Image encryption & recognition for signature & palm print using hybrid EWT & DFrFT averaging algorithm

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Abstract : **In this digital world, security to applications for data access, physical access and general security are of in great need. As more secure authentication methods are in need, many are turning to biometrics. A person attempting access to a system must prove who he or she really is by presenting a biometric. Experimentations are still going on with various biometrics solutions for identification such as recognition of eyes, faces, fingerprints, palm prints, voice and signatures. With the development of technology, these solutions are vulnerable to counterfeit and theft. Therefore, we propose a novel encryption algorithm based on hybrid average of empirical wavelet transform and discrete fractional fourier transform, thereby enabling a high level of security. The features extracted from the proposed algorithm are also tested with an SVM classifier. The maximum recognition rate of 94% is achieved for the palmprint using COEP database and 98% for signature using CEDAR database.**

Index Terms - **Biometric, Signature, Palm Print, Empirical Wavelet transform, Discrete Fractional Fourier Transform, Hybrid Averaging, Support Vector machine(SVM)**

I. INTRODUCTION

We are living in a digital world. With the advancement in technology, we are advancing day by day. The idea of personal identification is very old. Methods like signatures and imprints are still used for identification. Identification cards with photographs are still an important way for verifying the identity of a person. With the advancement in technology, everything is turning digital now a day. So digital security for our data stored is also of great importance, especially the biometric data of people. Therefore, for improved security, the security field uses three types of authentication methods:

- Something you know—a password, PIN, or piece of personal information (such as your dog’s name, nickname);
- Something you have—a card key, smart card, or token (like a SecurID card);
- Something you are—a biometric.

As more secure authentication methods are in need, many are turning to biometrics. As a reliable, highly accurate and efficient method of confirming a person's identity, biometrics is gaining attention. Biometrics are expected to add a much advanced security to applications for data access, physical access and general security. A person attempting access to a system must identify himself/herself by presenting a biometric. Various biometrics solutions for identification such as recognition of eyes, faces, fingerprints, palm prints, voice and signatures are used in the field. In this paper, recognition of palm prints and signature are considered.

The advancements in the biometrics area have led to smaller, faster and cheaper biometric systems, thus increasing the number of possible application areas. As biometric uses and databases grow, so grows the concerns about the security of personal data. Privacy concerns also arise when news became known on biometric data being used illegally by organizations for data matching, aggregation, surveillance and profiling of users. The biometric data once entered are transmitted across networks and are stored in various databases. This database can be stolen, copied, or misused in ways that can affect the individual. The privacy of the person is also an important factor as the lines in palm prints contain personal characteristics, a person can be identified from face images, and fake signatures can be signed by practicing the signature images available in the database.

A cryptographic approach is proposed for the palm prints and signature images using an advanced hybrid average algorithm. During the feature extraction, the features are extracted from the image using the hybrid average scheme of EWT and DFrFT, and this hybrid-averaged output is stored in the database and is used for identification or verification thus providing security to these images from being attacked.

A. Signature

The way a person signs her name is analyzed in the signature verification process. Signing pressure and speed can also be taken as features together with finished signature’s static shape. Signature verification enjoys a synergy with existing processes that other biometrics do not. People are used to signatures as a means of identity verification.

B. Palm print

Palm print recognition is a biometric authentication method based on the unique patterns of various characteristics in the palms of people's hands. The palm print consists of principal lines, wrinkles (secondary lines), and epidermal ridges. It is different from a fingerprint that it also contains other information such as texture, indents and marks. Palm print recognition systems use a scanning device or a camera-based application, along with associated software that processes image data from a photograph of an individual's palm and compares it to a stored record for that person. Palm prints are used for criminal, forensic, or security applications.

II. THEORY

In this paper, we discuss signature and palm print recognition using hybrid average algorithm of EWT and DFrFT.

2.1 Empirical wavelet transform (EWT)

In mathematics, a wavelet series is a representation of a square-integrable (real- or complex-valued) function by a certain orthonormal series generated by a wavelet.
The fundamental idea of wavelet transforms is that the transformation should allow only changes in time extension, but not shape. This is affected by choosing suitable basis functions that allow for this. Changes in the time extension are expected to conform to the corresponding analysis frequency of the basis function.[8]
Based on the uncertainty principle of signal processing,

$$\Delta t \Delta w \geq \frac{1}{2} \tag{1}$$

Where t represents time and ω angular frequency (ω = 2πf, where f is temporal frequency). The higher the required resolution in time, the lower the resolution in frequency has to be. The larger the extension of the analysis windows is chosen, the larger is the value of Δt.

When Δt is large,

1. Bad time resolution
2. Good frequency resolution
3. Low frequency, large scaling factor

When Δt is small

1. Good time resolution
2. Bad frequency resolution
3. High frequency, small scaling factor

In other words, the basis function Ψ can be regarded as an impulse response of a system with which the function x(t) has been filtered. The transformed signal provides information about the time and the frequency. Therefore, wavelet-transformation contains information similar to the short-time-Fourier-transformation, but with additional special properties of the wavelets, which show up at the resolution in time at higher analysis frequencies of the basis function. In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. [8]
The empirical Wavelet transform (EWT) is used to realize the image decomposition by constructing an adaptive filter bank. The main idea is to extract the different modes of an image by designing an appropriate wavelet filter bank. This construction leads us to a new wavelet transform, called the empirical wavelet transform.

The Empirical Wavelet Transform (EWT) aims to decompose a signal or an image on wavelet tight frames that are built adaptively. In 1D, the procedure consists in detecting the supports of some "modes" in the Fourier spectrum and then using these supports to build Littlewood-Paley type wavelets. The advantage of this empirical approach is to keep together some information that otherwise would be split in the case of dyadic filters.[1]

The definition of the empirical wavelets is based on the formulation of a Littlewood-Paley wavelet where the choice of their supports in the Fourier domain is not prescribed to a dyadic tiling but chosen accordingly to the analyzed signal. It is possible to build a wavelet tight frame that corresponds to an adaptive filter bank. The empirical wavelet transform (EWT) consists of two major steps: detect the Fourier supports and build the corresponding wavelet accordingly to those supports; filter the input signal with the obtained filter bank to get the different components. [2]

The basic idea to build a 2D-EWT is to use a tensor product, which means process the rows and then the columns of the input image by using the 1D-EWT. A simple way is to consider a mean spectrum for the rows, then perform the detection of the Fourier supports based on this mean spectrum and finally use the same filters for all columns. The complete algorithm corresponds to perform the following steps (we denote the input image as f):

1) Take the 1D FFT of each rows i of f and compute the mean row spectrum magnitude:

$$F_{row} = \frac{1}{N_{row}} \sum_{i=0}^{N_{row}} \mathrm{f}(\mathrm{i}, \omega) \tag{2}$$

2) Take the 1D FFT of each columns j of f and compute the mean row spectrum magnitude:

$$F_{column} = \frac{1}{N_{column}} \sum_{i=0}^{N_{column}} \mathrm{f}(\omega, \mathrm{j}) \tag{3}$$

3) Perform the boundaries detection on F_{row} and build the corresponding filter bank
4) Perform the boundaries detection on $F_{columns}$ and build the corresponding filter bank
5) Filter f along the rows provides $N_R + 1$ output images.
6) Filter each previous output image along the columns provides at the end (N_R+1) $(N_C + 1)$ sub band images.

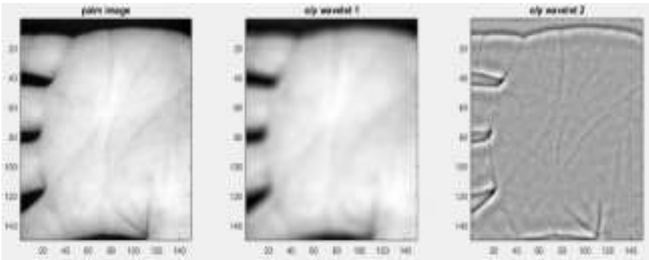

Fig 2.1 Empirical wavelet transform of a palm print image

2.2 Discrete fractional fourier transform

The fractional Fourier transform (FRFT) has proved to be useful in solving many problems in signal processing, quantum physics and optics [4, 7, 13]. The Hilbert transform plays an important role in signal analysis and optics. In 1950 Kastler [6], introduced an optical implementation of the Hilbert transform that is used for image processing, especially for edge enhancement. In 1996, Lohmann et al. [7] generalized the Hilbert transform and showed how these fractional Hilbert transforms could be easily implemented optically and called it fractional Hilbert transform. In [18], Zayed introduced another generalization of the Hilbert transform in order to obtain that part of the signal that is obtained by suppressing the negative frequencies of the signal's FrFT i.e., the analytic part of a signal that is associated with the signal's FrFT.

Sampling expansions for the fractional Fourier transform of band-limited and time-limited signals have been derived in [11,16] and they can be used to reconstruct the signal or its fractional Fourier transform from their samples at a discrete set of points satisfying the Nyquist rate.

The fractional Fourier transform (FrFT) is more flexible than the conventional Fourier transform (FT) due to the extra parameter of the transform order. With the transform order gradually varying from zero to one, the FrFT of a signal can develop from the original function to its FT [4,5]. Thus, it has recently shown its potential in the fields of the image and the optical encryption. Using the transform order to enlarge the key space, the systems based on the FrFT are of a higher security than the corresponding systems based on the FT or cosine transform [6,13,22,23].

The ordinary Fourier transform and related techniques are of great importance in many areas of science and engineering. The fractional Fourier transform is a generalization of the ordinary Fourier transform with an order (or power) parameter ‘α’. The FrFT belongs to the class of time–frequency representations that have been extensively used by the signal processing community [14]. The FrFT is defined for entire time-frequency plane (time and frequency are orthogonal quantities). The angle parameter “a” associated with FrFT, governs the rotation of the signal to be transformed in time-frequency plane from time-axis in the time-frequency plane. The FrFT is defined with the help of the transformation kernel Kα [20, 21], as

$$K_{\propto}(t,u) = \begin{cases} \sqrt{\frac{1-icot\propto}{2\pi}}\, e^{\frac{jt^2+u^2}{z}cot\propto - jut\, csc\propto} \\ \quad ,if \ \propto not\ a\ multiple\ of\ \pi \\ \delta(t-u), if\ \alpha\ multiple\ of\ 2\pi \\ \delta(t+u), if\ \alpha+\pi\ \ multiple\ of\ 2\pi \end{cases} \tag{4}$$

The FrFT defined using this kernel is given by:

$$X_{\alpha}(u) = \int_{-\infty}^{\infty} x(t) K_{\alpha}(t,u)\, , where\ \alpha = a\frac{\pi}{2} \tag{5}$$

The inverse FrFT is given by:

$$x(t) = \int_{-\infty}^{\infty} X_{\alpha}(u) K_{-\alpha}(u,t) du \tag{6}$$

When FrFT is analyzed in discrete domain, there are many definitions of Discrete Fractional Fourier Transform (DFrFT) [16]. FrFT computation involves following steps:

• Multiply by a chirp.
• Fourier transform with its argument scaled by 'csc'.
• Multiply with another chirp.
• Product by a complex amplitude factor.

The one-dimensional FrFT is useful in processing single dimensional signals such as speech waveforms. For analysis of two-dimensional (2D) signals such as images, we need a 2D version of the FrFT. For an M×N matrix, the 2D FrFT is computed in a simple way: The 1D FrFT is applied to each row of matrix and then to each column of the result. Thus, the generalization of the FrFT to two dimensions is given by

$$X_{\alpha\beta}(u,s) = \iint_{-\infty}^{\infty} k_{\alpha\beta}(u,s;t,r)\, x(t,r)\, dt\, dr \tag{7}$$

Where $k_{\alpha\beta}(u,s;t,r) = k_{\alpha}(u,t)k_{\beta}(s,r)$

In the case of the two-dimensional FrFT we have to consider two angles of rotation α=aπ/2 and β=bπ/2. If one of these angles is zero, the 2D transformation kernel reduces to the 1D transformation kernel.

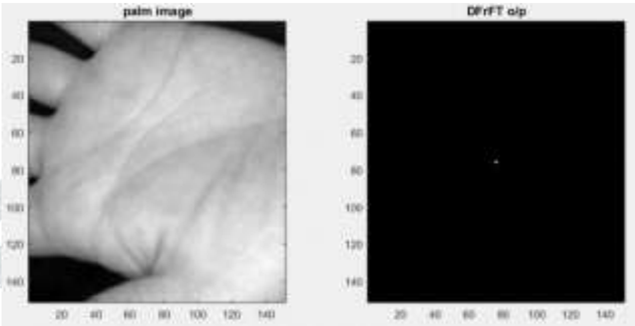

Fig 2.2 DFrFT of a palmprint image

2.3 SVM classifier

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. In two-dimensional space this hyperplane is a line dividing a plane in two parts where in each class lay in either side.[19]

III. METHODOLOGY

In this paper, a hybrid averaging approach is used on the biometric. The output of the hybrid average obtained is an encrypted reduced size output that can be stored as biometric database without fear of hacking and stealing biometric.

3.1 Hybrid

In this work, a hybrid algorithm of EWT and DFrFT for image processing is implemented. First DFrFT is done on the biometric input images (palm print/ signature). Then EWT is done on the DFrFT output. Thus, the output obtained is a hybrid of EWT and DFrFT. The number of modes for EWT is set as two wavelets. Almost all the features are retained in two modes of empirical wavelet transform of the biometric image.

3.2 Averaging

In this averaging algorithm, the output of the hybrid of DFrFT and EWT is averaged. As stated before the output of the hybrid is the output of EWT. The EWT output has two modes. In this averaging method, the average of corresponding pixels of the two modes of EWT is calculated. Thus, an average image is formed from the two modes of EWT.

$$x_{ave}(i,j) = (x_{mode1}(i,j) + x_{mode2}(i,j))/2 \tag{8}$$

After that, the image is divided into patches. Then the average of pixels of each patch is calculated.
Let the number of patches be n and dimensions of each patch be (a, b)

$$X_{ave}(n) = (\sum x(a,b))/(a*b) \tag{9}$$

A new image is formed by the average values X_{ave} of each patch representing the corresponding patch. Thus, the averaging algorithm reduces the output image size.

IV. RESULTS AND DISCUSSIONS

The EWT, DFrFT, Hybrid and hybrid-averaged features thus extracted from the images of both the signature and palmprint are tested using SVM classifier. The results are shown in Table1 and Table2. The COEP,Pune database is used for the palmprint recognition which has 8 images for each person and CEDAR database is used for signature which has 24 images for each person. 70% of the images of each person is used for training and 30% for testing.

Table 3.1 Recognition results for signature using CEDAR database

Recognition % for Signature using SVM			
	Poly 1	Poly 2	Poly 3
EWT	86	87%	87
DFrFT	98	98	98
Hybrid	96	95	95
Hybrid Average	98	98	98

Table 3.2 Recognition results for palm print using COEP,Pune database

Recognition % for Palm print using SVM			
	Poly 1	Poly 2	Poly 3
EWT	80	80	80
DFrFT	89	90	90
Hybrid	90	92	92
Hybrid Average	92	94	94

Results show the accuracy is higher with hybrid features in both palmprint and signature and Hybrid Average features gives the maximum recognition rate of 98% when tested with SVM as classifier in case of signature and 94% recognition rate in case of palmprint. It shows the effectiveness of the hybrid features as compared to the features extracted individually using EWT and DFrFT thus making the algorithm suitable for biometric applications.

V. CONCLUSION

A new type of image encryption algorithm is developed for the biometrics. The training data once entered into the biometric scanner is saved in the biometric database in an encrypted form. Even if the database is stolen from the servers by some means, the encrypted database cannot be decrypted without the hybrid-averaging algorithm developed here. Thus, the security as well as privacy of the biometric database is maintained. In addition, the size of the biometric database is reduced by the use of hybrid averaging algorithm, hence making it less space consuming. It has also been shown that the recognition rate of signature being 98% and palmprint being 94% is highest when we use these features and test the recognition using SVM as classifier. This is mainly because all the relevant features of the palmprint and signatures are considered and patch based hybrid averaging takes into account all the minute features of the image.

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