Offline Handwritten Signatures Features Extractions and Classifications Using Hybrid Transform & Self-Organizing Feature Map

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ABSTRACT

In this paper images of signature have been introduced to sequences of transforms, to obtain the final features of the given image. The hybrid transform has been used which transforms images of signature into another form such that it is partially invariant to scale and rotation. The transforms used in this research, such as 2-D Fast Fourier Transform, Radon Transform, 1-D Inverse Fast Fourier Transform and 1-D Discrete Multiwavelete Transform have been considered for feature extraction. In the hybrid transform, images of the signature have been introduced to the sequences of transforms, to obtain the final coefficients matrix of the given image. The obtained transform coefficients can be as affine invariant pattern features. The experiments showed that a small subset of these coefficients is enough for reliable recognition of complex patterns. A Dataset of personal signatures had been collected and used from homogenous groups of people in the implementation of the hybrid transform. Then Kohonen Self Organizing Feature Map (SOFM) for pattern clustering has been used to cluster the discriminated information vectors extracted from the hybrid transforms matrix's coefficients. The variations of the transforms used in order to improve generalization and performance with (95%) accuracy on 9 classes of signatures. The proposed technique in this research can serve as a step in the pre-processing computer vision in which capable of recognizing the signature and identity of the signatory.

Author Key: Offline signature recognition, Two Dimensional Fast Fourier Transform, Radon transform, One Dimensional Inverse Fast Fourier Transform, One Dimensional Discrete Multiwavelet Transform, and Self Organizing Feature Map.

المستخلص

في هذا البحث تم استخدام صور تواقيع الاشخاص في متواليات من التحويلات وذلك للحصول على الخصائص النهائية لكل توقيع. التحويل الهجين الذي استخدم يقوم بتحويل التواقيع الشخصية إلى شكل آخر يكون غير متأثرجزئيا بالتدوير والتقييس.ا لتحويلات المستخدمة في هذا البحث هي تحويل ٢-D فورييه السريع، تحويل الرادون ، تحويل ١-D معكوس فورييه السريع ،و تحويل١-D المتقطع للمويجات المتعددة جميعها استخدمت لاستخراج الخصائص الخاصة بالتواقيع الشخصية. في التحويل الهجين ، أدخلت صور من التواقيع الشخصية إلى متواليات من التحويلات، للحصول على معاملات المصفوفة النهائية لصورة معينة. ان المعاملات التي تم الحصول عليها ذات ميزات نمطية ثابتة. وأظهرت التجارب أن مجموعة صغيرة من هذه المعاملات تكون كافية في عملية تعرف موثوقة للأنماط المعقدة منها. وقد استخدمت قاعدة بيانات من التواقيع الشخصية والتي تم جمعها من مجموعات متجانسة من الاشخاص وذلك في تنفيذ التحويل الهجين، ثم استخدمت طريقة خريطة التنظيم الذاتي للخصائص لكوهونين الخاصة بفصل المجموعات النمطية وذلك لفصل الخصائص المميزة والمتشابهة لكل نمط والمستخرجة من مصفوفة المعاملات الخاصة بالتحويل الهجين. الأشكال المختلفة من التحويلات تستخدم من أجل تحسين التعميم، مع دقة أداء مقداره (٩٥٪). التقنية المقترحة في هذا البحث يمكن أن تكون بمثابة خطوة في المعالجة التمهيدية لتطبيقات الحاسوب القادرة على التعرف على التوقيع و هوية الموقع.

1-Introduction

Recently commercial products such as computers, mobiles, tablet PC, PADs and others incorporating the process of signatures recognition. Signatures recognition is defined as “the ability of a computer to receive and recognize signature input from sources such as paper documents, photographs, touch-screens and other devices”[1]. In principle there are two ways to recognize signature, online and offline, the online method considered to be simpler than the offline method because its depend on previously collected information regarding the tracking of the movement of the tip of the pen, while the offline method attempted to recognize the images of the signature after long process of scanning the document, scanned image preprocessing and feature extraction, classifications and recognition.

"The preprocessing usually consists of binarization, normalization, sampling, smoothing and de noising for signature extraction"[10]. Feature extraction methods used to extract most distinguishable features in the image to be used as a measure of similarity between objects of similar group. For the classification and segmentation process in which similar group of objects can be classified or clustered in the same class, Kohonen Self Organizing Feature Map [3] for pattern clustering has been used to cluster the discriminated information vectors extracted from the hybrid transforms matrix's coefficients.

Each subject's signature has more than one form depending on variety of reasons, the signatures are handwritten, where the components are joined together, this make the task of feature extracting more difficult task.

In this research the attempt is made to overcome some of the above mentioned difficulties in which face the task of recognition, such the problem of partial rotation and scaling of the signatures. The suggested approach is to transform the image from the special domain into the frequency domain using a sequence of transforms to extract affine invariant features to be used in the process of signature recognition process.

In general transforms provide information regarding the spatial frequency content of an image. The transform maps image data into a different mathematical space via transformation equations. It maps the image data from the spatial domain to the frequency domain (also called the spectral domain). These transforms are used as tools in computer imaging. The goal in pattern recognition is to extract information useful for the recognition task and this is done by reducing the amount of image data with the transformations. The images then are modified from the lowest level of pixel data into higher-level representation. Now the feature extraction is considered to solve the recognition problem. The image transforms provides features based on spatial frequency information-spectral features. The method suggested here applies affine invariant feature extraction to the images; each image is described by a subset of hybrid transform Coefficients [2].

These coefficients characterize the image features which allow form compact and meaningful feature vector. Then Self-Organizing Feature Map neural network [3] is used to arrange the feature vectors on the map according to their topological relationship order. Non-normalized images causes distortion in which plays an important role in determining the end result of pattern recognition process (face recognition, fingerprint matching, signature matching etc.).

The technique suggested in this paper can serve as a pre-processing step in computer vision applications, without the need to perform the tedious handwork for image normalization (scaling, rotation and alignment). The focus here is on a particular method for handling in variances, which has the capability of extracting all of the invariant features from an image using only a small amount of information about the image (such as a few low of low coefficients). The invariant features extraction separate the problem of finding the image viewing transformations, from the problem of deciding which features of the image are needed for a classification process. Intuitively, affine invariant features are simply a systematic method for transforming from observer–based to image–based coordinates; in the former the image depends on the view, whereas in the latter the image is viewing transformation independent.

The experiments are carried out on a set of signatures taken from dataset of signature for nine different classes' image sets. These signatures images are pre-processed and transformed using the suggested hybrid and the resulting feature vectors are classified using Self-Organizing Map neural network. Three separable classes were presented one for each class of images. The experiment results showed that the method were highly capable of preserving the actual image features invariant to different signature shapes of the same signatory.

The experiment conducted on signature dataset, the dataset is collected from 50 students at computer science department. Signatures were collected after allowing the students to sign on white sheets where each signatory signed ten signatures in different periods of times up to several days between each consecutive signing, thereafter the signed sheets were scanned. The next step was the cropping of the signature images for each individual and these images were stored in separate files to be process in the next step (pre-processing step).

2– Pre–processing

The pre-processing stage is composed of signature cropping, thinning.

1. Signature cropping: Initially, the original colored image is cropped from the white sheet in an approximation size of width and height no precise size is required since the image must be resized in the feature extraction stage.

2. Noise removal: There were not an attempt to remove noise from the image of the signature because the signatures were signed on the white papers prepared in advance; it was not signed on documents or bank statements.

3. Skeletonization: for the purpose of minimizing the thickened line of the signature while maintaining the structure of the original signature structure, thinning algorithm was a morphological operation on binary images [7].

3- The Hybrid.

Recently Walidlet Hybrid Transform is used in image enhancement. The main reason is that a complete framework has been recently built [2]. The structure of the Hybrid transform is given in Figure (1).

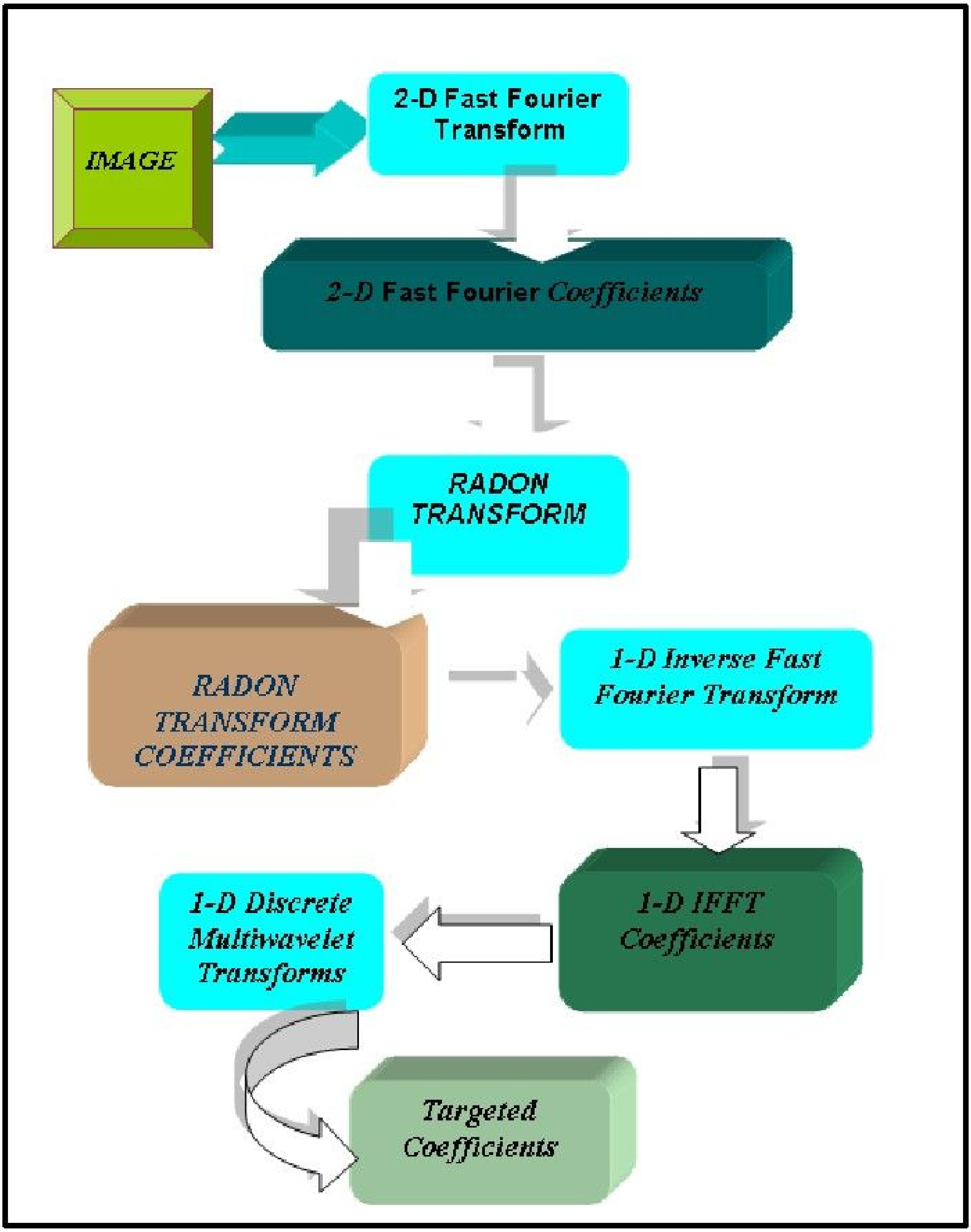

Figure (1) Flow diagram of Hybrid Transform

3.1 Fast Fourier Transform (2-D FFT)

The multidimensional DFT:

$$X_{\mathbf{k}} = \sum_{\mathbf{n}=0}^{\mathbf{N}-1} e^{-2\pi i \mathbf{k}\cdot(\mathbf{n}/\mathbf{N})} x_{\mathbf{n}}$$

"transforms an array $x_{\mathbf{n}}$ with a d-dimensional vector of indices $\mathbf{n} = (n_1, n_2, \ldots, n_d)$by a set of d nested summations (over $n_j = 0 \ldots N_j - 1$ for each j), where the division $\mathbf{n}/\mathbf{N}$, defined as $\mathbf{n}/\mathbf{N} = (n_1/N_1, \cdots, n_d/N_d)$,."[4].

3.2 Radon transform [5]

"Let f(x) = f(x,y) be a continuous function vanishing outside some large disc in the Euclidean plane R_2. The Radon transform, Rf, is a function defined on the space of lines L in R_2 by the line integral along each line:" [5]

$$Rf(L) = \int_L f(\mathbf{x})\,|d\mathbf{x}|.$$

3.3 Inverse Fast Fourier Transform (1-D IFFT) [6]

The inverse discrete Fourier transform (IDFT) is given by

$$x_n = \frac{1}{N} \sum_{k=0}^{N-1} X_k e^{\frac{2\pi i}{N} kn} \qquad n = 0, \ldots, N-1.$$

"A simple description of these equations is that the complex numbers X_k represent the amplitude and phase of the different sinusoidal components of the input signal x_n." [6]

3.4 Multiwavelet transform

Multiwavelets provide one alternative to the wavelet transform. "Despite its general success, the wavelet transform often fails to accurately capture high frequency information, especially at low bit rates where such information is lost in quantization noise". [9]

4. Feature Vectors Extraction

Before proceeding with feature extraction, no normalization step is performed on the signatures images selected, regarding the translation, rotation and scaling and no lighting equalization is performed. Hybrid transform is performed on the whole image but the hybrid coefficients will be considered only in the column wise aspect. The first four columns of the coefficients matrix are considered (Low resolution information). There is no need to consider more columns because, the size of the coefficients is becoming too large and no more valuable information is obtained. Therefore, the signatures images are described by 256 hybrid coefficients vector which represents reasonable amount of information. It is important to take decisions only on the most essential, so-called discriminatory information, which is conveyed by the extracted features. Each of the 256 coefficient vectors contains information about the signatures images.

4.1 Feature Vectors Clustering

The problem is how to face the dimensionality reduction? An efficient way of reducing dimensionality and clustering expression information is to compute the topological relationships between these feature vectors. Thus, Self Organizing Map neural network is used, the dimensionality is reduced to two dimensions instead of 256.

4.2 Discriminate Feature's Vectors of hybrid transform.

Several experiments have been performed to decide which columns among the first four coefficients columns of the hybrid transform may hold the most discriminating information. Self-Organizing Map neural network is used to show the topological relationships between these features vectors regarding the entire facial image data collected from the set of the facial images.

4.3 The experiment conducted and the result obtained:

The experiment is performed as follows:

١) Several different signatures images selected from the Dataset, each one is for different person. (Figure 3).

٢) The Hybrid Transform is applied to these collected images individually to obtain the coefficient matrix for each single image figures (5 &6).

٣) The first four columns coefficients of the hybrid transform final matrix are extracted for each image of the total 40 images.

٤) Each signature then has its own file that contains four sub-files one for each different column (column 1, column 2 column 3 and column 4) a total of 264x4 sets of data.

٥) All the coefficients for all signatures images for each column are appended to construct a source file, a total of 40 sets of data for each column.

٦) In order to cluster the coefficient vectors for all signatures images, the Self-Organizing Feature Map neural network is used which is considered an unsupervised classification method.

٧) The SOFM is applied to the coefficients columns constructed in step 6. The clustering of the image coefficients, such that similar coefficient vectors are grouped together. From the experimental work done on all the four columns, column one is found to be the most significant feature vector in which capture the features irrelevant to the signatories. Therefore only column one is considered in this study and neglecting columns (2, 3 and 4).

In figure (2) below samples of signatures are presented before and after skeletonization operation had been attempted:

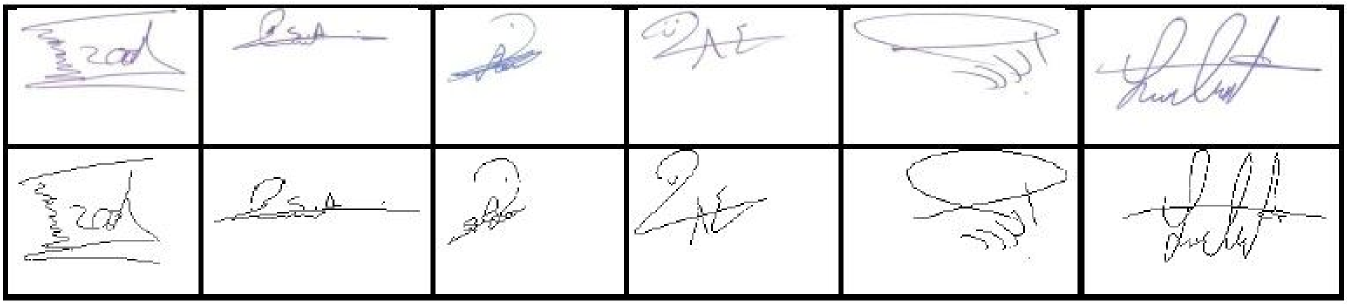

Figure (2) Thinned signature sample images

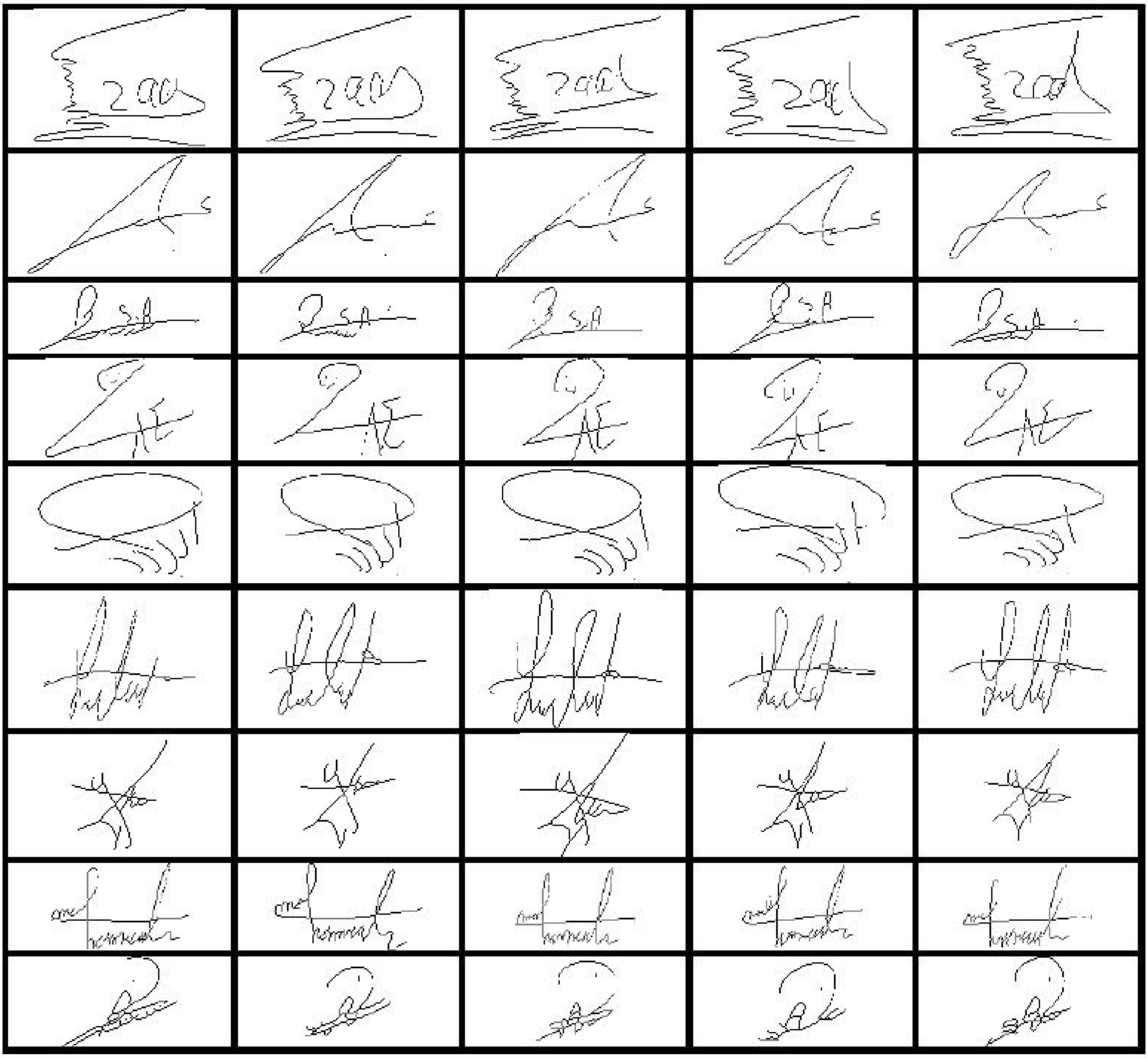

Figure (3) a sample of signatures images

for five different signatories signature instances (5 columns) written by nine different signatories s (9 rows) one row for each signatories .

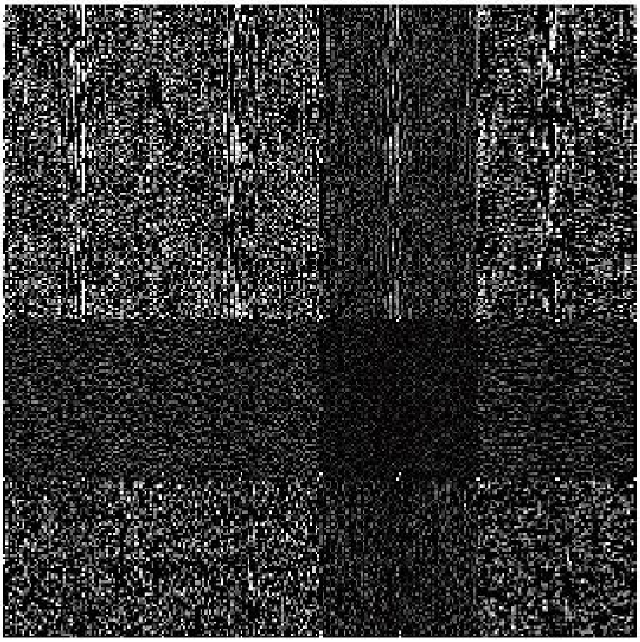

Figure (4) Hybrid transforms coefficients' representation.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0		#4		#3		#22			#27		#28	#29		#30		#32	#34
1		#0					#24		#25			#26		#21			#31
2																	
3	#49		#47		#2		#1			#23				#15			
4												#20					#14
5	#45			#12						#13							
6						#11		#38				#48		#16			#33
7				#10						#35							
8														#39			
9				#18					#37		#46						#36
10		#19											#40				
11																	
12				#17					#42		#43				#44		#41

Signatory 1 0-4	Signatory 2 10-14	Signatory 3 15-19	Signatory 4 20-24	Signatory 5 25-29	Signatory 6 30-34	Signatory 7 35-39	Signatory 8 40-44	Signatory 9 45-49

Figure (5) SOFM's nodes clusters for 45 patterns, using hybrid Transform coefficients for five signature signed by nine signatories s labeled from 1-45, presented on their relative feature's position on the (13x17) map of the self-organized feature map neural network.

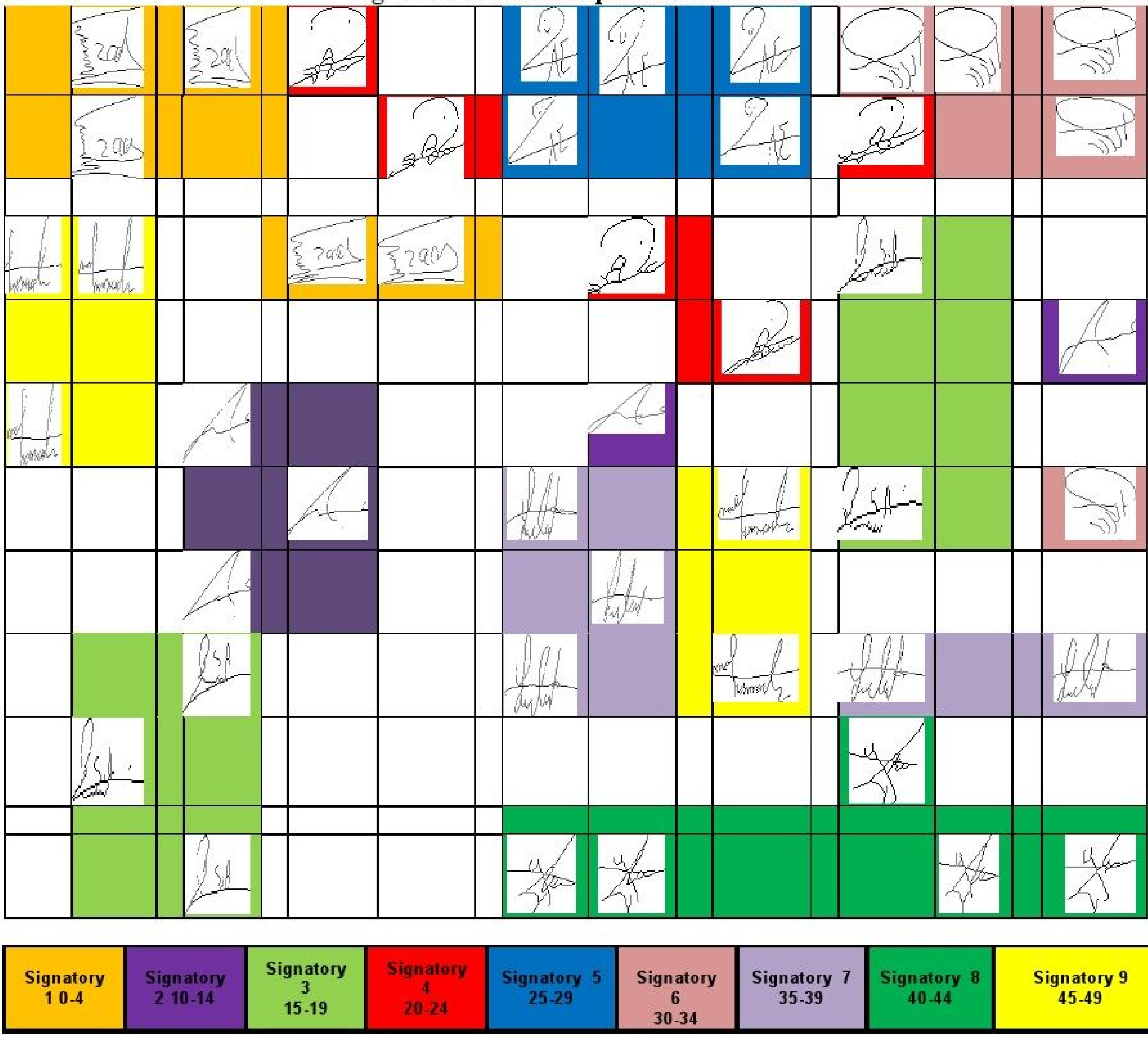

Figure (6) SOFM's nodes clusters for 45 images, using hybrid Transform for five signature signed by nine signatories s, presented on their relative feature's position on the map of the self-organized feature map.

The summary of SOFM parameters used is shown in (Table 1) and the topological relationships between the signatures images coefficient vectors are shown in (Figure 5 & 6).

Pattern Vector Size	No. Of Patterns	Map size	Accepted Error	No. of iterations (Epochs)	Convergence Time
264	45	13X17	1.E-7	<8000	4.5 minutes

Table 1 Parameters used in SOFM for the classification task.

In order to determine the ability of the Hybrid Transform to capture the signatures images identity's discriminatory information, the code-book vectors (every node in the map may be thought of as code-book vector) are compared with each input vector (45 image vectors). Since the labels of the input vectors are arranged in ranges according to different signatures images, then every node on the map is labeled by assigning it a label of the input vector most similar to it (difference value between the two vectors is less than 1.E-7). This allows the topological structure of the map to be examined as shown in Figure 5&6). The detail clustering information is presented in (Table 2). It can be observed from the results presented in the first column map and as shown in (Figure 5&6) that the hybrid transform possesses the following properties:-

The pattern identity is not filtered out by the transform, so that the different signatures patterns for the same signatories are well clustered within their similar pattern group. This property is considered most important in pattern recognition, since the identity features could not overcomes by the identity of different signatories' features.

The clustering efficiency is described using equation (3) in which calculate the overlapping of signatures patterns.

The Clustering Efficiency:

$$\frac{(\text{Number Of ClusterNodes}) - (\text{Number Of NonClusterNodes})}{(\text{Number Of PatternNodes})} \quad \text{............ (3)}$$

The results of (Table 2) show the clustering efficiency with overlapping percentage for each signatory were no overlapping had occurred except for three clusters. The test showed that the clustering efficiency with overlapping percentage was 95%.

Feature similarity is also calculated for each group to measure the overall similarity efficiency for the hybrid approach suggested. The similarity measure represents the missing signatures in which they do not classified in their own classes (in our case 9 classes or groups). The Feature similarity measure is calculated according to the following rule:

$$\text{Feature similarity measure} = 1 - \frac{\textit{Missed signatures of a class}}{\textit{No.of signatures in the same class on the Map}} x100$$

Cluster No.	Singer No.	Nodes in Cluster	No. of Overlapping	Overlapping Percentage	Cluster Efficiency
1-1	Signatories 1	3	0	0%	100%
1-2	Signatories 1	2	٠	%٠	100%
2-1	Signatories 2	3	0	0%	100%
2-2	Signatories 2	2	2	40%	60%
3-1	Signatories 3	2	٠	0%	100%
3-2	Signatories 3	3	٠	0%	100%
4-1	Signatories 4	2	٠	0%	100%
4-2	Signatories 4	2	٠	0%	100%
4-3	Signatories 4	1	1	20%	80%
5	Signatories 5	5	٠	0%	100%
6	Signatories	٥	1	20%	80%

	6				
7-1	Signatories 7	3	0	0%	100%
7-2	Signatories 7	2	0	0%	100%
8	Signatories 8	5	0	0%	100%
9-1	Signatories 9	3	0	0%	100%
9-2	Signatories 9	2	0	0%	100%

Table 2 Clustering Efficiency with overlapping percentage

Signatories	Missed of a class	No. of signatures in the same class on the Map	similarity measure percentage
Signatory 1	0	5	100%
Signatory 2	2	5	60%
Signatory 3	0	5	100%
Signatory 4	0	5	100%
Signatory 5	٠	٥	100%
Signatory 6	1	5	80%
Signatory 7	0	5	100%
Signatory 8	0	5	100
Signatory 9	0	5	100
Total	3	50	93%

Table 3 Feature similarity measure

Table (3) above shows that the overall Feature similarity measure was 93%, in which considered a very good result regarding feature extracting problem for a difficult task of signatures classification problem.

The analysis of such little deficiency in the result is attributed to the lack of homogeneity of the signatures of the signatories of the groups affected by the results of the proficiency. The hybrid transform performed very well regardless of the relative signature style differences encountered in most of the groups of signatories.

In most cases the homogeneity of the signatures was accepted to some limitations, therefore we can observe some shifting in the position of the features on the map of the same group. At the same time the prodigal signatures (not in their related class or group) were extremely varied and not similar in their

shapes. We believe that if the signatures are collected from experience people in whom they spend long time practicing their signing process, the result will be dramatically different on the map.

5- Conclusions

The hybrid Transform is used in order to capture the discriminating information for each basic handwritten signatures image. The SOFM neural network is used to cluster the feature vectors extracted from hybrid coefficients, using a feature map of (n X m) pattern nodes. Only low resolution information is extracted from its coefficient matrix, this information lie in first coefficient vectors. Research shows that the first column is the most significant in its discriminating power. The test showed that the clustering efficiency with overlapping percentage was 95%. The overall Feature similarity measure was 93%. It can be concluded from these results that, the hybrid coefficients of low resolution can be used as a discriminating features for the task of signature images recognition invariant to rotation scaling and translation with a very high percent of accuracy. The interesting features of this Hybrid transform are as follow:

١- **Its ability to capture the images without normalization which is considered an excellent achievement since the process of precise normalization is a quite expensive task in terms of the time and efforts. Even with an automatic normalization a human subject must interfere at one or more stages of the process.**

٢- **The signatories' identities not filtered out by the transform, so that different pattern images for different signatures of the same signatories are well clustered within their own pattern groups (same signature group). This leads to clustering all the pattern images of the same object in one group regardless of the texture is involved.**

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