A ROBUST NON-LINEAR FACE DETECTOR

Antonio Rama, Francesc Tarrés
Dept. Teoria del Senyal i Comunicacions, Universitat Politècnica de Catalunya (UPC), Barcelona, Spain

Jacek Naruniec
Faculty of Electronics and Information Technology, Warsaw University of Technology (IPW), Warsaw, Poland

Keywords: Face detection, fuzzy integral, adaboost.

Abstract: A novel face detector using the non-linear Fuzzy Integral operator is presented in this paper. The main advantage of this method is that it has a much lower false detection rate with the same optimal set of features as the state-of-the art Adaboost face detector. Furthermore, this novel face detector seems to have a better generalization capability than the Adaboost method. Preliminary results show a positive face detection rate higher than the 92% having a false detection rate lower than the 2% when using a four stage cascade scheme.

1 INTRODUCTION

Face detection is a fundamental first-step in many applications based on face processing, such as face recognition, video coding, and intelligent human-computer interfaces. The goal of this step consists in detecting and localizing an unknown number of faces in an image. Since human faces are rigid and have high variability in size, shape, color, and texture, face detection is still a difficult problem. The proposed techniques can be broadly classified into two main categories:

- ***Knowledge-based methods***. These algorithms express the a priori information of the face in terms of rules. Typically, these rules are based on the relationships between the facial features (Yang, 1994) (Yang, 2002).
- ***Appearance-based methods***. On the other hand, this second group tries not to assume any prior knowledge about the appearance of the face but rather to extract some important features directly from a representative training set of faces. In other words, appearance-based techniques incorporate the *a priori* information of the face implicitly into the system through training schemes (Rowley, 1998), (Turk, 1991). This category includes the state-of-the-art ***AdaBoost face detector*** (Viola, 2001).

For a comprehensive review of face detection methods, the reader is referred to (Yang, 2002), (Hjelmas 2001).

Face detection approaches should have two important properties: high performance and low computational cost in the recognition stage. Usually, face detection is the previous stage in a complete face recognition system. Thus, the face should be well localized, for a latter normalization step, and it should also require a low percentage of the processing time of the system since the recognition stage demands usually a higher computational burden, especially for huge databases. Adaboost face detector fulfills the previous two requirements (fast and robust); therefore it has been quite accepted for real-time applications, like a control access point or an intelligent cash machine.

In this paper we present a novel face detector based on the non-linear Fuzzy Integral operator. This technique, as preliminary results stated, could be a good alternative to the Adaboost method.

The rest of the paper is organized as follows. In section 2 and 3, the fundamentals of the Adaboost method and the Fuzzy Integral operator are reviewed. Section 4 describes the proposed Fuzzy Integral face detector, whereas section 5 describes the experiments performed so far and some preliminary results. Finally, section 6 contains the conclusions together with the future research.

Rama A., Tarrés F. and Naruniec J. (2007).
A ROBUST NON-LINEAR FACE DETECTOR.
In *Proceedings of the Second International Conference on Signal Processing and Multimedia Applications*, pages 411-416
DOI: 10.5220/0002137704110416

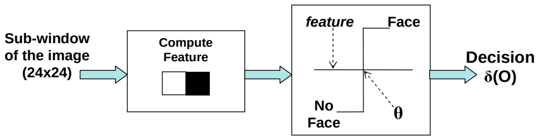

Figure 1: Adaboost weak classifier.

2 ADABOOST: A QUICK REVIEW

Object detection using AdaBoost classifier was introduced by Viola and Jones (Viola, 2001). Their face detection approach has shown how local contrast features found in specific positions of the object can be combined to create a strong face detector. The main idea is that each feature (different Haar filters at different positions of an image sub-window) will be evaluated by a weak classifier in order to decide if the sub-window corresponds to a face (accept) or not (reject) as shown in Figure 1. If the feature is above a certain threshold θ then the sub-window will be classified as a face. Separately, each weak classifier achieves a low performance but when combining some of them into a strong classifier the detection rate grows exponentially as depicted in the dashed rectangle of Figure .

Nevertheless, although the detection rates of a strong classifier can reach more than the 99%, achieving very low false detection rate, computation time of a very large set of features is very long. For this reason, Viola and Jones proposed a cascade scheme of strong classifiers like the one presented in Figure . Each stage corresponds to a strong classifier and is trained with all the examples that the previous stage has misclassified plus some new ones. This leads to an optimal selection of features in each cascade which are able to detect always harder examples. In other words, the first stages can discard sub-windows which are very different from faces, whereas the latter stages could reject more difficult examples like balloons, soccer balls, etc… For more details about the Adaboost face detection approach, the reader is addressed to the original paper (Viola, 2001).

3 FUZZY INTEGRAL BASICS

The theory of Fuzzy Measures is based on the work of Sugeno (Sugeno, 1974). The introduction of fuzzy sets (Zadeh, 1965) encouraged the redefinition of set measures. Sugeno achieved this

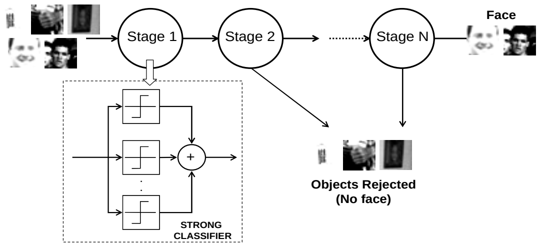

Figure 2: Adaboost cascade scheme.

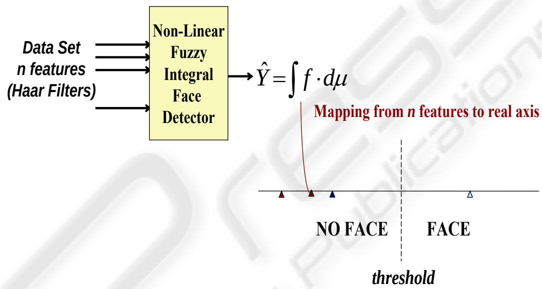

Figure 3: Fuzzy Integral face detector.

definition by introducing so-called fuzzy measures, with respect to which fuzzy Integral can be defined. Thus, fuzzy measures generalize classical measures, i.e. probability measures. Here only a brief overview of how fuzzy integral can be used for classification problems is presented and the reader is addressed to (Aureli, 2004) for more precise details. The main idea is to use a fuzzy integral classifier with an extended set of Haar features for face detection. The fuzzy integral (Aureli, 2004) is a non-linear operator that can be used as a classifier. Fuzzy Integrals are generalizations of integral operators that include non-linear operations on the data set. In the context of classification, the most frequently used fuzzy integrals are the Choquet integral and the Sugeno integral. We propose to use a Choquet integral for the data fusion process. The main ideas and the process of computing the Choquet integral are given hereafter:

Consider we have a vector of feature attributes $X = \{x_1, x_2, ..., x_n\}$ where x_i may represent a pixel, an audio sample or (as in our case) a haar feature at a given position of the sub-window. Given this set of features we collect a number of M samples for the training stage. The attributes of the features at each sample are represented by a vector:

$$\mu = \{\mu(x_1), \mu(x_2), \mu(x_3), ..., \mu(x_1, x_3), ..., \mu(x_1, x_2, x_3), ...\} \quad (1)$$

The Choquet integral consist in a two stage process:

Rearrangement of the feature values vector in non decreasing order, such that

$$f(x_1') \leq f(x_2') \leq \cdots \leq f(x_n') \quad (2)$$

where $(x_1', x_2', ..., x_n')$ is a certain permutation of $(x_1, x_2, ..., x_n)$. And $f(x_i')$ can be any nonnegative function on X.

The Choquet integral is then obtained by computing:

$$\int f \cdot d\mu = \sum_{i=1}^{n} [f(x_i') - f(x_{i-1}')] \cdot \mu(\{x_i', x_{i+1}', ..., x_n'\}) \quad (3)$$

The training of the classifier consists in selecting the optimal fuzzy measures on the objective of minimizing the misclassification rate. There are a number of alternatives for estimating the fuzzy measures but most of them are based on soft-computing strategies. In this work, we are following an approach based on neural networks for estimating the set of fuzzy measures.

One of the interesting peculiarities of the Fuzzy Integral as a classifier is that once the fuzzy measures have been determined, the classification is computationally very efficient. As depicted in Figure the fuzzy integral maps the input set of features to a unique scalar (real axis). Then depending on a threshold, this mapped value is classified as face (*Class i*) or no face (*Class j*).

Good performance of this method comes from the use of the fuzzy measure and the relevant nonlinear integral, since the nonadditivity of the fuzzy measure reflects the importance of the feature attributes, as well as their inherent interaction, toward the discrimination of the points. In fact, each feature attribute has a respective important index reflecting its amount of contribution in the final decision. Furthermore, the global contribution of several feature attributes to the final classification is not just the simple sum of the contribution of each feature, but may vary nonlinearly. A combination of the feature attributes may have a mutually restraining or a complementary synergy effect on their contributions toward the final decision. In fact, this aspect of features being mutually restraining is the explanation of why the fuzzy integral face detector could reject the negative examples faster than the state-of-the art Adaboost approach.

In the next section the proposed face detector based on the Fuzzy Integral will be explained.

4 FACE DETECTOR BASED ON THE FUZZY INTEGRAL

4.1 Feature Selection

In this paper we propose a novel face detector based on a cascade of Fuzzy Integral classifiers as depicted in Figure . One of the main drawbacks when using the fuzzy integral is that the number of computational operations grows exponentially with the number of features used to train the system. Thus, it will be impractical to train the system like in (Viola, 2001) (Lienhart, 2002) considering all possible positions of each Haar feature in each image sub-window, i.e. 117,941 features for a 24x24 sub-window if we use the feature set depicted in Figure (Lienhart, 2002). Thus, a Fuzzy Integral face detector is proposed which uses the optimal subset of features computed by the Adaboost approach. For that, we have selected the following configuration of the Adaboost approach after some exhaustive probes (Braup, 2006):

- 11 stages of strong classifiers.
- 3325 face positive examples (the same set for all stages) + 4500 negative examples in each stage.
- All set of features presented in Figure .
- Minimum face detection rate at each stage of 99.5%.
- Maximum false detection rate at each stage of 30%.

Using this optimal configuration we train the system and get the optimal subset of features for each stage. For example, the first strong classifier (first stage) of the Adaboost detector includes only 6 features: Haar-Y2 at 3 different positions, Haar-X4 at 2 positions, and Haar-Y4 at one position. The same 6 features will be used to train the first stage fuzzy integral classifier of the cascade scheme presented in Figure .

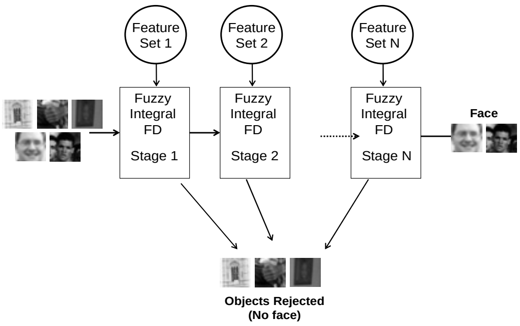

Figure 4: Fuzzy Integral Cascade Face detector.

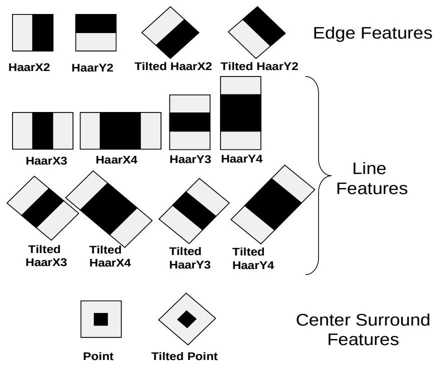

Figure 5: Feature Set used for training Adaboost.

4.2 Training Stage of the Fuzzy Integral Face Detector

In (Aureli, 2004) and (Sugeno, 1974) genetic algorithms have been proposed to train the system. In our case, we use a learning algorithm based on the following control equation:

$$\mu^{i+1}(\overline{f(x')}) = \mu^{i}(\overline{f(x')}) + \sigma \cdot error \cdot \overline{\Delta f(x')} \quad (5)$$

where $\overline{f(x')}$ are the feature values normalized by the power of the features. This normalization function is necessary to scale and balance the magnitudes of diverse feature attributes such that an optimal match of the feature attributes in the Choquet Integral toward the classification can be found. These feature values are then rearranged in non-decreasing order as mentioned in Eq. 3, σ is the adaptive step size and *error* is a parameter that can take the values -1, 0 or 1 depending on the decision of the classifier (0 means that the sample has been correctly classified). And finally $\overline{\Delta f(x')}$ is the difference between all the attributes involved in the fuzzy measure we are updating.

5 EXPERIMENTS AND RESULTS

5.1 Face Database

All experiments have been carried out on a database which is composed of 4000 face images which has been previously normalized to a 24x24 pixel resolution (see Figure). For the negative examples more than 2000 images of different resolutions that don't contain any face have been downloaded from the World Wide Web. Dividing these 2000 images in 24x24 sub-windows leads to a total of more than

Figure 6: Positive examples of faces.

. The half of the positive examples and only 50000 of the 2M negative examples have been used to train a 4-stage Fuzzy Integral Face Detector. The rest of samples have been used as test samples.

5.2 Face Detection Results: 4-Stage Classifier

A 4-stage fuzzy integral face detector has been implemented. The 4 stages will use 6, 9, 11 and 21 different Haar features respectively. The positive face detection rate is above the 92% but the most impressive thing is that more than 99 % of the non-faces have also been correctly discarded. The first stage of the fuzzy integral cascade face detector alone rejects more than the 95% of non-faces sub-windows. Figure 8 and Figure 7 represents an extreme example of this concept.

Figure 8 represents the outputs of a one-, two-, three-, and four-stages Adaboost cascade scheme, whereas Figure represents a one-, two-, three-, and four-stages Fuzzy Integral cascade scheme. For a more fair comparison between both techniques, no post-processing step for eliminating overlapped windows has been used.

Results show that our method (Figure 7) detects all faces and discard almost all negatives sub-windows (only 7 positive negatives and 6 correspond to complete overlapped windows). On the other hand, the Adaboost classifier detects also all faces (one is not totally detected) but still more than 25 non-faces are accepted (only half of them are partially overlapped).

The fuzzy integral face detector shows a better trade-off between detection rate and false detections. This is especially remarkable in the first stages (top pictures of Figures 7 and 8), where the Fuzzy Integral face detector rejects more than the half of false detections of the Adaboost approach. Furthermore, continuing with this example, if more stages are performed in the Adaboost classifier, the

Figure 7: Fuzzy Integral Results. (From Top to Bottom are the outputs of the 1st, 2nd, 3rd and 4th stage Fuzzy Integral face detector cascade scheme.).

Figure 8: Adaboost Results. (From Top to Bottom are the outputs of the 1st, 2nd, 3rd and 4th stage Adaboost cascade scheme).

best results are obtained for a 7-stages face detector which rejects all non-faces but only detects 8 of the 10 faces of the image as illustrated in Figure . These results are worse than the ones obtained for our 4-stages Fuzzy Integral Face Detector. Nevertheless, it should also be commented that if more stages of the Fuzzy Integral Face Detector are implemented, the two non-detected faces of Figure will be also misclassified.

6 CONCLUSIONS AND FUTURE WORK

In this paper a novel face detector approach based on the non-linear Fuzzy Integral operator has been presented. Preliminary results show a better trade-off between positive detection and negatives detection than state-of-the art Adaboost technique. Nevertheless, the face detection rate is similar on

Figure 9: Best Results for Adaboost Face Detector (7 stages)

both approaches, so a more extended analysis of the results should be done in order to determine under which conditions or constraints one approach is better than the other. This could lead to some hybrid approach where both classifiers could be fused at different levels (first stages using Fuzzy Integral, and the latter ones Adaboost, or combining the opinions of both classifiers).

Special attention should also be focused to the training stage. One main drawback of the Fuzzy Integral is that its computational cost during the training stage grows up exponentially with the number of features. Hence, it would not be possible to train the system for all Haar-features in all positions of the sub-window like explained in Section 4.1. On the other hand, once the features have been selected, the Fuzzy Integral face detector needs fewer positive and negative samples than the Adaboost approach. This could be foreseen as a better generalization capability of the Fuzzy Integral face detector.

Another important topic that should be also analyzed is the values of the fuzzy measures. These measures aim to evaluate the relative importance of each feature in the final classification. So it would be possible to reduce the set of features to an optimal smaller subset by analyzing the fuzzy measures. This would lead to a substantially improvement of the computational cost required in the detection stage since only the important ones will be considered.

Finally, a complete study, of the computational cost of each approach should be reported. In this paper, no results of this aspect have been presented since both techniques have been implemented under different frameworks with different programming languages.

Summarizing, the proposed novel technique not only shows very promising results but also opens some new issues that could be exploded in order to get even better results.

ACKNOWLEDGEMENTS

The work presented was developed within VISNET II, a European Network of Excellence funded under the European Commission IST FP6 programme.

REFERENCES

Yang, G., and Huang, T. S., 1994. "*Human Face Detection in Complex Background*" in Pattern Recognition, vol. 27, no. 1, pp. 53-63.

Yang, M.-H., Kriegman, D. and Ahuja, N., 2002. "*Detecting Faces in images: a Survey*", in IEEE Transactions on Pattern Analysis and Machine Intelligence 24, nº1, pp.34-58.

Rowley, H. A., Baluja, H. A., and Kanade, T., 1998. "*Neural network-based face detection*", in IEEE Transactions Pattern Analysis and Machine Intelligence 20, 23–38.

Turk, M. A., Pentland, A. P., 1991. "*Face recognition using eigenfaces*", in Proceedings of the IEEE Computer Society Conf. on Computer Vision and Pattern Recognition, pp. 586-591, Maui, Hawaii.

Viola P., Jones M., 2001. "*Rapid Object Detection using a Boosted Cascade of Simple Features,* in Computer Vision and Pattern Recognition.

Hjelmas, E., and Low, B. K., 2001. "*Face Detection: A Survey*", in Computer Vision and Image Understanding, vol. 83, no. 3, pp. 236-274.

Sugeno, M., 1974. "*The Theory of Fuzzy Integrals and Its Applications*", PhD thesis, Tokyo Institute of Technology, Japan.

Zadeh, L. A., 1965. „ *Fuzzy sets*", Information Control, pp. 338–353.

Aureli Soria-Frisch, 2004. "*Soft Data Fusion in Computer Vision*", PdD thesis, Fraunhofer Institut fuer Produktionsanlagen und Konstruktionstechnik, Berlin, Germany.

Lienhart, R., and Maydt, J., 2002. "*An Extended Set of Haar-like Features for Rapid Object Detection*". in IEEE International Conference on Image Processing 2002, Vol. 1, pp. 900-903, Sep. 2002.

Braup, J. M., Tarres, F., 2006. "*Anàlisi de vídeo per la detecció automàtica de cares*". Master Thesis in Catalan at the Technical University of Catalonia – Escola Politècnica Superior de Castelldefels.