Fast Pattern Matching Algorithm for detection of Wild Animal Hairs using SEM Micrographs

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Abstract— For hair detection of wild endangered animal species of feline family *viz. Panthera leo persica, Panthera pradus fusca* and *Panthera tigris tigris*, a fast pattern matching algorithm (FPMA) named as Dahiya and Yadav (DnY-FPMA) has been developed based on normalized cross correlation (NCC) and convolution techniques. The scanning electron microscopic (SEM) images were used for current forensic evaluation. FPMA method applied to recognize and/or locate specific objects in an image using correlation and convolution techniques. To improve the accuracy of the FPMA model, multiple reference templates were used for identification of unknown images. In this model, the best correlations of test SEM images at various magnifications have been made for getting clarity in results. The test images of above species were compared with standard images, which have proved that the correlation method found to be more accurate for evaluation than of the convolution method. FPMA method oriented the images properly and made them noiseless by rotating the inclined images with radon function having reference orientation. The obtained results revealed that the matching pattern for leopard, lion and tiger were up to a maximum of 99.64%,99.50% and 99.60% with convolution while 99.58%, 99.68% and 98.87% with NCC respectively.

Index Terms— Convolution, Direction Estimation, Fourier Transform, Normalized Cross-correlation, Pattern Matching, Radon Transform and Template Matching.

1. INTRODUCTION

The selection of control region for comparison with the standard images is the basic problem in forensic hair pattern investigation technique (FHPIT), which is a thrust of forensic researcher. For this purpose, the template matching method is often used which is basic approach. The template matching represents the object as we expect to find it in the image where the object can indeed be scaled or rotated which requires a separate template for each scale and orientation. In this method, the position of the given pattern is determined by the pixel-wise comparison of the images with the given template that contains desired pattern. Consequently, the template image is shifted *u*-step in the x-direction and *v*-step in the y-direction of the sample image, and then the comparison is calculated over the template area of each position *(u, v)* in percentage pixel. The popularity of template matching methods for applications of signal or image processing is mainly due to its ease of implementation with many fast algorithms and speed up the matching process for various applications [3], [8], [10], [13], [16].

On the other hand, there are already many methods for speeding up the process of template matching which are being used for the last decade [1], [7], [8], [9]. In this context, the normalized form of correlation (correlation coefficient) method is preferred for matching of templates which lacks efficient frequency domain expression as its drawback. To avoid this problem NCC method has been computed in the spatial domain. Due to high computational cost of NCC spatial domain convolution, several spatial domain matching methods have been developed but those are not that much accurate [9], [10]. Therefore, aim of this study was to develop a fast, accurate and precise identification tool for the investigation of the unknown hair samples using standard multiple-templates of SEM images.
Thus, to overcome the drawback of previously reported or applied methods for FPMA, a new algorithm of NCC from transform domain convolution (DnY-FPMA) has been developed and reported in this study. The newly developed algorithm of FPMA has been found to be speedier in computational approach for spatial domain of NCC. The DnY-FPMA has template matching inherently rely on a matching cost that, once minimized (or maximized, in case a similarity measure is deployed) allows locating the position of the template in the search space, which is its merit over the other FPMAs. Most significant feature of DnY-FPMA is that it stores the uploaded digitized images into database automatically obtained from the sample analysis which can be further used for the comparison of wildlife artifacts. To prove the validity and accuracy of the DnY-FPMA, the SEM images of three different wildlife species of feline family from Gujarat state *viz.* lion, leopard and tigers from three different regions were investigated which confirmed the validity of the developed DnY-FPMA.

Thus, our newly developed DnY-FPMA for NCC will be of great importance in wildlife crime investigation and this study also reported the first hair database of feline family for the wildlife crime investigation.

2. METHODS

2.1 Image Conversion

2.1.1 The Radon Transformation

The 2-D Radon transform is the projection of the image intensity along a radial line oriented at a specific angle. This transform is not by itself a tool for rotation estimation in an image; it may be used by some other tools to capture the directional information of an image which is necessary for rotation-invariant image analysis. Specifically, if we define the principle direction for an image as the direction along which the image has more straight lines, the Radon transform along this direction is usually expected to have larger variations, especially if we filter out the low frequency information from the image before applying the Radon transform. The Radon Transformation is a fundamental tool which is used in various applications [14] such as radar imaging, geophysical imaging, nondestructive testing and medical imaging.
Suppose a 2-D digital image have a function $f(x,y)$ (Fig. 3). Integrating along the line, whose normal vector is in θ direction, results in the $R(\rho,\theta)$ function which is the

projection of the 2D function $f(x,y)$ on the axis ρ of θ direction. When ρ is zero, the R function has the value $R(0,\theta)$ which is obtained by the integration along the line passing the origin of (x,y)-coordinate. The points on the line whose normal vector is in θ direction from x-axis and passes the origin of (x,y)-coordinate satisfy the equation:

$$x\cos\theta + y\sin\theta = 0 \quad (1)$$

The integration along the line whose normal vector is in θ direction and that passes the origin of (x,y)-coordinate means the integration of $f(x,y)$ only at the points satisfying the equation (1). With the help of the Dirac "function" δ, which is zero for every argument except to 0 and its integral is one, $R(0,\theta)$ is expressed as:

$$R(0,\theta) = \iint f(x,y)\cdot\delta(x\cos\theta + y\sin\theta)\,dxdy \quad (2)$$

Similarly, ρ is the smallest distance from the origin and θ is its angle with the x-axis. In this form, a line is defined as the following equation:

$$(x-\rho\cdot\cos\theta)\cdot\cos\theta + (y-\rho\cdot\sin\theta)\cdot\sin\theta = 0$$
$$\Rightarrow x\cos\theta + y\sin\theta - \rho = 0 \quad (3)$$

So the general equation of the Radon transformation is acquired. From equation (2) and (3) is combined as:

$$R(\rho,\theta) = \iint f(x,y)\cdot\delta(x\cos\theta + y\sin\theta - \rho)\,dxdy \quad (4)$$

There are two distinct Radon transforms. The source can either be a single point (not shown) or it can be an array of sources (as shown in Figure 1). The method are used in this project uses an array of sources.

These radon transform values (as using equation 4) are computed by fast Fourier transform (FFT) algorithm which is produced frequency term in each index of radon function. The FFT of the test image is defined by:

$$F_i(u,v) = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} R(\rho,\theta).e^{-j2\pi(\frac{um}{M}+\frac{vn}{N})} \quad (5)$$

Where $0 \le u,m \le M-1$ and $0 \le v,n \le N-1$ and $R(\rho,\theta)$ radon transform of the input image $I_i(x,y)$ is the projection of the image intensity along a radial line oriented at a specific angle. $F_i(u,v)$ Spatial frequency of the radon transforms of test image. The spatial frequency of the reference image $F_r(u,v)$ is defined in a similar way (same equation 5).

The zero mean value of spatial frequency of test image is defined as:

$$f_i(x,y) = F_i(x,y) - \mu(F) \quad (6)$$

Where $\mu(F_i)$ is the mean of the spatial frequency of the test image. However, the zero mean value of the spatial frequency of the reference image $F_r(x,y)$ is defined in a similar way (same equation 6).

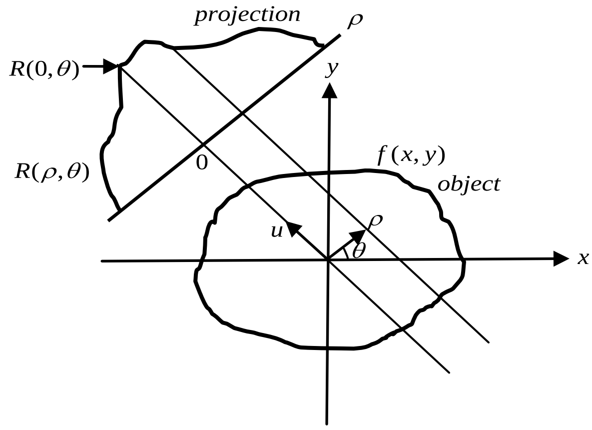

Figure 1: The source and sensor is rotated about the center of the object. For each angle θ the density of the matter the rays from the source passes through is accumulated at the sensor. This is repeated for a given set of angels, usually from θ ∈ [0:179).

Finally, calculated the cross correlation between zero mean value of test image and reference image which is given the maximum correlation index value. This index value is subtracted from length of the reference image has obtained the rotation angle. This angle is used for proper orientation of the test image as shown in figure 4.

2.2 Template Matching using Normalized Cross-correlation

The NCC method is a simple template matching method that determines the location of a desired pattern represented by a template function, *T*, inside a two dimensional image function *I*, the template image is scanned across the image forming a correlation plane that provides information of where the template best matches the image. Highest correlation value will indicate the location of the targeted object. To search the template in the image $I(x,y)$ of size $m_x \times m_y$ pixels where *I* at the intensity (x,y) where $x \in \{1,\ldots,m_x\}$ and $y \in \{1,\ldots,m_y\}$. Similarly the template $T(x,y)$ of size $n_x \times n_y$ pixels where $n_x \le m_x$ and $n_y \le m_y$. NCC is evaluated at every point (u,v) for *I* and *T*, which has been shifted over the original image $I(x,y)$ by *u*- steps in the *x* - direction and *v* - steps in the *y* - direction. All the NCC coefficients are stored in a correlation matrix $\gamma(u,v)$ can be written as:

$$\gamma(u,v) = \frac{\sum_x\sum_y [I[(x,y)-\mu(I(u,v))].[T(x-u,y-v)-\mu(T)]}{\sqrt{\sum_x\sum_y [I[(x,y)-\mu(I(u,v)]^2.\sum_x\sum_y\ [T(x-u,y-v)-\mu(T)]^2}} \quad (7)$$

Where $u \in \{1,\ldots,m_x - n_x + 1\}$ and $v \in \{1,\ldots,m_y - n_y + 1\}$ and $\mu(I(u,v))$ is the mean value of $I(x,y)$ within the template T shifted by (u,v) steps and can be defined as:

$$\mu(I(u,v)) = \frac{1}{n_x \times n_y}\sum_x\sum_y I(x,y) \quad (8)$$

Similarly $\mu(T)$ is the average value of the template image T is calculated. The denominator in equation (7) is the variance of the zero mean image function $I(x,y)-\mu(I(u,v))$ and shifted zero mean template function $T(x-u,y-v)-\mu(T)$ due to this normalization, $\gamma(u,v)$ is independent to changes in the brightness or contrast of the image, which are related to the mean value and standard deviation.

For the denominator, which normalized the cross-correlation coefficient, at every point (u,v), $u \in \{1,\ldots,m_x - n_x + 1\}$ and $v \in \{1,\ldots,m_y - n_y + 1\}$ of the image, at which $\gamma(u,v)$ is determined, energy of the zero mean image is defined as:

$$e_i(u,v) = \sum_x \sum_y [I(x,y) - \mu(I(u,v))]^2 \qquad (9)$$

And the zero mean $e_i(u,v)$ of the image within the area of the template function $\mu(I(u,v))$ have to be recalculated. The energy of the zero mean template function is defined as:

$$e_t(u,v) = \sum_x \sum_y [T(x-u,y-u) - \mu(T)]^2 \qquad (10)$$

And the zero mean $e_t(u,v)$ of the template function $\mu(T)$ have to be pre-calculated only once. The value of this coefficient $\gamma(u,v)$ (from equation 7) falls into the range [-1.0, 1.0]; a value of 1.0 corresponds to a perfect match. Where it is found maximum, a rectangle is drawn around it to show detected area.

2.3 Template Matching using Convolution

This method includes a simple but fast correlation based template matching algorithm. The correlation coefficient calculation is implemented with convolution technique. In this technique for template matching purpose is only considerations on controlling the boundary and selecting region of interest on the frame image. However, by using convolution technique, the template matching speed has been accelerated and run-time has reduced to a reasonable value.

2.3.1 Calculation of the denominator

To simplify the calculation of the denominator of the normalized cross correlation coefficient (from equation 7), the key idea is to use two standard deviation of image function $I(x,y)$ and standard deviation of the template function $T(u,v)$ is calculated over the template image. The standard deviation of the image function can be defined by:

$$\sum_x \sum_y [I(x,y) - \mu(I(u,v))]^2 = \sum_x \sum_y [I(x,y)]^2 - 2\mu(I(u,v)) \sum_x \sum_y I(x,y) + \sum_x \sum_y \mu(I(x,y))^2 \qquad (11)$$

And all equation are used in this model the double sum is evaluated over the region of the template which means $u \le x \le u + n_x - 1$ and $v \le y \le v + n_y - 1$. The third term of the equation (11) is written as:

$$\sum_x \sum_y [\mu(I(u,v))]^2 = n_x \times n_y [\frac{1}{n_x \times n_y} \sum_x \sum_y I(x,y)]^2 \qquad (12)$$

Can be simplified as the equation (12) is defined as:

$$\sum_x \sum_y [I(x,y) - \mu(I(u,v))]^2 = \sum_x \sum_y [I(x,y)]^2 - \frac{1}{n_x \times n_y} [\sum_x \sum_y I(x,y)]^2 \qquad (13)$$

Equation (13) is used for calculating the standard deviation of the image function over the template is simply written as:

$$\sigma_i(u,v) = \sqrt{\sum_x \sum_y \frac{[I(x,y)]^2}{n_x n_y} - [\sum_x \sum_y \frac{I(x,y)}{n_x \times n_y}]^2} \qquad (14)$$

The standard deviation $\sigma_i(u,v)$ of the image function have to be recalculated at each points of *u* and *v*. Similarly the standard deviation of the template function can be written as:

$$\sigma_t(i,j) = \sqrt{\sum_i \sum_j \frac{[T(i,j) - \mu(T)]^2}{n_x \times n_y}} \qquad (15)$$

Where $i \in \{1,\ldots,n_x\}$ and $j \in \{1,\ldots,n_y\}$ is same as the template size; this standard deviation $\sigma_t(u,v)$ of the template function have to be pre-calculated only once. Moreover, both equation (14) and (15) have to be used for calculating the correlation coefficient.

2.3.2 Calculation of the Numerator

A significantly more efficient way of calculating the NCC is by computing the numerator of Equation (7) via convolution. Application of the algorithm presented in the last subsection allows efficient calculation of the denominator, but the number of computations required to calculate the numerator of the NCC- coefficient is still comparatively high, even if it is done by convolution of two functions. Therefore, further simplification of this calculation has to be required. The numerator has to be written as:

$$N(u,v) = \sum_x \sum_y [I(x,y) - \mu(I(u,v))].\overline{T}(x-u,y-v) \qquad (16)$$

Where $\overline{T}(x-u,y-v)$ is a zero mean template function has to be defined by:

$$\overline{T}(x-u,y-v) = T(x-u,y-v) - \mu(T) \qquad (17)$$

For simplifying the equation (16) can be written as:

$$N(u,v) = \sum_x \sum_y I(x,y).\overline{T}(x-u,y-v) - \mu(I(u,v)) \sum_x \sum_y \overline{T}(x-u,y-v) \qquad (18)$$

Since $\overline{T}(x-u,y-v)$ has zero mean value of the template function and thus also their summation is zero, the term $\mu(I(u,v) \sum_x \sum_y \overline{T}(x-u,y-v)$ is zero as well. So we can be neglected this term in equation (17), therefore the numerator term can be written as:

$$N(u,v) = \sum_x \sum_y I(x,y).\overline{T}(x-u,y-v) \qquad (19)$$

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The numerator term $N(u,v)$ of the equation (19) is calculated simply shifted the zeros mean template over the image function $I(x,y)$ by u -step in x-direction and v-shift in y-direction.

By using equation (14), (15) and (19) are to be modified the equation (7) for normalized convolution calculation, then the approximated cross correlation function can be defined by:

$$\gamma(u,v) = \frac{N(u,v)}{n_x \times n_y \times \sigma_i \times \sigma_t} \qquad (20)$$

Where $u \in \{1,...,mx - nx + 1\}$ and $v \in \{1,...,my - ny + 1\}$

The template $T(x-u, y-v)$ is moved across image $I(x,y)$ in (u,v) plane and the correlation for each point is calculated. After complete scanning the related area, the highest correlation value representing the location of the target is obtained. Thus, position of the targeted template is known and its will be displayed. The range for the Correlation coefficient (from equation 20) $\gamma(u,v)$ is between -1 and 1. It is independent of scale changes in the amplitude of $I(x,y)$ and $T(x-u,y-v)$. The Value of 1 to show the maximum correlation of $I(x,y)$ and $T(x-u,y-v)$, a rectangle is drawn around it to show detected area. .

3. EXPERIMENTAL RESULTS

3.1 Image Conversion

In this section, the test image is used for pattern matching is stored in different data set of different species. However, this test image is firstly converted into a grayscale image. Later, this grayscale image is rotated automatically as per reference image because it is required for the large set of data. In this model pattern matching is based on the cross correlation, therefore it is necessary for proper orientation of image for finding best correlation. Figure (2) is shown the reference image at desired orientation as per template image. Figure (3) is shown the test image which is not desired orientation, therefore, it is rotated same as reference image automatically as shown in figure 4.

Figure 2: Reference image

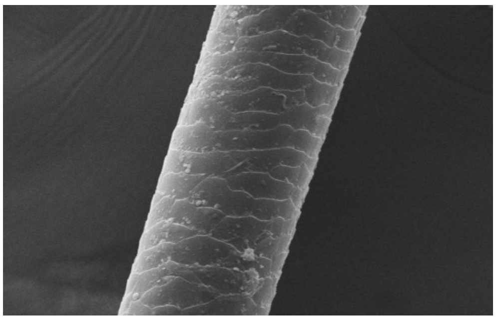

Figure 3: Test image

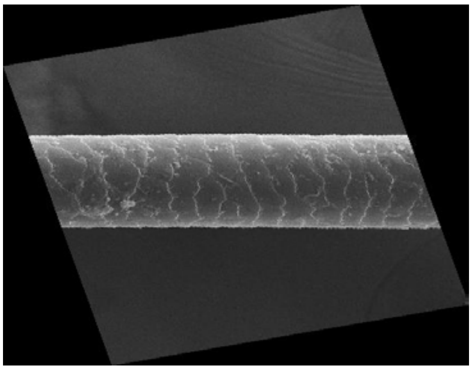

Figure 4: Rotated test image is same as reference image

3.2 NCC and Convolution Results

The method has been tested with several image and template. The goal of this experiment was mainly concerned with enhancing the performance of pattern matching system which is focused on two algorithm matching methods namely NCC and Convolution. In this experiment mainly three types of animal species were used. The pattern matching did not show proper result when the images are of degraded quality like zoom-in, zoom-out, different orientation etc. The investigations were based on three samples of source images and their templates in clean and noiseless data conditions.The template matching system to determine the best position for a template in a source image. Figure (5) is shown the template image and figure (6) is shown the correct matching of template over the test image is shown in the rectangle.

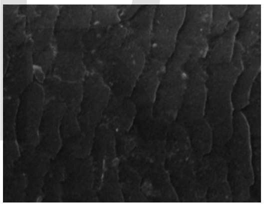

Figure 5: Template image

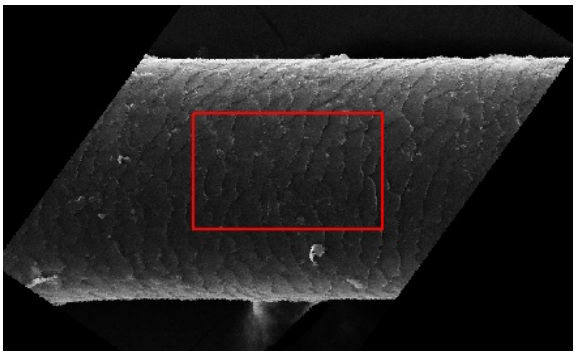

Figure 6: Detected area in test image

3.3 Pattern Matching Accuracy

Table 1-3 provides the experimental result obtained with three data set of Leopard, Lion and Tiger species. The table report, for the template of three species, the measured accuracy in term of percentage based on NCC and Convolution method.

The table 1 shows the data set of Leopard species that are matched with Leopard, Lion and Tiger species template. The results were obtained with maximum correlation of test image and template. Similarly results that are shown in table 2 and table 3 are of Lion and Tiger species respectively. Table 4 shows the average experimental result of three species.

Table 1: Pattern matching for Leopard hair species

Sr. no.	Leopard		Lion		Tiger	
	NCC (%)	Convo-lution (%)	NCC (%)	Convo-lution (%)	NCC (%)	Convo-lution (%)
1	92.09	95.45	65.87	62.52	58.28	57.27
2	91.56	93.67	62.57	64.31	59.36	56.98
3	95.24	98.99	69.47	66.98	61.57	58.01
4	99.58	99.64	67.45	65.28	64.24	57.32
5	97.58	99.34	61.89	59.03	56.52	57.20

Table 2: Pattern matching for Lion hair species

Sr. no.	Leopard		Lion		Tiger	
	NCC (%)	Conv-lution (%)	NCC (%)	Convo-lution (%)	NCC (%)	Convo-lution (%)
1	63.58	64.20	98.24	98.58	48.26	50.45
2	68.24	65.45	96.14	98.86	49.24	42.26
3	62.29	69.23	93.54	95.02	43.54	48.26
4	59.48	69.28	99.68	99.50	49.65	48.78
5	64..4	67.98	94.65	96.76	45.89	49.57

Table 3: Pattern matching for Tiger hair species

Sr. no.	leopard		Lion		Tiger	
	NCC (%)	Convo-lution (%)	NCC (%)	Convo-lution (%)	NCC (%)	Convo-lution (%)
1	51.36	57.27	49.35	50.45	96.01	98.78
2	59.33	56.98	43.20	42.26	95.68	97.15
3	53.25	58.01	39.58	48.26	98.87	99.60
4	53.25	57.32	49.05	48.78	94.21	98.02
5	68.87	59.20	59.56	49.57	97.68	98.34

Table 4: Total Accuracy for three species

leopard		Lion		Tiger	
NCC (%)	Convo-lution (%)	NCC (%)	Convo-lution (%)	NCC (%)	Convo-lution (%)
95.21	97.41	96.45	97.74	96.49	98.26

4. CONCLUSION

A novel pattern matching algorithm has been developed named as DnY-FPMA of NCC, which will be used in investigation of wildlife crime using hair as evidence. The newly developed DnY-FPMA is time saving approach with better accuracy. Using this DnY-FPMA a new data base of hair of feline family has been generated which will provide a hassel free reference database for further investigations.

In the current research model, it was explored that automatic hair pattern matching algorithm has revealed significant results in identification of hair images based on SEM micrographs of the hair samples thus it can be incorporated in wildlife crime investigation. The accuracy, reliability, time taken by processing, current digitalized method is significant and rapid over conventionally used identification techniques. This algorithm will be an useful aid for wildlife crime investigation. in addition to this human species can also be identified because of the presence of hair as most common evidence in cases of poaching, burglary, murder etc.

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