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.

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1. 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.

2. Literature survey

2.1 Hair and Its Importance: Mammals have hair all over their bodies as a unique character which differentiates them from other animals in the Animal Kingdom. Most human skin generates hair, except for some particular parts of the body, the glaborous skin, including the lips, palms of the hands and soles of the feet. Hairs are greatly variable in colour, diameter, length, and cross-sectional shape. There are three main types of hair: lanugo, vellus and terminal. Lanugo hair is soft and fine, and is formed in fetal life. This type of hair starts growing on human embryo skin at about the 20th week of pregnancy, and then sheds in uterus at about the 36th week of pregnancy. After birth, an infant has two types of hair, vellus and terminal. Vellus hair is tiny, small, fine, nonmedullated and nonpigmented hair. It is located in areas of the body described as hairless regions, for instance the facial hair of a child or adult women. Terminal hair is long, thick and pigmented, often with a modulated hair shaft. It grows on various parts of the human body such as the scalp, face, eyelashes, eyebrows, arms, legs and axillae.

The main functions of human hair are protection and communication. For example, eyebrows and eyelashes protect eyes from incoming objects. Scalp hair protects the head and neck from the dangerous effects of sunlight, ultraviolet light, cold and physical damage. In addition, scalp hair provides insulation for the head due to the lack of adipose tissues on the scalp. Thermoregulatory function is less important in human being; although the small amount of terminal hair on the human body helps to cool the body through evaporation from sweat glands. One of the most important functions of human hair is social and sexual communication. Hair plays a role in beauty; strong healthy hair indicates good health to others, whereas sparse and brittle growth of the hair indicates poor nutrition and bad health. Hair removal generally has strong depersonalizing roles, for instance shaving prisoners and Christian or Buddhist monks, however long uncut hair has

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positive connotations like power and its association with religion in Sikhs. There are clear differences in hair type and distribution between females and males, and between adults and children. The growth of pubic and auxiliary hair is a sign of maturation and puberty. In addition, hair disorders such as hirsutism or excessive hair growth and alopecia or hair loss can be negative effects on the standard of life such as social restriction and psychological distress to those who suffer from them. Although hair loss is not life threatening in human beings, but the important communication roles of hair explain its importance for most people. Since hair plays a vital role in a person's appearance, self-image and communication, it provides an perception into why it is possible for hair growth disorders to be at the root of serious psychological distress. Unfortunately, many hair disorders cannot currently be effectively treated, mainly due to our lack of understanding of hair follicle function. Thus a greater understanding of the mechanisms regulating hair growth, leading to the control of these conditions is of great interest worldwide.

2.2   Biology of Androgenic Hair: Hair follicles are to varying degrees sensitive to androgen, testosterone and its derivatives with various areas on the body having different sensitivity. The weight of the hairs and rate of hair growth increase as androgen levels increase. Genetic factors determine both individual levels of androgen and the hair follicle's sensitivity to androgen, and other characteristics such as type of hair, hair retention and hair color.

Rising levels of androgen during puberty cause transforming of vellus hair into terminal hair over many areas of the body. Sequence of appearance of terminal hair reflects the androgen sensitivity level, with pubic hair being the first to appear because of the area's special sensitivity to androgen. Appearance of pubic hair in both sexes is usually seen as an indication of the start of a person's puberty. Sexual differentiation in the amount and distribution of androgenic hair is there, with men's tending to have more terminal hair in more areas. This includes facial hair, chest hair, leg hair, arm hair, abdominal hair and foot hair. Women retain more of the less visible vellus hair, although arm, leg and foot hair can be noticeable on women. It's not unusual for women to have a few terminal hairs around their nipples also. In later decades of life, especially after the 5th decade, there begins a noticeable reduction in body hair especially in the legs. And the reason for this is not known but it could be due to lower free circulating hormone amounts, poorer circulation or other reasons.

2.3   Distribution of Androgenic Hair: Like much of the hair on the human body, leg, arm, chest, and back hair begin as vellus hair. As the age of people increasing, the hair in these regions will often begin to grow darker and more abundantly. During or after puberty it will typically happen. Men will generally have more abundant, coarser hair on the arms, legs, chest, and back, while women's tend to have a less drastic change in the hair growth in these areas. However, some women will grow longer, darker hair in one or more of these regions.

3.   Me   Methodology used

3.1 Gray Scale Conversions: 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

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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", method 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.]
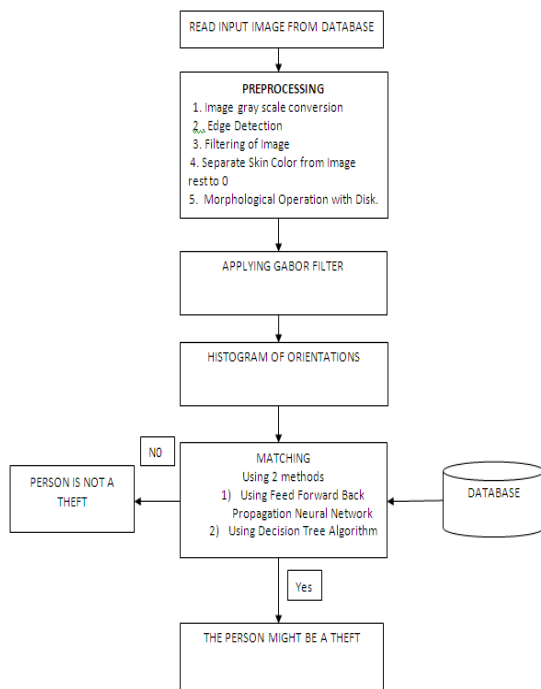

Figure 1.1 Flow Diagram of Androgenic Hair Pattern

Gabor Filter: Local androgenic hair patterns with different orientations and densities contain rich information. We have pinpointed that androgenic hair follicles are much stable; implicating that androgenic hair densities are also stable.4 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. Point-based feature extraction techniques such as Iris Code for iris identification and Competitive Code for palm print identification are thus not suitable. To capture orientation and density information in imperfectly adjusted images, Gabor orientation histograms on a dynamic grid system are proposed.

1) 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

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features. To capture orientation information and to handle scale variation, proposed algorithm uses real parts of Gabor filters, which are defined as

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

where $x' = x \cos \vartheta k + y \sin \vartheta k$ and $y' = -x \sin \vartheta k + y \cos \vartheta k$ are the rotated coordinates with orientation $\vartheta_k = k\pi/8$, 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.

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

4. ALGORITHM USED

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 $j\neq i$.

Input layer

Each neuron in the input layer represents a predictor variable. In categorical variables, *N-1* neurons are used when there are *N* number of categories. Then the input neurons feed the values to each of the neuron in hidden layer.

Pattern layer

This layer contains one neuron for each case in the training data set. It stores the values of the predictor variables for this case along with the target value. A hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function using the sigma value.

Summation layer

For PNN networks there is one pattern neuron for each category of the target variable. The actual target category of each training case is stored with each hidden neuron and also the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron's category. The pattern neurons add the values for the class they represent only.

Output layer

The output layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

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

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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).

$$h_i = E_i F$$

The class output activations are then defined as:

$$C_j = \Sigma e_{hi} - 1/\gamma 2 N_{i=1} N$$

where N is the total number of example vectors for this class, h_i is the hidden-node activation, and γ is a smoothing factor. The smoothing factor is chosen by doing experimentation. If the smoothing factor is too large, details can be lost, 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 dynamically as new classified examples are found. The PNN also generalizes very well when noisy data set is present
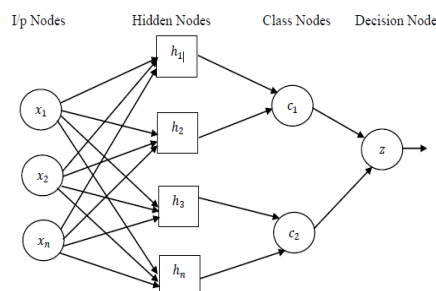
5. Conclusion

Till now we have studied basic information of project. I have selected the images and the algorithm used in this is feed forward neural network.

In next phase of this project plan to design the code and implement criminal identification using feed forward neural network algorithm.

6. References

[1]. IEEE transactions on information forensics and security, vol. 9, no. 4, april 2014

[2]. K. S. Stenn and R. Paus, "Controls of hair folliclecycling," Physiol. Rev., vol. 81, no. 1, pp. 449–491,2001.

[3]. R. E. Billingham, "A reconsideration of phenomenon of hair neogenesis with particular reference to the healing of cutaneous wounds in adult mammals," in.The Biology of Hair Growth, W. Montagna and R. A.Ellis, Eds. New York, NY, USA: Academic, 1958

[4]. A. Vogt, K. J. McElwee, and U. Blume-Peytavi, "Biology of the hair follicle," in Hair Growth and Disorders, U. Blume-Peytavi, Tosti, D. A. Whiting, and R. M. Trüeb, Eds. New York, NY, USA: Springer-

[5]. Verlag, 2008.

[6]. H. B. Chase, "Growth of hair," Phys. Rev., vol. 34, no.1, pp. 113–126,

[7]. V. A. Randall and N. V. Botchkareva, "The biology of hair growth," in Cosmetic Applications of Laser and Light-Based System, G. S. Ahluwalia, Ed. Norwich, NY, USA:William Andrew Inc., 2009.

[8]. V. A. Randall and E. J. G. Ebling, "Seasonal changes in human hair growth," Brit. J. Dermatol., vol. 124, no. 2, pp. 146–151, 1991.

[9]. Yusur Al-Nuaimi1,2, Gerold Baier1, Rachel E. B.Watson2, Cheng-Ming Chuong3 and Ralf

[10]. BBC News. London, U.K. (2001, Mar. 26).International Child Porn RingSmashed[Online].Available:http://news. bbc.co.uk/1/hi/world/amerIcas/1244457.st m

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[11]. [10] (2013). Canada's National Tipline for Reporting the Online Sexual Exploitation of Children [Online]. Available: http://www.cybertip.ca/pdfs/fact_sheet_pdfs/English/CyberStats_en.pdf

[12]. S. Bukhari, "Dress," Translation of Sahih Bukhari, vol.7, book 72, no. 815, Center for Muslim–Jewish Engagement. Los Angeles, CA, USA, 2002

[13]. N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in Proc. CVPR, 2005,pp. 886–893.

[14]. J. G. Daugman, "High confidence visual recognition of persons by a test of statistical independence," IEEE Trans. Pattern Anal. Mach. Intell., vol. 15, no. 11, pp.1148–1161, Nov. 1993