Highly Efficient Approaches for Biometric Security Systems

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Abstract— This paper proposes to implement the biometric security system spoofing detection on palm vein, face and iris image patterns. A Biometric system is essentially a pattern recognition system that makes use of bio-metric traits to recognize individuals. In a biometric security system, the data hiding approach is involved to conceal the secret personal informatics for enhancing the privacy protection. There are negative effects on recognition performance on fingerprint and palm print biometrics due to the some factors like the dryness or dirt in the finger and it also varies with age, for instance, this system is not appropriate for children, because the size of their fingerprint changes quickly. This paper depicts a proposed method which avoids the above negative factors. Palm vein, face and Iris patterns stand out from the host of intrinsic biometric traits for the development of a recognition system that can meet all the security expectations of a biometric system. In the proposed method palm vein, face and iris image patterns spoofing can be easily detected using Neural Network (NN) with the help of GLCM properties. Vein patterns are the network structure of blood vessels underneath the human skin that are almost invisible to the naked eye under natural lighting conditions and can be acquired only when employing infrared illumination. The texture of the blood vessels and Iris of different individuals has been proven to be distinctive even among identical twins. The selected image of palm veins, face and Iris is aligned and cropped according to the key points. The image is enhanced and resized. The features of palm vein, iris and face are compared with database image feature vectors and are recognized using Probabilistic Neural Network classifier (PNN). Finally the performance of multimodal system along with stenographic approach will be measured with accuracy and it proves to provide better matching rate than earlier approaches.

Keywords— Biometric, Artificial Neural Network, Probabilistic Neural Network Classifier, Gray-Level Concurrence Matrix, Non-Subsampled Contourlet Transform

1. Introduction

Human physiological features and behavioural characteristics and traits have become a way of identifying and authenticating people. Today's biometric systems are the main users of this feature for surveillance, access control and security purposes. This system gained rapid expansion and became a powerful tool in identifying and authenticating a person. There are many human traits which are considered in a biometric system such as face, iris, fingerprint, signature, handwriting and palm-print.

This paper presents an outline of an efficient biometric system with three important human characteristics-the face, iris and palm vein. The face is an important characteristic in identifying a person as it is the basis of authenticity. Iris is unique to every person and it helps in accurate identification. Palm vein patterns can uniquely identify a person because they are more difficult to forge as it is a characteristics which are deep within the body and becomes challenging while spoofing original information. Nevertheless, finger-print and palm-print's requirement come in contact with sensors for the purpose of acquisition of information is regarded to be unhygienic and some users may not be comfortable with the system. Handwriting and signature are also used widely to provide authenticity but they are more vulnerable to spoofing attacks.

The major type of attack on face images are basically impostors produced either by process of masking [10]or with the help of 3D model of a valid user[1].The types of attacks on iris images is through the usage of textured contact lenses which was a major concern and efficiently overcome by James et al. [4] and Daksha et al.[3] by presenting effective algorithms to prevent iris spoofing. The other type of iris spoofing is by recapturing printed photographs or display-screen images which are not real but seem to be real. This has been overcome by Xinyu et al.[6] by means of liveness detection approach of irises which provides evidence whether the image is real or spoofed.

The other challenges faced by the biometric system other than the above mentioned attacks are based on the natural changes that occur to the characteristics or traits of a person. For instance, the face can be used as the main characteristic for identifying a person but that may lead to ambiguities as face features may change dramatically over the years and could lead to loss in accuracy during recognition. In the context of iris, there is a possibility that the accuracy is low when the image is captured using normal camera and detailed features are not taken into consideration while recognizing. This can be improved by performing iris recognition in the near-infrared spectrum (NIR),which is very challenging to acquire. In order to overcome this Zhi et al.[15] proposed the new identification method using sclera recognition, and another efficient parallel approach for it was provided by Yong et al.[14].Javier et al.[11] performed research on all the spoofing attacks on various human characteristics used in the biometric systems and presented a method called Image Quality Assessment to overcome all the different spoofing using a single software tool.In the case of recognizing palm-vein patterns the results have been exemplary and new methodologies for accuracy have been presented by Yingbo et al. [12] and Yiding et al.[13]. Some major problems which are faced while processing an image are texture variance and liveness of the image which are address by Lin et al. [7] and T.W Lee et al[9] for best results.

This paper presents a new approach to spoofing detection with the use of Artificial Neural Networks (ANN) with a Probabilistic Neural Network Classifier(PNN) along with Gray-Level Co-occurrence Matrix(GLCM) properties which helps in examining the texture of the image. The transformation used is the NSCT (Non-subsampled Contourlet transform) for best multi-scaling and directionality property.

2. Architecture

The basic architecture is multi-staged which has been proven to be efficient in spoofing detection by Kevin et al.[2]. The images from the biometric interface are retrieved-iris, face and palm vein; they are transformed into frequency sub-bands by means of NSCT. The separated sub-bands are then subjected to Pixel-Level Fusion and then with the help of GLCM features are checked with the back-end database for consistency of the images through the use of Probabilistic Neural Network (PNN) Classifier.

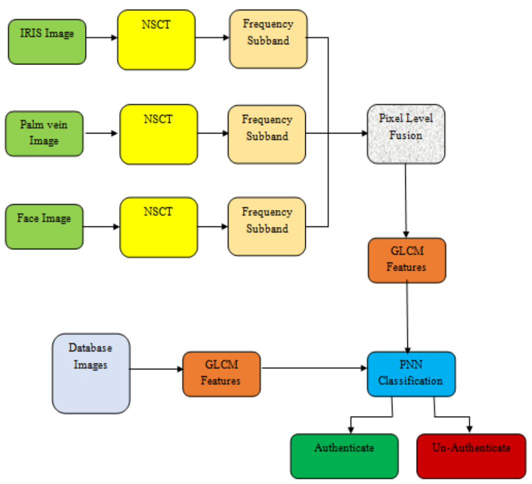

Fig 1.The general architecture of proposed system

The general architecture of the proposed system is depicted in Figure 1, consisting of three modules based on the function performed:

- Non-subsampled Contourlet Transform
- Gray-Level Co-occurrence Matrix
- Artificial Neural Network and Probabilistic Neural Network Classifier

2.1 Non-Subsampled Contourlet Transform

Picture compression and denoising are productively done in the wavelet transform domain. Available transform captures the substance of a given signal or a group of signals with very less number of basic functions. The basic functions completely portray the transform and this set can redundant based on whether the functions used are linearly dependent. By permitting redundancy, it is possible to improve the basic functions so that the representation is more effective in catching some signal behavior. The fully shift-invariant, multiscale, and multidirectional expansion transform is used here, the NSCT, which has a fast implementation and address the 2D properties of images which are not addressed in other transforms like Radon transform and Fast Fourier Transform. The structure of NSCT comprises a bank of channels that parts the 2-D frequency plane in the subbands depicted in Fig. 2(b). This transform is partitioned into two parts: 1) a nonsubsampled pyramid structure that guarantees the multiscale property and 2) a nonsubsampled Directional Filter Bank structure that gives directionality. This transform is the advance transform of Contourlet Transforms and has proven to provide efficient results.

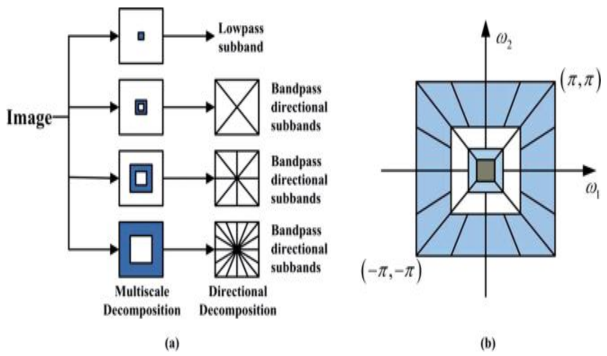

Fig 2: (a)Implementation of NSCT (b)Frequency division in subbands of NSCT

2.2 Gray-Level Co-occurrence Matrix

A co-occurrence matrix or co-occurrence distribution is a matrix that is used to characterize a picture to be the appropriation of distribution of co-occurring pixel values (grayscale values, or colors) at a given offset.The general Co-occurrence matrix(COM) helps in figuring the occurrence of a pixel with the intensity '*i*' which has a particular spatial relationship to a pixel with the value j. The quantity of gray levels in the picture decides the span of the co-occurrence matrix.

Energy: It is a measure of homogeneity of the image. Energy is calculated from the normalized COM. It is an appropriate measure for identification of disorder or distortion in texture image. Energy is given by,

$$J = \sum_{i=1}\sum_{j=1}(p(i,j))^2$$

Entropy: Entropy gives a measure of complexity of the picture. Complex textures have a tendency to have higher entropy. Entropy is given by,

$$S = -\sum_{i=1}\sum_{j=1} p(i,j)\log(p(i,j))$$

where *p(i , j)* is the co-occurrence matrix

A measurable strategy for examining surface textures that is determined based on the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), otherwise called the gray-level spatial dependence matrix. The GLCM capacities describe the texture of a picture by figuring how frequently pairs of pixel with particular values and predetermined spatial relationship are present in animage. The various properties of GLCM are enlisted in Table 1.

Statistic	Description
Contrast	Measures of the local variations in the gray-level co-occurrence matrix.
Correlation	Measures the joint probability occurrence of the predefined pixel sets.
Energy	Provides the sum of squared elements in the GLCM.
Homogeneity	Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

Table 1: Properties of GLCM

2.3 ArtificialNeural Network and Probabilistic Neural Network Classifier

2.3.1 ArtificialNeural Network

Neural networks have been found to outperform all the other classifiers for identifying two-dimensional (2D) images as proved in paper by Yann et al.[5].The Artificial Neural Network(ANN) is an inspired model of the natural neuron. Neurons are activated when signals are strong enough and these signals are emitted through the axon. These signals are used to trigger another neuron by sending signals to another synapse. In computing world, the Artificial neural network classifier takes the inputs(synapses) and multiply them by weights(signals) which determines activation of a neuron. When the Artificial neuron weight is high, the input which is multiplied tends to grow stronger. So, by adjusting the weights of the neuron the output can be obtained for the specific input.

2.3.2 Probabilistic Neural Network Classifier

Yann et al.[5] studied the various character recognition schemes using the back propagation algorithm in neural networks. Even though Back Propagation Algorithm is efficient, it takes long computational times for training a data set and it is susceptible to false measurements. To overcome this, the probabilistic neural network (PNN) was introduced by Donald F. Specht in 1990. It is a theory based on Bayesian classification and the estimation of probability density function (PDF). The PNN has a simplistic method of training and it lays a sound statistical foundation in the Bayesian estimation theory. In PNN, the sigmoid activation function which is often used in neural networks is replaced by exponential function. This makes PNN a effective tool for solving many classification problems and can compute nonlinear decision boundaries. The PNN was developed based on Parzen windows classifiers. The *Parzen windows* method is a non-parametric procedure that estimates the probability density function (*PDF*) by superposition of a number of windows, replicas of a function (often the Gaussian). A PNN comprises of several sub-networks which is a Parzen window pdf estimator for each class. The classification decision is taken after calculating the probability density function of each class using the given training set. The multi-category Classifier decision is expressed as follows:

$$p_k f_k > p_j f_j$$

Where, P_k is the prior probability of occurrence of set elements from class *k* and is the estimated PDF of class *k*. The major advantage of using PNN over BPN in neural network classification is that (i) the complexity does not degrade the system performance (ii) Erroneous samples are tolerated (iii) the classifier works at a higher speed than BPN.

This paper proposes a method where the Probabilistic Neural Network is used as means of retrieval of image values from the database for the purpose of matching with the biometric images captured. These results are presumed to be accurate with very few errors that its matching capabilities are highly efficient.

3. Literature Review

The following table shows literature review.

Table 2: Articles with its advantages and disadvantages

S.No	Reference Paper	Author Name	Publication Journal/Date	Advantages	Drawbacks	Technique Used
1	DeepFace: Closing the gap to human-level performance in face verification	Y. Taigman, M. Yang, M.Ranzato, and L. Wolf	Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2014	The main credit of this paper is that it demonstrates coup-ling a 3D model based alignment with large capacity feed forward models can be effective.	The draw-back is that 'DeepFace' algorithm needs to be trained on an extensive pool of faces to be able to perform accurately.	DeepFace algorithm, Deep Neural Net(DNN)
2	What is the best multi-stage architecture for object recognition?	K. Jarrett, K. Kavukcuoglu, M. Ranzato, and Y. LeCun	in Proc. IEEE 12th Int. Conf. Comput. Vis., Sep./Oct. 2009	This multi-stage architecture supports unsupervised learning	There are motivations to trust that better learning techn-iques with refined models and more powerful classifiers may yield better accuracy.	Predictive Sparse Decomposition (PSD)
3	Unraveling the Effect of Textured Contact Lenses on Iris Recognition	DakshaYadav, NamanKohli	IEEE Trans. Info. Forensics, Vol. 9, No. 5, May 2014	This approach per-forms efficiently on different lens detection algorithms and shows enhanced iris recognition execution.	There are chances that matches may occur even when images are not similar	Novel Lens Algorithm
4	Variation in accuracy of textured contact lens detection based on sensor and lens pattern	J. S. Doyle, K. W. Bowyer, and P. J. Flynn	Proc. IEEE 6th Int. Conf. Biometrics, Theory, Appl., *Syst. (BTAS)*, Sep./Oct. 2013, pp. 1–7	Decreases the performance degrad-ation during recognition	Use of binary patterns do not give exten-sively good results	Sensor detection
5	Gradient-Based Learning Applied to Document Recognition	YannLecun, L´EonBottou	Proceedings Of The IEEE, Vol. 86, No. 11, November 1998	Multimodal systems are used	Sensitivity is very high which may cause erroneous data and degradation of system	Convolution Neural Network (CNN), Chart Transformer system
6	An experimental study of pupil constriction for liveness detection	X. Huang, C. Ti, Q.-Z. Hou, A. Tokuta, and R. Yang	Proc. IEEE Workshop Appl. Comput. Vis. (WACV), Jan.2013	Efficient liveliness detection system	The SVM classifier needs to be trained to make a decision on liveness.	Support Vector Machine (SVM) Classifier
7	Binary Gabor pattern: An efficient and robust descriptor for texture classification	Z. Zhang, Z. Zhou, and H. Li	Proc. 19th IEEE Int. Conf.Image Process. (ICIP), Sep./Oct. 2012	Using *BGPri*, it is not necessary to pre-train or learn a text from dictionary.	Complexity of the process is high	Binay Gabor pattern,binarizi ng
8	Face spoofing detection through partial least squares and low-level descriptors	W. R. Schwartz, A. Rocha, and H. Pedrini	Proc. IEEE Int. Joint Conf. Biometrics (IJCB), Oct. 2011	Robust set of low-level feature descript-tors that are able to capture and distin-guish authenticity of the image	There are some mis-alignment of faces detected which is responsible for losing some accuracy in the spoofing detection.	Low-Level Descriptors

9	Liveness detection using frequency entropy of image sequences,	T.-W. Lee, G.-H. Ju, H.-S. Liu, and Y.-S. Wu	Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP), May 2013	It has capability to eliminate cross-channel image noise in the resulting images	This paper uses Fourier transform which address images only in one dimension and external storage for RGB seque-nces may be expensive.	Independent Component Analysis,Fast Fourier Transform
10	On the vulnerability of face recognition systems to spoofing mask attacks	N. Kose and J.-L.Dugelay	Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP), May 2013	It is a robust system	It does not address the 3D features of images which are important in recognition detections.	Masking detection
11	Image quality assessment for fake biometric detection: Application to iris, fingerprint, and face recognition	J. Galbally, S. Marcel, and J. Fierrez	IEEE Trans. Image Process., vol. 23, no. 2, pp. 710–724, Feb. 2014.	This system has been found to be less complex	There is no support for multimodal approach in this system	Image Quality Assessment(IQ A)
12	Contactless palm vein identification using multiple representations	Y. Zhou and A. Kumar	Proc. 4th IEEE Int. Conf. Biometrics, Theory Appl. Syst., Sep. 2010	Better Performance	The computation-nal complexity is observed to be high and further improvement can be made.	Hessisan Phase Informa-tion, Orientation encoding, Localized Randon Transform
13	Hand-dorsa vein recognition based on partition local binary pattern	Y. Wang, K. Li, and J. Cui	Proc. IEEE 10th Int. Conf. Signal Process., Oct. 2010	The system is inexpensive and produces convincing results	There is a possibility of losing data in the smoothing filtering process.	Local Binary Pattern
14	An efficient parallel approach for Sclera vein recognition	Y. Lin, E. Y. Du, Z. Zhou, and N. L. Thomas	IEEE Trans. Inf. Forensics Security, vol. 9, no. 2, pp. 147–157, Feb. 2014	The capacity of the system in matching images is high. This system also reduces GPU memory cost	It does not bolster multi-modular approach which is an important feature in biometric frameworks.	Weighted polar line sclera descriptor, Two level matching Descriptor

4. Conclusion

This paper successfully implements the various modules in biometric security system and also performs spoofing detection on palm vein, face and iris image patterns. In the proposed system, initially, NSCT(Non-Subsampling Contourlet Transform) transformation is used for best sub-sampling of the images. The GLCM properties help in determining the texture and its properties after fusion of the images. Later, spoofing can be efficiently detected and matched from database using ArtificialNeural Network (ANN) as the means of retrieval by using the Probabilistic Neural Network (PNN) Classifier.

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