Performance Evaluation of New Feature based on Ordinal Pattern Analysis for Iris Biometric Recognition

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Abstract—The Iris recognition technique is currently the most efficient biometric identification system and is a common system on the practical front. Though most of the commercial systems use the patented Daugman's algorithm, which mainly uses wavelet-based features, research is still active in identifying novel features that can provide personal identification. Here the first novel proposal of using ordinal pattern measure based on nonlinear time series analysis is put forth to characterize the unique pattern of the iris of individuals and thereby perform personal identification. Dispersion Entropy is a nonlinear time-series analysis method highly efficient in the characterization of the complexity of any data series with proven effectiveness in the characterization of model system dynamics as well as real-world data series. The results show that dispersion entropy can be used to identify iris images of specific individuals. The efficiency of this method is evaluated by computing correlation and RMSE between dispersion entropy values of normalized iris image rubber sheet data. The experimental results on the popular IRIS database- CASIA v1- demonstrate that the proposed method can effectively perform differential identification of iris images from different individuals. The results specifically indicate that the density of information along the angular direction of iris images which falls along the rows of rubber sheet data. This can be efficiently utilized with the method or ordinal pattern characterization and proves to be having promising potential for being incorporated into biometrics personal identification systems.

Keywords—Dispersion entropy; iris recognition; rubber-sheet data; ordinal patterns; correlation

I. Introduction

In the past few decades, Iris recognition system has gained the status of the most reliable biometric authentication system. The highly unique pattern for every individual iris has a wealth of texture detail which makes this system extremely outstanding compared to other physiological biometric features like face, palm print, and even fingerprint features. Iris pattern-based Personal Identification system gained popularity because of this texture patterns long-term stability with respect to aging and other physiological changes. Iris is defined as the colored muscular diaphragm located behind the cornea of the eye. It surrounds the pupil sharing a common center with it and controls its size to adjust the amount of light entering through it. It has been scientifically and genetically proven that the microstructure of the iris region of an individual is extremely unique and distinct with respect to

characteristics like shape, size, and shading, thereby sufficient enough to establish a person's identity [1].

Texture analysis in two-dimensional images is generally carried out using methods like Gray Level Co-occurrence matrix and texture entropy [2]. Recently, new approaches based on the quantification of image irregularity using nonlinear measures have proven to be efficient in the characterization of fine details of two-dimensional images [3]. Successful applications of such methods in the characterization and analysis of small fine textural details of images in various technological as well as biomedical fields have been reported in the literature [4]. Efficient characterization of the iris patterns is an ever-demanding research topic due to the fact that its success and failure will lead to extremely sensitive outcomes related to national and international security and related contexts, as well as the reliability of general commercial applications. An application of an efficient nonlinear method of dispersion entropy for iris image characterization and personal identification is proposed in this work. Nonlinear methods-based image processing is a very recent proposal, and only a few reports are available in the literature. These proposals are mainly based on two-dimensional extensions of measures like sample entropy [5], distribution entropy [6], and dispersion entropy [7]. Among these measures, dispersion entropy is focused on overcoming the drawbacks of all its predecessors. It is proven to be extremely efficient in the characterization of one-dimensional as well as multi-dimensional signals, including images [8][9].

Complexity analysis of the dynamical system, as well as real-world systems and signals using the nonlinear time-series analysis method, has gained extreme popularity among the research community and has successfully marked its own place in potential real-world application [10]. The entropy concept can be used to measure the complexity of signals and, thereby, their related system. High complexity is represented using high entropy values, whereas lower entropy values indicate more regularity of a time series [11]. Earlier methods like approximate entropy, sample entropy, permutation entropy, and distribution entropy were reported to be successful in the characterization of the complexity of short time series from various real-world systems [12]. Later research on these measures revealed shortcomings of these measures related to amplitude and noise ratios. Dispersion entropy was later proposed as a fast and powerful approach,

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together with successfully overcoming the drawbacks of the above-mentioned measures. The two-dimensional extension of all these measures, including dispersion entropy, has been reported for the characterization of image texture. When applied to image texture characterization, a high value of entropy indicates that the pixel values have high variance, whereas a low entropy value means the pixel values are relatively uniform. Among these measures, dispersion entropy is proven to be a fast and efficient method for the characterization of both small and large-scale image texture [13].

Considering the efficiency of dispersion entropy of both one and two-dimensional in the characterization of fine-scale irregularities, among all such analysis measures, it is proposed to apply this measure for the characterization of the texture feature of the iris image. Also, the peculiarity in the spread of patterns along the radial directions in iris images is of special concern while applying any measures for iris texture characterization. To the best of the current knowledge, this is the first proposal of applying nonlinear measures of time series analysis for the purpose of feature extraction for iris recognition application since the proposal of using fractal dimension for iris classification. However, it is noteworthy that fractal measures are based on conventional nonlinear time-series analysis methods, which are sensitive to noise and short data length [14].

Taking into consideration this peculiarity of iris images, it is proposed the use of one-dimensional dispersion entropy along the radial as well as angular directions to extract the wealth of information embedded in these images [15]. Further, the efficiency of the proposed method in personal identification is evaluated on the freely available dataset CASIA v1 [16].

The texture information contained in the iris images can be efficiently extracted by using the most appropriate methodology of image characterization. The wealth of information contained in iris texture can be efficiently extracted in the form of entropy values calculated based on dispersion entropy. In general, for image analysis, bi-dimensional extensions of the various ordinal pattern entropy measures are found to be useful, of which two-dimensional dispersion entropy ($DispEn_{2D}$) is reported to be comparatively more efficient. However, in iris images, local details spread is distributed in the radial direction, which corresponds to the columns of the rubber sheet images [17]. Correspondingly the information density will be higher along the angular directions of the corresponding rows of the normalized rubber sheet images [18]. In the information theory field, image predictability and regularity are evaluated using the recently developed two-dimensional sample entropy ($SampEn2D$). Though it is efficient in its function, some limitations hold it back. The major limitations: 1) for small images, $SampEn2D$ values are undefined; and 2) for real-world applications, $SampEn2D$ is computationally expensive. These limitations can be overcome by two-dimensional dispersion entropy ($DispEn_{2D}$) measure.

Section II of this paper elaborates the related works and the materials and methods and database descriptions illustrated in Section III. It is then presented the novel methodology for iris recognition by using the computation of Non-linear texture feature extraction. Section IV gives an overview of the experimental analysis and the obtained results of this proposed methodology. The conclusion of this methodology is narrated in Section V.

II. RELATED WORKS

Iris pattern-based personal identification was first proposed in 1987 by Flom and Safir, which further gained substantial research interest in the following years [19]. Further, in 1993, Daugman laid a strong foundation for an iris recognition algorithm based on statistical independence evaluated in terms of the phase-dependent feature of the variation in pixel intensity of the iris image. Applying the Gabor filter and Hamming Distance for the integrodifferential operator, a matching parameter was considered the door-opening for the iris recognition process [20]. For feature matching, many researchers have used Hamming Distance, Euclidean Distance, Weighted Euclidean Distance etc. [21]. Daugman's approach is still considered the most common technique applied to several personal identification and authentication systems till date.

The enormous literature on iris recognition systems can generally be classified into three groups based on the following feature identification technique: 1) Phase analysis, 2) Zero crossing, and 3) Texture analysis. The phase analysis approach follows the Daugman's methodology and related modifications, whereas the zero-crossing approach depends on methods like wavelet features [22]. Image texture-based methodology is a relatively recent approach proposed by Li Ma [23]. Further several other methodologies like Gray Level Co-occurrence Matrix (GLCM) [24] include Auto Correlation Function (ACF), Local Binary Pattern [25], Histogram Pattern [26], Haar wavelet [27], Contourlet [28] and Texture code [29] have been identified for iris recognition purpose. To measure the consistency of the iris image of the same eye, two dimensional correlation filters were used by Kumar et.al. [30].

III. MATERIALS AND METHODS

A. Dataset used

The proposed method is evaluated on a publicly available database which is captured with the help of a CASIA close-up iris camera. The database has 108 individuals, with seven images per individual. Out of the seven images of a single person, the first three images are in session 1, and the remaining four are acquired in session 2. A total of 756 images are available. The images are in JPG format.

B. Image Pre-processing

Iris recognition systems mainly involve the following steps: 1) Iris image capturing, 2) Pre-processing, Iris Localization, and Segmentation, followed by 3) feature normalization of the segmented iris region. In the iris localization step, the inner and outer boundaries of the iris portion are identified based on the Hough transform, which involves the Integro-differential operator and is segmented, as shown in Fig. 1(a). Further, the famous Daugman's algorithm is applied to convert the image from a cartesian coordinate

system to a pseudo-polar system. Thus, using the Daugman's algorithm, the circular-shaped Iris region is converted to a rectangular block of a specific size, as shown in Fig. 1(b). For the images investigated here, this Rubber sheet normalization generated images of size 240 x 20 pixels, which hold an immense amount of unique information about each individual [31].
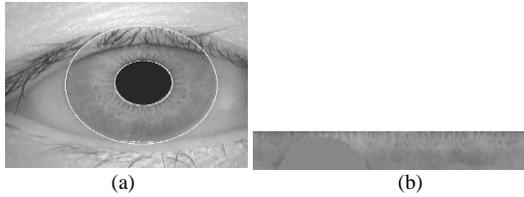

(a)   (b)

Fig. 1.   (a). Segmented Iris, (b). Iris Rubber Sheet Model.

C. Dispersion Entropy

Dispersion entropy is a metric that can be used to evaluate the irregularities of any given time series. The method is economical in terms of computational cost and has proven to be very efficient in characterizing the complexity or orderliness of various real-world time series data [32]. Dispersion entropy is an ordinal pattern-based entropy measure proposed for overcoming the limitations of earlier methods like permutation entropy [33]. Ordinal pattern-based entropic measures are generally evaluated based on the probability distribution of the different possible states of a system estimated from the distribution of its dynamical variables. Sample Entropy can be considered to be the first proposal characterizing uncertainty in system dynamics based on dynamical variables using such probability distribution [34], and has been applied to both signal and image characterization. Though the method was proved to be efficient for such application, in-depth analysis revealed that, certain limitations of Sample Entropy is with respect to signal length. Later research provided better methods like Permutation Entropy which could overcome several limitations of Sample Entropy, but it was again found to fail at certain instances, regarding amplitude differences within a signal [35]. Dispersion Entropy effectively extracts the specific patterns in the ordinal positions of elements in any signal or time series.

For any given time series of 'N' number of elements, $N : x = x_1, x_2, x_3, \ldots x_N$. Multiscale Dispersion Entropy is calculated on coarse-grained versions of the same as follows:

1) The elements x_1 to x_N of the time series are divided into non-overlapping segments of length 'τ'. The average of each segment of length 'τ' is calculated, thereby generating a coarse-grained version of the same time series. $x_{ki}(\tau) = 1/\tau$. In general, for any time series analysis, a range of scale factors 1 to n are chosen. Thus, for a given time series $X = \{x_1 \text{ to } x_N\}$, 'n' different coarse-grained versions are obtained, corresponding to each of the scale factors 1 to 'n'. Further dispersion entropy is calculated, for each of the coarse-grained time series [36].

2) The element of each of the coarse-grained series is mapped to different classes 'c' using linear or nonlinear mapping approaches. Normal Cumulative Distribution

Function (NCDF) is the most generally used function for this purpose. NCDF generates a new series $y = \{y_1, y_2, \ldots, y_N\}$.

3) The new time series y is embedded similar to the approach of Taken's embedding theorem. Thus generating short sequences or embedding vectors Z.

$$z_i^{m,c} = \{z_i^c, z_{i+d}^c, \ldots, z_{i+(m-1)d}^c\}$$

Each short sequence is further mapped to a dispersion pattern

$$\pi_{v_0 v_1 \ldots v_{m-1}}$$

where

$$z_i^c = v_0, z_{i+d}^d = v_1, \ldots, z_{i+(m-1)d}^c = v_{m-1}$$

As every element in any of the coarse-grained series is now represented by integers from 1 to c, according to its class, the number of possible dispersion patterns that can be assigned to each time series $z_i^{m,c}$ is equal to c^m, where 'm' is the number of elements in that coarse-grained series.

4) For each coarse-grained series, the relative frequency of each of the possible dispersion pattern is calculated as follows. $p(\pi_{v0, v1 \ldots vm-1})$

$$= \frac{Number\{i | i \leq N - (m-1)d, z_i^{m,c} \text{ has type } \pi_{v_0 v_1 \ldots v_{m-1}}\}}{N - (m-1)d}$$

Finally, dispersion entropy for each coarse-grained series is defined according to Shannon's information theorem $DE(x, m, c, d)$.

$$= -\sum_{\pi=1}^{c^m} p\left(\pi_{v_0 v_1 \ldots \ldots \ldots v_{m-1}}\right) . \ln \left(p(\pi_{v_0 v_1 \ldots \ldots \ldots v_{m-1}})\right)$$

An extension of $DispEn_{1D}$ is then applied, which is named as $DispEn_{2D}$ to verify the effectiveness of this methodology [37]. The result of both DispEn1D and DispEn2D is illustrated in the following section.

D. Iris Feature Extractions

For extracting the texture information, Dispersion Entropy values of order '4' and delay '1' is computed for every row and column of the rubber sheet matrix corresponding to each iris image of the dataset. The dispersion entropy file size of an image is only 12KB. The size of the images in the dataset is in the range of 70KB to 95KB, whereas its Rubber sheet matrix ranges from 33KB to 44KB. Therefore it is recommended to use this dispersion entropy matrix, which can then be modified to make it a code and stored for further iris matching.

For every image of a given subject, the dispersion entropy of order '4' and delay '1' is calculated for the Rubber sheet matrix of images of the size of 20 rows and 240 columns. Considering each of these rows as $\emptyset_1$ 1-D series dispersion entropy values computed for every row and column of the Rubber sheet matrix of the image. Thus Dispersion Entropy matrix of rows contains 20 values. Similarly, for columns, each column will be represented by one dispersion entropy value, and hence a total of 240 dispersion entropy values will be obtained for columns also. These values can be stored as

the representational feature for use in further recognition processes.

The efficiency of the $DispEn_{2D}$ is verified with real and synthetic datasets in the following sections. $DispEn_{2D}$ is an extension of $DispEn_{1D}$.

E. Iris Feature Matching

Further investigation focused on the match between the iris entropy features of different images of the same person as well as the mismatch between different persons. If this entropy value matches the images of the same person and differs widely between the images of two subjects, then it can be used as an identification feature. The feature-matching process is depicted in Fig. 2. This is carried out as follows. For an iris, Rubber sheet of 20 rows and 240 columns, 20 dispersion entropy values for rows and 240 dispersion entropy values for columns were obtained. The correlation between dispersion entropy sets of every image pair is calculated for images of the same person as well as a different person.
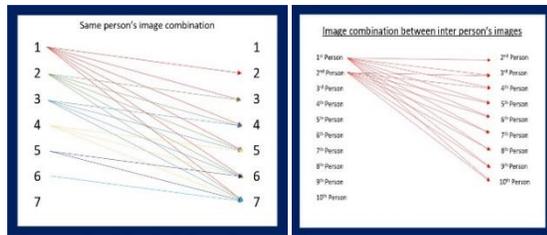

Fig. 2.   Feature Matching Process.

In this work, investigation was carried out to find out the effectiveness of this method in the personal identification and classification of iris images. For this purpose, the iris matching between the images of a person and matching between two different persons were evaluated using correlation values between row-wise and column-wise dispersion entropy. From the two separate plots, it is evident that it should be widely different from the same image of a person with another person's image.

Correlation values are calculated between the dispersion entropies of images of the same subjects and that between different subjects to evaluate the efficiency of dispersion entropy in performing personal identification. These values are calculated for every image pair within the seven images of each subject. The average correlation value for all combinations is used as a measure of match between the dispersion entropies of two images of the same eye of a single subject, represented as $CORR_{same}$. Similarly, these values are calculated for every image pair among all images between each pair of subject combinations. The average values of these measures are calculated for all image combinations for a given subject for all other subjects in the database represented as $CORR_{diff}$. This is performed for the rows and columns separately.

IV. Result Analysis and Discussion

Considering the peculiar nature of pattern spread in iris images, it was hypothesized that one-dimensional dispersion entropy along rows and columns of iris rubber sheets would provide a specific advantage in texture characterization. To test the hypothesis, investigation was done for verifying the differences in values of these measures for the datasets given in section III. The efficiency of the proposed method of feature representation using investigated in terms of $DispEn_{2D}$ as well as $DispEn_{1D}$ along rows and columns for iris recognition purposes is evaluated separately. Subsets of images from the Kylberg dataset and CASIA v1 are chosen for initial screening of the performance of the two measures in the characterization of general texture images and iris images, as well as in representing the uniqueness of iris patterns of individuals.

Four groups of images, such as blanket1, ceiling1, canvas1, and floor1, were used to analyze the textural information. Four sample images from the Kylberg dataset [38] are shown in Fig. 3, and two images of four different persons taken from CASIA v1 are shown in Fig. 4. Table I below shows the $DispEn_{1D}$ for four scale factor values and $DispEn_{2D}$ values of the four texture image samples. Similarly, Table II and Table III show mean values of the $DispEn_{1D}$ for four scale factor values and $DispEn_{2D}$ values of Iris columns and rows, respectively.
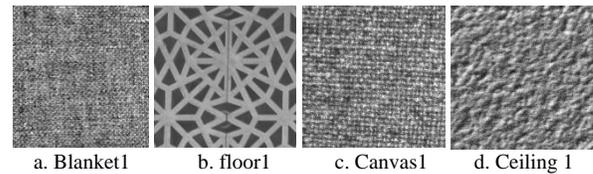

a. Blanket1   b. floor1   c. Canvas1   d. Ceiling 1

Fig. 3.   Sample Set of Images from Kylberg Dataset.

Subject 1a,   1b   Subject 2a,   2b

Subject 3a,   3b   Subject 4a,   4b
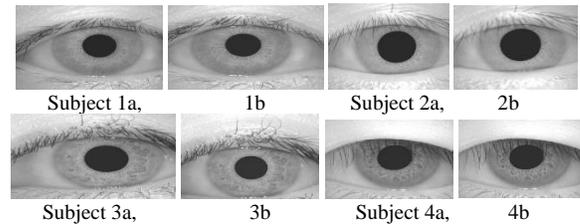
Fig. 4.   Sample Images of 4 Different Subjects from CASIA v1 Dataset.

TABLE I.   DispEn_Texture

		Entropy Values		
		DispEn_Column	*DispEn_Row*	*DispEn_2D*
Blanket 1	Scale1	5.12	5.052	
	Scale2	5.11	4.836	
	Scale3	4.95	4.686	6.735992
	Scale4	4.77	4.537	
Canvas1	Scale1	5.34	5.254	
	Scale2	5.31	5.273	
	Scale3	5.06	5.049	7.262997
	Scale4	4.83	4.825	
Ceiling 1	Scale1	4.88	4.803	
	Scale2	4.75	4.747	
	Scale3	4.65	4.615	6.249361
	Scale4	4.53	4.528	
Floor1	Scale1	2.58	2.543	
	Scale2	2.87	2.827	
	Scale3	3.06	2.997	2.929589
	Scale4	3.20	3.141	

TABLE II.   DISPEN_ IRIS_COLUMN

	DispEn_Column			
	Scale1	*Scale2*	*Scale3*	*Scale4*
1a	3.059	3.264	3.232	3.214
1b	3.197	3.381	3.365	3.344
2a	2.917	3.148	3.160	3.124
2b	2.897	3.111	3.111	3.104
3a	3.131	3.323	3.324	3.304
3b	2.849	3.009	3.007	3.002
4a	2.714	2.872	2.879	2.884
4b	2.889	3.115	3.113	3.126

TABLE III.   DISPEN_IRIS_ROW

	DispEn_Row			
	Scale1	*Scale2*	*Scale3*	*Scale4*
1a	3.680	3.703	3.626	3.567
1b	3.756	3.771	3.663	3.592
2a	3.260	3.351	3.321	3.294
2b	3.163	3.275	3.275	3.243
3a	3.853	3.855	3.754	3.668
3b	3.875	3.891	3.794	3.704
4a	3.571	3.566	3.462	3.388
4b	3.728	3.695	3.572	3.483

Table IV gives the mean correlation and RMSE values between $DispEn_{1D}$ of rows of iris rubber sheets of iris images of every subject in the sample dataset of texture image represented as $DispEn_{1D}\_Row_{same}$. Similarly, Table V gives the mean $DispEn_{1D}\_Row_{diff}$ values of correlation between rows of iris rubber sheets of every image of each of the subjects with every image of all of the other subjects in the sample data taken from CASIA v1. In the same way, mean correlation and RMSE values between $DispEn_{1D}$ of columns of iris rubber sheets of iris images of the same subject as well as different subjects, are listed in Table VI and Table VII. Table VIII and Table IX show the mean correlation and RMSE values between $DispE_{2D}$ between the same subject images as well as between images of different subjects represented as $DispEn_{2D\_same}$ and $DispEn_{2D\_diff}$.

From these values, it can be observed that the correlation values between iris images of the same subject for both rows as well as columns are very high values, all of which fall above 0.95, indicating high similarity, whereas the same values between images of different subjects are all below 0.6. In the case of RMSE, between images of the same subjects are all less than 0.4 and between different subjects is above 0.6. The difference in these values for cases of same subject's images and for images of different subjects is very promising. In the case of $DispEn_{2D}$ the values of correlation and RMSE for images of same subject and those between different subjects in not as widely separated as observed in the case of $DispEn_{1D}$ in both cases of rows and columns. These results indicate the suitability of $DispEn_{1D}$ for personal identification. Further, the efficiency of one-dimensional dispersion entropy for iris biometric identification is explored in the following section, in which its rows and columns features are separately verified.

TABLE IV.   ROW_CORRELATION AND ROW_RMSE FOR SAME SUBJECT.

	scale1		Scale2		Scale3		Scale4	
	Corr	*Rmse*	*Corr*	*RMSE*	*Corr*	*RMSE*	*Corr*	*RMSE*
Sub1	0.99	0.25	0.99	0.21	0.99	0.20	0.98	0.21
Sub2	0.98	0.33	0.97	0.30	0.97	0.25	0.97	0.23
Sub3	0.93	0.39	0.95	0.33	0.95	0.31	0.95	0.29
Sub4	0.96	0.38	0.97	0.31	0.96	0.30	0.96	0.27

TABLE V.   ROW_CORRELATION AND ROW_RMSE FOR DIFFERENT SUBJECT

	scale1		Scale2		Scale3		Scale4	
	Corr	*Rmse*	*Corr*	*Rmse*	*Corr*	*Rmse*	*Corr*	*Rmse*
Sub1	0.9190	0.630	0.928	0.5263	0.93262	0.4565	0.9359	0.40
Sub2	0.9189	0.629	0.9287	0.5252	0.93269	0.4556	0.93592	0.40
Sub3	0.9190	0.629	0.9286	0.5259	0.93265	0.4561	0.93592	0.40
Sub4	0.9191	0.629	0.9287	0.5260	0.93272	0.4563	0.93597	0.40

TABLE VI.   COLUMN _CORRELATION AND COLUMN_RMSE FOR SELF MATCH.

	scale1		Scale2		Scale3		Scale4	
	Corr	*RMSE*	*Corr*	*RMSE*	*Corr*	*RMSE*	*Corr*	*RMSE*
Sub1	0.98	0.29	0.96	0.25	0.64	0.18	0.48	0.08
Sub2	0.99	0.21	0.99	0.17	0.90	0.19	0.36	0.17
Sub3	0.93	0.42	0.86	0.35	0.41	0.29	0.26	0.19
Sub4	0.83	0.19	0.42	0.10	0.29	0.02	1.00	0.00

TABLE VII.   COLUMN _CORRELATION AND COLUMN_RMSE FOR DIFFERENT SUBJECT

	scale1		Scale2		Scale3		Scale4	
	Corr	*RMSE*	*Corr*	*RMSE*	*Corr*	*RMSE*	*Corr*	*RMSE*
Sub1	0.516005	0.641	0.4740	0.373	0.6107	0.133	0.7702	0.053
Sub2	0.516355	0.639	0.4745	0.372	0.6119	0.132	0.7723	0.052
Sub3	0.516314	0.641	0.4743	0.373	0.6115	0.133	0.7724	0.053
Sub4	0.515480	0.643	0.4732	0.375	0.6085	0.134	0.7695	0.053

TABLE VIII.   DISPEN_{2D _ SAME} FOR IRIS

	Corr	Rmse
Sub 1	0.876	0.348
Sub 2	0.887	0.506
Sub 3	0.762	0.458
Sub 4	0.576	0.247

TABLE IX.   DISPEN_{2D _ DIFF} FOR IRIS

	Corr	*RMSE*
Subject 1,3	0.873	0.509
Subject1,5	0.628	0.506
Subject 1,6	-0.445	0.749
Subject 3,5	0.688	0.624
Subject 3,6	-0.377	0.974
Subject 5,6	-0.054	0.608

A. Iris Recognition Analysis using $DispEn_{1D}$

The proposed method of dispersion entropy is applied to iris images of 108 subjects from the CASIA v1 dataset. The dataset contains iris images of 108 subjects; wherein seven images correspond to a single subject. The efficiency of dispersion entropy in characterizing the unique texture of an individual's iris, thereby performing personal identification, is evaluated in terms of correlation, as explained in Section II.

Fig. 5(a-d) depicts the mean values of dispersion entropies of all the images corresponding to each of the subjects along rows, and Fig. 6(a-d) shows the corresponding values for columns. The values of dispersion entropy for the columns fall within the range of 1.8 - 2.8 for scale factor 1 and within the range of 1.5 – 2 for scale factor 2. In the case of rows, the values range between 3 and 4 in both cases of scale factors of 1 and 2. Higher values of dispersion entropy indicate more randomness in pixel intensity values within rows of the Rubber sheet images. It is also noteworthy that in the case of row-wise dispersion entropy, the values are almost in the same range for both instances of scale factors of 1 and 2.

Further investigations on the efficiency of the dispersion entropy feature in characterizing the uniqueness of iris image pattern of an individual and thereby performing personal identification are carried out using a measure of the correlation between different images of the same eye of each of the subjects and between images of eyes of different subjects. Fig. 7(a) to 7(d) show the mean correlation values between row-wise dispersion entropy values of all images of each subject, with its own images represented in green and mean values of correlations between images of each subject with that of all other subjects represented in red. It can be clearly observed that the correlation values between the dispersion entropy of rows of different subjects are lower than between images of the same subject, and these values do not cross over into each other, even in the case of higher scale factors.
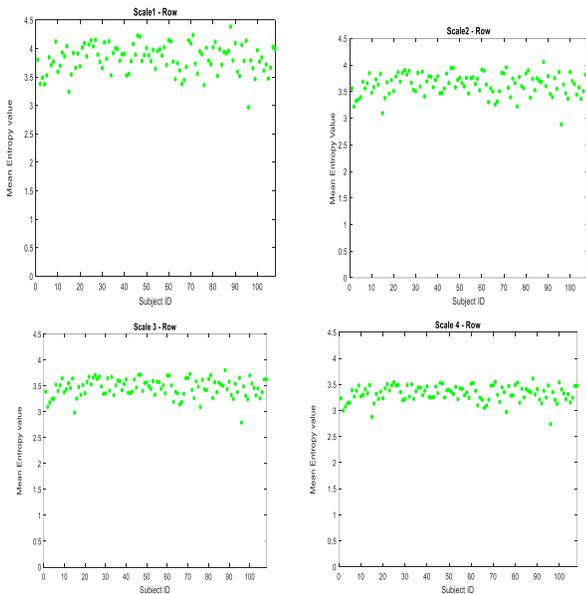

Fig. 5. MVDE Plot, Fig. 5(a) – 5(d). Mean Value Plot for the Row-scale1, Row-scale2, Row-scale3, Row-scale4.
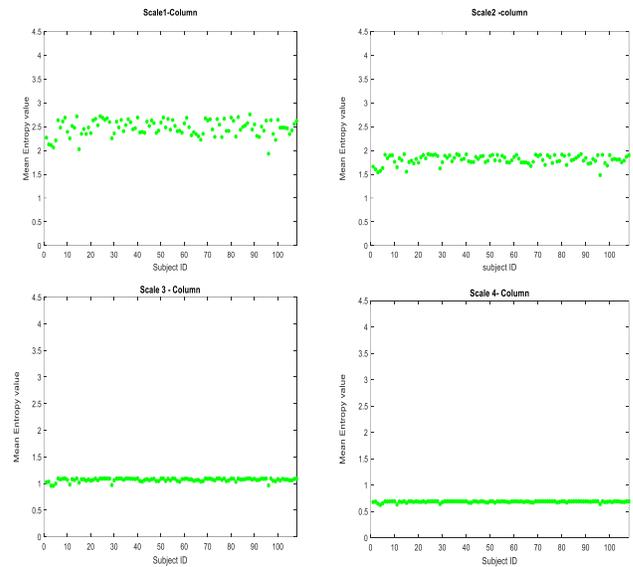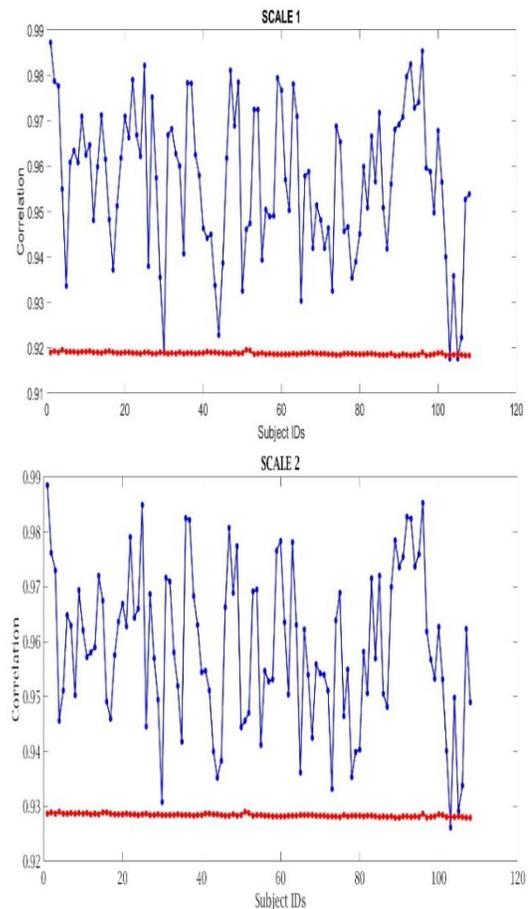

Fig. 6. MVDE Plot, Fig. 6(a) – 6(d). Mean Value Plot for the Column-scale1, Column-scale2, Column-scale 3, and Column-scale 4.
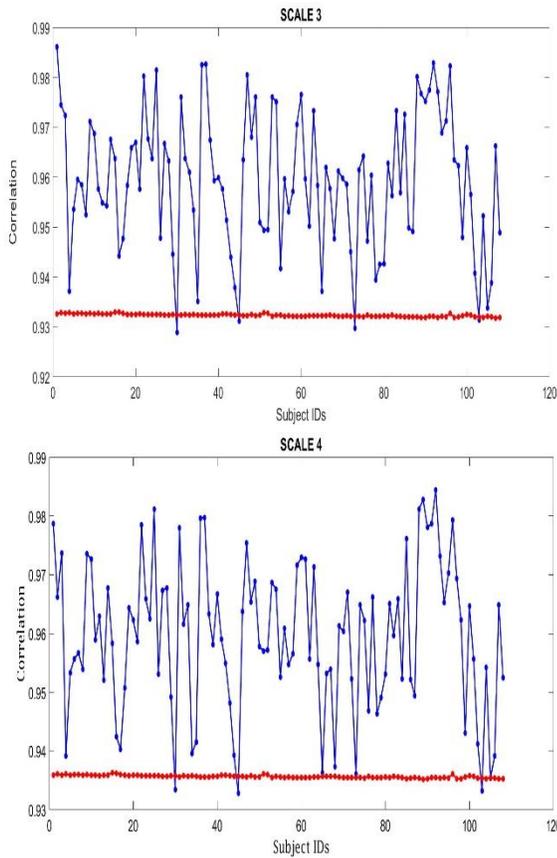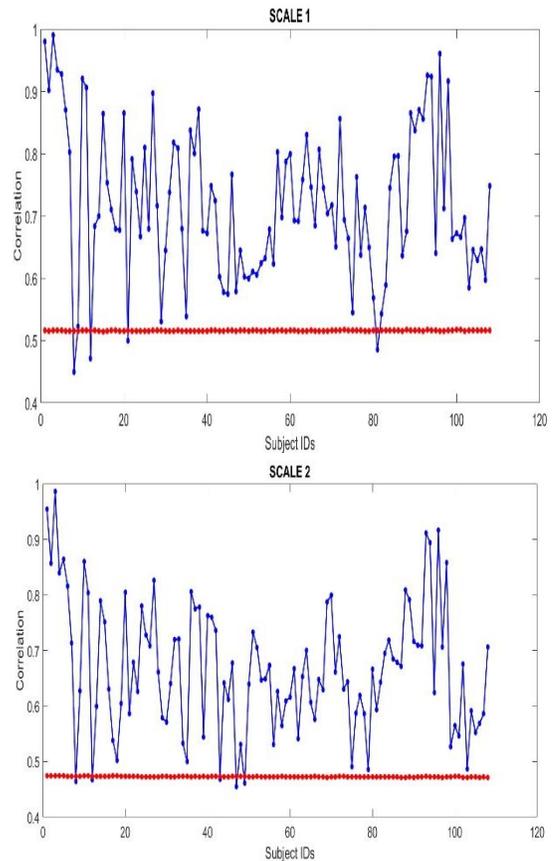
1) Correlation-row

Fig. 7. Correlation Plot for Row Values. 7a. Scatter Plot of Scale 1, 7b.Scatter Plot of Scale 2, 7c: Scatter Plot of Scale 3, 7d. Scatter Plot of Scale 4.

Though it was observed that the dispersion entropy values themselves get reduced with higher scale factors indicating decreased pattern, this however is not drastically hindering the efficiency of this feature in differentiating the images of different subjects. This is especially interesting because the correlation values are around 0.9 for all cases of varying subject correlations, and it is getting slightly increased with an increase in the scale factor. This can be viewed as a consequence of the decrease in dispersion entropy value as a result of the averaging of more and more neighboring pixel intensities with increasing scale factors. In the case of correlation values for the same subject images, the values range between 0.92 – 0.99, indicating very high similarity.

A very encouraging finding in these figures is that the correlation value of the same subject images never crosses below those of different subject values. Though the variation of these values of correlation for the whole dataset of 108 subjects is higher than the variation observed for correlation of different subject images, a majority of these values fall around 0.95 – 0 .98. The overall results indicate that the correlation will never be higher than 0.92 or 0.925 for any case of images of different subjects. This is a very strong factor to recommend this feature for the purpose of personal identification, as the chances of wrongly identifying images of different people to be the same are very low.

Fig. 8(a) to 8(d) show the mean correlation values between column-wise dispersion entropy values of all images of each subject, with its own images represented in green and mean values of correlations between images of each subject with that of all other subjects represented in red. The figures indicate that the values of correlation values for images of different subjects fall around the range of 0.5-0.8, which is much low compared to that observed for row-wise dispersion entropy. However, the values of the same subject images show wide variation, with values falling between 0.5 and 1, with a majority of values falling between 0.6 and 0.8. It is noteworthy that though there is not much cross-over of the same subject image correlation into the range of correlation values of different subject images in the cases of scale factors 1 and 2, the different subject image correlation values increase and cross over into the same subject correlation value range in the cases of scale factors of 3 and 4. The better stability of results in the row-wise analysis is in good agreement with the observations and recommendations, which stated that information is more independent along the angular direction [39]. The different rows correspond to different circles, and the pixels along each row represent angular direction. The present results indicate that ordinal pattern-based Dispersion entropy is very efficient in extracting the maximum utility of the statistical independence between the pixel intensity values along the angular direction in each circle.
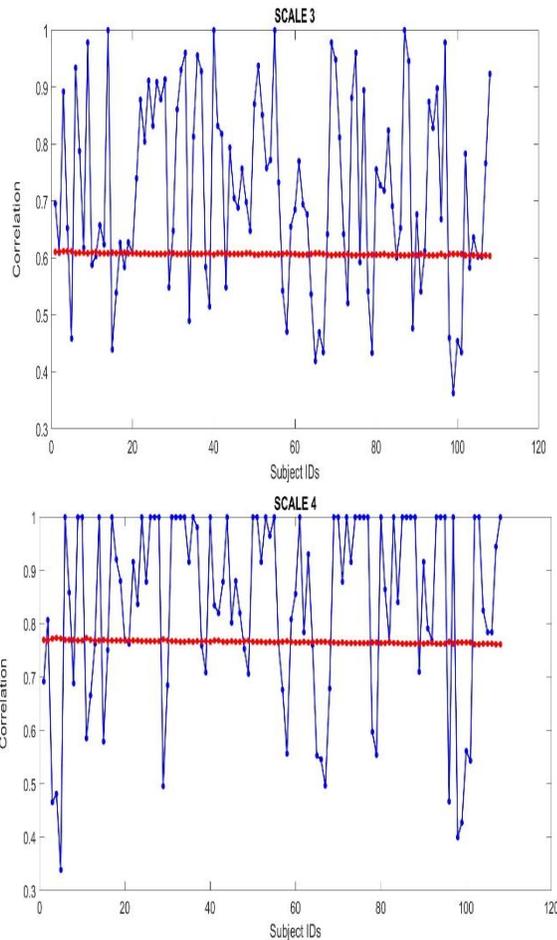
2) Correlation-column

Fig. 8.   Correlation Plot for Column Values. 8a. Scatter Plot of Scale 1, 8b. Scatter Plot of Scale 2, 8c. Scatter Plot of Scale 3, 8d. Scatter Plot of Scale 4.

B. Performance Evaluation Measures

The effectiveness of this proposed work is verified using the performance measures such as False Acceptance Rate (FAR), False Rejection Rate (FRR), False Positive Rate (FPR), Specificity, Sensitivity and Equal Error Rate (EER). Following equations are used to formulate the performance evaluation measures

False Acceptance Rate (FAR) = FP / (FP + TN)

False Rejection Rate (FRR) = FN / (FN + TP)

Equal Error Rate (EER) = (FAR + FRR) / 2

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

Sensitivity = TP / (TP + FN)

Specificity = TN / (TN + FP)

Where TP and TN represent true positive and true negative, FP and FN represent false positive and false negative. For row values, if the threshold value of scale 1 is set for 0.92 then the FRR is zero, which indicates that no person will be falsely rejected. The threshold can be selected based on the dataset which is used. The Specificity and Sensitivity value shows that this system gives accurate True Negative Rate and True Positive Rate. The results are shown in Table X and Table XI for rows and columns, respectively. By examining the values of the threshold, it can be clearly understood that the row values gives better results than column values. Lower the EER higher the accuracy of the biometric system.

TABLE I.   PERFORMANCE EVALUATION OF ROW_DISPEN$_{1D}$

Threshold		FAR	FRR	FPR	Specificity	Sensitivity	EER
Scale 1	0.92	0.028	0	0	1	0.972	0.014
	0.919	0.028	0.167	0.166	0.833	0.972	0.097
Scale 2	0.93	0.019	0	0	1	0.981	0.009
	0.9287	0.009	0.103	0.102	0.897	0.990	0.056
Scale 3	0.934	0.046	0	0	1	0.953	0.023
	0.9327	0.037	0.093	0.092	0.907	0.962	0.065
Scale 4	0.934	0.056	0	0	1	0.944	0.028
	0.9327	0.037	0.074	0.074	0.925	0.962	0.056

TABLE II.   PERFORMANCE EVALUATION OF COLUMN_DISPEN$_{1D}$

Threshold		FAR	FRR	FPR	Specificity	Sensitivity	EER
Scale 1	0.527	0.044	0	0	1	0.953	0.022
	0.5167	0.039	0.0833	0.08	0.916	0.962	0.061
Scale 2	0.478	0.044	0	0	1	0.953	0.022
	0.4737	0.049	0.093	0.09	0.907	0.953	0.071
Scale 3	0.613	0.239	0	0	1	0.685	0.120
	0.609	0.248	0.102	0.10	0.898	0.703	0.175
Scale 4	0.774	0.25	0	0	1	0.666	0.125
	0 . 7 7	0.25	0.056	0.06	0.944	0.682	0.153

V. CONCLUSION

A new method for iris recognition is a nonlinear time series analysis based on Dispersion entropy proposed in this work. Dispersion entropy is estimated based on the complexity of ordinal patterns of elements in a time series. The method is tested on the standard CASIA v1 dataset. The rows and columns of normalized iris images are considered one-dimensional time series, and the corresponding dispersion entropy values are calculated. Correlation between mean dispersion entropy values is calculated to evaluate how efficiently two images of the same subjects can be identified as well as how well two images of different subjects can be differentiated. This is carried out for the dispersion entropy of rows and columns separately. High correlation and values are obtained between different images of the same individual, whereas low correlation values are obtained between images of different subjects. The results of the row-wise analysis demonstrated much higher performance than the column-wise analysis. The results indicate that the dispersion entropy values of one-dimensional series of pixel intensities along rows of normalized iris images are very efficient in characterizing the uniqueness of the iris texture of individuals. The results also point towards the extreme possibility of utilizing the capabilities of nonlinear analysis for iris recognition purposes. These results prove the potential of nonlinear analysis-based texture entropy to be further developed into a tool that can provide a group of features to constitute a feature vector based on ordinal pattern measures of iris image texture for personal identification. This methodology has to be evaluated with other datasets. Also, it is considered the future scope of this work. In addition, similar nonlinear entropy measures can be used to build a feature vector so that the proposed novel approach can be developed.

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