Face Recognition with a Sobel Edge Detector and the Choquet Integral as Integration Method in a Modular Neural Networks

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Abstract In this paper a method for response integration of Modular Neural Networks, based on Choquet Integral applied to face recognition is presented. Type-1 and Type-2 fuzzy systems for edge detections based on the Sobel, which is a pre-processing applied to the training data for better performance in the modular neural network. The Choquet integral is an aggregation operator that in this case is used as a method to integrate the outputs of the modules of the modular neural networks (MNN).

1 Introduction

A mechanism which takes as input a number n of data and combines them to result in a representative value of the information is called integration method. In the literature there exist methods which combine information from different sources. In a MNN it is common to use different methods for integrate the information, such as Type-1 and Type-2 fuzzy logic for Multimodal Biometrics [3], for Human Recognition Based on Iris, Ear and Voice Biometrics [17], for Pattern Recognition [16], the fuzzy Sugeno integral for Pattern Recognition of human face and fingerprint [10], Interval Type-2 Fuzzy Logic Sugeno Integral for Face Recognition [11], a probabilistic sum integrator in Classification using Redundant Mapping [9], a novel Bayesian learning method for information aggregation in modular neural networks [23], Self-Organizing Maps for Japanese Historical Character Recognition [4], Choquet Integral in a modular neural network [8], among others.

The Choquet integral was created by the French mathematician Gustave Choquet in 1953 [2]. The Choquet integral with respect to a fuzzy measure is a very

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P. Melin et al. (eds.), *Design of Intelligent Systems Based on Fuzzy Logic, Neural Networks and Nature-Inspired Optimization*,
Studies in Computational Intelligence 601, DOI 10.1007/978-3-319-17747-2_5

popular data aggregation approach. The generalized Choquet integral with respect to a signed fuzzy measure can act as an aggregation tool, which is especially useful in many applications [6, 21, 24].

This paper is organized as follows: Sect. 2 shows the technique that is applied for the combination of the several information sources: the concepts of Fuzzy Measures and Choquet integral. Section 3 presents Edge detection based on Sobel with type-1 and type-2 fuzzy systems. Section 4 describes the architecture of the modular neural network proposed and in the Sect. 5 the simulation results are shown. And finally in Sect. 6 the Conclusions are presented.

2 Fuzzy Measures and Choquet Integral

In 1974 the concepts of "fuzzy measure and fuzzy integral" were defined by Sugeno [20] in order to define sets that do not have well-defined boundaries. A fuzzy measure is a nonnegative function monotone of values defined in "classical sets". Currently, when referring to this topic, the term "fuzzy measures" has been replaced by the term "monotonic measures", "non-additive measures" or "generalized measures" [14, 18, 22]. When fuzzy measures are defined on fuzzy sets, we speak of fuzzified monotonic measures [22].

2.1 Fuzzy Measures

A fuzzy measure can be defined as a fuzzy measure μ with respect to the dataset X, and must satisfy the following conditions:

1. $\mu(X) = 1;\ \mu(\emptyset) = 0$ Boundary conditions
2. $Si\, A \subset B,\ then\ \mu(A) \leq (B)$ Monotonicity

In condition two, A and B are subsets of X.

A fuzzy measure is a Sugeno measure or λ-fuzzy, if it satisfies the condition (1) of addition for some λ > −1.

$$\mu(A \cup B) = \mu(A) + \mu(B) + \lambda\mu(A)\mu(B) \tag{1}$$

where λ can be calculated with (2):

$$f(\lambda) = \left\{ \prod_{i=1}^{n} (1 + M_i(x_i)\lambda) \right\} - (1 + \lambda) \tag{2}$$

The value of the parameter λ is determined by the conditions of Theorem 1.

Theorem 1 *Let* $\mu(\{x\}) < 1$ *for each* x ∈ X *and let* $\mu(\{x\}) > 0$ *for at least two elements of X*, *then* (2) *determines a unique parameter in the following way*:

$$If \sum_{x \in X} \mu(\{x\}) < 1, \quad then\ \lambda\ is\ in\ the\ interval\ (0, \infty).$$

$$If \sum_{x \in X} \mu(\{x\}) = 0, \quad then\ \lambda = 0;\ That\ is\ the\ unique\ root\ of\ the\ equation.$$

$$If \sum_{x \in X} \mu(\{x\}) > 1, \quad then\ \lambda\ se\ is\ in\ the\ interval\ (-1, 0).$$

The fuzzy measure represents the importance or relevance of the information sources when computing the aggregation. The method to calculate Sugeno measures, carries out the calculation in a recursive way, using (3) and (4).

$$\mu(A_1) = \mu(M_i) \tag{3}$$

$$\mu(A_i) = \mu(A_{(i-1)}) + \mu(M_i) + \left(\lambda\mu(M_i) * \mu(A_{(i-1)}\right) \tag{4}$$

where A_i represents the fuzzy measure and M_i represents the fuzzy density determined by an expert, where $1 < M_i \leq \cdots \leq$ n, should be permuted with respect to the descending order of their respective $\mu(A_i)$.

In the literature there are 2 types of Integral, the integral of Sugeno and the Choquet Integral.

2.2 Choquet Integral

The Choquet integral can be calculated using Eq. (5) or an equivalent expression (6)

$$\begin{aligned} &Choquet = \sum_{i=1}^{n} \left\{ \left[A_i - A_{(i-1)}\right] * D_i \right\} \\ &\text{With } \mathrm{A}_0 = 0 \end{aligned} \tag{5}$$

Or also

$$\begin{aligned} &Choquet = \sum_{i=1}^{n} A_i * \left\{ \left[D_i - D_{(i+1)}\right] \right\} \\ &With\, D_{(n+1)} = 0 \end{aligned} \tag{6}$$

In this case A_i represents the fuzzy measurement associated with a data D_i.

3 Edge Detection

Edge detection can be defined as a method consisting of identifying changes that exist in the light intensity, which can be used to determine certain properties or characteristics of the objects in the image. A number of edge detectors have been developed by various researchers. Amongst them, the most important operators are the Sobel Operator [19], Prewitt operator [15], Robert operator [15], Canny operator [1] and Kirsch operator [5]. The resultant images of the edge detectors preserve more details of the original images, which is a desirable feature for a pattern recognition system.

We used the Cropped Yale database to perform the training of the modular neural network, which has images of 38 people with 60 samples of each individual. To each of the images we applied a pre-processing by making use of Sobel edge detector with type-1 and type-2 fuzzy logic systems [7] in order to highlight features, some of the images can be displayed in Fig. 4a. Each image of the Cropped Yale database has a size of 168 × 192.

3.1 Sobel

The Sobel operator is applied to a digital image in gray scale, is a pair of 3 × 3 convolution masks, one estimating the gradient in the x-direction (columns) (7) and the other estimating the gradient in the y-direction (rows) (8) [12].

$$sobel_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{7}$$

$$sobel_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{8}$$

If we have $I_{m,n}$ as a matrix of m rows and r columns, where the original image is stored, then g_x and g_y are matrices having the same dimensions as I, which at each element contains the horizontal and vertical derivative approximations and are calculated by (9) and (10) [12].

$$g_x = \sum_{i=1}^{i=3}\sum_{j=1}^{j=4} Sobel_{x,ij} * I_{r+i-2,c+j-2} \quad \begin{array}{l} for = 1,2,\ldots,m \\ for = 1,2,\ldots,n \end{array} \tag{9}$$

$$g_y = \sum_{i=1}^{i=3}\sum_{j=1}^{j=4} Sobel_{y,i,j} * I_{r+i-2,\, c+j-2} \quad \begin{array}{l} for = 1,2,\ldots,m \\ for = 1,2,\ldots,n \end{array} \tag{10}$$

In the Sobel method the gradient magnitude g is calculated by (11).

$$g = \sqrt{g_x^2 + g_y^2} \tag{11}$$

For the type-1 and type-2 fuzzy inference systems, 3 inputs can be used as can seen in Figs. 1 and 2, two of them are the gradients with respect to the x-axis and y-axis, calculated with (9) and (10), which we call DH and DV, respectively. The third variable M is the image after the application of a low-pass filter hMF in (12); this filter allows to detect image pixels belonging to regions of the input where the mean gray level is lower. These regions are proportionally affected more by noise, which is supposed to be uniformly distributed over the whole image [12].

$$hMF = \frac{1}{25} * \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{12}$$

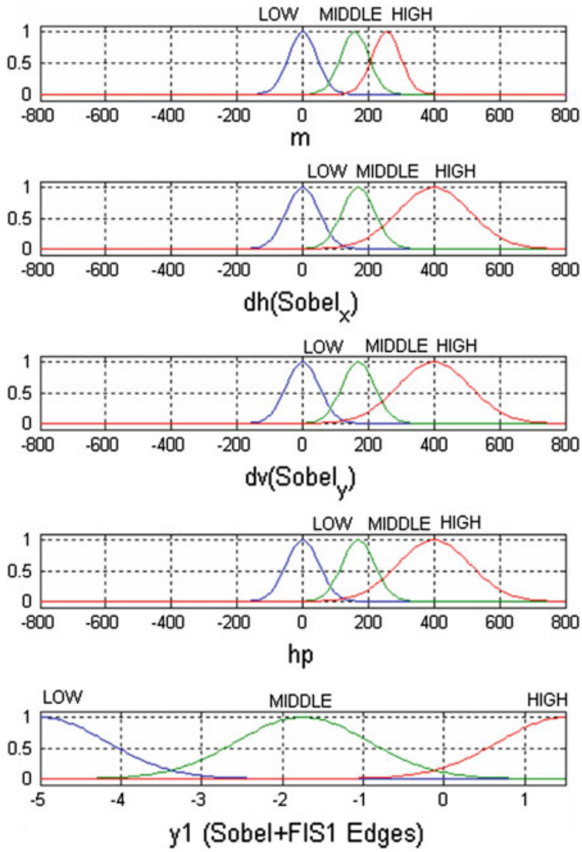

Fig. 1 Variables for the edge detector with the type-1 fuzzy Sobel

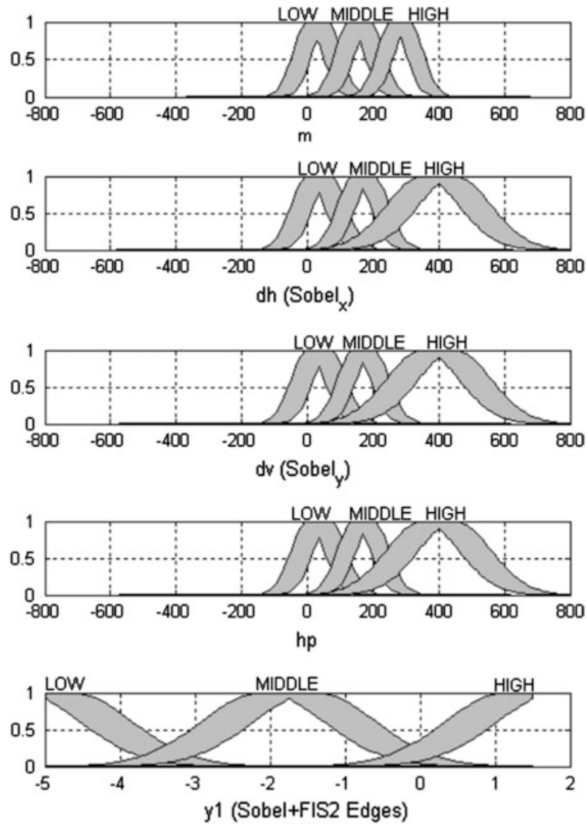

Fig. 2 Variables for the edge detector with the type-2 fuzzy Sobel

After applying the edge detector of Type-1 with Sobel, the resulting image can be viewed in Fig. 3b.

The rules used for the tests in the Type-1 and Type-2 Sobel edge detectors are [12]:

1. If (dh is LOW) and (dv is LOW) then (y1 is HIGH).
2. If (dh is MIDDLE) and (dv is MIDDLE) then (y1 is LOW).
3. If (dh is HIGH) and (dv is HIGH) then (y1 is LOW).
4. If (dh is MIDDLE) and (hp is LOW) then (y1 is LOW).
5. If (dv is MIDDLE) and (hp is LOW) then (y1 is LOW).
6. If (m is LOW) and (dv is MIDDLE) then (y1 is HIGH).
7. If (m is LOW) and (dh is MIDDLE) then (y1 is HIGH).

The images generated by the Type-2 Sobel edge detector are shown in Fig. 3c.

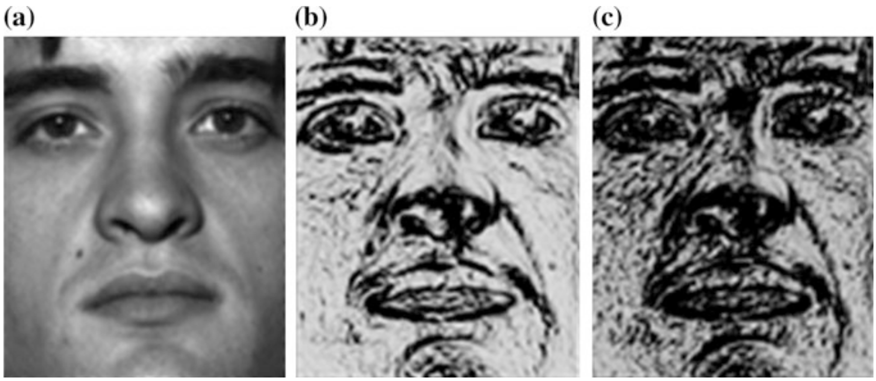

Fig. 3 **a** Original image database Cropped Yale, **b** image with type-1 Sobel edge detector, **c** image with interval type-2 Sobel edge detector

4 Modular Neural Networks

To each image of the Cropped Yale database we applied a preprocessing with the Type-1 and Type-2 Sobel edge detector, after this, each image is divided into 3 sections horizontal. Each section was used as training data in each one of the three modules of the modular neural network, as shown in Fig. 4. The integration of the simulation of each module is made with the Choquet integral.

The Training Parameters are:

Training method: gradient descendent with momentum and adaptive learning rate back-propagation (Traingdx).

Each module has two hidden layers [200 200].

Error goal: 0.0001

Epochs: 500

In Table 1 the distribution of the training data is shown.

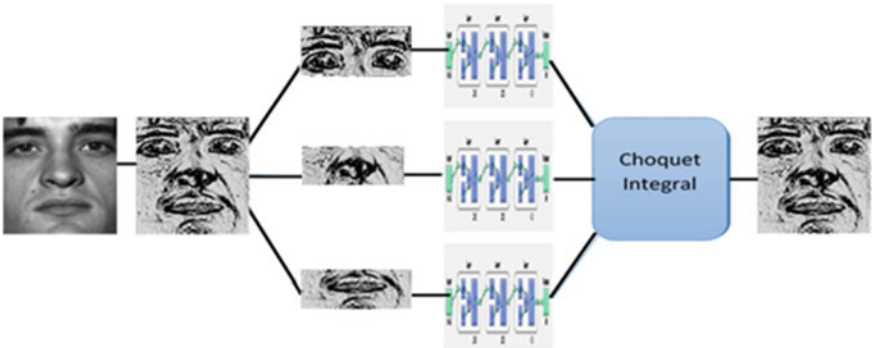

Fig. 4 Architecture proposal of the modular neural network using type-1 Sobel edge detector

Table 1 Distribution of the training data

Training	Validation	Test
70 %	15 %	15 %

4.1 The Experiment with a Modular Neural Network Recognition System and the Choquet Integral for the Modules Fusion

The experiment consist on applying each evaluated edge detector to obtain a data set of same well know benchmark data bases of images, like Cropped Yale database of faces and then train a neural network to compare the recognition rate using the k-fold cross-validation method [13].

Table 2 Fuzzy densities and λ parameter

Test	FD1	FD2	FD3	Lambda
1	0.1	0.1	0.1	−1.40165E−16
2	0.1	0.1	0.5	2.8008E−16
3	0.1	0.1	0.9	−0.540135346
4	0.1	0.5	0.1	2.76119E−16
5	0.1	0.5	0.5	−0.291796068
6	0.1	0.5	0.9	−0.910717424
7	0.1	0.9	0.1	−0.540135346
8	0.1	0.9	0.5	−0.910717424
9	0.1	0.9	0.9	−0.989141968
10	0.5	0.1	0.1	2.76119E−16
11	0.5	0.1	0.5	−0.291796068
12	0.5	0.1	0.9	−0.910717424
13	0.5	0.5	0.1	−0.291796068
14	0.5	0.5	0.5	−0.763932023
15	0.5	0.5	0.9	−0.964686549
16	0.5	0.9	0.1	−0.910717424
17	0.5	0.9	0.5	−0.964686549
18	0.5	0.9	0.9	−0.994458264
19	0.9	0.1	0.1	−0.540135346
20	0.9	0.1	0.5	−0.910717424
21	0.9	0.1	0.9	−0.989141968
22	0.9	0.5	0.1	−0.910717424
23	0.9	0.5	0.5	−0.964686549
24	0.9	0.5	0.9	−0.994458264
25	0.9	0.9	0.1	−0.989141968
26	0.9	0.9	0.5	−0.994458264
27	0.9	0.9	0.9	−0.998971986

5 Simulation Results

In the experiments we performed 27 tests in simulation of the trainings with each edge detectors making variations in the fuzzy densities with the values of 0.1, 0.5 and 0.9 and performing the calculation of the parameter λ with the bisection method, and these parameters can be find in Table 2.

In Table 3, the results obtained using preprocessing of the image, with the type-1 Sobel edge detector, are shown. The first column represents the number of tests performed for each simulation, of the column M1 to M5 the average obtained in each module for each training is displayed and finally the last three columns present

Table 3 Results of one simulation using type-1 Sobel edge detector, in test 1

Test	M1	M2	M3	M4	M5	Mean	Std.	Max.
1	100	96.0526	96.0526	98.6842	97.3684	0.9763	0.0172	1
2	100	96.0526	97.3684	98.6842	97.3684	0.9789	0.0150	1
3	100	96.0526	97.3684	98.6842	97.3684	0.9789	0.0150	1
4	100	96.0526	96.0526	98.6842	97.3684	0.9763	0.0172	1
5	100	96.0526	97.3684	98.6842	97.3684	0.9789	0.0150	1
6	100	96.0526	97.3684	98.6842	97.3684	0.9789	0.0150	1
7	100	96.0526	96.0526	98.6842	97.3684	0.9763	0.0172	1
8	100	96.0526	97.3684	98.6842	97.3684	0.9789	0.0150	1
9	100	96.0526	97.3684	98.6842	97.3684	0.9789	0.0150	1
10	100	98.6842	96.0526	98.6842	98.6842	0.9842	0.0144	1
11	100	98.6842	97.3684	98.6842	98.6842	0.9868	0.0093	1
12	100	98.6842	97.3684	98.6842	98.6842	0.9868	0.0093	1
13	100	98.6842	96.0526	98.6842	98.6842	0.9842	0.0144	1
14	100	98.6842	97.3684	98.6842	98.6842	0.9868	0.0093	1
15	100	98.6842	97.3684	98.6842	98.6842	0.9868	0.0093	1
16	100	98.6842	96.0526	98.6842	98.6842	0.9842	0.0144	1
17	100	98.6842	97.3684	98.6842	98.6842	0.9868	0.0093	1
18	100	98.6842	97.3684	98.6842	98.6842	0.9868	0.0093	1
19	100	98.68421	96.05263	98.68421	100	0.98684	0.01612	1
20	100	98.68421	97.36842	98.68421	100	0.98947	0.01101	1
21	100	98.68421	97.36842	98.68421	100	0.98947	0.01101	1
22	100	98.68421	96.05263	98.68421	100	0.98684	0.01612	1
23	100	98.68421	97.36842	98.68421	100	0.98947	0.01101	1
24	100	98.68421	97.36842	98.68421	100	0.98947	0.01101	1
25	100	98.68421	96.05263	98.68421	100	0.98684	0.01612	1
26	100	98.68421	97.36842	98.68421	100	0.98947	0.01101	1
27	100	98.68421	97.36842	98.68421	100	0.98947	0.01101	1
					Mean	0.98421	0.01315	1

Table 4 Results of training with type-1 Sobel edge detector

Test	Mean	Std.	Max.
1	0.98421	0.01315	1
2	0.98743	0.01523	1
3	0.98333	0.01606	1
Mean	0.98499		

Table 5 Results of training with type-2 Sobel edge detector

Test	Mean	Std.	Max.
1	0.98684	0.02942	1
2	0.98421	0.01915	1
3	0.98947	0.01715	1
Mean	0.98684		

the mean of the five trainings, the standard deviation and the maximum of each simulation.

In Table 4 we show the percentages of recognition of the Modular neural network using the Choquet integral as integration method with a preprocessing in the images with the Type 1 Sobel edge detector. Each result of the tests is the average of 27 simulations with different fuzzy densities, as seen in Table 3.

In Table 5 we can find the results of the simulations using the Type-2 Sobel edge detector as preprocessing method.

It can be noted that when using the Type-2 Sobel edge detector it was obtained 98.49 % of recognition whereas with type-2 Sobel edge detector a 98.68 % was obtained.

6 Conclusions

The use of the Choquet integral as an integration method of responses of a modular neural network applied to face recognition has yielded favorable results when performing the aggregation process of the preprocessed images with the detectors of Sobel edges. The resultant images of the edge detectors preserve more details of the original images, which is a desirable feature for a pattern recognition system. However it is still necessary to use a method that optimizes the values of the Sugeno measure assigned to each source of information because these were designated arbitrarily.

Acknowledgment We thank the MyDCI program of the Division of Graduate Studies and Research, UABC, Tijuana Institute of Technology, and the financial support provided by our sponsor CONACYT contract grant number: 189350.

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