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A NEW RECOGNITION TECHNIQUE NAMED SOMP BASED ON PALMPRINT USING NEURAL NETWORK BASED SELF ORGANIZING MAPS

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Abstract
The word biometrics refers to the use of physiological or biological characteristics of human to recognize and verify the identity of an individual. Palmprint has become a new class of human biometrics for passive identification with uniqueness and stability. This is considered to be reliable due to the lack of expressions and the lesser effect of aging. In this manuscript a new Palmprint based biometric system based on neural networks self organizing maps (SOM) is presented. The method is named as SOMP. The paper shows that the proposed SOMP method improves the performance and robustness of recognition. The proposed method is applied to a variety of datasets and the results are shown.

Keywords:
Biometrics, Palmprint, Self Organizing Maps (SOM)

1. INTRODUCTION

The increase of terrorism and other kinds of criminal actions, such as fraud in e-commerce, increased the interest for more powerful and reliable ways to recognize the identity of a person [1, 2, 3]. To this end, the use of behavioral or physiological characteristics, called biometrics, is proposed. Biometrics is best defined as measurable physiological and or behavioral characteristics that can be utilized to verify the identity of an individual [3]. Many physiological characteristics of humans, i.e., biometrics, are typically invariant over time, easy to acquire, and unique to each individual. Therefore the biometrics traits are increasingly adopted for civilian applications and no longer confined for forensic identification.

The recognition of individuals without their full co-operation is in high demand by security and intelligence agencies requiring a robust person identification system. Many face recognition algorithms have been proposed so far [4, 5, 6, 7, 8, 9, 10, 11, 12]. Algorithms related to recognition of Palmprint, hand geometry, iris, voice recognition have also been proposed [6, 13, 14, 15, 16, 17]). It is estimated that 5% of the population does not have legible fingerprints [1], a voice could be altered by a cold and face recognition systems are susceptible to changes in ambient light and the pose of the subject. Palmprint recognition refers to the process of determining whether two palmprints are from the same person based on line patterns of the palm. Palmprint serves as a reliable human identifier because the print patterns are not duplicated in other people, even in monozygotic twins.

The Palmprint is an important biometric due to the following reasons:

1. stable structure that is preserved since birth and is quite unique in individuals
2. invariable to the changes in expression
3. immune from anxiety, privacy, and hygiene problems

Due to the above mentioned reasons, automated personal identification using Palmprint images has been increasingly studied for possible commercial applications recently.

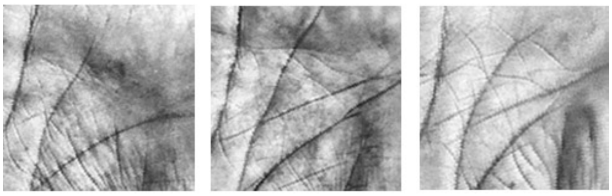
A typical biometric system usually consists of that specific biometric detection scheme followed by an extraction methodology (which shrinks the dimensionality of useful information) and then a classifier to make the appropriate decision.

Literature talks about two approaches towards palm print recognition – one related to structural and the other related to statistical. In the structural approach, the creases, best lines etc are considered as features and are analyzed. [18] talks about extracting ridges from the palm print by eliminating the creases. Alternatively, [19] determined the datum points derived from the principal lines by using the directional projection algorithm. It has been said that, the structural based approaches could extract ridges mostly correctly. However, they are limited in determining the placements of the line structures. Apart from all these, high quality images (as large as around 800x800 pixels) are needed to extract the fine palm print details and hence these algorithms might not be practical to suit real time applications.

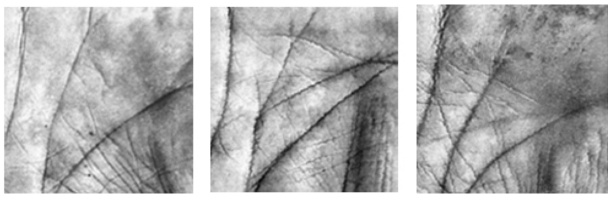
The dominant approach towards using palmprint for recognition is based on the statistical features. For statistical based palmprint recognition approach, the works that appear in the literature include eigenpalm (where the original palm print images were projected to a relatively lower dimensional space called eigen palms) [20], fisherpalms (which uses fisher linear discriminant to reduce the dimension) [21], Gabor filters [22, 11], Fourier Transform [23], and local texture energy [24] (Out of these approaches, eigen palm and fisher palm are used for comparing with our approach).

In this paper, a new approach for appearance-based Palmprint based recognition called as SOMP is presented. SOMP stands for Self Organizing Maps (SOM) for Palmprint recognition. It is shown that our proposed SOMP method improves the performance and robustness of recognition when compared to some of the methods proposed in literature. This paper uses the preprocessed palm print (left hand and right hand) dataset obtained from IIT Delhi [25]. A snapshot of some of the images from this preprocessed dataset is shown in Fig.1.

The remainder of this paper is organized as follows: In section 2 self organizing maps (SOM) are explained. Section 3 explains the proposed approach (SOMP). Section 4 discusses the results obtained using this SOMP method. Paper concludes with conclusion and future direction.



(a)



(b)

Fig.1. Example images from the dataset of IIT Delhi [25]
(a) left hand samples (b) right hand samples

2. SELF ORGANIZING MAPS (SOM)

Self Organizing Map (SOM) is a special kind of unsupervised computational neural network [26] that combines both data projection (reduction of the number of attributes or dimensions of the data vectors) and quantization or clustering (reduction of the number of input vectors) of the input space without loss of useful information and the preservation of topological relationships in the output space.

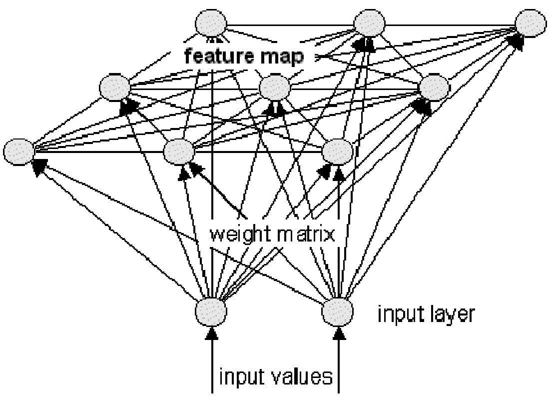


Fig.2. Self Organizing Map (SOM)

A few concepts are useful to understand the workings of the technique. The input space (also called signal) is the set of input data employed to feed the algorithm; typically, the observations are multidimensional and are thus expressed by using a vector for each of them. On the contrary, the output space (trained network, network or SOM) refers to the low-dimensional universe in which the algorithm represents the input data. It usually has two-dimensions, and is composed of a set of elements called neurons (or nodes) which are interconnected, hence the network. What the algorithm does is to represent the input space onto the output space, keeping all the relevant information and ordering observations in a way such that topological closeness in the output space implies statistical similarity in the input space.

The input space is composed by n-dimensional vectors which shall be visualized/clustered in a low-dimensional environment. The neurons are arranged on a flat grid not as a multilayer perceptron (input, hidden, output). All inputs are connected to every node in the network. The input layer consists of m source nodes, where m is the dimensionality of the input vector x. One can express the input vector t as:

$$x = [\xi_1(t), \xi_2(t),\ldots,\xi_n(t)]^T \in R_n, \quad (1)$$

where, $\xi_i(t)$ represents the value for each dimension.

The output space is an array of x by y neurons (nodes) topologically connected following a kind of geometrical rule (the most common topologies being circles, squares and hexagons). Each of the nodes is assigned a parametric real vector (also referred as codebook vector) of initially random values that is referred as model, and expressed as:

$$m_i = [\mu_{in}, \mu_{in}, \ldots, \mu_{in}]^T \in R_n \quad (2)$$

Last, $d(x, m_i)$ is defined as any distance metric between two vectors x and m_i. The most widely used is the Euclidean distance, although other specifications are also valid.

What one is looking for is a topologically-ordered representation of the signal space into the network. That is done by the SOM in an iterative process called training, in which each signal vector is sequentially presented to the output space. The best matching unit (b.m.u.) for x is defined as the neuron minimizing the distance to x. When this is found, the b.m.u. is activated and an adaptive process starts by which such neuron and its topological neighbours are modified by the following scheme:

$$m_i(t + 1) = m_i(t) + h_{ci}(t)[x(t) - m_i(t)], \quad (3)$$

where, t and $t + 1$ represent, respectively, the initial and the final state after the signal has activated the neuron; $h_{ci}(t)$ is called neighbourhood function and expresses how the b.m.u. and its neighbours are modified when activated by a signal; usually, the linear or Gaussian versions are used. This process is repeated over many cycles before the training is finished. The neighbourhood function depends on several parameters relevant for this stage: the distance between the b.m.u. and the modified neuron (so the further away the neuron is, the smaller the adjustment); a learning rate $\alpha(t)$ that defines the magnitude of the adjustment, and gradually decreases as the training cycles advance; and the neighbourhood radius, which decides which of the surrounding neurons of the b.m.u. are also modified, and also decreases over the training stage and the self arranging (organization) of the input observations.

This procedure may be used as a visualization tool for multidimensional datasets as well as a clustering method. In the first case, one would want to see how the different observations are mapped into the SOM to discover (dis)similarities, making use of the topological preservation of the statistical characteristics, and study how the different dimensions are distributed; in the second one, the network would have a relatively small number of neurons (as many as clusters one would want to obtain) and one would focus on analyzing which observations are grouped with which.

The description of SOM given above (also referred as unsupervised SOM) focusses on unsupervised exploratory analysis. However, SOMs can be used as supervised pattern recognizers, too. This means that additional information, e.g., class information, is available that can be modelled as a dependent variable for which predictions can be obtained. The original data are often indicated with X; the additional information with Y. An approach suggested by Kohonen [27] for supervised SOM is to perform SOM training on the concatenation of the X and Y matrices.

Although this works in the more simple cases, it can be hard to find a suitable scaling so that X and Y both contribute to the similarities that are calculated. Melssen et al. [28] proposed a more flexible approach where distances in X and Y space are calculated separately. Both are scaled so that the maximal distance equals 1, and the overall distance is a weighted sum of both:

$$D(o, u) = Dx(o, u) + (1 - \alpha)Dy(o, u) \qquad (4)$$

where, $D(o, i)$ indicates the combined distance of an object o to unit u, and Dx and Dy indicate the distances in the individual spaces. Choosing $\alpha = 0.5$ leads to equal weights for both X and Y spaces. Scaling so that the maximum distances in X and Y spaces equal one takes care of possible differences in units between X and Y. Training the map is done as usual; the winning unit and its neighbourhood are updated, and during training the learning rate and the size of the neighbourhood are decreased. When compared to other neural network based approaches, it shall be noted that in SOM - the neurons are arranged on a flat grid not as a multilayer perceptron (input, hidden, output).

3. PROPOSED APPROACH (SOMP)

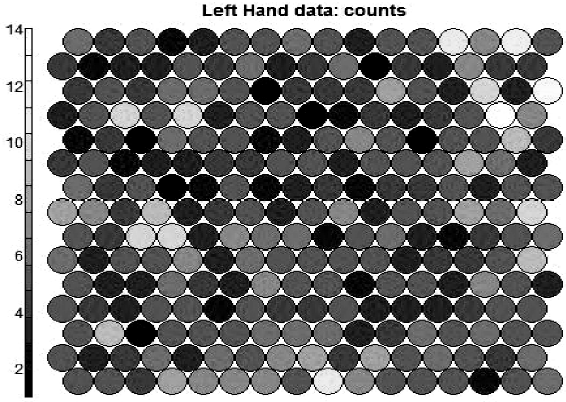
SOM has been used for palm print recognition and hence call the approach as SOMP. The input layer consists of m source nodes, where m is the dimensionality of the input vector x. The set of input data in our case refers to the set of images that is used; the observations refer to the pixels present in each image. In our case, the dimensionality of the input vector is 625 (this is because of the normalized size of the palm print image that is used – 25 x 25 size). The output space is an array of a x b neurons (nodes) topologically connected following a kind of geometrical rule (a rectangular topology has been used). In our case a = 15 and b = 16. The experimental results obtained using SOM in unsupervised mode and supervised modes are explained in the next section.

4. EXPERIMENTS & RESULTS

4.1 PALMPRINT DATABASE

This paper uses the preprocessed palm print (left hand and right hand) dataset obtained from IIT Delhi [25]. There are 235 subjects. Each subject has 5 images each for left and right palm prints.

The first experiment which was performed was to find the total number of output nodes which are required. Unsupervised SOM was ran over the given 235 image related palmprint dataset. In the plot shown in Fig.3, the background color of a unit corresponds to the number of samples mapped to that particular unit; one shall observe that they are reasonably spread out over the map (one unit is empty for left hand and two units are empty for right hand: no samples have been mapped to them). The plot in Fig.4 shows the mean distance of objects, mapped to a particular unit, to the codebook vector of that unit. A good mapping should show small distances everywhere in the map. These show that the number of output nodes which are chosen (15x16) are good enough for our purpose.



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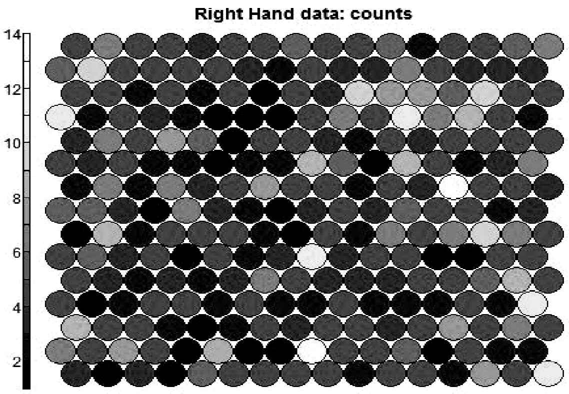
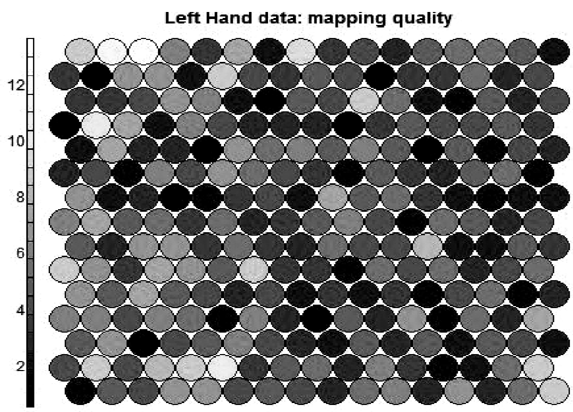


(b)

Fig.3. (a) left hand (b) right hand: Counts plot of the map obtained from the Palmprint dataset. Empty units are depicted in gray. The color in each cell represents the number of Palmprint images which went into that went into that cell



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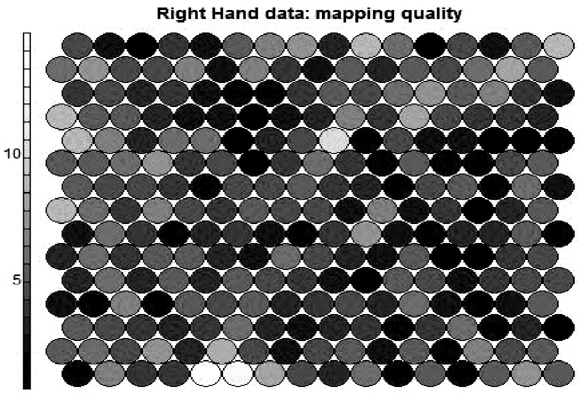
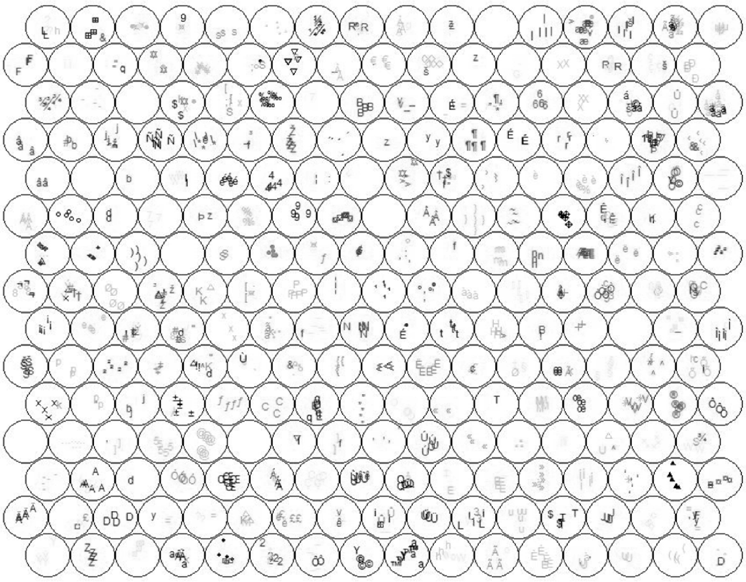


(b)

Fig.4. (a) left hand (b) right hand: shows the quality of the mapping

The second experiment which was performed was to do an exploratory analysis using unsupervised SOM. Fig.5 shows the mapping of images related to unsupervised SOM. Each color/shape in the figure is used to represent a particular subject. From the dataset, one shall infer that each subject has 5 Palmprint images related to him which are more or less mapped into different unique cells. Fig.5 reveals this out clearly. For instance in Fig.5(b), if one looks at the first cell, approximately 5 similar units are mapped onto that cell. The similar units indicate that they belong to the same subject. This explains that even without any training, unsupervised SOM was able to more or less grossly able to put the subjects into different cells. The error rate in grouping in this case was observed to be approximately 27% (out of the 1175 images of 235 subjects, 858 went into the appropriate cells which belonged to similar subjects and 317 images did not gets mapped properly).



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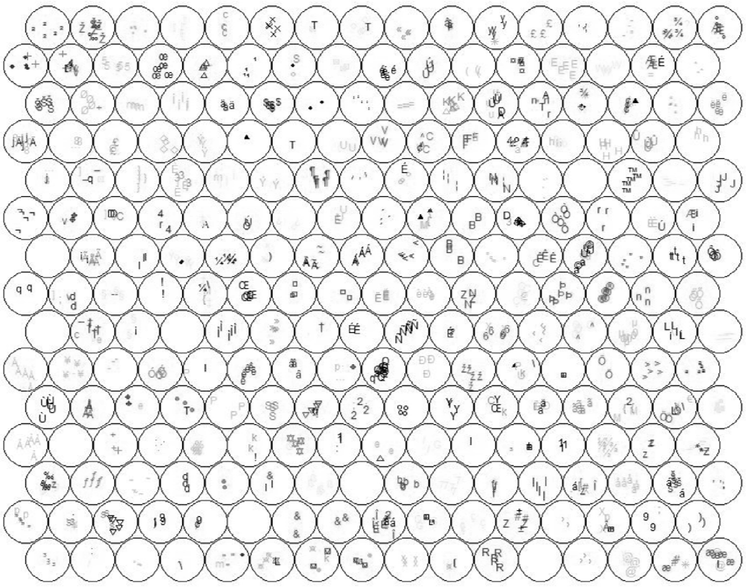

(b)

Fig.5. (a) left hand (b) right hand: Mapping of the 235 Palmprint subjects in a fifteen-by-sixteen SOM

The third experiment that was used is to use the classifier information – information related to which image belonged to which subject using supervised SOM. In this experiment, the subject has been considered as the dependent variable (variable Y as explained in the earlier section) and the pixel values of the image as the independent value (variable X as explained in the earlier section). 2 random images from each subject has been chosen for training and the rest of the 3 images of each subject has been used for testing. The weights for X and Y has been varied with supervised SOM and the following characteristics as mentioned in Table.1 has been observed (the weights in a way indicate the relative strength between X and Y for recognizing a subject).

Table.1. Error rate with supervised SOM by varying X and Y weights

X Weightage	Y Weightage	Error Rate
0.9	0.1	19.7
0.8	0.9	17.2
0.7	0.3	14.8
0.6	0.4	13.5
0.5	0.5	12.7
0.4	0.6	10.9
0.3	0.7	9.7
0.2	0.8	6.1
0.1	0.9	5.3

The above Table.1 shows that, if one uses the classification information also (using supervised SOM), then the recognition rate improves significantly (when compared to not using it – as earlier seen with unsupervised SOM). The fourth experiment that was conducted was to vary the number of images used for training and testing. For this experiment, the weight of X has been chosen as 0.1 and weight of Y has been chosen as 0.9. Table.2 shows the inferences of this experiment.

Table.2. Error rate with supervised SOM by varying the number of images for training and testing

No. of Images for Training	No. of Images for Testing	Error Rate
1	4	11.2
2	3	5.3
3	2	4.8
4	1	4.2

The fifth experiment that was done was a comparative analysis of SOMP with other standard methods. Table.3 and Fig.6 shows the comparative results between Eigen Palm (PCA), Fisher Palm (FLD) and Self Organizing Map for Palm print (SOMP).

The size of the training set varied from 1 to 4 images per person and the remaining of the images for each subject form the test set. For the PCA and the FLD, the experiments that were conducted showed that all the training images during the training phase are classified correctly (Table.3). On the other hand, the SOMP could not classify correctly all the training images. Furthermore, Fig.6 and Table.3 shows a greater improvement in the performed experiment with SOMP than PCA or FLD when using one number of training sample for each person. Using SOMP with one image per person during training phase gives 11.3% error recognition rate (incorrectly classified 107 images of 940 test images) against 19.3% error recognition rate (incorrectly classified 181 images of 940 test images) using the PCA, and 17.7% error recognition rate (incorrectly classified 166 images of 940 test images) using the FLD method.

Table.3. Test error recognition rate (%) with varying number of images per person

Number of training images per person	Number of testing images per person	Training phase			Testing phase		
		Eigen Palm	Fisher Palm	SOMP	Eigen Palm	Fisher Palm	SOMP
1	4	0	0	0	19.3	17.7	11.2
2	3	0	0	2.8	14.8	12.9	5.3
3	2	0	0	3.5	10.2	8.3	4.8
4	1	0	0	3.7	8.5	7.8	4.2

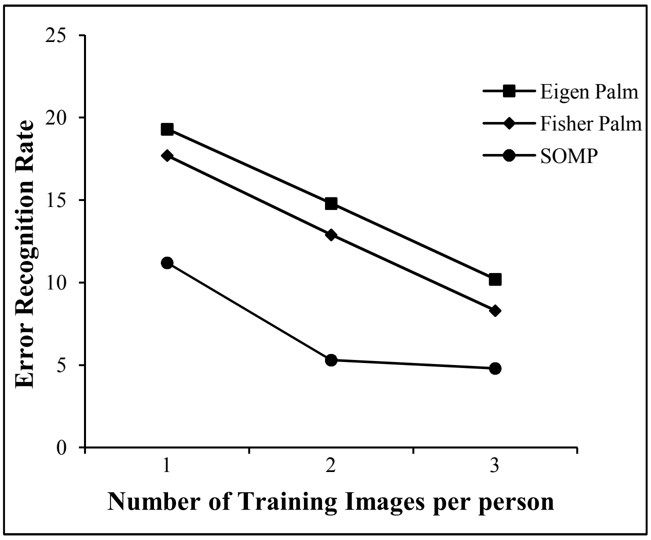

Fig.6. The error recognition rate with varying number of training images per person in PCA (Eigen palm) FLD (Fisher palm) and SOMP. The x axis represents the number of images used for training and the y axis represents the error rate

Table.3 shows that SOMP can provide an improvement in error recognition rate when compared to the other standard approaches based on literature.

Opencv libraries [29] have been used for image processing and statistical R [30] has been used for the SOM experiments. All the software code, datasets, image results are archived for reference purpose at [31].

5. CONCLUSION

A new feature extraction metric (named SOMP) has been proposed. SOMP has been shown both in unsupervised case and supervised case. It is shown that the proposed SOMP method improves the performance and robustness of recognition when compared to methods proposed in literature.

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