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Automatic gender classification using neuro fuzzy system

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Abstract

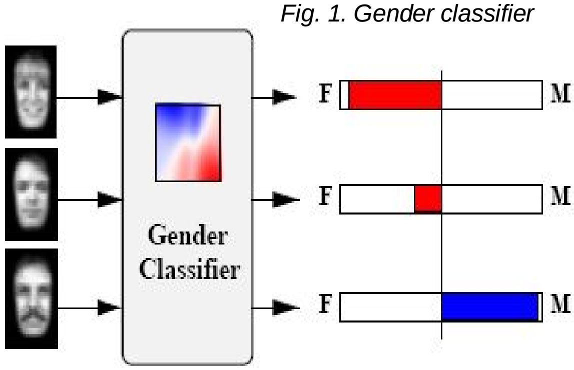
The automatic classification of gender has important applications in many commercial domains. Existing systems mainly use features such as words, word classes, and POS (part of speech) n-grams, for classification learning. In this paper, we propose a novel automatic classifier which applies accurately designed fuzzy inference system. This system is 2-inputs, 1-output Sugeno type one, applies facial characteristics as inputs and reveals the probability of being male face or not. Choosing proper threshold value, the decision about gender is made. 87.5% rate of obtained classification proves the efficiency of the proposed method.

Keywords: Gender classification, Fuzzy inference system, Neuro fuzzy, Face database.

Introduction

Human gender classification is arguably one of the important visual tasks as many social interactions critically depend on the correct gender perception. Arguably, visual information from human faces provides one of the important sources. A generic gender classifier is shown in Fig.1. Gender classification has been especially interesting for psychologists but automatic gender classification has applications also in other fields (Erno Mäkinen & Roope Raisamo, 2008). For an example, it is applied in demographic data collection (Jain & Huang, 2004). Automatic gender classification is also useful preprocessing step for face recognition since it is possible to halve, in case of equal amount of both genders, the number of face candidates before the recognition of the person and thus make the face recognition process almost twice as fast.

Fig. 1. Gender classifier



Moreover, separate face recognizers can be trained for the genders and in this way increase the face recognition accuracy. This has been successfully experimented in facial expression recognition in (Saatci & Town, 2006). Finally, the same methods can often be used both in gender classification and other face analysis tasks. For example, methods developed for gender classification can be applied to face recognition and vice versa. The research on automatic gender classification goes back to the beginning of the 1990s (Cottrell & Metcalfe, 1990). In the same way as with face detection, gender classification methods can be roughly divided in feature-based and appearance-based methods. The first two methods were appearance based and both used a multi-layer neural network approach. Faces were manually aligned for the experiments.

Many different methods have been further tried after the two first methods published. Brunelli and Poggio, (1995) experimented with HyperBF networks. They extracted a set of geometrical features from faces and used them as input to the networks that learned differences between the genders. The 79% classification rate for the novel faces was achieved without hair in the face images. Abdi *et al*. (1995) experimented with a radialbasis function (RBF) network and a perceptron with and without eigen decomposition as a preprocessing step. They found out that as good classification results can be achieved with pixel-based input as can be achieved with measurement-based inputs.

Wiskott *et al*. (1997) presented a system where a model graph was placed manually to a face and gender classification was based on the Gabor wavelets placed on the model nodes. They also used the system for face recognition. Tamura *et al*. (1996) experimented with very low resolution face images and neural networks. They achieved 93% classification rate with only 8 _ 8 size face images. Lyons *et al*. (2000) used Gabor wavelets with principal component analysis (PCA) and linear discriminant analysis (LDA) to detect a face and classify gender. The graph similar to that of Wiskott *et al*. (1997) was placed on the face automatically. They achieved 92% classification.

Shakhnarovich *et al*. (2002) combined the cascaded face detector by Viola and Jones (2001) with threshold Adaboost trained classifiers for gender and ethnicity classification. There is a direct connection to our experiments because we used the cascaded face detector by Viola and Jones (2001) in the experiments and one of the compared gender classifiers is a threshold Adaboost classifier.

Sun *et al*. (2002) claimed that feature selection is an important issue for the gender classification and showed that genetic algorithms (GA) fit well for the task. They created feature vectors from face images using principal component analysis (PCA). Then they selected a subset of the features from the vectors using genetic algorithms and used the features as input to a gender classifier. Performance of four different classifiers was compared: Bayesian, neural network, support vector machine (SVM) and linear discriminant analysis (LDA). The SVM classifier achieved the best classification rate 95.3%.

Wu *et al*. (2003) used Look up Table (LUT) based weak classifiers that were selected with Adaboost. They showed that LUT Adaboost can model features that have multi-peak value distributions while the threshold Adaboost is constricted to single-peak distributions. We also experimented with LUT Adaboost classifiers to find out if LUT Adaboost is superior to threshold Adaboost in gender classification problem and to see how it performs compared to other kind of classifiers.

Jain and Huang (2004) used independent component analysis (ICA) to extract features from the face images and LDA to classify gender. They achieved impressive 99.3% classification rate with manually cropped and normalized FERET face images. Sun *et al*. (2006) tried two different classifiers: Self Organizing Map (SOM) and threshold Adaboost. The novelty with their approach was that they used Local Binary Patterns (LBPs) to create features for the input. The best classification rate, 95.75%, was achieved with the Adaboost classifier. Also Lian and Lu (2006) experimented with LBPs. However, they used SVM as a classifier and achieved 96.75% classification rate. We decided to experiment somewhat similarly to Lian and Lu (2006) with SVMs and LBPs. However, we also experimented with pixel-based input in addition to LBP features.

Saatci and Town (2006) experimented with a SVM that was trained with the features extracted by an active appearance model (AAM). They had a two phase classifier. First the expression of the face was classified (categories: happy, sad, angry, neutral, and unrecognized). Then a gender classifier that was specific to the expression was used to recognize gender. This way they aimed to improve gender classification rate. However, the gender classification rate was decreased although they were able to improve facial expression classification rates by having separate expression classifiers for both genders. They suggested that the reason for the decrease in gender classification task was in the small amount of training images.

In this paper a novel method is described to classify gender. Using accurately designed fuzzy inference system (FIS) which is supposed to successfully overcome the complexity and uncertainty of gender classification, acceptable results are obtained. To show efficiency of designed algorithm, it is compared to some well known algorithms and better performance is observed.

Proposed algorithm

Fuzzy systems

Fuzzy sets theory provides a framework to materialize the fuzzy rule-based (or inference) systems which have been applied to many disciplines such as control systems, decision-making and pattern recognition (Yen & Langary, 1998). The fuzzy rule-based system consists of a fuzzification interface, a rule base, a database, a decision-making unit, and finally a defuzzification interface (Sivanandumet *et al*., 2007). These five functional blocks are: A rule base containing a number of fuzzy IF-THEN rules, a database which defines the membership functions (MF) of the fuzzy sets, a fuzzification interface which transforms the input crisp values to input fuzzy values, a decision-making unit which performs the inference operation on the rules and producing the fuzzy results and a defuzzification interface which transform the fuzzy results of the decision-making unit to the crisp output value.

In order to perform the inference operation in the fuzzy rule based system, the crisp inputs are firstly converted to the fuzzy values by comparing the input crisp values with the database membership functions. Then IF-THEN fuzzy rules are applied on the input fuzzy values to make consequence of each rule, as the output fuzzy values. The outputs obtained for each rule are aggregated in to a single output fuzzy value, using a fuzzy aggregation operator. Finally, defuzzification is utilized to convert the output fuzzy value to the real world value as the output.

Sugeno type is one the commonly used fuzzy inference method which is employed in this study as well. The Sugeno fuzzy model was proposed by Takagi, Sugeno, and Kang in an effort to formalize a system approach to generating fuzzy rules from an input-output data set. Sugeno fuzzy model is also known as Sugeno-Takagi model. Fig. 2 depicts an example of Sugeno fuzzy model. A typical fuzzy rule in a Sugeno fuzzy model has the format:

IF x is A and y is B THEN $z = f(x, y)$,

Where AB are fuzzy sets in the antecedent; $Z=f(x,y)$ is a crisp function in the consequent. Usually $f(x,y)$ is a polynomial in the input variables x and y, but it can be any other functions that can appropriately describe the output of the output of the system within the fuzzy region specified by the antecedent of the rule. When $f(x,y)$ is a first-order polynomial, we have the *first-order* Sugeno fuzzy model. When f is a constant, we then have the *zero-order* Sugeno fuzzy model, which can be viewed either as a special case of the Mamdani FIS where each rule's consequent is specified by a fuzzy singleton, or a special case of Tsukamoto's fuzzy model where each rule's consequent is specified by a membership function of a Step function centered at the constant. Moreover, a zero-order Sugeno fuzzy model is functionally equivalent to a

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Fig. 2. An example of Sugeno fuzzy system

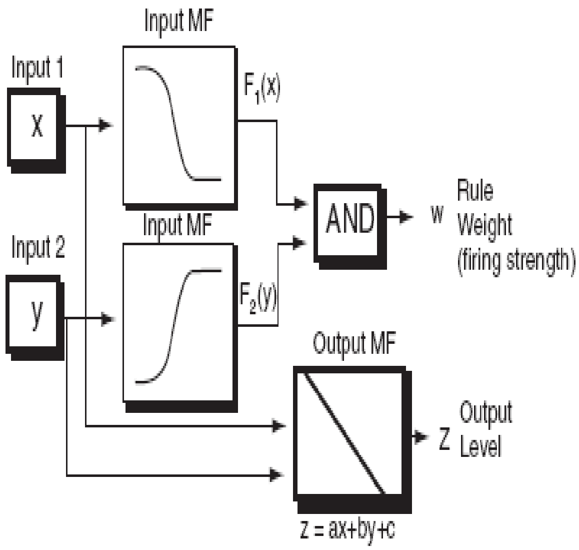

Fig. 3. Training data

radial basis function network under certain minor constraints.

Designed algorithm

The proposed system is a Sugeno type fuzzy inference system which has 2-inputs and 1-output. After investigating, comparing and face processing of various male and female sample pictures, inputs are defined as: a) the ratio of lip area to the face area. As the face area of male is usually more than female, this value would be different for them and b) Eye distance. Eyes' location is estimated relative to lip detected area, and distance between two eyes center is applied as the second input.

Three different clusters are consider for each input. To better understanding the semantic meanings, which are: *Male, Rather Male, Not Male*, are assigned to these three clusters. The inputs are defined in the way that output shows the probability of being male face sample. 42 different male and female sample images are provided as a training data set. Fig.3 illustrates these images.

Our FIS is designed by neuro-adaptive learning techniques. These techniques provide a method for the fuzzy modelling produce to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks.

Here, hybrid learning algorithm is applied to identify parameters of Sugeno-type fuzzy inference system. It utilizes a combination of the least-square method and the backpropagation gradient descent method for training FIS membership function parameters to emulate a given training data set. The outputs are linear and *weighted average* method is used for defuzzification (Sivanandumet *et al*., 2007). Designed system contains 20 nodes and 3 fuzzy rules. If we define: Z= {*Male, Rather Male, Not Male*}, then the rules are: IF input is *Z* THEN output is *Z*.

Fig. 4 shows obtained input membership functions. When the sample image is used as an input for designed FIS, an output express the probability of being male face image. After investigating various results, 75% is chosen as the best threshold value. It means that the face image with 75% probability or more are regarded as male face image, and with probability less than this value, are female face image.

Experimental results

To demonstrate effectiveness of proposed approach, it is applied on IMM face image database (http://www.imm.dtu.dk/~aam/aamexplorer). This database comprises 240 still images of 40 different human faces. The gender distribution is 7 females and 33 males and various facial expression and poses are contained. Samples of this database images are shown in Fig.4. The obtained classification rates for LBP+SVM, Neural network, Neural network, SVM and Threshold Adaboost methods, beside classification rate for the proposed method are presented in Table 1. Our proposed method shows better result when compared to other classification rates reported.

Table 1. Classification rates

Method	Classification rate (%)
LBP+SVM	79.17
Neural network	83.30
SVM	83.38
Threshold Adaboost	82.60
Proposed Method	87.5

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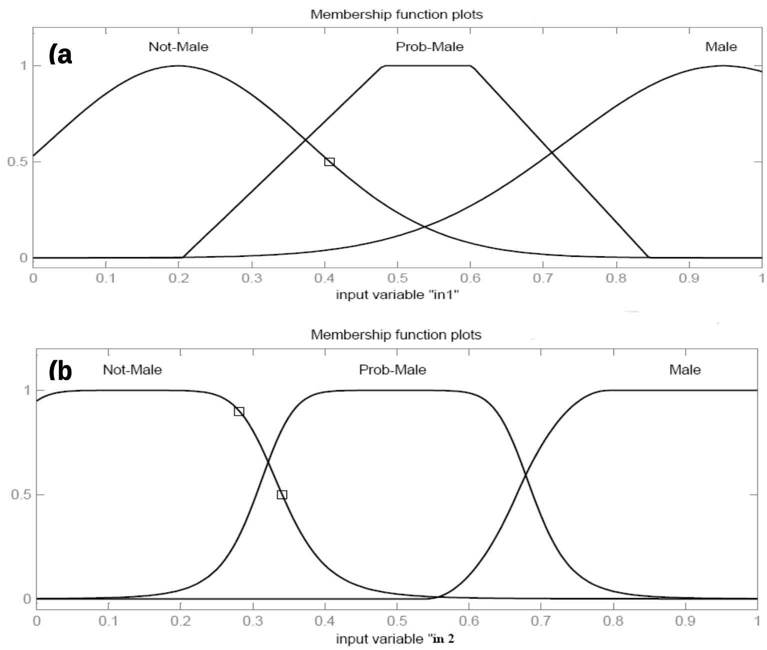
Fig.4. (a) and (b) input membership functions



Conclusion and future works

This paper addresses the problem of gender classification using neuro-fuzzy system and also proposed a novel method to improve the current state-of-the-art. This system has 2-inputs, 1-output. Sugeno type one, applies facial characteristics as inputs and revealed the probability of being male face image in output. After selecting 75% probability as threshold value, 87.5% classification rate is obtained which is acceptable compare to other methods. Adding more facial feature as inputs and using other optimizing methods to increase accuracy, are our next aims.

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