An Artificial Neural Network Based Approach to Mass Biometry Dilemma Taking advantage from IBM ZISC-036 Neuro-Processor Based Massively Parallel Implementation

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Abstract: *Over the recent past years, new public security tendency to fit up public areas with biometric devices has emerged new requirements in biometric recognition dealing with what we call here "mass biometry". If the main goal in "individual biometry" is to authenticate and/or identify an undesired individual within a set of favored folk, the main goal in "mass biometry" is to authenticate and/or identify an unusual (suspect) behavior within a flow of mass customary behaviors. So, in "mass biometry" the ability of handling patterns containing relatively poor information and the skill of high speed processing in order to treat a mass number of patterns in real-time are chief requirements. These antagonistic requirements make authentication and identification tasks very challenging for the "mass biometry" related applications.*

In this paper we present an Artificial Neural Network (ANN) based face recognition system in a "mass biometry" context using facial biometric features. The proposed system takes advantage from kernel functions based ANN model and its IBM ZISC-036 based massively parallel hardware implementation. Experimental results validating the issued prototype mass biometric system is been presented and discussed.

Keywords: Mass Biometry Applications, Artificial Neural Networks, Real-Time, ZISC-036 Neuro-Processor, Parallel Implementation.

I. INTRODUCTION

Over the past decades, biometry (e.g. biometric authentication/identification methods) has been the centre of a particular attraction. Especially, during the last decade a particular attention has been devoted on biometry based security issues and related applications, leading to a large variety of available products. However, the major efforts in investigation of the aforementioned area as well as the majority of issued products have concerned individual authentication or identification: what also could be called "individual biometry". The main goal of "individual biometry" is to authenticate and/or identify an undesired individual within a set of favored folks. In this case, both authentication and identification assume a precise biometrical characterization of concerned individuals, even if requirements differ between authentication and identification tasks. In fact, in authentication (detection of undesired individual) the precision of biometrical characterization concerns exclusively desired individuals, which should be precisely and reliably recognized as those belonging to the set of authorized individuals. An example is biometric access control, where the biometric system identifies the authorized persons only (on the basis of their biometrical features: fingerprint, iris, hand geometry, thermal infrared issues, etc...). In identification (recognition of incriminated individual) the precision of biometrical characterization concerns the incriminated (blamed or suspected) or hunted (pursued, tracked, etc...) individuals, which could be unknown. An example is criminal investigations based on DNA, fingerprint, or other biometric features. In fact, in this case, the individual's biometric features are not always available in advance. Finally, in "individual biometry" for both cases (authentication or identification) if the processing delay remains an important requirement, it occupies a second rank comparing to the recognition precision.

On the other hand, over the recent past years, new tendency to fit up public areas with biometric devices has emerged new requirements in biometric recognition dealing with what we call here "mass biometry". Contrary to "individual biometry", the main goal in "mass biometry" is to authenticate and/or identify an unusual (suspect) behavior within a flow of mass customary behaviors. An example is authentication of an individual (or a set of individuals) with aggressive attitude within passengers of a subway carriage. Another example is matching the presence (or identification) of an individual (or a group of individuals) with a heavy "police record" within a flow of passengers in a rail station or in an airport. In fact, in both above-mentioned examples the processing (authentication or identification) delay remains the chief requirement. That's why, between biometric features' precision and processing speed the preference goes to the second one. Additionally, due to the technological lake (technological poorness) of mass oriented biometric devices, the biometric information involved in "mass biometry" remains relatively poor and represents a lower quality comparing to the case of the "individual biometry": it doesn't still exist, a mass oriented technology to handle the acquisition of a large number of iris's images or fingerprints in real time; in the same way, the cost's exponentially incensement with sensors' precision (resolution) or with computing devices' processing performances (execution speed, digital precision, etc...) exclude today a mass installation of high resolution sensors or complex computational devices. The most accessible devices are those which fit up the aforementioned public areas, as: digital cameras installed in streets, in rail stations or in airports – or – as electric or magnetic field effect devices fitting up airports' terminals. On the side of biometric features, even if the fingerprint ([1], [2], [3]) remains the most popular biometric feature, over the past decade, an increasing number of works have concerned other biometric features (and issued biometric systems). Some of them investigated voice biometry, using speech processing issues ([4] and [5]). Elaborated during the recent years, other approaches propose hand geometry based biometry as a promising solution in the biometric access control area, which has captured almost a quarter of the physical access control market ([1] and [6]). Another works deal with more complex biometric features or processing approaches. For example, those extracting cognitive or mental characteristics ([7] and [8]), those working with facial asymmetry and ophthalmologic geometry [9] or those involved in human psychology [10]. Concerning more complex computational approaches, one can mention those dealing with fusion between different biometric traits using data fusion issues [11].

Taking into account the introductory reflections and the above-listed points concerning the state of biometric devices' technology, one of the most promising issues for "mass biometry" and related applications remains the facial biometry based approach. Two reasons boost us to keep on this direction. The first one is related to the recent popularity of face recognition and facial biometry involving a large variety of concurrent or complementary scientific communities. In fact, both of those topics have been centres of attention in a wide spectrum of works involving as well the image processing related community as artificial intelligence and neural networks issued communities. The second reason takes its origin from following statement of fact: it is reliable and realistic enough to state today that the near future years will be those of fitting up the public areas with digital cameras (came scopes) than to imagine that they will be those of public areas' entrapment with other (more complex or still very expensive) apparatuses (devices).

In this paper we investigate an Artificial Neural Network (ANN) based face recognition system in a "mass biometry" context using facial biometric features. Our motivation to investigate an ANN based solution has been stirred by three points. One hand, we have been stimulated by their successes in solving nontrivial problems as those dealing with optimization, modeling, decision making, classification, data mining or nonlinear functions (behavior) approximation. On the other hand, we have been enthused by their learning and generalization capabilities (extrapolation of learned tasks to unknown or unlearned situation), which remain among their most appealing properties. Finally, we have been encouraged by availability of massively parallel electronic implementation for some of these bio-inspired models: one of them is the IBM ZISC-036 neuro-processor, involving standard digital CMOS technology, offering reliable functional and programming environments.

Based on those motivations as well as on our experience concerning ANNs and image processing areas, the proposed system takes advantage from kernel functions based ANN model and its IBM ZISC-036 based massively parallel hardware implementation.

The paper has been organized as follows: the next section will present a brief overview of kernel functions based neural networks focusing their structure and learning principle. The section III will concern IBM ZISC-036 neuro-processor. The section IV will present the proposed solution and issued biometric system's prototype. The section V will detail experimental protocol and validation results. Finally, the last section will conclude the paper.

II. BRIEF OVERVIEW OF KERNEL FUNCTIONS BASED ANN MODELS

This kind of neural models belong to the class of "evolutionary" learning strategy based ANN ([12], [13], [14], [15]). That means that the neural network's structure is completed during the learning process. Generally, such kind of ANNs includes three layers: an input layer, a hidden layer and an output layer. Figure 1 represents the bloc-diagram of such neural net. The number of neurons in input layer corresponds to the processed patterns dimensionality e.g. to the problem's feature space dimension. The output layer represents a set of categories associated to the input data. Connections between hidden and output layers are established dynamically during the learning phase. It is the hidden layer which is modified during the learning phase.

A neuron from hidden layer is characterized by its "centre" representing a point in an N dimensional space (if the input vector is an N-D vector) and some decision function, called also neuron's "Region Of Influence" (ROI). ROI is a kernel function, defining some "action shape" for neurons in treated problem's feature space. In this way, a new learning pattern is characterized by a point and an influence field (shape) in the problem's N-D feature space. In other words, the solution is mapped thank to learning examples in problem's N-D feature space.

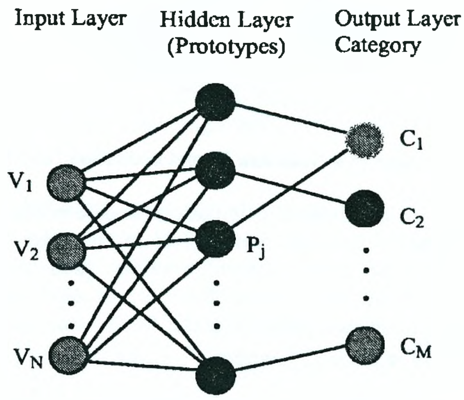

Fig.1 - Radial Basis Functions based ANN's bloc-diagram.

The goal of the learning phase is to partition the input space associating prototypes with a categories and an influence field, a part of the input space around the prototype where generalization is possible. When a prototype is memorized, ROI of neighbouring neurons are adjusted to avoid conflict between neurons and related categories. Figure 2 shows the learning mechanism's principle for a 2-D feature space. The neural network's response is obtained from relation (1) where C_j represents a "category", $V = [V_1 \ V_2 \ \mathrm{K} \ V_N]^T$ is the input vector, $P^j = [P_1^j \ P_2^j \ \mathrm{K} \ P_N^j]^T$ represents the j-th "prototype" memorized (learned) thanks to creation of the neuron j in the hidden layer, and λ_j the ROI associated to this neuron (neuron j).

$$\begin{array}{lll} C_j = F\left(dist\left(V,P^j\right)\right) & \mathit{If} & dist\left(V,P^j\right) \le \lambda_j \\ C_j = 0 & \mathit{If} & dist\left(V,P^j\right) > \lambda_j \end{array}, \qquad (1)$$

where, F(.) – neuron's activation (decision) function. Usually, this function is a kernel like function (radial basis function). Figure 3 shows an example of such kernel like activation function. In the given example, the activation function is a Gaussian one.

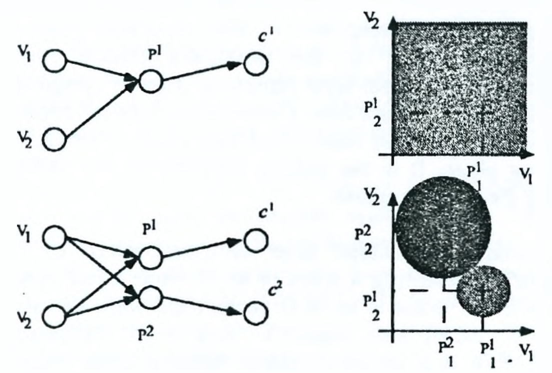

Fig.2 - Example of learning process in 2-D feature space.

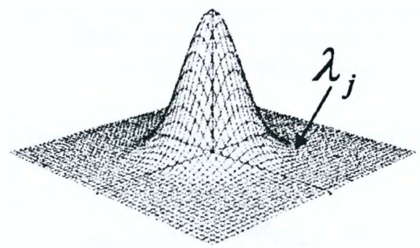

Fig.3 - Example of a Gaussian kernel activation function.

The choice of the distance calculation (choice of the used norm) is one of the main parameters in the case of the kernel functions based neural models (and derived approaches). The most usual function to evaluate the distance between two patterns is the Minkowski function expressed by relation (2), where V_i is the i-th component of the input vector and P_i^j the i-th component of the j-th memorized pattern (learned pattern). Manhattan distance ($n = 1$, called also L1 norm) and Euclidean distance ($n = 2$) are particular cases of the Minkowski function and the most applied distance evaluation criterions. One can write relation (3).

$$dist = \sqrt[n]{\sum_i \left|V_i - P_i^j\right|^n} \qquad (2)$$

$$\sum_i \left|V_i - P_i^j\right| \le \left(\sum_i \left(V_i - P_i^j\right)^2\right)^{\frac{1}{2}} \le \max_i \left|V_i - P_i^j\right| \qquad (3)$$

III. IBM ZISC-036 NEURO-PROCESSOR

The IBM ZISC-036 ([16], [17], [18]) is a parallel neural processor based on the RCE and KNN algorithms. Each chip is able of performing up to 250 000 recognitions per second. Thanks to the integration of an incremental learning algorithm. This circuit is very easy to program in order to develop applications; a very few number of functions (about ten functions) are necessary to control it. Each ZISC-036 like neuron implements two kinds of distance metrics called L1 and LSUP respectively. Relations (4) and (5) define the above-mentioned distance metrics. The first one (L1) corresponds to a polyhedral volume influence field and the second (LSUP) to a hyper-cubical influence field.

$$\text{L1: } dist = \sum_{i=0}^{n} \left|V_i - P_i\right| \qquad (4)$$

$$\text{LSUP: } dist = \max_{i=0...n} \left|V_i - P_i\right| \qquad (5)$$

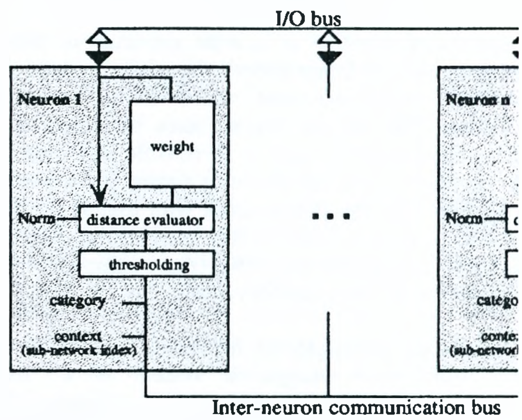

Fig. 4 – Neuron's bloc diagram in IBM ZISC-036 chip.

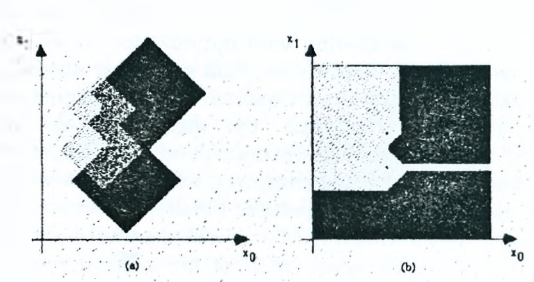

Fig. 5 - Example of input feature space mapping in a 2-D space using ROI (a) and k-NN (b) modes, using L1 norm.

Figure 4 shows the ZISC-036 chip's neuron's bloc diagram. Figure 5 gives an example of input feature space mapping in a 2-D space using ROI and KNN modes, respectively. In this example, the used distance is the L1 one, given by relation (4). A ZISC-036 chip is composed of 36 neurons. This chip is fully cascadable which allows the use of as many neurons as the user needs (a PCI board is available with 684 neurons). A neuron is an element, which is able to:

- memorize a prototype (64 components coded on 8 bits), the associated category (14 bits), an influence field (14 bits) and a context (7 bits),
- compute the distance, based on the selected norm (norm L1 or LSUP) between its memorized prototype and the input vector (the distance is coded on fourteen bits),
- compare the computed distance with the influence fields,
- communicate with other neurons (in order to find the minimum distance, category, etc.),
- adjust its influence field (during learning phase).

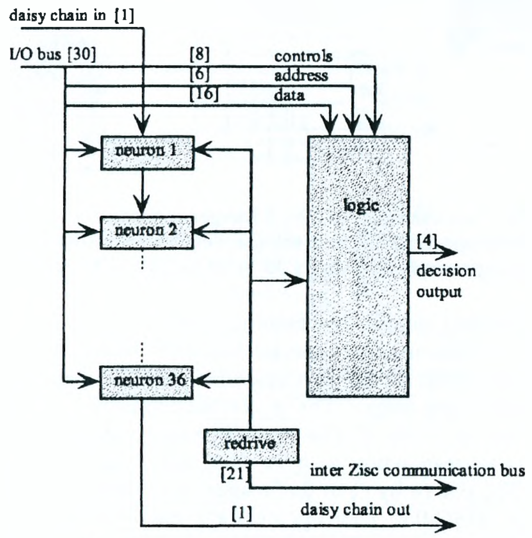

Fig. 6 - IBM ZISC-036 chip's bloc diagram.

A 16 bit data bus handles input vectors as well as other data transfers (such as category and distance), and chip controls. Within the chip, controlled access to various data in the network is performed through a 6-bit address bus. Controlling the ZISC036 is, by definition, accessing its registers, and requires an address definition via the address bus, and data transfer via the data bus. The inter-ZISC communication bus which is used to connect several devices within the same network, and the decision bus which carries classification information allow the use of the ZISC in a 'stand alone' mode. All neurons communicate via the 'inter-neuron communication bus. This bus is internally driven to allow the connection of several ZISC modules without impact on performance. An efficient protocol allows a true parallel operation of all neurons of the network even during the learning process. Because ZISC is a coprocessor device, it must be controlled by a master (state machine or controller). This can be done by a standard I/O bus. The I/O bus of ZISC036 has been designed to allow a wide variety of attachments from simple state machine interface to standard micro-controllers or buses. Figure 6 shows the bloc-diagram of a IBM ZISC-036 chip.

Two kinds of registers hold information in ZISC-036 architecture: global registers and neuron registers. Global registers hold information for the device or for the full network (when several devices are cascaded). There are four global registers implemented in ZISC-036: a 16-bits Control & Status Register (CSR), a 8-bits Global Context Register (GCR), a 14-bits Min. Influence Field register (MIF) and a 14-bits Max. Influence Field register (MAF). Neuron registers hold local data for each neuron. Each neuron includes five neuron registers: Neuron Weight Register (NWR), which is a 64-by-8 bits register, a 8-bits Neuron Context Register (NCR), Category register (CAT), Distance register (DIST) and Neuron Actual Influence Field register (NAIF). The last three registers are both 14-bits registers. Association of a context to neurons is an interesting concept, which allows the network to be divided in several subsets of neurons. Global Context Register (GCR) and Neuron Context Register (NCR) hold information relative to such subdivision at network and neuron levels respectively. Up to 127 contexts can be defined. When a neuron is committed, only the neurons having the same context as the GCR are activated. When GCR is set to zero, all neurons are activated whatever their specific context. The NCR register's value could be used to select sub-networks of neurons, which contribute to solve the same problem. The 7-th bit of both GCR and NCR registers corresponds to the norm (distance metrics) witch should be used ([16], [17]).

IV. FACIAL RECOGNITION BASED MASS BIOMETRIC SYSTEM USING KERNEL FUNCTIONS ANN

The facial recognition based mass biometric system we propose includes three main stages. The first one is a video (image flow) acquisition device, which could be a standard digital video camera. The second stage is essentially an image processing stage, which on the one hand, performs a set of image pre-processing operations, and on the other hand, extracts a number of facial biometric features. The last one is a kernel functions based ANN stage carrying out classification and decision operations.

Before detailing each of aforementioned stages, it is pertinent to notice that one of the chief goals of the present work was realization of an effectively operational prototype. So, the real-time operability constraint was a central point. That is why our choice concerning some of the aforementioned stages has been guided by implementation viability related items. In other words, the preference has been given to conventional but viable solution instead the innovative but unrealizable ones.

A. IMAGE FLOW ACQUISITION

As it has been mentioned before, image flow acquisition could be done by standard or specialized (dedicated) video devices. In fact, the most of market available standard video devices offer "face tracking" function which is proposed as associated software option or is implemented as hardware associated function. On the side of the dedicated (specialized) camera, several products offer sophisticated functions allowing face tracking and a number of face related features extraction or measurements. An example of such face dedicated cameras is commercialized by "Seeing Machines" [19] corporation. The proposed camera integrates head and eye tracking facilities. Today, such sophisticated digital cameras are still costly, needing a consequent investment. However, the cost of such devices should decrease in near future conformably to electronic devices market's tendency. We have preferred to consider a standard digital video camera including a face tracking standard function.

B. IMAGE PRE-PROSESSING AND FEATURES EXTRACTION STAGE

In principle, this stage could be a software based stage a hardware module. However, either software or hardware, the processing (feature extraction) performed by this stage should satisfy real-time requirements in order to permit to take advantage from ZISC-036 neuro-processor's high operating speed. In other words, if the learning phase (e.g. the learning time) doesn't require real time capabilities, the operation phase (face detection and identification) of a biometric system should swear real-time operation condition. In our case, the second stage has been realized as a software module on PC. As the face tracking function is performed by the first stage, this second stage has essentially been dedicated to face characteristic areas (eyes, nose and mouth) detection and to the associated biometric features extraction.

Fig. 7 – Example of first stage operation where a grey-level image (left) is transformed a binary image (right).

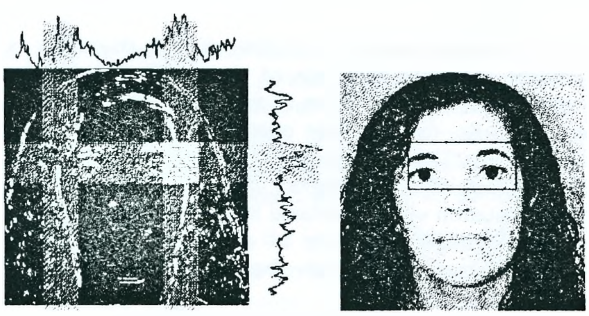

Fig. 8 – Example of "eyes area" detection (second stage operation) showing histogram computing (left) and associated area (right).

We propose to perform the above-mentioned features extraction in two steps. During the first step the face image is converted to a binary image and filtered using a conventional Sobel ([20] and [22]) transformation. Figure 7 shows the principle of this first step. During the second step, the white pixels spatial histogram in each dimension, representing number of white pixels for all columns (dimension X) and for all rows (dimension Y), is realized ([21] and [23]). These histograms are then used as some kind of signatures to detect eyes area, nose area and mouth area. Figure 8 gives an example of eyes area detection using such approach. Detection of each area (eyes, nose or mouth) using the above-described approach takes less than 60 ms remaining compatible with real-time requirements.

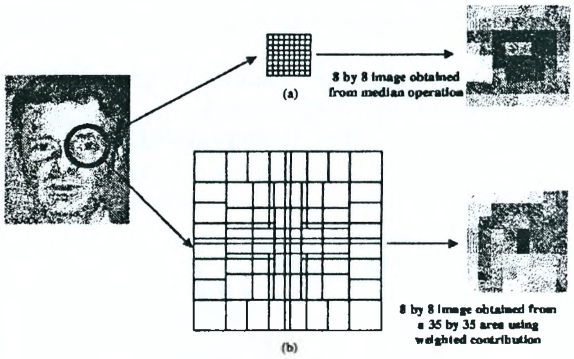

Fig. 9 - Two examples of 8 by 8 images construction using median operation (a) and using a weighted contribution based approach involving a 35 by 35 neighbourhood (b).

The obtained images representing eyes, noise or mouth areas, are then used to generate biometric features which compose inputs of the next stage (kernel function neural network based stage). The generated biometric features are a set of "8 by 8" (64 pixels) images obtained from images corresponding to eyes area, nose area or mouth area. The size (8 by 8) of the images is conditioned by the size of ZISC-036 neuro-processor's input vector: a 64 components vector. Two strategies could be adopted to construct the "8 by 8" features (8 by 8 representations). The first one is the simplest strategy consisting on successive consideration of pixels and their neighbours in a 8 by 8 neighbourhood. The main drawback of this simple strategy is the large number of generated features. In fact considering a 40 by 100 (400 pixels) areas (eyes, nose or mouth areas), it leads to 3000 features per area. Based on natural vision principle, the second strategy is a more sophisticated way to construct those features. The 8 by 8 biometric feature image is constructed using higher level information (obtained from the pixels). Figure 9 shows two examples of 8 by 8 images construction using median operation (pixels value average) for the first one, and using a weighted pixels contribution based approach (second one). The basic advantage to use features obtained from higher level information is the consequent reduction of number of generated features. The main difficulty remains to find the compromise between representation's sophistication and the processing complexity.

In our case, we chose an intermediate approach consisting on generation of a set of three median operation based different features (8 by 8 images). The main advantages of such choice are related on the one hand, to the weak number of generated features (one feature for each area) and the reasonable processing time due to the median (average) operation simplicity (less than 100 ms for whole face's image).

C. ZISC-036 NEURO-PROCESSOR BASED CLASSIFICATION/DECISION STAGE

The third and last stage of the proposed "mass biometry" oriented face recognition system is a kernel functions ANN based stage including three neural nets conceived acc^rding to a parallel architecture. Figure 10 gives the bloc diagram of the whole proposed face recognition system, detailing this third stage.

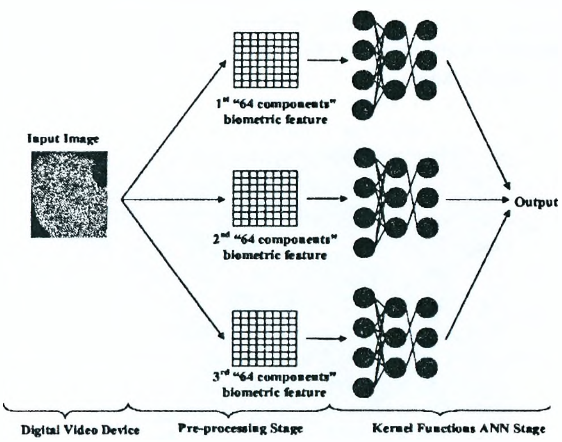

Fig.10 - Whole face recognition system's bloc diagram showing "Classification/Decision" stage's detailed architecture.

Each ANN is specialized in processing of a specific kind of biometric feature extracted from the input image. Then a decision logic based procedure performs (on the basis of classification results relative to each biometric feature) the identification of the concerned individual. As it has been emphasized in section 3, Global Context Register (GCR) of ZISC-036 allows a versatile implementation of several neural nets by dividing ZISC-036 neurons in distinguished subsets of neurons, committing only neurons relative to a same context (up to 127 contexts can be defined). Moreover, using Neuron Context Register's (NCR) value a several sub-networks could contribute to solve a same problem. This appealing ability of ZISC-036 neuro-processor's architecture has been used to realized (implement) the three above-mentioned dedicated neural networks.

V. PROTOTYPE IMPLEMENTTATION AND VALIDATION RESULTS

A first prototype of the proposed "mass biometry" oriented face recognition system has bee, realized using a ZISC-036 based board including 16 chips making available approximately 700 parallel hardware (electronic) neurons. The second stage has been implemented as software module on PC. Image acquisition in this first prototype has been implemented as a standard Web camera simulating limited resolution and noisy nature of input information conformably to the mass biometry context (contrary to the individual biometry context, information in mass biometry context is supposed to be poorer).

Two different identification strategies (cases), have been considered:

- In the first one, called "global biometric features" based identification, the three "64 components" biometric features are "8 by 8" images extracted from the input image (face) involving (corresponding to) whole face. The first and second "8 by 8" images, representing some face directional global feature, are obtained from median operation performed on input image's rows and columns. While, the third one, representing some face morphology related global feature, has been obtained from median operation performed on 64 equal slices of the input image. In other words, first the input image has been divided in 64 sub-images. Then, the median (average) of each region (sub-image) leaded to the corresponding pixel of the resulted 8 by 8 image. Finally, the decision logic (threshold based logic) has been built privileging (allowing higher weight) to the third neural net's response. Figure 11 gives an example of such "global 8 by 8 biometric features".

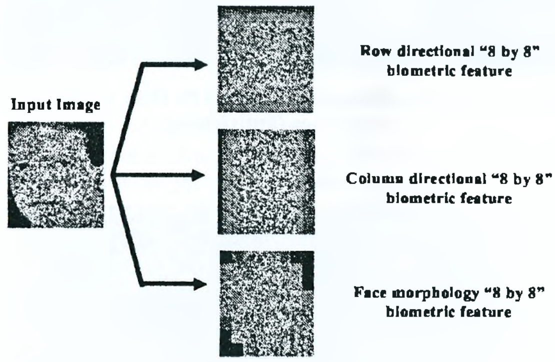

Fig.11 - Example of "global 8 by 8 biometric features".

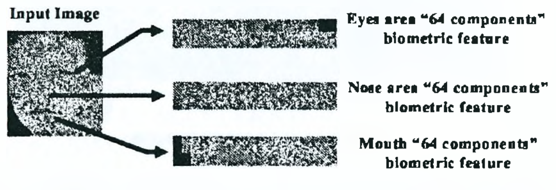

Fig.12 - Example of "localized biometric features".

- In the second one, called "localized biometric features" based identification, the three "64 components" biometric features are not regular images. They are 4 by 16 images extracted from the input image (face) involving specific localized face's areas. All of them result from median operation performed on a localized area (part) of face (input image). The first one is obtained from "eyes area", the second fashioned from "nose area" and the last one constructed using the "mouth area". The decision threshold based logic has been fashioned in order to privilege (giving higher importance) to the "eyes area". Figure 12 gives an example of such "localized 64 components biometric features".

The experimental validation has been done using the ORL (Olivetti Research Laboratory, Cambridge) faces database. This database is composed of 400 images representing 40 individuals. In other words, the database offers 10 different pictures of a set of 40 faces (corresponding to different individuals), each one representing a different situation : different mimics, with and without glasses, different degrees of rotation, etc....Figure 13 gives an example of images set corresponding to a given individual (face) of ORL database. The database has been divided into two equal parts. The first one including 5 pictures of the whole individuals (40 individuals) has been used for learning phase. The other 5 images (unlearned pictures) of each individual have been used for testing phase.

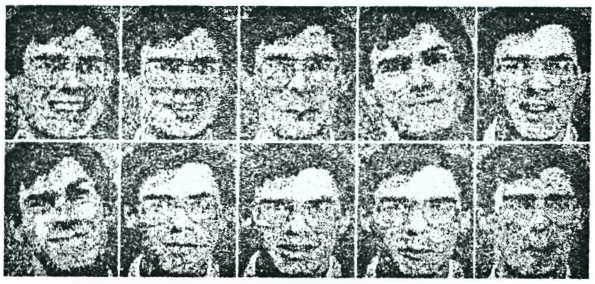

Fig.13 - Example of images set offered by ORL database for a same face (individual).

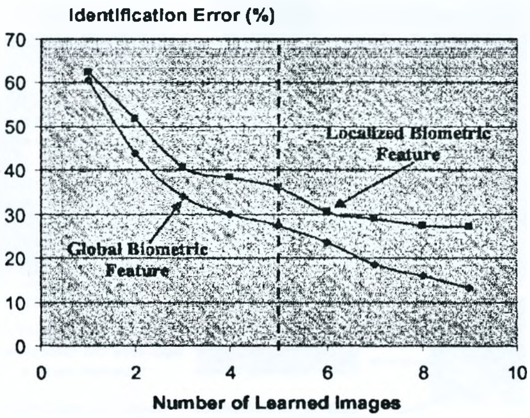

Fig.14 –"Identification error" versus learned samples using ROI operation mode and L1 metrics.

Figure 14 gives identification error versus number of learned samples of each individual. These results correspond to the use of ROI mode with L1 metrics (distance evaluated according to L1 norm). As it could be observed in this figure, the above-described experimental protocol leaded to 73% of correct identification (e.g. identification error of 27%) using "global biometric feature" based strategy. The same experimental protocol leaded to 64% of correct identification (so, a higher identification error) when the identification has been based on the second strategy: "localized biometric feature" based identification. The same figure shows results corresponding to the enlargement of the number of learning samples (learning of additional samples). As it could be remarked from that figure, the "global biometric feature" based identification is significantly enhanced by learning additional samples, reaching 85% of correct identification when 9 samples of each face have been trained. Nevertheless, for the "localized biometric feature" strategy is less sensible to the additional samples. In fact as it could be seen (in figure 14) the identification error remains relatively important (about 30%) even when 9 among 10 samples of each face have been learned by the system. This shrink of performances could probably be related to the relative poorness of localized features as they have been considered in this first experimental validation. In fact, eyes, nose or mouth characterization using an equally weighted "4 by 16" image representation seems be insufficient to typify correctly the corresponding individuals (faces).

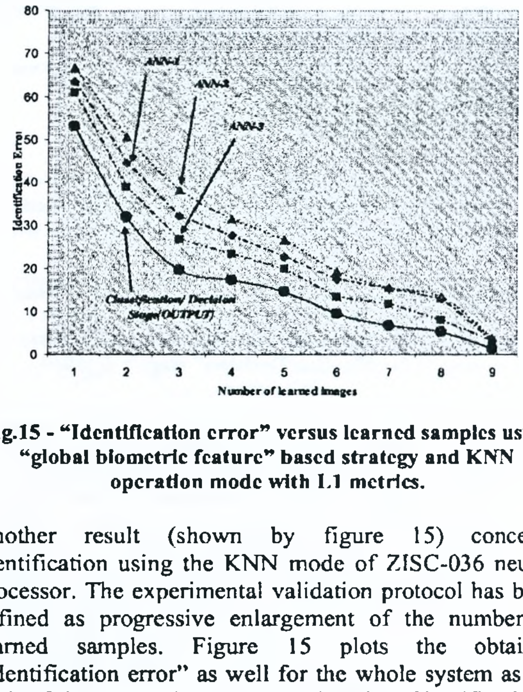

Fig.15 - "Identification error" versus learned samples using "global biometric feature" based strategy and KNN operation mode with L1 metrics.

Another result (shown by figure 15) concerns identification using the KNN mode of ZISC-036 neuro-processor. The experimental validation protocol has been defined as progressive enlargement of the number of learned samples. Figure 15 plots the obtained "identification error" as well for the whole system as for each of three neural nets composing the "Classification / Decision" stage. The first comment concerns the significantly improved identification rate, reaching 85% for 5 leaned samples (of each face) and more than 98% (e.g. less than 2% "identification error") for 9 learned samples. This could be explained by the fact that contrary to the ROI operation mode, the KNN recognition mode (in ZISC-036 neuro-processor) doesn't depend to "region of influence" (neuron's influence shape) value avoiding undefined regions in the input parameter's feature space. The second interesting remark related to this figure concerns the comparison of whole system's "identification errors" with those obtained for each neural net composing the system. In fact, as it could be remarked from figure 15, the "identification error" of the whole system remains lower than "identification errors" affecting each individual neural network composing the system: especially (and even) when the number of learned samples remains relatively fairly small (3 to 5 learned samples). For example, in the case of 4 learned samples of each face, first, second and third (ANN-1, ANN-2 and ANN-3) commit 27%, 31% and 23% "identification errors", respectively, while the whole system's "identification error" remains about 17% (e.g. 83% of correct identification).

VI. CONCLUSIONS

Contrary to "individual biometry" where both authentication and identification operations assume a precise biometrical characterization of concerned individuals, the main goal in "mass biometry" is to authenticate or identify an unusual (suspect) behavior within a flow of mass customary behaviors. That's why, in "mass biometry" the chief requirements concern on the one hand, the ability of handling patterns containing relatively poor information and on the other hand, the skill of high speed processing in order to treat a mass number of patterns in a reasonably acceptable delay (real-time). These antagonistic requirements, making authentication and identification tasks very challenging for the "mass biometry" related applications, motivated us to investigate a ZISC-036 neuro-processor based facial recognition biometric system. Our solution takes advantage at the same time from kernel functions based ANN's image processing ability implemented by ZISC-036 and from the massively parallel architecture of this neuro-processor allowing very high processing speed.

A first prototype of the proposed system has been realized combining software (biometric features extraction stage) and hardware (ZISC-036 neuro-processor's based "Classification / Decision" stage) implementations. The obtained very promising results show feasibility and effectiveness of the proposed solution reaching 85% correct identification involving a relatively weak number of learned samples (5 samples per face).
These promising results open a number of auspicious perspectives concerning as well the proposed solution as the 'mass biometry" related applications in general. We are working now on two directions. On the one hand we are investigating new "64 components biometric features" (representations), and on the other hand we develop more sophisticated learning strategies on ZISC-036.

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