Modular Neural Networks with Fuzzy Sugeno Integral for Human Face and Fingerprint Recognition

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Abstract
We describe in this paper a new approach for pattern recognition using modular neural networks with a fuzzy logic method for response integration. We proposed a new architecture for modular neural networks for achieving pattern recognition in the particular case of human faces and fingerprints. Also, the method for achieving response integration is based on the fuzzy Sugeno integral with some modifications. Response integration is required to combine the outputs of all the modules in the modular network.

Keywords: Face, Fingerprint, Neural Networks

1. Introduction

Response integration methods for modular neural networks that have been studied, to the moment, do not solve well real recognition problems with large sets of data or in other cases reduce the final output to the result of only one module. Also, in the particular case of face recognition, methods of weighted statistical average do not work well due to the nature of the face recognition problem.

The basic idea of the new approach is to divide a human face into three different regions: the eyes, the nose and the mouth, and the fingerprint also into three parts, top, middle and bottom. Each of these regions is assigned to one module of the neural network. In this way, the modular neural network has three different modules, one for each of the regions of the human face and the fingerprint. At the end, the final decision of face and fingerprint recognition is done by an integration module, which has to take into account the results of each of the modules. In our approach, the integration module uses the fuzzy Sugeno integral to combine the outputs of the three modules. The fuzzy Sugeno integral allows the integration of responses from the three modules of the eyes, nose and mouth of a human specific face and the integration of the responses from the three modules of the fingerprint parts. Other approaches in the literature use other types of integration modules, like voting methods, majority methods, and neural networks.

The new approach for face and fingerprint recognition was tested with a database of students and professors from our institution. This database was collected at our institution using a digital camera for the faces and a special scanner for the fingerprints. The results with our new approach for face and fingerprint recognition on this database were excellent.

2. Methods for Response Integration

In the literature we can find several methods for response integration, that have been researched extensively, which in many cases are based on statistical decision methods. We will mention briefly some of these methods of response integration, in particular the ones based on fuzzy logic. The idea of using these types of methods, is that the final decision takes into account all of the different kinds of information available about the human face and fingerprint. In particular, we consider aggregation operators, and the fuzzy Sugeno integral [9].

Yager [10] mentions in his work, that fuzzy measures for the aggregation criteria of two important classes of problems. In the first type of problems, we have a set $Z=\{z_1,z_2,\ldots,z_n\}$ of objects, and it is desired to select one or more of these objects based on the satisfaction of certain criteria. In this case, for each $z_i \in Z$, it is evaluated $D(z_i)=G(A_i(z_i),\ldots,A_j(z_i))$, and then an object or objects are selected based on the value of G. The problems that fall within this structure are the multi-criteria decision problems, search in databases and retrieving of documents.

In the second type of problems, we have a set $G=\{G_1,G_2,\ldots,G_q\}$ of aggregation functions and object z. Here, each G_k corresponds to different possible identifications of object z, and our goal is to find out the correct identification of z. For achieving this, for each aggregation function G, we obtain a result for each z, $Dk(z)=Gk(A1(z), A2(z), \ldots ,An(z))$. Then we associate to z the identification corresponding to the larger value of the aggregation function.

A typical example of this type of problems is pattern recognition. Where A_j corresponds to the attributes and $A_j(z)$ measures the compatibility of z with the attribute. Medical applications and fault diagnosis fall into this type of problems. In diagnostic problems, the A_j corresponds to symptoms associated with a particular fault, and G_k captures the relations between these faults.

2.1Fuzzy Integral and Sugeno Measures

Fuzzy integrals can be viewed as non-linear functions defined with respect to fuzzy measures. In particular, the "$g\lambda$-fuzzy measure" introduced by Sugeno [9] can be used to define fuzzy integrals. The ability of fuzzy integrals to combine the results of multiple information sources has been mentioned in previous works.

Definition 1. A function of sets $g:2^x$-(0.1) is called a fuzzy measure if:

1) $g(0)=0 \quad g(x)=1$
2) $g(A) \leq g(B)$ if $A \subset B$
3) if $\{A_i\} i^{\alpha} = 1$ is a sequence of increments of the measurable set then

$$\lim_{i \to \infty} g(A_i) = g(\lim_{i \to \infty} A_i) \qquad (1)$$

From the above it can be deduced that g is not necessarily additive, this property is replaced by the additive property of the conventional measure.

From the general definition of the fuzzy measure, Sugeno introduced what is called "gλ-fuzzy measure", which satisfies the following additive property: For every A, B ⊂ X and A ∩ B = θ,

$$g(A \cup B) = g(A) + g(B) + \lambda g(A)g(B), \quad (2)$$

for some value of $\lambda > -1$.

This property says that the measure of the union of two disjunct sets can be obtained directly from the individual measures. Using the concept of fuzzy measures, Sugeno [9] developed the concept of fuzzy integrals, which are non-linear functions defined with respect to fuzzy measures like the gλ-fuzzy measure.

Definition 2 let X be a finite set and $h:X \rightarrow [0,1]$ be a fuzzy subset of X, the fuzzy integral over X of function h with respect to the fuzzy measure g is defined in the following way,

$$h(x) \circ g(x) = \max_{E \subseteq X} [\min(\min_{x \in E} h(x), g(E))] \qquad (3)$$
$$= \sup_{\alpha \in [0,1]} [\min(\alpha, g(h_\alpha))]$$

where h_α is the level set α of h,

$$h_\alpha = \{ x \mid h(x) \geq \alpha \}. \qquad (4)$$

We will explain in more detail the above definition: h(x) measures the degree to which concept h is satisfied by x. The term $\min(h_x)$ measures the degree to which concept h is satisfied by all the elements in E. The value g(E) is the degree to which the subset of objects E satifies the concept measure by g. As a consequence, the obtained value of comparing these two quantities in terms of operator min indicates the degree to which E satifies both criteria g and $\min(h_x)$.

3. Proposed Architecture and Results

In the experiments performed in this research work, we used 20 photographs that were taken with a digital camera and 20 fingerprints from students and professors of our Institution. The photographs were taken in such a way that they had 148 pixels wide and 90 pixels high, with a resolution of 300x300 ppi, and with a color representation of a gray scale, some of these photographs are shown in Figure 1. In addition to the training data (20 photos) we did use 10 photographs that were obtained by applying noise in a random fashion, which was increased from 10 to 100%.

Fig. 1 Sample Faces Used for Training.

The images of fingerprints [11] were taken in such a way that they had 198 pixels wide and 200 pixels high, with a resolution of 300x300 ppi, and with a color representation of a gray scale, some of these images are shown in Fig. 2. In addition to the training data (20 fingerprints) we did use 10 images that were obtained by applying noise in a random fashion, which was increased from 10 to 100%.

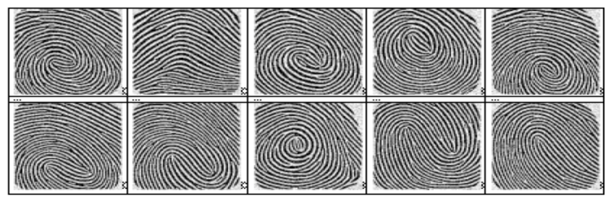

Fig. 2 Sample Fingerprints Used for Training.

3.1 Proposed Architecture

The architecture proposed in this work consist of three main modules, in which each of them in turn consists of a set of neural networks trained with the same data, which provides the modular architecture shown in Figure 3.

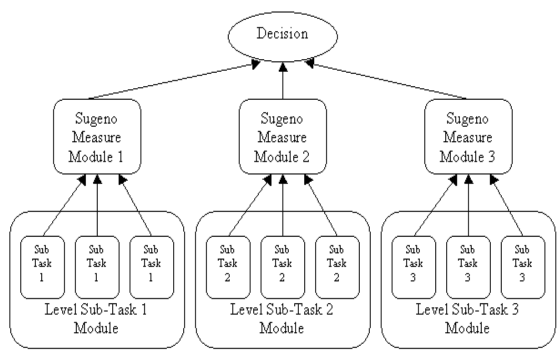

Fig. 3 Final Proposed Architecture.

The input to the modular system is a complete photograph. For performing the neural network training, the images of the human faces were divided in three different regions. The first region consists of the area around the eyes, which corresponds to Sub Task 1. The second region consists of the area around the nose, which corresponds to Sub Task 2. The third region consists of the area around the mouth, which corresponds to Sub Task 3. An example of this image division is shown in Figure 4.

Fig. 4 Example of Image Division.

As output to the system we have an image that corresponds to the complete image that was originally given as input to the modular system, we show in Figure 5 an example of this for face recognition. In the same way the fingerprints are divided in three parts and given to the corresponding Sub task module.

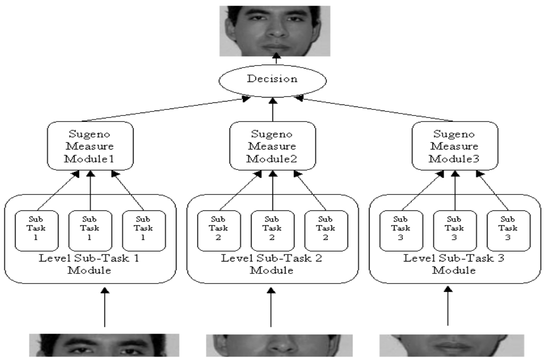

Fig. 5 Final architecture showing inputs and outputs.

3.2 Description of the Integration Module

The integration modules performs its task in two phases. In the first phase, it obtains two matrices. The first matrix, called h, of dimension 3x3, stores the larger index values resulting from the competition for each of the members of the modules. The second matrix , called I, also of dimension 3x3, stores the photograph number corresponding to the particular index.

Once the first phase is finished, the second phase is initiated, in which the decision is obtained. Before making a decision, if there is consensus in the three modules, we can proceed to give the final decision, if there isn't consensus then we have search in matrix g to find the larger index values and then calculate the Sugeno fuzzy measures for each of the modules, using the following formula,

$$g(M_i) = h(A) + h(B) + \lambda\, h(A)\, h(B) \qquad (5)$$

Where λ is equal to 1. Once we have these measures, we select the largest one to show the corresponding photograph.

3.3. Summary of Results

We describe in this section the experimental results obtained with the proposed approach using the 20 photographs as training data. We show in Table 1 the relation between accuracy (measured as the percentage of correct results) and the percentage of noise in the figures.

In Table 1 we show the relation that exists between the % of noise that was added in a random fashion to the testing data set, that consisted of the 20 original photographs, plus 200 additional images. We show in Figure 6 sample images with noise.

In Table 2 we show the reliability results for the system. Reliability was calculated as shown in the following equation.

$$\text{Reliability} = \frac{\text{correct results-error}}{\text{correct results}} \qquad (6)$$

Table 1 Relation between % noise and % of correct results

% of noise	% accuracy
0	100
10	100
20	100
30	100
40	95
50	100
60	100
70	95
80	100
90	75
100	80

Fig. 7 Sample images with noise.

Table 2 Relation between reliability and accuracy.

% errors	%reliability	%correct results
0	100	100.00
0	100	100.00
0	100	100.00
0	100	100.00
5	94.74	95.00
0	100	100.00
0	100	100.00
5	94.74	95.00
0	100	100.00
25	66.67	75.00
20	75	80.00

We show in Figure 8 a plot relating the percentage of recognition against the number of examples used in the experiments.

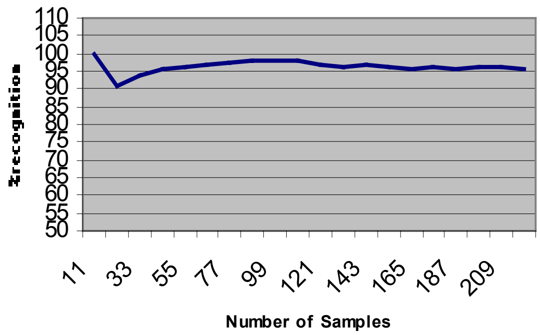

Fig. 12 Relation between recognition and number examples

In addition to the results presented before, we also compared the performance of the modular approach, against the performance of a monolithic neural network approach. The conclusion of this comparison was that for this type of input data, the monolithic approach is not feasible, since not only training time is larger, also the recognition is too small for real-world use. We show in Figure 9 a plot showing this comparison but now in a graphical fashion.

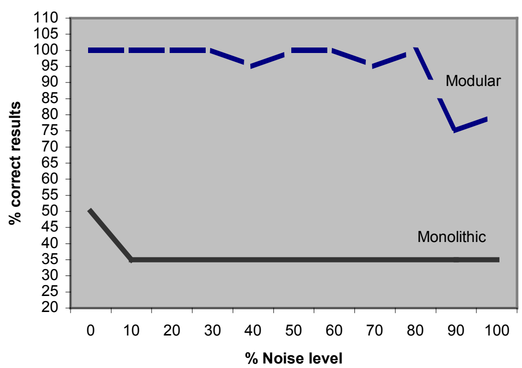

Fig. 9 Comparison between the modular and monolithic approach.

4. Conclusions

We showed in this paper the experimental results obtained with the proposed modular approach. In fact, we did achieve a 98.9% recognition rate on the testing data, even with an 80% level of applied noise. For the case of 100% level of applied noise, we did achieve a 96.4 % recognition rate on the testing data. The testing data included 10 photographs for each image in the training data. These 10 photographs were obtained by applying noise in a random fashion, increasing the level of noise from 10 to 100 %, to the training data. We also have to notice that it was achieved a 96.7 % of average reliability with our modular approach. This percentage values was obtained by averaging

In light of the results of our proposed modular approach, we have to notice that using the modular approach for human face pattern recognition is a good alternative with respect to existing methods, in particular, monolithic, gating or voting methods. As future research work, we propose the study of methods for pre-processing the data, like principal components analysis, eigenfaces, or any other method that may improve the performance of the system.

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