering the face detection as a binary classification task. That is, given a part of image, the task is to decide whether it is a face or not. This is achieved by first transforming the given region into features and then using classifier trained on example images to decide if these features represent a human face.

GENDER CLASSIFICATION

After faces are detected by face detection algorithm, they need to be decided if they are his or her faces. This is the task achieved by gender classification systems .Similar to the face detection task, the gender classification task is also considered as a binary classification problem but now with the result being male or female instead of face or non-face. Essentially, gender classification consists of 4 main steps: (1) Pre-processing (2) feature extraction (3) Gender classification.

PREPROESSING

Since, in real-life, it is unlikely that people will face directly and frontally towards the camera, face images often consist of some in-plane and out-of-plane rotations. Moreover, it is also unlikely that the light condition will be the same for all images. These variations greatly affect an accuracy of gender classifiers. The purpose of pre-processing step is thus to remove these variations as much as

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possible.

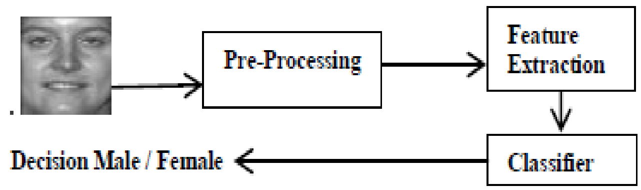
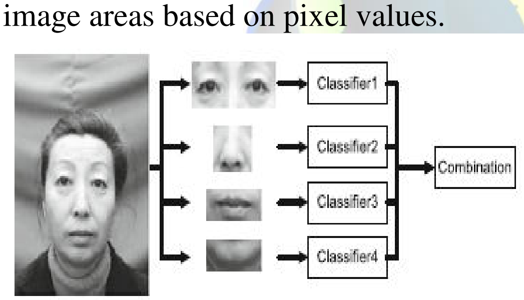


Figure.1. Gender recognition system

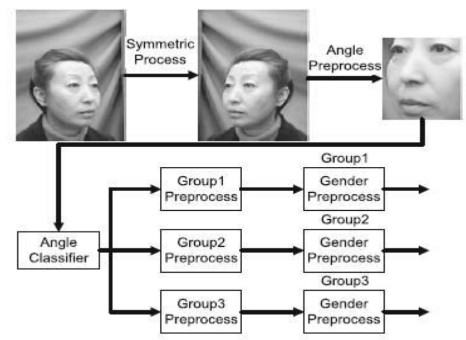
FEATURE EXTRACTION

Generally there are two types of features presented in the gender classification context, geometric-based features and appearance-based features. Geometric-based features (also called local features) came from psychophysical explorations. They represent high-level face descriptions such as distances between nose, eyes and mouth, face width, face length, eyebrow thickness and so on. Appearance-based features (also called global features) use low-level information about face image areas based on pixel values.



GENDER CLASSIFICATION

Alignment is important for gender classification based on facial images. First, faces are fixed in the centre of the result pictures. Facial components are in certain places for feature extraction after alignment. ASM is used to get the locations of eyes and mouth, and then we cut out a rectangle with the facial image. The bilaterally symmetrical characteristic of the human face is used. The images facing right are turned to face left. Then, the images are classified according to the angle of the faces. Images in different angle classes are taken to their own gender classifiers. Now we have converted the original problem to gender classifications based on facial images of fixed angle, a well-studied problem with many good approaches.



Simple arithmetic combination:

The following sum, maximum, and product rules are the simplest computationally efficient rules for combination. (C indicates the result of certain classifier and O means the label which is male orfemale):

$$\mathrm{Prob}_{\mathrm{sum}}(x_i = \mathcal{O}) = \sum_{t=1}^{T} \mathcal{C}_t(x_i; \mathcal{O})$$

$$\mathrm{Prob}_{\mathrm{max}}(x_i = \mathcal{O}) = \max\{\mathcal{C}_1(x_i; \mathcal{O}), \ldots, \mathcal{C}_T(x_i; \mathcal{O})\}$$

$$\mathrm{Prob}_{\mathrm{prod}}(x_i = \mathcal{O}) = \prod_{t=1}^{T} \mathcal{C}_t(x_i; \mathcal{O}).$$

Weber's Law: Ernst Weber, an experimental psychologist in the 19th century, observed that the ratio of the increment threshold to the background intensity is a constant. This relationship, known

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since as Weber's Law, can be expressed as

$$\frac{\Delta I}{I} = k,$$

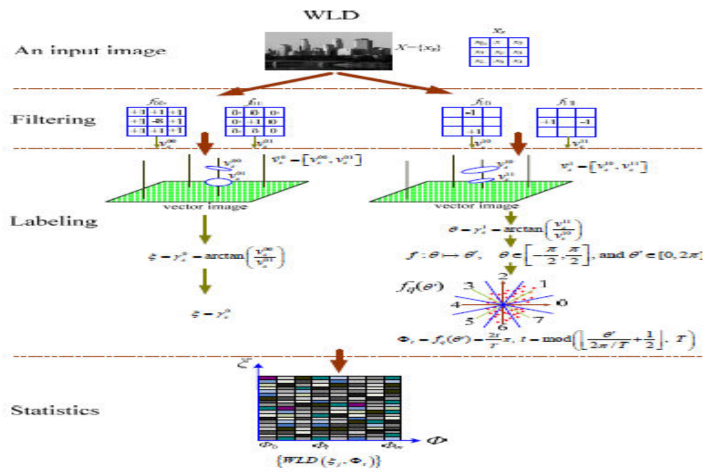

Fig. 1. Illustration of the computation of the WLD descriptor

Intuitively, one often pays more attention to the regions of high variances in a given image compared with the flat regions. So, the different frequency segments should play different roles in a classification task. Thus, we can assign different weights to different segments for a better classification performance.

Table 1 Weights for a WLD histogram

	H_0	H_1	H_2	H_3	H_4	H_5
Frequency percent	0.2519	0.1179	0.1186	0.0965	0.0875	0.3276
Weights (ω_m)	0.2688	0.0852	0.0955	0.1000	0.1018	0.3487

CONCLUSION

In this paper we have classified the gender of an image using Artificial Neural Network which gives much better accuracy i.e. 99.08% with lesser algorithmic complexity than state-of-the-art gender recognition approaches. In appearance based methods, the whole image is considered rather than the local features corresponding to different parts of the face. While in geometric based methods, the geometric features like distance between eyes face length and width, etc., are considered. But in this paper accurate features will be detected. Each and every changes in the face will be extracted with less complexity.

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