IRIS IDENTIFICATION USING THE PRAM NEURAL NETWORK

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ABSTRACT

In this paper we propose a new approach to performer is identification. In contrast to existing approaches that consider the Hamming distance measure to perform identification, the new approach considers the addition of a well trained neural network to identify the iris. The disadvantage of previous schemes is the difficulty to deal with the variability of irises within the same iris class due to noise and movement of the eye as well as difficulties in capturing a clear image of the eye, which makes the choice of threshold values to identify the class to which belong the iris a difficult and a time consuming task. The new approach is based on a digital neural network pRAM.

We operate using two alternatives. The first one is based on the application of the raw multi grey level iris image, handled by the bit plane encoding scheme. Whereas, the second alternative is based on the iris code obtained by applying Daugman's method to represent the distinguishing features of the iris within a binary image. We developed a pRAM net simulator in C++ to handle images taken from a public iris image database. The simulator was exercised with images in an extensive manner. The results obtained are very encouraging as we succeeded to train appropriately the pRAM net and to perform identification with a high identification rate. The obtained results show that identification based on the use of the iris code is more appropriate than applying the normalized multi-grey level iris image.

KEYWORDS: pRAM neural network, iris identification, iris code.

1 INTRODUCTION

Iris identification is the most accurate biometric method used to identify individuals. It is composed of two parts: obtaining the iris image and recognizing it. After capturing the eye image, the iris area should be extracted from it, Canny and the circular Hough transform are used for this purpose. Then the extracted iris is normalised to get a 2-D rectangular representation in order to avoid differences in the irises of the same pattern class. The extraction of iris features using the Gabor wavelet transformation, recognized for its good performance [1], is applied to get the iris code, which is a binary image. Our contribution is to process the iris image by the pRAM net and to perform a comparative study to determine the best way to use the pRAM net in terms of the identification rate.

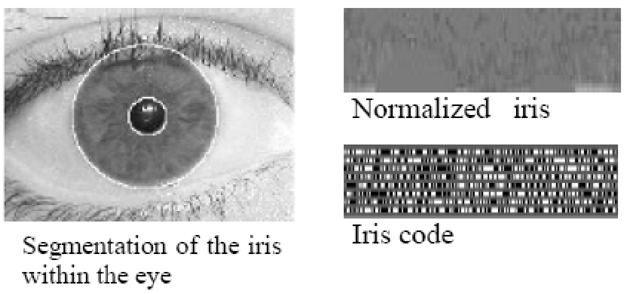

Figure 1 Iris image and iris code extraction

2 THE *P*RAM NETWORK

The *pRAM* network is a Boolean neural network based on the probabilistic random access memory (*pRAM*) as the main artificial neuron. This type of neural network has been applied previously to solve different recognition problems such as digit recognition, and proved to be adequate [2].

The pRAM stores a M bit number representing the probability to fire (outputs 1). This is achieved by adding the stored probability to a M-bit random number G according to equation 1**[2, 3]**.

$$out = 1 \; if \;\; \propto + G \geq 1 \, , or \; 0 \; otherwise \qquad (1)$$

The conditional probability for a *pRAM* to output a 1, given a specified input vector **i**, is $\alpha_{\mathbf{u}}$ which represents the probability stored at address **u**. We can estimate $\alpha_{\mathbf{u}}$ during R time steps by the unary stochastic representation of a spike train of length R appearing at the pRAM's output [3].

pRAM nodes are used in different layers and connected from input layer to the output layer using the pyramid topology. Where the node connectivity is varying from a higher to a smaller value from the input to the output layers [4]. We used the reinforcement learning algorithm, based on a reward/punishment mechanism, where the learning phase is based on the adjustment of the contents of the *p*RAM α's at each time step, according to the rule given in equation 2 **[4].**

$$\Delta\alpha_u = \alpha_u(t+1) - \alpha_u(t) = \Delta\alpha_{ur} + \Delta\alpha_{up} \quad (2)$$
$$= \delta(r(a-\alpha_u) + \lambda(\bar{a} - \alpha_u)p)$$

Where $\bar{a}$ =1-a, a is the *pRAM*'s output, r and p are respectively the reward and penalty parameters, $0<\delta<1$ and $0 < \lambda < 1$ are the learning constants. The reward r and the penalty p terms will increase or decrease the memory contents αu acting in a way to reinforce the probability of making similar moves in the next time step. The learning constants λ and δ are selected by trial and error with previously set up conditions as constraints. From equation 2, we derive the mean value of the updating rule for R time steps, that is:

$$\Delta\alpha_u = \frac{\sum_t \Delta\alpha_{ur}(t)}{R_{r+p}} + \frac{\sum_t \Delta\alpha_{up}(t)}{R_{r+p}} \quad (3)$$

Where R_{r+p} is the number of times a given memory location is accessed during the R time steps. The training is performed over several iterations, it stops when the error rate is low and stable. During the testing phase we load all *pRAM* contents with the values obtained at the end of the training session. The training regime is interleaved so that we can update the memory contents by taking averages of the contributions of different exemplars of the main pattern classes. The performance measure is based on the root mean square error given by equation 4.

$$(RMS) = \sqrt{\sum_p \sum_j \frac{(t_{pj} - o_{pj})^2}{n_p n_j}} \quad (4)$$

Where np is the number of pattern classes to be identified, nj the different exemplars of each pattern, tpj the desired output and opj the actual output mean firing rate. The error is computed by scanning the whole training set (batch processing). However, the memory contents are updated on a pattern by pattern basis during R time steps.

3 INPUT DATA

We operate on 2D images to exercise the *pRAM* net. We focussed on the spatial representation of the image. 200x150 multi-grey level eye images taken from the public database Ubiris V1 **[1]**, were used to extract the irises. We construct the iris database, which consist of 240x20 iris images obtained after performing an adequate segmentation process.

In the case of binary images the input to the pRAM net is the raw contents of the image itself. To use the grey scale images with *pRAM* net in its simple form, we transform the grey scale image using the bit plane decomposition technique to avoid the loss of relevant features within the iris image a seen in Figure 2. This scheme replaces the iris image by a set of the four most significant binary images having the same spatial resolution as the original one. As we believe that the highest order binary planes contain relevant distinguishing features of the iris. On the other hand the low order binary planes contain either irrelevant or redundant information. Each binary plane will be handled by a dedicated *pRAM* net. Thus, four *pRAM* nets are jointly used to decide on the identification of the iris, with the added advantage of being able to train all *pRAM* nets in parallel.

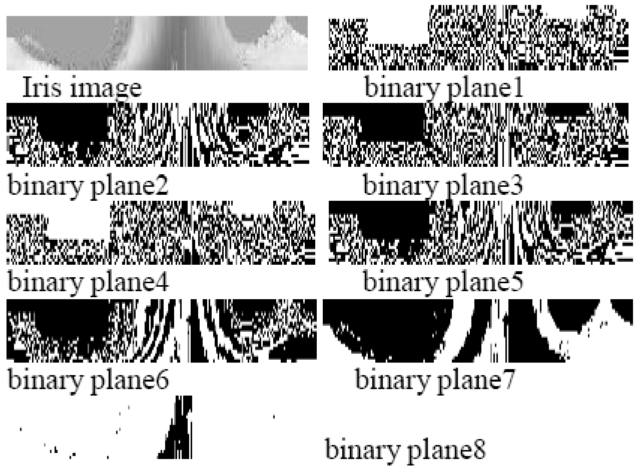

Figure 2: An iris image and its eight binary planes

4 THE INPUT SAMPLING SCHEME

The manner with which the n-pixels are extracted from the image, to form the input to the *pRAM* node, is referred to the input sampling or mapping. These combined pixel values are a sequence of zeros and ones which forms the sub-pattern, called *n-tuple* state, used as an address to a single *pRAM.* To decode the corresponding *n-tuple* state, we propose an input mapping based on data analysis. Since extracting knowledge from the actual data, taken from the iris database, is the most appropriate way to extract the salient features of the iris image, based on which the net derives the decision rules of identification.

We consider the local variations seen by each pixel within the image according to the data used in the training set. Since each individual pixel goes through a cycle of variations, we suggest to compute the resultant probability of a given *n-tuple* to be in a given state based on the individual probability densities of the constituent pixels. Hence, we use the frequency of occurrence of a pixel to be in the state 1, as the main metric to represent changes at the pixel level while handling one training set at a time. Normally, if a *ntuple* state is a characteristic one for a given training set, this state should be approximately constant (i.e. occurs with a high probability) and that particular state must have a low probability to occur for other training sets. Thus, to group pixels in *n-tuples* we must test for their frequency of occurrence to be in a particular state. This idea was applied and after test we conclude that for better performance, we need to adequately distribute these pixel groupings by permuting their positions at the input level to the *pRAM* net.

5 IRIS IDENTIFICATION

Iris identification is carried out by having an iris scanned by a suitable camera. The data from the scan is converted to a unique template. The identification requires the individual to present his iris for comparison with the data previously recorded. Daugman's method is based on isolating the iris from the human eye based on edge detection techniques **[1]**. And, normalising the image using the rubber sheet method to transform the doughnut iris image into a rectangular 2-D image. Then, extracting the iris features using Gabor wavelets and transforming the result to get a 2-D binary image representing the iris code. Finally, performing the identification based on a hamming distance comparison **[5, 6]**. This standard measure is used as the main metric for comparison of binary strings x and y corresponding to the two iris codes of length *n*, and counts bits that disagree. An exclusive OR logical operation (⊕) can be used to get the Hamming distance D, as given in equation 5.

$$D = \frac{1}{n}\sum_{k=1}^{n} x_k \oplus y_k \qquad (5)$$

We propose as an alternative to this technique, the use of a *pRAM* neural net with a judiciously selected data based input mapping in an attempt to perform the feature extraction task in an appropriate manner. We extract the iris from the eye after a segmentation process then, we normalize it as a 2D image that is a 240x20 multi-grey level image. The obtained image is converted to four binary images using the previously stated method as shown in Figure 2. The second variant consists of handling the iris code which is the 480x20 binary image to be applied as an input to the *pRAM* net.

6 TESTS AND RESULTS

A number of computer simulations were carried out to highlight the possibility of using a pyramidal *pRAM* neural network to perform iris identification based on binary images. We apply the data based input mapping derived using the proposed method given in the previous section, and a permuted version of the later. We restrict the study to the 10 class problem.

The net's performance is measured using the convergence error and the identification rates, as these are the most common metrics used for pattern identification problems. The obtained results are illustrated in Figure 3. This figure shows that the network's convergence is achieved using iris images. Using the permuted mapping we managed to achieve low convergence error rate approximated at 2% compared to 8% without using a pre-processing stage of the input mapping when we used the iris code as input to the *pRAM* net. In the case of applying directly the iris image to the *pRAM* net, we noticed that the error convergence rate is worst as it is around 15% and this *pRAM* net needed more than 400 iterations in order that the value of this error drops below 10%, as it is shown in Figure 3. The fluctuations seen are the result of changes in the *pRAM* memory contents which vary in the range [0,1]. The network using the permuted mapping based on the iris code achieves an acceptable identification rate of 93% of the 10 iris classes. Whereas we achieved 80% as an identification rate without a pre-processing stage. This result allows us to state that we must provide a uniform distribution of the *n-tuple* types at the network input to preserve better the propagation of these distinguishing characteristics from input layer to the output layer of the net where the decision of identification is performed.

The bit plane encoding scheme does not assume any underlying constraints on the images and allows the use of the same *pRAM* net to exercise different types of data i.e. the binary planes corresponding to each grey scale image, which makes the computer simulation much more easier. As a result, the obtained *pRAM* net was extensively exercised to handle successively iris images.

Two different architectures of the pRAM net are used. The first one handles the multi-grey scale iris image where 8-4-8 *pRAM* nodes were chosen for the input, the hidden and the output layers respectively whereas for the second alternative we used the architecture based on the 8-8-4 *pRAM* nodes.

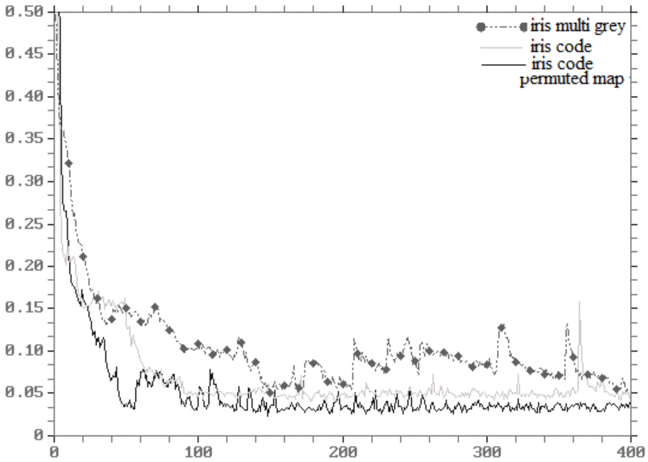

Figure 3 convergence error function of the numberof the net iterations.

7 CONCLUSION AND FURTHER WORK

In this paper pRAM nets were simulated and used to tackle the iris identification problem. This study emphasized the benefit in using a pRAM net with an input mapping based on data analysis. The first stage applies discrimination among iris patterns at the input level. Which allows a single pyramidal pRAM net to perform identification of irises. The application of these propositions to iris identification was successful and confirmed their effectiveness when handling this type of problems. Using bit plane encoding scheme while handling a multi-grey level iris image complicates the task of identification and the fact that we restrict our study to only the four highest binary planes, is probably the main reason that justifies why we got low identification rate, compared to the other alternative based on the iris code. The obtained results are very motivating and encouraging. The use of more than one pyramid, so as to allow for the overlap among the n-tuples at the input level, plays a positive role to enhance the performance. This suggestion is left as a possible continuation to this work.

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