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CRIMINAL AND VICTIM IDENTIFICATION USING ANDROGENIC HAIR PATTERNS IN LOW RESOLUTION IMAGES

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***Abstract* - In the forensic department and in the scientific field identifying criminals and victims in images can be a challenging task, especially when neither their faces nor tattoos are observable. Skin mark patterns and blood vessel patterns are widely used to manipulate this condition in the older days. However, they are invisible in low-resolution images and dense androgenic hair can cover them completely. Results in medical research have implied that androgenic hair patterns are a stable biometric trait and have potential to overcome the weaknesses of skin mark patterns and blood vessel patterns. An algorithm designed for this paper uses Gabor filters to compute orientation fields of androgenic hair patterns, histograms on a dynamic grid system to describe their local orientation fields, and the block wise Chi-square distance to measure the dissimilarity between two patterns. The experimental results indicate that androgenic hair patterns even in low-resolution images are an effective biometric trait and the proposed Gabor orientation histograms are comparable with other well-known texture recognition methods, including local binary patterns, local Gabor binary patterns, and histograms of oriented gradients. There are no additional follicles naturally formed after birth in human beings. All androgenic hairs manifest a cycle. When one hair drops, another new hair grows at the same follicle. They are two different hair shafts, but appear at the same location. Androgenic hair cycle is long. This implies that human hair does not fall out at the same time and we can always find some corresponding androgenic hairs for matching. Only around 10% androgenic hair follicles exit permanently from cycling.**

***Index Terms* - Local Binary Pattern(LBP), Cumulative Match Curves(CMC), Local Gabor Binary Pattern(LGBP), Histograms Of Oriented Gradient(HOG),**

I.INTRODUCTION

Identifying criminals and victims is always an important task in police investigation and forensic evaluation. Finger marks, blood samples, DNA, dental records, tattoos, face images and face sketches are used regularly by law enforcement agents all around the world. However, they cannot handle the cases, where only images describing crime scène specimens are available, but neither faces nor tattoos1 are observable. These cases include but not limited to child pornography, violent masked gunmen and terrorist attacks, where criminals always cover or hide their faces and tattoos to avoid identification. Because of the recent advances in imaging technology and the popularity of digital cameras, images with criminals and victims have been increasing significantly.

However, hair follicles have their own rhythm and their cycles are asynchronous, except in groups of three follicles called Demeijère. This implies that human hair does not fall out at the same time and we can always find some corresponding androgenic hairs for matching. The vellus-to-terminal hair follicle switch is irreversible. Even if men are castrated, their beards would not return to prepubertal level. Only around 10% androgenic hair follicles exit permanently from cycling. Others cycle throughout the entire lifespan to produce hair. Show two skin images from the same leg collected in August 2009 and October 2008 respectively. The colour circles in indicate the partial corresponding androgenic hair follicles. From this small area, we can find more than 40 corresponding androgenic hair follicles. The remaining images in show four image pairs collected in different time periods. A lot of corresponding androgenic hair follicles can be identified. However, androgenic hair follicles are only observable in high resolution images.

This paper studies matching performance of androgenic hair patterns in low resolution images as an alternative biometric trait for criminal and victim identification. shows four male legs with distinctive androgenic hair patterns. As with other biometric traits, including face and fingerprint, androgenic hair can be modified (e.g. laser hair removal). This paper does not consider modification of androgenic hair. Forensic scientists have studied hairs for many years. There are two common

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approaches, microscopic examination and mitochondrial DNA (mtDNA) comparison to analyse hairs collected from crime scenes.

II. ANDROGENIC HAIR PATTERN

Hair is a very actively growing organ in the body. Hair growth is mediated by many factors. At puberty, androgens affect hair growth in a paradoxical way depending on body site. Androgens stimulate vellum hairs to form terminal hair follicles in the axilla and pubis in both sexes and on the chest and face in men. At the same time, androgens inhibit the hair growth in a patterned distribution in the scalp of genetically predisposed people. In this article, we review androgen etic alopecia (AGA) in men or male pattern hair loss (MPHL) as pattern hair loss in females is affect ornithine decarboxylase gene polymorphism and AGA.

A. GENETICS

Although the genetic background for AGA was assumed for a long time, the mode of inheritance is still not clear. Carey et al. reported an association of AGA with polycystic ovaries in autosomal dominant inheritance. Other researchers showed an association between Ornithine decarboxylase plays a role in the regulation of the hair cycle. Several studies showed that genetic variants in, or in proximity to, the androgen-receptor (AR) gene have been associated with AGA. Another genetic study showed that EDA2R is associated with AGA Ed by other factors in addition to the androgens.

B. ANDROGENS

The hair is an endocrine target tissue for androgens. Also, it is regarded as a peripheral organ that synthesizes significant amounts of androgens with intracranial or paracrine action (fig 1). The major circulating androgens, dehydroepiandrosterone sulphate (DHEA-S) and androstenedione are mainly produced in the adrenal gland, and the testosterone and Dihydrotestosterone (DHT) are synthesized mainly in the gonads.

C. ANDROGEN RECEPTOR

AR is an intracellular transcription factor that belongs to steroid/nuclear receptor superfamily. AR is a complex that includes heat shock proteins 70, 90, 56. The combination of androgens with AR results in dissociation of heat shock protein, which, in turn, exposes a nuclear translocation signal and initiates the transport of the ligand receptor complex to the nucleus. The androgen and AR complex ligate to promote DNA sequences of androgen-regulated genes. This results in stimulation or inhibition of messenger proteins or receptors, which alter cellular processes stimulating or inhibiting hair follicle growth. Several researchers showed that the ARs were significantly higher in dermal papilla cells from balding compared with non-balding scalp follicles.

D. ANDROGEN RECEPTOR COACTIVATOR

As shown before, the sensitivity of hair follicle to androgen is regulated through the pre-receptor 5a-reductase enzyme and ARs; it is also mediated through post receptors androgen coactivators. Although many AR coactivators have been identified, their physiological and pathological significance is still not fully understood.

Fig.1 Different androgenic hair patterns

E. EFFECTS ON THE HAIR CYCLE AND HAIR PARAMETERS

A normal hair cycle of scalp hair involves anagen (a growing period of 2–6 years on average), catagen (transitional period of approximately 2–3 weeks) and telogen (a resting period of around 12 weeks). In AGA, there is progressive reduction in the mean duration of anagen with each passage through the hair cycle. Because the duration of the anagen phase is the main determination of hair length, the maximum length of the new anagen hair is shorter than its predecessor. The duration of telogen hair is unchanged, but the time when the follicle is empty, referred to as the latent period, becomes longer. Also, hair follicles become progressively miniaturized over the course of successive hair cycles. The hair follicles become narrower and shorter. The shorter, finer hairs are

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absent more frequently and absent for longer periods and this contributes to the effect of alopecia.

F. CLINICAL FEATURES

AGA is a slow hair-loss process in patterned distribution. Any time after puberty, AGA in men begins with temporal recession of the frontal hairline. The bald patch progressively enlarges and ultimately this may lead to complete baldness except at the lateral and occipital margins of the scalp. Variations in the pattern baldness depend on the difference of hair-loss rate in various scalp areas. A small proportion of men show preservation of frontal hairline, although they have hair loss in frontal and vertex areas of the scalp, similar to female pattern hair loss (FPHL), which is characterized by diffuse thinning of the centro-parital area of the scalp and usually preservation of frontal hairline. The affected area shows miniaturized hairs (finer, shorter hairs) and decreased hair density in comparison with unaffected areas in the same person.

III. GABOR FILTER

According to computer vision segmentation can be define as the process of partitioning a digital image into multiple segments, where multiple segments are sets of pixels, in other words super pixels. Main objective of segmentation is to change and, or simplify the representation of a digital image into something that is much more significant and easier to analyse. Objects and boundaries like lines, curves, etc. in images can be normally located by using image segmentation. More accurately, the process of assigning a tag to every pixel in an image such that pixels with the same label share specific visual characteristics is known as image segmentation.

A.IMAGE SEGMENTATION

The outcome of image segmentation is a set of surface (especially of a curving form) extracted from the image, a set of segments that as a group cover the entire image. In a segment every pixels are similar with regard to computed property or some characteristic, such as intensity, texture, or colour. Neighbouring segments are considerably different with regard to the same characteristics. Image segmentation can also be considered as partition of an image into set of non- overlapping areas, whose combination is the complete image, few rules to be followed for regions resultant from the image segmentation fi All segments should be uniform and homogeneous with regard to some characteristics fi Region's interiors should be uncomplicated and without many small holes .Neighbouring segments should have significantly different values with regard to the characteristic according which they are uniform fi Every segment's boundaries should be simple, not blurring, and must be spatially accurate

$$g(t) = ke^{j\theta} w(at)s(t)$$

.

$$g_r(t) = w(t)\sin(2\pi f_o t + \theta)$$

$$g_i(t) = w(t)\cos(2\pi f_o t + \theta)$$

B.TEXTURE SEGMENTATION

For more than 50 years understanding of processes occurring in the early stages of visual perception has been a primary research topic. For regular properties like colour, brightness, size and the slopes of lines composing figures preattentively segmentation occurs strongly (Beck 1966, 1972, 1973, 1983; Olson and Attenuate 1970). Research into the statistical properties of preattentively discriminable texture was started by 3 Julesz in early 1960's. Complex topic where psychophysics meets physiology Beck and Jules were among the first to deep in.

A measurement of the variation of the intensity of a surface, quantifying properties such as regularity, smoothness and coarseness. You can also explain with term is colour map. Texture is mapped onto an already available surface. A surface texture is created by the regular repetition of an element or pattern, called surface Texel, on a surface. In computer graphics there are deterministic (regular) and statistical (irregular) texture it's often used as a region descriptor in image analysis and computer vision.

The three principal approaches used to describe texture are structural, spectral and statistical. Apart from the level of gray and colour texture is a spatial belief indicating what characterizes the visual homogeneity of given zone of an image in a infinite(true) image which generate another image based on the original texture and finally analyse these two fragments by classifying them in a deferent or a same category. In other words we can also say that the main objective is to decide if texture samples belong to the same family by comparing them. By using filter-bank model the process is bring to conclusion, dividing and decomposing of an input image into numerous output image is prepared by a set of linear image filters working in parallel which is used by the filter-bank model. These filters gives rise to concept of joint space/ spatial-frequency decomposition by simultaneously concentrate on l local spatial interactions and on particular range of frequencies.

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C. FILTER

In optics, device that let light pass on which have certain properties like particular range of wavelengths, i.e., range of colours of light, while blocking the rest. Mathematical operations carry out on an image represented as a sampled, discrete-time signal to enhance or reduce certain aspects of that signal in digital image processing is a Filter. Filtering is process which is used in Fourier transform for signal processing in frequency domain. Depending upon the relationship between input and output, filter may be linear or non-linear. For the detection or removal of anomalous or unwanted frequencies from an input 4 signal linear filters are used behaving according to the Gaussian statistical law. In high frequency components like small details and edges blurring is caused by linear filter. Being derived from the neighbouring pixels non-linear filters use estimates to detect anomaly. When applied for edge detection or spike detection non-linear filters normally provide better outcomes. Examples of filters are Long-pass, Polarizer, Band-pass, Median, Laplacian, Sobel, Short-pass, etc.

.

$$\|g(f)\| = \frac{k}{a}\hat{w}\left(\frac{f - f_c}{a}\right)$$

D. BANDPASS FILTERS

Filter that rejects frequencies outside given range by only allowing frequencies within that range to pass is known as a band-pass filter. We can also create band-pass filters by combining a high-pass filter with a low-pass filter. Band-pass is frequently confused with pass bad, which refers to the actual portion of exaggerates spectrum, actually it is adjective that describes a type of filtering or filter process. Band pass and pass band are both compound words that follow English rules of formation: the primary meaning of the later part of the compound, while modifier is the first part. Here fore, we may acceptably say \A dual band pass filter has two pass bands".

An ideal band pass might have a complete pass band with no gain/attenuation and complete attenuate all frequency outside the pass band. The pass band out of the transition might be instantaneous in frequency. Practically ideal band-pass filter do not exist. All frequencies outside the desired frequency range are not completely attenuate by the filter; actually, frequencies are attenuated but not rejected in a region just outside the intended pass band. Normally, the roll-off are designed made as narrow as possible, which only allows the filter to perform as close possible to its intended design.

IV.THE PROPOSED ANDROGENIC HAIR PATTERN IDENTIFICATION ALGORITHM

The proposed androgenic hair pattern identification algorithm has three computational components, pre-processing, feature extraction and matching. The schematic diagram of the proposed algorithm is given in Fig. 8. The algorithm takes a colour leg image as an input and compares it with templates n a given database. First, the input leg image is segmented and normalized. The segmentation process is to remove all irrelevant information e.g. background. The normalization process is to identify the common region and standardize the image size for matching. Real parts of Gabor filters with different scales and orientations are then applied to the pre-processed image to compute Gabor magnitudes. These magnitudes are combined to extract local orientations and form an orientation field. It is divided into small regions for computing local orientation histograms as features. Each small region is composed of about 300 pixels. Finally, these histograms are matched with those in the database.

$$X(H_{O_i}, H_{O_d}) = \sum_{t-1}^{N}\sum_{k-1}^{K}\frac{(h_{O_iB_t}(k) - h_{O_dB_t}(k))^2}{h_{O_iB_t}(k) + h_{O_dB_t}(k)}$$

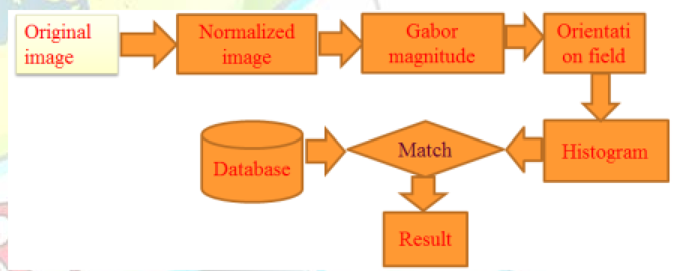

Fig.2 Block diagram for proposed method

A.GABOR ORIENTATION HISTOGRAMS ON A DYNAMIC GRIDSYSTEM

Local androgenic hair patterns with different orientations and densities contain rich information. We have pinpointed that androgenic hair follicles are very stable, implying 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.

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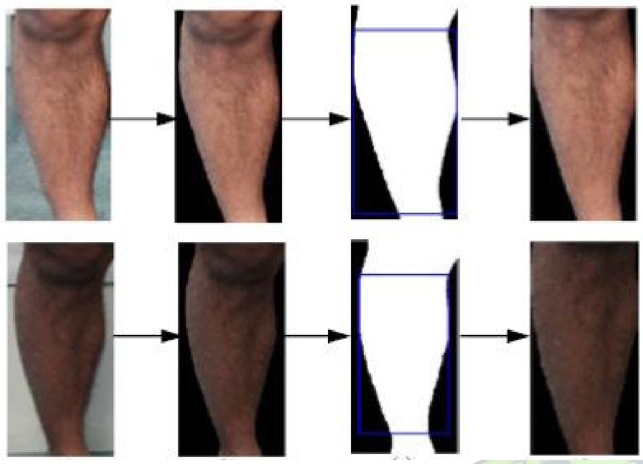

Fig. 3 Proposed pre-processing scheme

Gabor filters reaching the theoretical limit of uncertainty relation for information offer spatial locality, spatial frequency and orientation selectivity. Numerous scientific studies and commercial systems have demonstrated their feature extraction capability. A 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 filters 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 handle scale variation, the proposed algorithm uses real parts of Gabor filters, which are defined as

Input images can be collected in uncontrolled environments such as crime scenes, implying that perfect image alignment is difficult to be achieved. This imperfection 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 methods 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 aligned images, Gabor orientation histograms on a dynamic grid system are proposed.

This paper exposes a new way to address the challenging criminal and victim identification problem. 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 pedophiles 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 good quality images are obtained. 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.

Though low resolution images are the focus of this paper, androgenic hairs and their follicles in high resolution images should also be studied, because 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 assign evidential values in the form of a likelihood ratio to androgenic hair patterns is also equally important .More detailed description of forensic biometric applications can be found. In this paper, a list of medical studies and images are given to justify that androgenic hair is a stable biometric trait.

V. CONCLUSIONS

In the experiments, the images collected in the first occasion were considered as a probe set and the images collected in the second occasion were considered as a gallery set. Cumulative match curves (CMC) and rank-one accuracies were used as performance indicators. Note that the database information has been given in Section II. Most of the legs in the database have two images in the gallery and probe sets. The first experiment aimed to determine the parameter E, which controls the number of blocks. 128 Gabor filters with 32 orientations and 4 scales were used. The size of the pre-processed images was 142×298 pixels. The rank-one accuracies for $E = 8$, $E = 16$ and $E = 32$ were 76.17%, 77.91% and 57.74% respectively. The second experiment aimed to determine the parameter K in the Gabor filter bank, which controls the number of orientations. In this experiment, E was set to sixteen and the corresponding total number of blocks was 108. The rank-one accuracies for $K = 8$, $K = 16$, $K = 32$ and $K = 64$ were 75.83%, 76.87%, 77.91% and 76.17% respectively. In the rest of the experiments, E was set to 16 and K was set to 32. We compared the proposed algorithm with the local binary pattern (LBP) methods , including $LBPriu2$ 8,1 , $LBPri$ 8,1, $LBPu2$ 8,1, $LBPriu2$ 8,2 , $LBPri$ 8,2, $LBPu2$ 8,2, $LBPriu2$ 16,2 and $LBPu2$ 16,2, the local Gabor binary pattern (LGBP) methods [15], including $LGBPriu2$ 8,1 , $LGBPu2$ 8,1, $LGBPriu2$ 8,2 and $LGBPu2$ 8,2 and the histograms of oriented gradients (HOG) method [16] on grayscale images and red, green and blue channel images. In these comparisons, the size of the pre-

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processed images was 142 × 298 pixels.$LBPu2$ 8,1 on the green channel is the best LBP method and $LGBPu2$ 8,1 on the green channel is the best LGBP method. HOG performs the best on the grayscale images. In this comparison, the proposed algorithm is the best. The rank-one accuracy of the proposed algorithm on the grayscale images is 1.91% higher than that of $LBPu2$ 8,1 on the green channel images. It is also 1.91% higher than that of $LGBPu2$ 8,1 on the green channel images and 19.82% higher than that of the HOG method on the grayscale images. The numbers of images which were correctly identified by the proposed algorithm, but incorrectly identified by $LBPu2$ 8,1, $LGBPu2$ 8,1 and HOG on the corresponding optimal channels are 58, 53 and 133, respectively. 31 of them were incorrectly identified by $LBPu2$ 8,1, $LGBPu2$ 8,1 and HOG. Fig. 19 shows some of these images. The feature dimensions of the proposed algorithm, $LBPu2$ 8, 1, $LGBPu2$ 8,1 and the HOG method are 3456, 6372, 254880 and 8748, respectively. Most of the legs in our database have androgenic hair and therefore, the discriminative power is from androgenic hair patterns, instead of skin texture. This experiment aimed to evaluate the proposed algorithm on androgenic hair patterns in very low resolution images. The pre-processed images were first resized to 142 × 298, 106 × 223, 71 × 149 and 35 × 74 pixels and the corresponding resolutions were respectively 25, 18.75, 12.5 and 6.25 dpi. Then, we scaled these images up back to 142 × 298 pixels so we did not need to change the parameters in the proposed algorithm. The images with resolutions of 25 and 18.75 dpi provide a similar performance. The performance drops relatively significant for the images with resolutions of 12.5 and 6.25 dpi. Their rank-one accuracies are still over 71% and 64%, respectively.

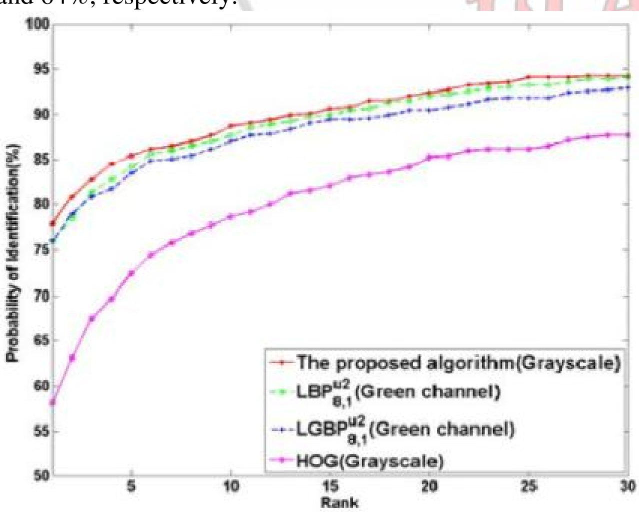

Fig. 4 Cumulative match curves of the best LBP,LGBP and HOG methods and the proposed algorithm from the corresponding optimal channels

These experimental results demonstrate that androgenic hair patterns even in low resolution images are an effective biometric trait. This experiment aimed to evaluate the proposed algorithm on androgenic hair patterns from the same race. 52.7%, 32.2%and 7.4% of the subjects in our database are Chinese, Malays and Indians, respectively. More clearly, the gallery and probe sets were all from the same race and the resolution of the images was 25 dpi. These figures show that androgenic hair patterns from the same race are different enough for identification. The last experiment aimed to evaluate androgenic hair patterns and the proposed algorithm for identification with a large gallery set. Even though the gallery set was increased to 1,111 images, the rank one identification accuracy is still over 72%. It shows the effectiveness of androgenic hair patterns for identification with a large gallery set.

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