Identification of Criminal and Victim by Using Low Resolution Androgenic Hair Patterns

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Abstract— Criminals and victims verification is always an important task in police investigation and forensic evaluation. Blood samples, Finger Marks, DNA, dental records, tattoos, face images and face sketches are used constantly by enforcement laws agents in the world. But they cannot handle the cases, where only images describing crime scene samples are available nowadays verifying criminals and victims in images (e.g., child pornography and masked gunmen) can be a difficult work, especially when even their faces or any mark are observable. The Skin mark patterns and blood vessel patterns are just proposed to address this problem. However, they are invisible in low-resolution images and dense androgenic hairs can cover them completely. Results of medical research have implied that androgenic hair patterns are a stable biometric trait and have ability to overcome the problems of skin mark patterns and blood vessel patterns. To the best of our knowledge, no one has worked before on androgenic hair patterns for criminal and victim identification. This paper aims to study performance of matching of androgenic hair patterns in low resolution images.

Key words: Androgenic Hair Patterns, Criminal and Victim Identification

I. Introduction

Identifying criminals and victims in images describing crime-scenes specimen is a challenging task, especially when both faces and tattoos are not observable. Though blood vessel patterns and skin mark patterns have been proposed to solve this problem, they demand high resolution images to visualize hidden blood vessels and accurately detect skin marks.

Some regular users of adult pornography may get tired with these images and begin to watch for pictures of different types of sexual encounters. Not everybody who views child pornography is sexually enticed to children. They may be finding the images arousing because they are new or different from sexual situations they have seen before. They might get a thrill from the taking risk involved in looking at something that is illegal.

Child pornography is a rising issue in India. Images describing crime-scene specimen, other body sites are often apparent. we likely obtain close up images with backs, chests In child pornography cases . To address this challenging problem of identification, skin mark patterns and blood vessel patterns are proposed recently. Blood vessel patterns are universal and over a long period of time they are considered stable. Traditionally, near infrared imaging systems are used to capture blood vessel patterns. The methods are developed latterly to visualize blood vessel patterns hidden in color images captured by consumer digital cameras. However, their visibility depends on image quality and the thickness of the subcutaneous fat layer in the skin and its pigmentation level of physiological factors. Skin marks, occurring on the skin surface, are more observed easily than blood vessel. Both Skin mark and blood vessel patterns require high resolve image and they are covered completely by dense androgenic hairs. New biometric traits have thus to be developed.

By evaluating one or more distinguishing biological traits a person can be uniquely identified in Biometric verification. Unique identifiers include hand geometry, fingerprints, earlobe geometry, retina and iris patterns, voice waves, DNA, and signatures. Fingerprinting is the oldest form of biometric verification. In ancient China Historians have established examples of thumbprints being used as a unique identification on clay seals. Biometric verification has advanced considerably with the advent of the digitization of analog data and computerized databases, allowing for almost instantaneous personal identification retina-pattern and Iris-pattern authentication methods are previously employed in some automatic teller machines of banks. Voice waveform recognition is a method of confirmation which has been used for many years with tape recordings in telephone wiretaps, is now being used for access to proprietary databanks in research facilities. The technology has been used by law enforcement to pick out individuals in large crowds with considerable reliability is Facial Recognition. Hand geometry is being used in industry to provide physical access to buildings. To mismatch the identity of individuals who claim to be someone they are not (identity theft) is Earlobe Geometry. Signature comparison is not as reliable, by itself, as other biometric identification methods but offers an extra layer of verification when used in conjunction with one or more other methods. No matter what biometric methodology is used, the verification process remains the same. Record of a person's unique characteristic is captured and kept in a database. Later on, when identification verification is required, then new record is captured and compared with the previous record in the database. If the data in the new record matches that in the database record, the person's identity is confirmed.

II. Previous work

This paper first provides a list of medical studies and images to justify that androgenic hair patterns are a stable biometric trait. Even though the hairs collected in crime scenes are regularly used for forensic analysis, as per our best knowledge, androgenic hair patterns in images were never studied for criminal and victim identification.

Han Su and Adam Wai Kin Kong presents the study on low resolution Androgenic Hair Patterns for Criminal and victim identification [1]. For matching androgenic hair patterns, they propose an algorithm based on a dynamic grid system and Gabor orientation histograms. The experimental results on a database containing 4,552 images from 283 different legs with resolutions of 25, 18.75, 12.5 and 6.25 dpi demonstrate two points: androgenic hair patterns in low resolution images are an effective biometric trait and the proposed Gabor orientation histograms are comparable with other well-known texture recognition methods, inclusive of local binary patterns, local Gabor binary patterns and histograms of oriented gradients.

In forensic identification, image quality is always a problem. Images of child pornography, masked gunmen and violent protestors are our targets. Child pornographic images often have good quality because paedophiles enjoy high quality images. For cases of masked gunmen and violent protectors, the original images can be taken by reporters, who always use professional DSLR cameras, e.g. Canon EOS 10DX. Sometimes standard images are obtained. And for web images describing crime-scene specimen, no matter what cameras are used to take the original images, one great challenge is low resolution, which is the focus of this paper. While the resolution of surveillance videos is also very low, the challenges in surveillance images and web images are different. Surveillance cameras are always mounted in high positions. They probably capture head-print, instead of androgenic hair. This paper demonstrates that androgenic hair patterns in low resolution images can be used as a biometric trait for victim and criminal identification. But, low resolution is only one of the problems. For robust identification, for viewpoint and pose variations and occlusions new algorithms should be developed. This algorithm can enhance the performance of the proposed algorithm, which uses the dynamic grid system and the features to absorb all variations and distortions. In adjunct, an automatic segmentation algorithm should be developed to reduce manpower, even though a semi-automatic approach is not uncommon in forensic analysis. Our database size is comparable with other biometric databases for scientific studies e.g. West Virginia University iris database, but it is small comparing with fingerprint databases in law enforcement agents. We will continue collecting more images for algorithm development and evaluation. Once law enforcement agents use androgenic hair patterns in real applications, for this research direction numerous images can be collected from inmates and suspects. Although low resolution images are the focus of this paper, androgenic hairs and their follicles in high resolution images should also be studied, since in child pornography cases, high resolution and close up images are commonly obtained. In addition to searching a suspect in a given database, how to allocate evidential values in the form of a probability ratio to androgenic hair patterns is also equally important. More detailed description of forensic biometric applications can be found in. In this paper, a list of medical studies and images are given to justify that androgenic hair is a stable biometric trait. A large-scale study for determining the permanence of androgenic hair is still demanded. Since each hair has its own rhythm and hair shafts fall out at different time, how these issues impact matching accuracy should also be further studied.

Sangita Nikumbh after working on this project conclude that Gabor filter is much more advantageous and efficient in image processing to detect hair pattern. It works similar to those of human visual system. The Androgenic hair patterns in low resolution images can be used as a biometric trait for criminal and victim identification. However, Low resolution is only one of the problems. For much perfect identification, new algorithms should be developed for viewpoint and pose variations and occlusions. These algorithms can enhance the performance of the proposed algorithm, which uses the dynamic grid system and the features to absorb all variations and distortions.

III. METHODOLOGY

A. Gray Scale Conversion

Humans come to know color through wavelength-sensitive sensory cells called cones. There are three different types of cones, each and every with a different sensitivity to electromagnetic radiation (light) of different wavelength. Mostly one type of cone is sensitive to red light, one to blue light, and one to green light. By emitting a controlled combination of these three basic colors (green, red and blue), and therefore stimulate the three types of cones at will, and almost any perceivable color we are able to generate. And it is the reasoning behind why color images are often stored as three different image matrices; one storing the amount of red (R) in each pixel, one the amount of green (G) and one the amount of blue (B). Such color images we called as stored in an RGB format.

In grayscale images, however, we do not differentiate how much we emit the different colors, and we emit the same amount in each channel. What we can differentiate is the little light gives dark pixels and total amount of emitted light for each pixel; and much light is perceived as bright pixels.

At the time of converting an RGB image to grayscale, we have to take the RGB values for each and every pixel and make it as output a single value reflecting the brightness of that pixel. One such approach is to take the average of the contribution from each channel average: (R+B+C)/3. However, since the perceived brightness is often dominated by the green component, the different, and more human-oriented, procedure is to take a weighted average, e.g.: 0.3R + 0.59G + 0.11B.

A distinct approach is to let the weights in our averaging be dependent on the true image that we want to convert, i.e., be adaptive. Somewhat simple take on this is to form the weights so that the resulting image has pixels which have the most variance, since pixel variance is linked to the contrast of the images. The “Optimal projection" computes how we should combine the RGB channels in the selected image to make a grayscale image that has the most variance in the applet above,. [For the more technically advanced; we find the weights by taking the principal eigenvector of sample covariance matrix of the RGB channels.]

B. Gabor Filter:

Local androgenic hair patterns with distinct orientations and densities hold rich information. We have pinpointed that androgenic hair follicles are much stable; implicating that androgenic hair densities are also stable. Androgenic hair orientations are partially determined by their follicle directions. There are different androgenic hair types, including straight, curly and afro-textured. They are genetically dependent. Input images can be collected in uncontrolled environments such as crime scenes, implying that perfect image arrangement is difficult to be achieved. This defect can be due to nonlinear distortion from muscle movement and from the capture conditions e.g. camera position, angle and focal distance. As Iris Code for iris identification and Competitive Code for palm print identification are point-based feature extraction techniques are not suitable. To capture orientation and density information in imperfectly adjusted images, Gabor orientation histograms on a dynamic grid system are proposed.

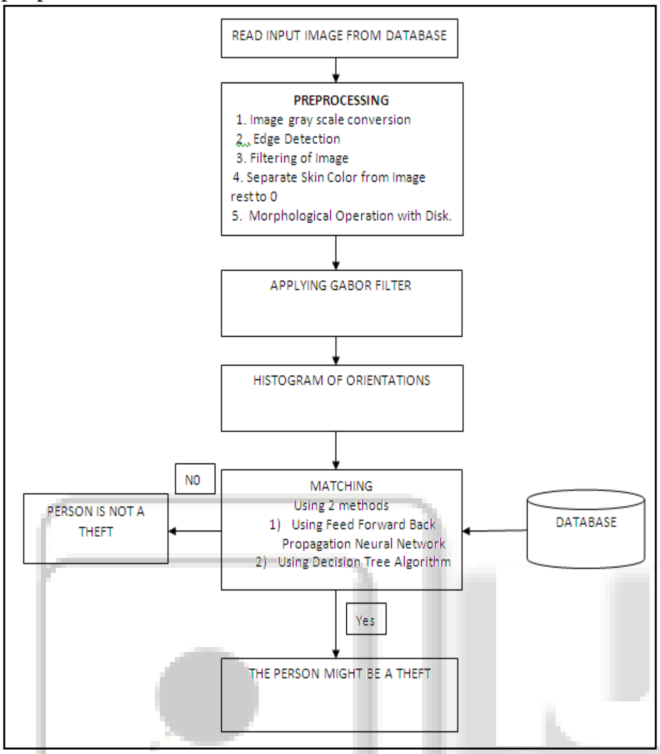

Fig. 1: Flow Diagram of Androgenic Hair Pattern

C. Orientation Field Computation:

Gabor filters reaching the theoretical limit of uncertainty relation for information offer spatial place, spatial frequency and orientation selectivity. Numerous scientific studies and commercial systems have demonstrated their feature extraction capability. The study pointed out that Gabor filters can be utilized as a Gabor atom detector and the magnitude and phase of a target Gabor atom can be approximated by the magnitude and phase of the corresponding Gabor response. Gabor filter produce three raw features, phases, magnitudes and orientations. Another study compared these features on face images and concluded that the orientation feature is the most distinctive and robust feature. The orientation feature was also used for palm print identification. Though face, palm print and androgenic hair images are different types of images, their orientation information is clear. Androgenic hairs can be regarded as line segments with different orientations and scales. In high resolution images, if locations of follicles and directions of androgenic hairs can be extracted, androgenic hair features are similar to minutia features. To capture orientation information and to handle scale variation, proposed algorithm uses real parts of Gabor filters, which are defined as

$$G(x, y, \lambda_{mk}, \Theta_k, \sigma_m, \gamma) = \frac{\gamma}{2\pi\sigma_m^2}\exp\left(\frac{-x'^2 + \gamma y'^2}{2\sigma_m^2}\right)\cos\left(\frac{2\pi x'}{\sigma_m k}\right)$$

where $x' = x \cos \theta k + y \sin \theta k$ and $y' = -x \sin \theta k + y \cos \theta k$ are the rotated coordinates with orientation $\theta_k = k\pi/8$, λ_{mk} denotes the wavelength of the sinusoidal component, σm is the standard deviation of the elliptical Gaussian window along with x'direction, γ is the spatial aspect ratio, $m \in \{1, \ldots, M\}$ and $k \in \{1, \ldots, K\}$ are the scale and orientation indexes respectively. To increase robustness against brightness variation, the direct current (DC) component in Eq. 1 is removed. In total, $M \times K$ real parts of Gabor filters with zero DC are applied to the preprocessed images.

D. Histogram Orientation:

The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique computes occurrences of gradient orientation in localized portions of image. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, shape contexts, but differs in that is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy The essential idea behind these histogram of oriented gradients descriptor is that local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions. The image is split into small connected regions called cells, and for the pixels within each cell, a histogram of gradient directions is compiled. The descriptor is then the concatenation of these histograms .And for improved accuracy the local histograms can be contrast-normalized by calculating a measure of the intensity across a larger region of the image called a block, and then using this value to normalize all cells within the block. And this normalization results in better invariance to changes in illumination and shadowing.

The HOG descriptor has a few key advantages over the other descriptors. Considering it operates on local cells, it is invariant to geometric and photometric transformations, except for object orientation. Such changes would only appear in larger spatial regions. The Coarse spatial sampling, fine orientation sampling, and strong local photometric normalization permits the individual body movement of pedestrians to be ignored so long as they maintain a roughly upright position. Thus the HOG descriptor is particularly suited for human detection in images.

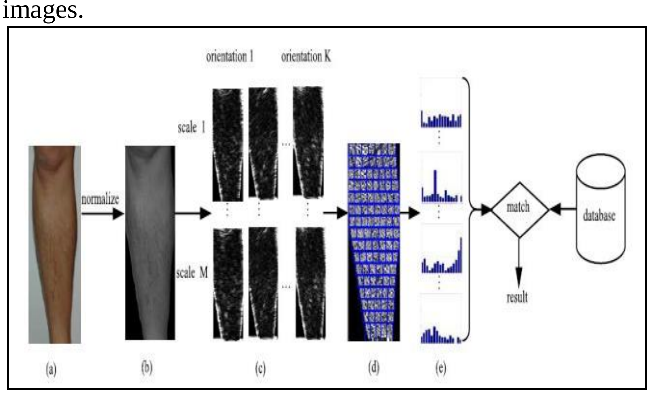

Fig. 2: Schematic diagram of proposed algorithm.(a) Original Image (b) Normalized Image (c) Gabor Magnitude (d) Orientation Field (e) Histograms

IV. RECOGNITION ALGORITHM

A. Probabilistic Neural Network (PNN)

A probabilistic neural network (PNN) is a feed forward neural network, which was derived from the Bayesian network and a statistical algorithm Kernel Fisher discriminant analysis. It was introduced by D.F. Specht in the early 1990s [10]. PNN is a type of RBF network, which is suitable for classification of patterns. The architecture has four layers, an input layer, a hidden layer, a pattern layer and an output layer. The pattern layer constitutes a neural implementation of a Bayes classifier, where the class dependent Probability Density Functions (PDF) is approximated using a Parzen estimator. Parzen estimator gives the PDF by minimizing or reducing the expected risk in classifying the training set incorrectly. Hence, with the use of Parzen estimator, the classification gets closer to the true underlying class density functions as the number of training samples increases.

The pattern layer is made of a processing element corresponding to each input vector in the training set. Each output class must consist of equal number of processing elements otherwise some classes may be inclined falsely which will result in poor classification results. Each processing element in the pattern layer is trained once. An element is trained in such a way that it will return a high output value when an input vector matches the training vector. In order to obtain more generalization or accuracy, a smoothing factor is included while training the network. This smoothing factor is also called as a spread value. The pattern layer classifies the input vectors based on competition, where only the highest match to an input vector wins and generates an output. Therefore only one classification category is generated for any given input vector. If there is no relation between input patterns and the patterns programmed into the pattern layer, then no output is generated.

If we compare PNN to the feed forward back propagation network, training of PNN is very much simpler. Basically, probabilistic networks classify on the basis of Bayesian theory, hence it is necessary to classify the input vectors into one of the two classes in a Bayesian manner.

In a PNN, the operations are organized into a multilayered feed forward network with four layers. When an input is present, the first layer computes the distance from the input vector to the training input vectors. This produces a vector where its element indicates how close the input is to the training input. The second layer sums the contribution for each class of inputs and produces its net output as a vector of probabilities. Then a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes.

If the probability density function of each of the populations is known, then an unknown, X, belongs to class "i" if $(x)> (x)$, all $j\neq i$.

B. PNN Training

PNN is a useful neural network architecture with slightly different in fundamentals from back propagation. The architecture is feed forward in nature which is similar to back propagation, but vary in the way that learning occurs. The PNN is supervised learning algorithm but includes no weights in its hidden layer. Each hidden node represents an example vector with the example acting as the weights to the hidden node. It is not adjusted at all. PNN consists of an input layer, which represents the input pattern or feature vector. The input layer is fully interconnected with the hidden layers which consist of the example vectors (the training set for the PNN). The actual example vector serves as the weights as applied to the input layer.

Finally, output layer represents each of the possible classes for which the input data can be classified. However, the hidden layer is not fully interconnected to the output layer. The example nodes for a class connect only to that class's output node and none other. One other important element of the PNN is the output layer and the determination of the class for which the input layer fits. It will do through a winner-takes-all approach. The output class node with the largest activation represents the winning class. While the class nodes are connected only to the example hidden nodes for their class and the input feature vector connects to all examples, and hence influences their activations. Hence, it is the sum of the example vector activations which determines the class of the input feature vector.

In PNN algorithm, calculation of the class-node activations is a simple process. For each class node, the example vector activations are summed which are the sum of the products of example vector and input vector. The hidden node activation, shown in the following equation is the product of the two vectors (E is the example vector, and F is the input feature vector).

$$hi=EiF$$

The class output activations are then defined as:

$$Cj=\Sigma ehi-1/\gamma 2Ni=1N$$

Where N is the total number of example vectors for this class, hi is the hidden-node activation, and γ is a smoothing factor. The smoothing factor is chosen by doing experimentation. Details can be lost if the smoothing factor is too large, but if the smoothing factor is too small, the classifier may not generalize well. There is no real training that occurs since the example vectors serve as the weights to the hidden layer of the network. If we have given an unknown input vector, the hidden node activations are computed and then summed at the output layer. The class node with the largest activation determines the class to which the output feature vector belongs. As no training required, classifying an input vector is fast, depending on the number of classes and example vectors that are present. It is also easy to add new examples to the network by simply add the new hidden node, and its output is used by the particular class node. This can be done actively as new classified examples are found. And the PNN also generalizes very well when noisy data set is present

PNN is a classifier which maps any input pattern to a number of classifications. PNN is famous for its fast training process. PNN converges to an optimal classifier as the size of the training set increases. Training samples can be added or removed without extensive retraining. Even though PNN has many advantages, it has several disadvantages too. PNN has large memory requirements. PNN requires a representative training set even more than other types of neural networks. One of the most important point in case of PNN is that training set should be thoroughly representative of the actual population for effective classification. If we are going to add or subtract training samples, it is similar to adding or removing of neurons in pattern layer. If we are going to increase training set, PNN asymptotically converges to Bayes classifier

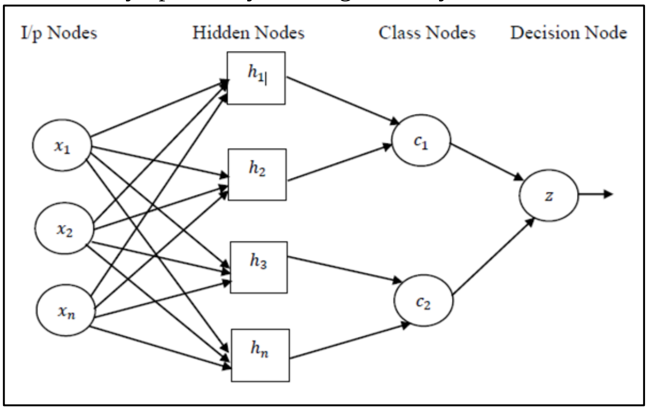

Fig. 3: Probabilistic Neural Network

V. RESULT

In this project Identification of criminals and victim using Androgenic hair pattern is done by using matching performance of ANN i.e. Feed Forward Neural Network. And we have discussed the whole result thoroughly as follows using clinical measures and performance measures.

A. *Clinical Measures for Feed Forward Network:*

We have divided dataset into two parts in which first part is of training images that consist of 20 images including both criminals images and non criminals images and second part is testing that consists of 37 images. The training set was used to train the PNN classifier whereas testing dataset was used to verify the accuracy and effectiveness of the trained network for the classification of criminals

– True Positive (TP): The classification result is positive in the presence of the clinical abnormality and.
– True Negative (TN): The classification result is negative in the absence of the clinical abnormality.
– False Positive (FP): classification result is positive in the absence of the clinical abnormality.
– False Negative (FN): The classification result is negative in the presence of the clinical abnormality.

Out of the above four terms, TP and TN are not errors while FP and FN are error terms

Sr. No.	TP	TN	FP	FN
1	0	30	7	0

Table 1:

B. *Performance Measures:*

Performance measures are calculated in the following way.
Sensitivity = TP/ (TP+FN) ×100%
Specificity = TN/ (TN+FP) ×100%
Accuracy = (TP+TN)/ (TP+TN+FP+FN) ×100 %

Sr. No.	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	0	81.0811	81.0811

Table 2:

1) *Recall*

Recall is the ratio of modules correctly classified as fault-prone to the number of entire faulty modules.

$$\text{Recall}= \frac{\text{TP}}{\text{TP+FN}}$$

2) *Precision*

Precision is the ratio of modules correctly classified to the number of entire modules classified fault-prone. And It is nothing but proportion of units correctly predicted as faulty.

$$\text{Precision} = \frac{TP}{TP+FP}$$

3) *F-Measure*

FM is a combination of recall and precision. It is also defined as harmonic mean of precision and recall.

$$\text{F-Measure} = \frac{2*\text{Recall}*\text{Precision}}{\text{Recall+Precision}}$$

4) *Accuracy*

It is defined as the ratio of correctly classified instances to total number of instances.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

No of Images	Recall	Precision	F-Measure	Accuracy
57	0.875	0.6	0.7118	70.17

Table 3:

The overall result obtained is 70.17%

VI. CONCLUSION

In conclusion we have implemented the criminal and victim identification using androgenic hair pattern. For matching androgenic hair patterns we used the algorithm Feed Forward Neural Network.

The average accuracy of this proposed system is approximately 70.17%.

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