Image processing techniques in Dermatoglyphic fingerprint analysis: A review

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Abstract: Dermatoglyphics studies the patterns of an individual's fingerprints, the AtD angle in palm, number of ridges between core and farthest delta of each pattern on every fingertip, to analyse the personality and intelligence a person is born with. This paper gives an overview of how different image processing tools and techniques can be applied in this front. The techniques are applied for pattern matching, pattern identification as well as ridge identification and segmentation.

Keywords: Dermatoglyphics, Pattern matching, Pattern recognition, Ridge identification, Ridge segmentation

1. INTRODUCTION

Fingerprints are patterned ridges. Quite surprisingly, there are fixed set patterns they can occur. Though, count of a pattern may vary in an individual. Occurrence of one or more pattern and that too, in which finger, accounts for dermatoglyphics study of human intelligence and personality type.

Hence, a flexible method of automatic pattern classification is needed. To understand the effect the prints of either hands are going to have on the algorithm, we need to know that an ulnar loop on right hand is a radial loop on left hand and vice versa. The images are captured and saved in png format so as to keep the maximum possible image information. The images are 8 bit, 256 grayscale and of equal dimensions of 480 * 320 pixels. The image can be taken as a rectangle on a 2D plane with axes u and v. The number of pixels in image on u axis are m whereas on v axis in image are n. Although, when images are captured, they are in 3 dimensional grayscale format with red-green-blue compositions.

2. PRE-PROCESSING TECHNIQUES FOR IMAGE ENHANCEMENT

Enhancement is a very important for improving the relative appearance of an image for the purpose of extracting features and do pattern recognition. Every application of image processing requires customized processed images. Sometimes, the process of acquiring them results in incorporation of unnecessary noises like smudges, false prints. For the sake of maximal accurate processing, the enhancement algorithm [1-7] must be stable and robust enough to clean patterns off any corruptions, correctly. The phenomenon resulting from enhancement techniques include noise removal, edge enhancement, image zooming, image subtraction, pseudo - colouring, contrast enhancement as well as geometric distortion correction. They are outcome of various types of algorithm including grey scale transformation, spatial operations and transform domain operations. Point wise operations include contrast enhancement and stretching, grey scale clipping, binarization or thresholding, inversion or negation, grey scale slicing, bit extraction, contrast compression, image subtraction and operations including histogram modelling or equalization.

A. Point wise operations

When an operation is applied on pixels such that a central pixel value gets manipulated, such spatial transformations are known as point wise pixel operations. The new grey level or intensity value of pixel in question is the result of grey levels of surrounding pixels in neighbourhood of original image in same spatial location (m, n).

$$v(m, n) = f {u(m, n)}$$
, ∨ $m = 0, 1, ..., N - 1$;
f: {0,1,...,L_{max}}

B. Contrast enhancement and contrast stretching

The contrast of an image can be well enhanced by linear stretching, histogram equalization or Gaussian stretching. In this study, we have implemented the conventional histogram equalization method.

i) Linear stretch

The linear stretch method is usually considered the standard method. This is because all the pixel intensity values are stretched or distributed homogenously across the complete range of intensity values. The pixel values range from 0 to 255. The pixels with most common intensity values are stretched the most.



Fig 1: Effects of Linear Stretching

ii) Histogram equalization

Here, the pixels having same intensity values are increased in and around same location. Another aspect to be kept in mind is that pixels with most equal intensity values are stretched the most. In equalization, every grey scale level gets equally distributed number of pixels. Hence, every grey scale level holds almost equal number of pixels. A histogram does not contain any information about the spatial distribution of pixels. It is a nonlinear kind of stretching technique. The image gets darker at dark pixels and lighter at light pixels. Hence the contrast is well enhanced.



iii) Gaussian stretch

The original histogram is fitted to a normal Gaussian curve distribution. The mathematical expression for Gaussian curve is given by

$$F = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

The images undergoing this operation showcase similar effects. Although the effects can be manipulated by the sigma (σ) and mu (μ) parameters, which denote standard deviation of intensity value of current pixel from the local average and mu, which signifies the mean intensity in local neighbourhood of pixel in question.

C. Spatial operations

A spatial operation performed on an image refers to discrete convolution or correlation implemented to local neighbourhood of a pixel. The common operations applied, are averaging and low pass filtering. There is an image of size $m \times n$. A kernel, with fixed or function dependent values is moved over the whole image in a set pattern. It is also termed as template or window. The kernel is either smaller or of same size as that of the image. In practice, a kernel is smaller and contains odd dimensions. This is due to the fact that central pixel of this template shall bring the change upon the pixel in question, of original image. If kernel dimensions are even, we cannot place (0, 0) on its central a (i, j) pixel. The values contained in the kernel matrix are called filter weights. Spatial domain operations are expressed in terms of following notation

Impact Factor: 2.5

g(x, y) = T[f(x, y)]

where g (x, y) is input image, f (x, y) is output image and T is the operator on f defined over neighbourhood (x, y)y).

i) Smoothing and low pass filtering

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A common class of spatial averaging filter has equal weights. In the averaging operation, the weighted average replaces the central pixel. Averaging filters are better known as low pass filters. Since every pixel undergoes a change in its intensity values which is highly dependent upon its neighbouring pixels, there hardly remains any scope for abrupt intensity changes. As a result, high intensity components of image are removed. If a (k, l) be assumed weight matrix with dimensions $k \times l$, then, filter is given by

$$\mathbf{a} (\mathbf{k}, \mathbf{l}) = \begin{bmatrix} a(i-1,j-1) & a(i-1,j) & a(i-1,j+1) \\ a(i,j-1) & a(i,j) & a(i,j+1) \\ a(i+1,j-1) & a(i+1,j) & a(i+1,j+1) \end{bmatrix}$$

 $v(m, n) = \sum_{(k,l) \in w} \sum a_{k,l} y(m-k, n-l)$ where y (m, n) and v (m, n) are input, original image and output, transformed image respectively. $v(m, n) = \frac{1}{N_w} \sum_{(k,l) \in w} \sum y(m-k, n-l)$ where a (k, 1) = $\frac{1}{N_w}$

 N_w is the number of pixels in the window. Another spatial averaging filter used often is given by $v(m, n) = \frac{1}{2} \left[y(m, n) + \frac{1}{4} \{ y(m-1, n) + y(m+1, n) + y(m, n-1) + y(m, n+1) \} \right]$



Fig 3: Effect of smoothing filter on image

ii) Sharpening and high pass filtering

A sharpening filter enhances the darkness or brightness of pixel. The key to its operation is that all values in the kernel sum up to one. As a result, the kernel odes not bring about any change in pixels with constant intensity values. But if there is an abrupt change in grey level, high or low, the contrast gets boosted. Such an example of kernel is given below

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$



Fig 4: Effects of sharpening an image

3. PATTERN MATCHING TECHNIQUES

A. Fourier Mellin transform

Image registration is a technique that aligns two similar images after they have undergone affine transforms. Some fixed data points are decided upon the image in the coordinate plane. The affine transforms shall shift them from initial coordinates. The transformed data points are again observed at a different time, from a different angle or level or even from a separate sensor. The affine transformations [8] once detected, can be used to set the test image in a manner so that it can be perfectly superimposed with the available template. When they are perfectly aligned, the algorithm finds a central pixel which is used a point of reference, against the correlation between the images.

Any affine transformation [9] is given by the transform which preserves the translation, rotation, shear, scaling, reflection, homothety etc. The affine transform is such that the transform perceives the input as original even after there has been a rotation angle change in same plane, translation along horizontal and vertical direction. This is the reason why affine transforms are suitable for cylindrical coordinate system and not spherical coordinate system. When there is any rotational change on an image, it occurs on same plane of cylindrical coordinate system. The spherical coordinate have two angular dimensions wherein images cannot be included. The z axis is taken as reference, as it is common to both Cartesian and cylindrical coordinate systems. Also, spherical coordinate cannot contribute to the understanding of translation given by x_0 and y_0 . Hence, cylindrical coordinates are the base for preserving collinearity of points in a straight line or proportionate ratio of distances and angles even after transformation. For example, if an image goes through scaling s, horizontal and vertical transformation of x_0 and y_0 and some rotation given by θ , then the rotation – enlargement algorithm is given by

$$\begin{bmatrix} x'\\ y' \end{bmatrix} = s \begin{bmatrix} \cos \alpha & \sin \alpha\\ -\sin \alpha & \cos \alpha \end{bmatrix} \begin{bmatrix} x - x_0\\ y - y_0 \end{bmatrix}$$
$$= s \begin{bmatrix} \cos \alpha & (x - x_0) + \sin \alpha & (x - x_0) \\ -\sin \alpha & (x - x_0) + \cos \alpha & (x - x_0) \end{bmatrix}$$

If $a = s \cos \alpha$ and $b = s \sin \alpha$ Then scale factor, s is given by

And the rotation angle is given by

$$\alpha = \tan^{-1}\left(-\frac{b}{a}\right)$$

 $s \equiv \sqrt{a^2 + b^2}$

The Fourier – Mellin is an important tool for image registration. The resulting spectrum is invariant to rotation, scaling, translation etc.

B. Phase Only Correlation (POC) Based PatternMatching

The correlation based analysis is one of the most inevitable parts of pattern matching. An image is a display of colours, whether the frequency component lying in VIBGYOR or truecolor range or 8 bit grayscale range. It is an inevitable means of finding correlation between frequency components of each and every pixel of the test image and find the score of matching to the pixel wise frequency component of template image. The most efficient form of correlation is the normalized cross correlation.

Mathematically, cross correlation measures the lag between the phase angles of a function at two different time periods. Since frequency is related to time, the lag concept can be applied to the frequency term also. Hence, when there are two images, one smaller than other or both are of same sizes, then the relative phase lag is calculated. If the two images are equal in size, then the template is placed over the test once, and every pixel is compared to its counterpart on the other image. When the template is smaller than test, then it is moved over the image as long as all the pixels have not been covered. In general, the correlation is the analysis of how much two identical functions are shifted or translated from each other in a particular axis. Maximum correlation is achieved when the shift has been nullified and both images are superimposed. Then, each and every point of the test image corresponds to the similar point on the template image. It is to be noted that, correlation can only be found in real valued functions and that imaginary quantities are not physically realizable for any matching. If by any chance, the function happens to be having any imaginary component, then conjugate of template image is taken for correlation calculation. As a result, conjugate of the template image shall result in positive aligned peaks corresponding to imaginary components.

4. PATTERN RECOGNITION TECHNIQUES

A. Gradient based method

In this algorithm, we make use of the ridges and their orientation in the pattern to extract feature corresponding to every class of pattern. Herein, the gradient map of original image is generated after it has been slightly pre-processed off any minor corruptions. This method incorporates various ridges, valleys and the direction in which they turn. As a result of which, the intensity field follows the ridge pattern [10]. The ridges are long, continuous, and thin with ends and bifurcations in between. Ridge ends are termination points of ridges. A bifurcation point is where a single ridge bisects into two sections. Although there are about 150 characteristic features of ridges, known as minutiae, we limit our directional field study only to ridges. A welldefined fingerprint image should be available with clean ridges and furrows. The pre-processing needs to cleanse the ridges off all falsely acquired smudges.



Fig 5: High resolution image of loop fingerprint pattern gradient field

Application of Gaussian filter i)

The Gaussian operator two dimensional filter is one of the blurring or smoothing filters. The Gaussian filter is based on the "bell shaped" Gaussian curve distribution. Although, the function does the work of an averaging or mean filter, but the kernel used, takes the typical shape of Gaussian curve. The Gaussian distribution for one dimension, dependent upon single variable x, is given by

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}}$$

Where G(x) is the Gaussian distribution, x is the variable and σ is the standard deviation.

Usually, with zero mean, the Gaussian distribution curve is centred at zero. In case of a two dimensional system like image, where there are two axes, isometrically symmetric, the Gaussian distribution takes a three dimensional form. The base of the distribution lies on the x-y plane whereas the G(x,y) determines the height.



Fig 6: Two dimensional Gaussian distribution

The mathematical expression for the Gaussian distribution filter for two dimensional image space, is given by

$$G(x,y) = \frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where the parameters have their usual meaning. The value of standard deviation is taken 0.5, by default.

ii) Assigning optimal values to parameters

The significant Gaussian parameters are the window size of the kernel and the standard deviation. It has been observed that majority of the ridges are four to six pixel broad. A window size of 3*3 assures that the filter shall remove or zero down edges beyond the scope of its kernel size. The choice of window size depends on the application. A 3*3 kernel size would mean that the filter decays down till it reaches the third pixel, on either sides. Since we want to suppress the unwanted smudges that come along with the ridges, a sigma should be chosen accordingly. A sigma should make the Gaussian curve big enough to remove the smudge. All the operations are based on simple two dimensional convolution. The prime factor to be kept in consideration, while using the Gaussian mask is that it must die down to zero around the edges of the kernel.

iii) Covariance calculation

To determine the edges, the sharpness of the boundary needs to be specially determined. This differentiates the edges or objects in this case, from the background. Hence, a difference lies between the texture and the sharpness details of the image. While the basic image retains all the details that have not been filtered out by the Gaussian filter as well as the first order differentiation, the image reproduced after differentiation is different. This image has already secured information regarding the locations and curvatures of edges. The covariance finds the degree of variation between the original and the reproduced images. This difference shall correspond to the effect of changes made by the first and second order differentiation. This difference is mainly due to contrast. Larger the covariance value, higher is the variation. It can be mathematically represented as

$$cov(X,Y) = \frac{1}{N} \sum_{i=1}^{n} (X_i - X) (Y_i - Y)$$

iv) Gradient direction and orientation calculation

The direction and orientation can be found by taking magnitude and angle of double differentiated x and y components of the gradient. The gradient components in horizontal and vertical direction are given as

$$G_{xx}(x,y) = \sum_{\substack{i=-\omega/2 \\ \omega/2}}^{\omega/2} \sum_{\substack{j=-\omega/2 \\ \omega/2}}^{\omega/2} 2 G_x (x+i,y+j) G_y (x+i,y+j)$$

$$G_{xy}(x,y) = \sum_{\substack{i=-\omega/2 \\ i=-\omega/2}}^{\omega/2} \sum_{\substack{j=-\omega/2 \\ j=-\omega/2}}^{\omega/2} (G_x (x+i,y+j)^2 - G_y (x+i,y+j)^2)$$

$$\emptyset (x,y) = \frac{1}{2} \tan^{-1} \frac{G_{xy}(x,y)}{G_{xx}(x,y)} + k\pi$$

Where

$$k = \begin{cases} \frac{1}{2} & \text{when } (\emptyset(x,y) < 0 \cap G_{xy}(x,y) < 0) \cup (\emptyset(x,y) \ge 0 \cap G_{xy}(x,y) > 0) \\ & 1 & \text{when } \emptyset(x,y) < 0 \cap G_{xy}(x,y) \ge 0 \\ & 0 & \text{when } \emptyset(x,y) \ge 0 & \cap G_{xy}(x,y) \le 0 \end{cases} \end{cases}$$

The results obtained for the gradient based method for pattern identification based on ridge curvature is discussed further below.

The gradient image [11-12] of a fingerprint pattern is the representation of direction in which the intensity of adjacent pixels either increase or decrease. The ridges in fingerprint images are brighter at the centre and becomes lesser bright as one moves towards the edge of the ridges. All the explanations are made on the basis of the ridges being white or one intensity value and background pixels being black or zero valued.

The Sobel filter is applied to the image and the gradient is calculated. The horizontal and vertical components of the gradient provide local intensity orientation on a ridge. Hence, a continuous vector field is obtained. This is shown in figure 7. The markings have been made prominent using 'quiver', which is the outcome of point wise cosine and sine of local estimated orientation.



Fig 7: Local Intensity Orientation Field of Loop

Ridge extraction by Control Point Selection and then identification В.

For a well enhanced fingerprint image, the following algorithm holds effective. The method yields all ridges of the fingerprint separately in different output graphic windows. The N – point connectivity of pixel [15] of interest is core of this approach. This algorithm also takes into account, non-linear operations on specific image regions and pixels. The operations depend upon how different intensity pixels are arranged in a neighbourhood. A sequence or pattern of similar or pixels

i) Gravscale thresholding

The input image undergoes grey scale thresholding which is automatic. The user cannot define the multiple intensity levels at which each grey value can be coerced into. Hence, an equalization of intensity levels, leads to fair thresholding of each pixel into its nearest grey value.

ii) **Binarization**

Next is the binarization operation. This parameter is user defined. It divides all the pixels into pixels with two intensity levels, one above the threshold value and one below. Since this categorisation is normalized into range from 0 to 1. There are infinite values between 0 and 1 which can be applied by user by hit and trial method. So, an algorithm was developed using simple image enhancement techniques that could handle false ridge lines, dots on ridges or irregular width of ridges. The images need to be sized equally.

iii) Morphological transformation

Skeletonization

The skeletonization operation when applied to specific image regions, narrows the pixel width and creates spurs or single pixel width formations. This operation allows removal of pixel boundaries around a central region of interest without causing any breakage or disruption to the original continuous region. MatLab has the provision to repeat same morphological operation infinite number of times, given that the user requires enhanced results.

This helps in removing bridges between the concentric ridges because even true minutiae do not concern the scope of this study. The study is focussed solely on pattern of core of fingerprint. Also, it is most suitable morphological operation that effectively clears fingerprints of any unnecessary ridge formations that do not contribute to major pattern classes.

Region filling

Sometimes fingerprint ridges have regular dots on them. When acquired as an image, these dots emerge as dark spots at regular intervals on the relatively brighter ridges. It is important that these dots should not be confused with minutiae dots or interfere with feature extraction mechanism of processing. Hence, it is crucial to remove such dots or 'holes', as they appear on ridges.

In such cases, the area within which this hole is present is considered to be the foreground whereas the region encompassing the ridge including hole come under the background pixel region. Region filling makes use of dilation and intersection operations. When a structuring element of suitable shape and size probes the region using dilation, the holes get filled up. The complement of image power set shows only the foreground regions, but with pixel value of background region from original image set. This complement of image is operated with intersection on dilated original image. This mechanism is well off made clear using following expressions.



Fig 8: Effect of Region filling

Let A be a set of pixels and B be its structuring element. If all the pixels to be filled are numbered from 1 to p, then the hole filling is mathematically expressed as

$$X_k = (X_{k-1} \oplus B) \cap A^c$$
, $k = 1, 2, 3, ...$

where $X_o = p$, is the number of iterations in the algorithm and it stops when $X_k = X_{K-1}$.

iv) Region selection based on concept of pixel connectivity

The pixel connectivity implements the idea of extracting image components that are connected to each other through pixels within a neighbourhood. For example, let there be a component A, defined by some pixels, within an image I. Assume a pixel, P, connected to one of the pixels of A such that this pixel, P shares its neighbourhood with some pixel of A too. As a result, a pixel of A is known. Then, all the remaining pixels of A can be very well identified by the following mathematical expression

$$X_k = (X_{k-1} \oplus B) \bigcap I$$

where B is the structuring element used to probe the image in order to extract connected regions. In this algorithm, a pixel is treated for extracting its neighbouring regions based on the condition that every pixel in the resized image is checked for being a ridge pixel. If it is one, then its 8 point connective neighbourhood pixels are extracted. If any one of those neighbourhood pixels are ridge pixels, then, that consequent neighbourhood is further extracted. This phenomenon keeps on occurring in the form of iterations until the following condition of convergence occurs. The loop stops when

$$X_k = X_{k-1}$$

As a result, the final steady condition becomes $A = X_k$. This method has some loopholes, such as all ridge pixels are valued at 1. As a result, the above stated condition holds ineffective in terms of non-repeatability.

An image feature is any portion of an image that can potentially be identified and located in both images. Features can be points, lines or corners. Once selected, they need to be matched. For a feature in one image, one must determine the corresponding feature in other image. The command *cpselect* selects different user defined control points. For the image to be registered against, these are called the base points whereas for the image to register, the control points are known as input points. From a set of matched feature points, a geometric transformation function is inferred that maps features in one image to the locations on other image. The image we undertook in our case, might be rotated, shifted horizontally, that is, translated or even scaled. Together these features are called *affine transformations*. Once these transformations have been detected, the unknown image can be registered to be a modulated version of the original.

Ridges extracted

The control point selection tool gives a wide applicability to the user, as shown in figure 9. The tool comes with other sister tools where a unit vector matrix can be transformed according to the test image to detect the transformations that the test image itself goes through. The template can be much related to the test only with some non-symmetric or reflective or even affine type. The affine transform includes all possible changes that occurred on spatial level.



Fig 9 - Control point selection

As a result, when the foreground pixels of a pattern are selected, the connected neighbourhood pixels get selected too. Using Graphic User Interface (GUI), the ridges can be extracted by choosing some of the pixels on the ridges.



Fig 10 :

Α.



from Arch pattern

5. RIDGE SEGMENTATION TECHNIQUES

Application of Gabor Filter for ridge segmentation

Gabor filters were first given by Dennis Gabor. They are a bank of linear filters. They specialize in cases where there are abrupt intensity changes. Hence, play crucial role in determining edge detection. They perform better in case of recognising dominant spatial frequencies and their respective orientations. A zero mean Gaussian curve is used as envelope function along with complex number oscillations oriented perpendicular to laid pattern. Multiple resolution versions of image filtered by Gabor bank [17-22] are obtained after subsampling, by keeping sizes of filter results and input images same. While detecting edges, an abrupt intensity change needs to be detected. If adjacent lighter or darker region represents the inner or outer areas around boundary, then, mathematically the edge is denoted by peak of a sinusoid. This sinusoidal form is obtained by doing a Gabor spectral analysis. If g is Gabor function, it is mathematically represented by

$$g(x, y, \theta, \phi) = \exp\left(-\frac{x^2 + y^2}{\sigma^2}\right) \exp\left(2\pi\theta i(x\cos\phi + y\sin\phi)\right)$$

where, x and y represent the coordinates of the plane, θ be spatial frequency and φ be the orientation. σ denotes standard deviation of Gaussian kernel. It depends upon the distribution of spatial frequencies all through the image. The mathematical operation implemented by filter bank on image, is convolution. At any arbitrary point (x, y) on image I, when Gabor filter bank $g(x,y,\theta,\varphi)$ is applied, the convolution is given as,

$$g(x, y, \theta, \varphi) = \iint I(p, q)g(x - p, y - q, \theta, \varphi)dp dq$$

The crucial part of a Gabor filter is that it can be moved at any angle, over the image. Most effective results are obtained from images that have periodic high and low intensity pixels. For example, ridges of fingerprints, image of a zebra, and so on. The constant white pixels correspond to crest whereas the dark pixels signify the trough of complex sinusoid of filter. This is due to the fact that Gabor filters are phase sensitive. Response of real and imaginary parts of the complex sinusoid to any such sinusoid, shall result in a sinusoid. The angles and number of times the filters can be superimposed on the image, are user defined. It is exclusively based upon the requirement. The researcher finalises the most suitable projection.



Fig 11: Effects of variable Gabor parameters on an image

A. Temporal Gabor filter

This is exclusively used for one-dimensional signals like speech and audio signals. Gabor filter bank used for such purposes prove to be excellent band pass filters. Though phase sensitive, the response is squared so that oppositely polarised sinusoid responses do not cancel each other. In frequency domain, the magnitude of response is simply the modulus of complex frequency response or the real part of Fourier response. Taking Fourier response of Gabor function, we get

$$\hat{g}(f) = ke^{j\theta} \int_{-\infty}^{\infty} e^{-j2\pi ft} w(at) s(t) dt$$
$$= ke^{j\theta} \int_{-\infty}^{\infty} e^{-j2\pi (f-f_0)t} w(at) dt$$
$$= \frac{k}{a} e^{j\theta} \widehat{w} \left(\frac{f-f_0}{a}\right)$$

where $\widehat{w}(f) = w(f) = e^{-\pi f^2}$

B. Spatial Gabor filter

Spatial filter is applied on two dimensional envelope signals. Image is one such kind of signal. The image is characterised by such an envelope, defined by a single dimension carrier signal. This envelope is Gaussian in nature of its distribution. The formula for Gaussian kernel in space domain is given as follows

$$g(x, y) = s(x, y) w_r(x, y)$$

where s(x, y) is a complex sinusoid, known as carrier and $w_r(x, y)$ represents the two dimensional Gaussian envelope. Since an image enhancement requires a spatial Gabor filter, it is compulsory to know the nine parameters that govern the outcome. They include six variables of envelope and three of carrier - K, scale or magnitude factor of Gaussian envelope, the abscissa and ordinate of envelope, as well as angle of rotation of the envelope, location of peak of Gaussian envelope. Also, Cartesian coordinate components of spatial frequency (u_0, v_0) and phase of sinusoid carrier are taken into consideration.

The window function applied in a Gabor transform is a Gaussian distribution curve. Parameters included are psi, gamma or aspect ratio, lambda or wavelength, psi or phase angle. Every pattern has its unique spatial frequencies and their orientation. A range of frequencies and orientations have been chosen to view the response of the Gabor filter banks. The observations have been made in the range of 0° to 180° , at every 30° of orientation. It has been observed that patterns can be best classified according to the orientation of the ridges. The orientation angles need to be defined in the algorithm.



Fig 12: Gabor bank filtered

6. RIDGE IDENTIFICATION TECHNIQUES

The hough transform is used to detect objects within an image which are lines, circles or ellipses. Here, the ridge count present on a fingertip, between the core of the pattern and the farthest delta needs to be counted. Hence, classical hough transform [23-26] is applied. The line in cartesian plane is converted into its polar coordinates. Since only preliminary study has been done in this method, few of the line segments with high accumulator bins have been identified and marked. The original image and the image with marked/detected ridges and corresponding phase plot is illustrated in figure 13 and 14 respectively. The vertical and horizontal axes of the phase plot denote the radius (ρ) and angle of point wise polar coordinate, respectively.







Fig 14 - Ridges detected as part of line segment recognition (left); Hough peaks detected in phase plot, corresponding to ridge detection (right)

7. CONCLUSION

The methods of Fourier Mellin transform and Phase correlation effectively match same patterns while the pattern identification or recognition can be done on the basis of gradient based method and ridge extraction using control point selection. The ridges themselves can be extracted to study the pattern using Gabor bank of filters and the ridges can be counted by applying Hough transform. The total ridges on all the fingers of a person relate to his/her potentials.

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