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Fingerprint Matching using Graph Structure based Symmetric Ternary Pattern

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Abstract: Fingerprint matching, one of the sophisticated biometric authentication techniques, is popular for its easy implementation, persistent nature of the fingerprint and non-similarity nature of two fingerprints. Uniqueness of fingerprint is characterized by distinctive features present in fingerprint image. This paper presents a novel relational descriptor based fingerprint matching process using pattern matching concept called Multi-Variant Symmetric Ternary Pattern (MVSTP). Orientation and illumination invariant local descriptor MVSTP extract distinct features from fingerprint image by referring non-overlapping neighbor pixels in symmetric way with respect to source pixel positioned at the center of 5×5 pixel area. After feature extraction from query fingerprint image and stored fingerprint images in the database, features are compared to find similarity match. MVSTP aims to increase fingerprint matching accuracy in contrast with other processes by addressing challenges related to fingerprint pattern's appearance variation with slight orientation and the variations present in image properties. The computational proficiency of the proposed fingerprint matching process is tested on FVC 2004 database and local database of fingerprint images with higher note of matching accuracy, manifesting its intensity in the process.

Keywords: Fingerprint Matching, Local-Feature Descriptor, Symmetric Patterns

1. Introduction

Biometrics is a technology that measures and analyses the physical and behavioral characteristics of any individual that is used for authentication. They are proven and more reliable than traditional authentication techniques because they provide unique and accurate evidence. Along with numerous biometric techniques available, fingerprint authentication technique [1] has made itself most popular among others owing to its uniqueness and degree of accuracy that supersedes other authentication techniques. Fingerprint verification refers to authenticity of a person by fingerprint of that person. Fingerprint remains more or less same for entire life time of a person. For this reason, fingerprint impression is used for authentication in many dynamic systems such as law enforcement, border control, ATM, airport entry, attendance of employees, attendance of students, bank document checking, property document verification etc. Intersected or parallel or terminated ridge lines present on the finger, form fingerprint. Each ridge is delineated by distinct features called minutiae. The user provides fingerprint pattern, features are extracted from that and compared with the features of stored fingerprint images for similarity measurement. Mainly, performance of modern automated fingerprint authentication systems is dependent on the accuracy of the feature extraction [2] algorithm.

Key features of fingerprint are:

- Accuracy – Since the surface of human skin (in the finger) consists of ridges in form of arches, loops and whorls, it is easy to train a machine by providing variety of data sets as samples. Since there are many distinct points on which these fingerprints can be classified, thus the chances of getting accurate results is higher than in any other biometric identification.
- Uniqueness – Fingerprint of any human being is unique because of the skin pattern (whorls, loops and arches)

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- No two human beings have same fingerprints and the best part is it has nothing to do with heredity.
- Ease – A system used to recognition fingerprints is less complex easy to use as compared to others.

But, similar to other authentication techniques, fingerprint matching process also faces some challenges like, False Rejection, False Acceptance, Duplication, Illusion, Occlusion etc.

In presence of these challenges, it is very much difficult to achieve high degree of fingerprint matching accuracy. Because to achieve high degree of fingerprint matching accuracy, two action pillars of fingerprint matching process – feature extraction and feature matching process should be implemented efficiently. For an image, pixel intensity value represents the property of the image. Slight change in pixel intensity value makes a change in the image property and feature extraction algorithm should be able to keep track of these changes in pixel level. For this, implementation of strong inter-association between pixels in small region is necessary to address the problems like occlusion, image property variations creating illusion, false rejection, false acceptance and duplication. To formulate the strong inter-association between pixels in small region, graph structure based local relational descriptor is a good candidate. In graph structure, there are various points known as nodes and the line between the nodes are known as edges. Graph can be directed or undirected. In pattern matching, undirected graph is considered. The nodes of the graph are the pixel values of an image. The node at the center contains the value of the source pixel. The edges represent the neighbors of the source pixel. Local descriptor extracts distinct features by identifying a source pixel and referred neighbor pixels around the source pixel.

Pattern matching refers to the process of checking the presence of pattern's constituents within a large image. Integral components of pattern matching are token pattern and scene image. Searching of pattern in the main image is the main requirement of pattern matching. To do this, large scene image is logically divided into number of candidate windows of pattern image size. This is because two different size images can't be the candidates for matching process. Feature extraction algorithm is applied on both pattern image and on all candidate windows of large image. Then extracted features of pattern image are compared with extracted features of individual candidate windows of large image for similarity measurement. If match is found, then pattern is localized on the scene image in proper location.

2. Literature Survey

Among several processes of biometric authentication, fingerprint recognition gives the unique results because of the consistency and uniqueness. As it is known that, no two fingerprints have the same features as the ridges and arches are different for every individual, so fingerprints are very unique. The main objective of fingerprint recognition is comparing the pattern of the two different fingerprints. Fingerprint recognition process is structured on some sequential phases called image preprocessing, feature extraction, fingerprint pattern matching and fingerprint pattern localization. The main concept of fingerprint feature extraction is the extraction of distinct features of individuals by means of ridges and arches, which make loops and whirls that are found to be unique to each person. Every loop's curve, ending loop, and their pattern are detected to identify the ridges pattern. During the ridges detection some distortion may occur like noisy, unclear, overlapping image. To overcome these problems, efficient feature extraction and pattern matching process is to be used to distinguish every pattern according to the distortion. In [12], Gabor filter and Fast Fourier Transform are used to extract minutiae features like ending line and bifurcations for fingerprint matching. But, when two different impressions with complex distortions of same finger is considered for minutiae-based matching, then matching becomes very much challenging. Author of [13] presents a fingerprint matching mechanism where orientation local binary pattern (OLBP) is used for orientation analysis of fingerprints. OLBP features are those LBP features which are extracted from orientation field image. In this approach, alignment is done by maximizing mutual information between extracted orientation features from fingerprint images. It has been seen in many real life dynamic problems like fingerprint matching, system parameters are estimated as they are not fully known. In [14], for joint state and parameter estimation of partially-observed Boolean dynamical systems under model uncertainty, an optimal Bayesian framework is proposed. In [15], automated fingerprint detection system is proposed on the basis of effective feature extraction methodology and efficient fingerprint detection method. Here the proposed algorithm uses Discrete Wavelet Transform (DWT) based features and Stationary Wavelet Transform (SWT) based Local Binary Pattern (LBP) features for fingerprint detection. An image based matcher Gabor is proposed in [16], where fingerprint images are represented by Gabor features.

There are several graph structure based feature extraction algorithms have been developed for feature extraction. Local graph structure (LGS) [7] is a local feature extraction approach where left and right side neighbor pixels of interest source pixel is taken as reference to extricate inter-association between interest source pixel and its neighbor pixels as distinctive image features. But the number of neighbor reference pixels in left and right side of interest source pixel are not taken symmetrically. So, LGS is extracting features in asymmetric way. Improvement over LGS is made as Symmetric local graph structure (SLGS) [2], [5], which is more symmetric than LGS, taking into account equal number of reference pixels in both the left and right side of interest source pixel to extract features. For weighted value calculation of each interest source pixel, LGS takes reference of 5 neighborhood pixels from a 3×4 adjacent neighbor area of source pixel, whereas SLGS operates on a 3×5 adjacent neighbor area of the source pixel taking reference of 6 neighborhood pixels to form an 8-bit binary sequence, which is converted to decimal weighted value for the corresponding interest source pixel. This weighted value represents spatial information around that source pixel. In [6], both shape and texture data is considered to represent a face image and the basic Local Binary Pattern (LBP) based face recognition process has been proposed. Various other local texture features such as modified census transform, MB-LBP, LBP histogram and locally assembled binary feature have been introduced in [8], [9], [10] and [11] respectively. Whereas, MB-LBP approach encodes rectangular regions using LBP operator. The MB-LBP features can capture large scale structure by comparing central rectangle's average intensity value with all neighborhood intensity values.

3. Motivation

Along with innumerous biometric techniques available, fingerprint has made itself most popular among others owing to its uniqueness and degree of accuracy that supersedes other authentication techniques available. Fingerprint verification refers to authenticity of a person by his/her fingerprint. The user provides fingerprint to get authenticated with their prior identity information. For any biometric authentication like fingerprint, feature extraction is the vital factor. There is various graph structure based algorithms have been developed for feature extraction. They have been used mainly for facial recognition.

LBP is a non-linear method which works on 3×3 block (radius = 1) of pixels and center pixel within the block is treated as source pixel. To calculate source pixel's weighted value, intensity value of source pixel is used as threshold and compared with the 8 neighbor pixel's intensity value within 3×3 block to form 8-bit binary string sequence and that will be converted to a decimal value. If intensity value of source pixel is found to be less than or equal to the intensity value of a neighbor pixel, then 1 else 0 is placed in the binary sequence. This decimal value will be the updated weighted value of the source pixel. In this operation, LBP can handle the effect caused by variations in illumination, though variations in illumination make changes in the way the monotonic gray value or scale is changed. The Graph Structure of LBP is shown in Fig. 1.

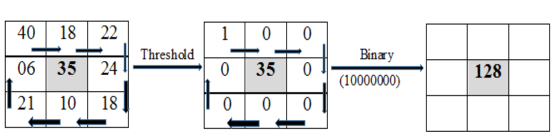


Figure 1. Local Binary Pattern (LBP) Operator

Orientation local binary pattern (OLBP) is based on LBP and extracts image information with respect to orientation field image. Fig. 2 shows 8 neighbor pixels present on imaginary circle with radius = 1 corresponding to the central pixel. In the same way, by taking radius = 2, 16 neighbor pixels present on the imaginary circle with respect to the central pixel can be used to get mutual image information for that central pixel. Using orientation feature OLBP tries to maximize mutual image information.

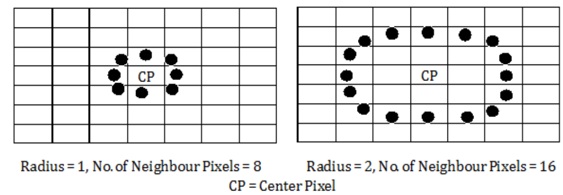


Figure 2. Circular neighbourhood area for OLBP with different orientation

LGS extracts the information from neighborhood pixel and based on the direction of graph, all neighborhood pixels get threshold with the source pixel. Neighborhood pixels are at a radius of one and two from the source pixel. LGS is illumination invariant [3] and computationally simple [4]. The Graph Structure of LGS is shown in Fig. 3.

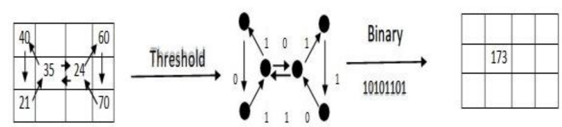


Figure 3. Local Graph Structure (LGS) Operator

LGS extracts more pixel information from right side than left. Due to this drawback, SLGS was introduced to balance the pixel information from both sides. Pattern's candidate window value is checked with every candidate windows of the main image.

SLGS operates on its neighborhood pixels for every source pixel and finally calculates a binary value, which is then converted to a decimal value. The most important specialty of SLGS is its symmetric structure, for that, it extracts more spatial information. The graph structure of SLGS and SLGS operation is shown in Fig. 4. Pattern's candidate window value is checked with every candidate windows of the main image.

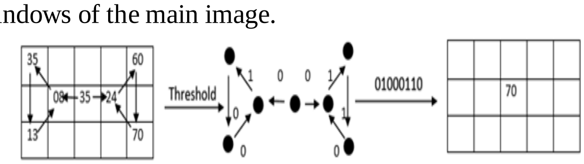


Figure 4. Symmetric Local Graph Structure (SLGS) Operator

LBP is a robust descriptor, but if any changes occur in image property outside of 3×3 block and that can be nearby location from source pixel, then also LBP is unable to reflect the impact of pixel property change on source pixel's updated weighted value. So, it is with narrow coverage of neighbors (8 neighbors) and extracts smaller spatial information. For this, OLBP takes reference of different orientation. There is also challenge for different orientations. Like, when pixels present on imaginary circle of radius = 2, then pixels present on imaginary circle of radius = 1 are not taken for reference, though they are closer to center pixel than others. Local Graph Structure (LGS) is based on directionality of the graph. But it too has drawbacks of symmetry that results in unbalanced pixel reference structure which is further addressed by Symmetric Local Graph Structure (SLGS). SLGS works on balanced graph structure taking equal number of pixel references from both left and right side of source pixel. SLGS is capable to extract equal spatial information from both sides. But SLGS does not have any pixel reference in upper and lower side of source pixel and hence extract less spatial information.

So, if the graph structure is unbalanced i.e. the source pixel has more neighbors on right than on the left, then the information extracted from such graphs are more from the right side than from the left. So, it is not very accurate. Neither the feature extraction can be done with better accuracy nor can the matching process work very efficiently in such cases. A solution to this is considering equal number of neighbors for the source pixel from adjacent four sides of the source pixel. In order to retrieve maximum spatial information, neighbors from all the four sides of the source pixel (top, down, left and right) along with the directional coverage of neighbor pixels should be done properly.

4. Proposed Fingerprint Matching Methodology – Multi-variant Symmetric Ternary Pattern (MVSTP)

A. Problem Formulation

The fingerprint matching methodology is carried out in number of stages – image acquisition, image pre-processing, image segmentation, feature extraction, matching and localization. Fingerprint images are acquired and stored in the database in image acquisition stage. In image pre-processing stage, the quality of image data is improved and the unwanted distortions are removed. Pattern is identified by using image segmentation and graph partitioning. Suppose, input fingerprint image size is $Y_1 \times Y_2$ pixels and query fingerprint pattern size is $P_1 \times P_2$ pixels where $P_1 < Y_1$ and $P_2 < Y_2$. So to have fingerprint matching, input fingerprint image is logically fragmented into number of candidate windows of query fingerprint pattern image size. MVSTP works with 5×5 reference grid pixels to find updated weighted value in decimal for each source pixel by thresholding neighbourhood pixels around the source pixel, which helps to find fiducial distinctive points from fingerprint image samples and fingerprint pattern image. Then for each feature of fingerprint image, feature histogram will be generated and concatenating all feature histograms candidate histogram will be formed which will be compared with candidate histogram of query fingerprint pattern for similarity measurement in terms of matching accuracy using minimum distance metric. In the fingerprint localization stage, the matched portion in the fingerprint image is localized with respect to query fingerprint pattern image. Block diagram of MVSTP based fingerprint matching process is shown in Fig. 5.

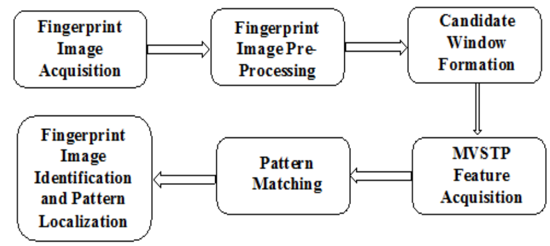


Figure 5. Block diagram of MVSTP based fingerprint matching process

B. Proposed Methodology – Multi-Variant Symmetric Ternary Pattern (MVSTP)

Multi-Variant Symmetric Ternary Pattern (MVSTP), a relational descriptor, aims to increase matching accuracy compared to existing approaches LGS and SLGS by addressing the problems related to variation in image property due to illumination, orientation, resolution and partial occlusion. MVSTP characterizes the interrelationship between distinct fingerprint features called minutiae, which is an important factor for fingerprint matching. MVSTP uses 5×5 grid size neighbourhood area of pixels for each source pixel. Within that area 12 neighbourhood pixels, out of which 3 pixels from left side, 3 pixels from right side, 3 pixels from upper side and 3 pixels from lower side with respect to source pixel, are taken symmetrically to extract spatial information symmetrically about source pixel. The source pixel's initial intensity value is updated with decimal equivalent of binary value which is calculated by comparing two consecutive pixels present in pixel sequence path. As MVSTP takes reference of 12 neighbour pixels in symmetric way, it can extract more spatial and textural information compare to LGS and SLGS approach.

C. MVSTP Pixel Group Formation

The weighted and updated value of the source pixel mainly depends on original intensity value of its 12 neighbour pixels present in left, right, top and bottom sides of the source pixel. The location of the neighbour pixels with respect to the source pixel (SP) is shown in the Fig. 6. The updated intensity value of the source pixel depends on the pixels present in the coloured location cell.

In MVSTP, 12 neighbour pixels are divided into 3 groups by using the Equation 1.

$$\sum_{i=1}^{N/4}[s(n_{(i-1)} - n_{((i+2)+(N/4))})3^0 + s(n_{(i-1)+(N/4)} - n_{(i+2)+2(N/4)})3^1] \quad (1)$$

	11		**10**	
7		**9**		**2**
	6	**SP**	**0**	
8		**3**		**1**
	4		**5**	

Figure 6. Source pixel and source pixel's neighbour pixels location with respect to MVSTP

Where N = Total no of neighbour pixels. So for 12 neighbour pixels (N=12), the loop will go from i = 1 to i = 3. This means, selection of neighbourhood pixels is done in three groups with four neighbourhood pixels in each group. In first group (i = 1), four neighbourhood pixels are selected from adjacent left, right, top and bottom positions (pixels at positions 0, 3, 6, 9) with respect to source pixel. These 4 pixels are grouped into pixel group 1 (PG1). In second group (i = 2), four neighbourhood pixels are selected with respect to two-and-half pixel movement (like Knight's movement in Chess board) in clockwise direction from source pixel and the selected pixels positions are 1, 4, 7, 10 with respect to source pixel. These 4 pixels are grouped into pixel group 2 (PG2). And in the third group (i = 3), four neighbourhood pixels are selected with respect to two-and-half pixel movement (like Knight's movement in Chess board) in anti-clockwise direction from source pixel and the selected pixel positions are 2, 5, 8, 11 with respect to source pixel. These 4 pixels are grouped into pixel group 3 (PG3). These 3 pixel groups are shown in the Table I.

TABLE I. PIXEL GROUP OF MVSTP

Pixel Group	Source Pixel	Neighbour Pixel Locations with respect to Source Pixel			
PG1	SP	0	3	6	9
PG2	SP	1	4	7	10
PG3	SP	2	5	8	11

D. *MVSTP Variants*

For each pixel group, 4 variants are formed i.e. total 12 'variants' for 3 pixel groups are formed. In Table II and Table III, location-wise sequence of pixel selection and MVSTP variant formation is shown respectively with respect to the following matrix of pixel intensity values.

$$\begin{matrix} 35 & 25 & 34 & 30 & 35 \\ 35 & 40 & 18 & 22 & 60 \\ 05 & 08 & 35 & 24 & 50 \\ 13 & 21 & 10 & 18 & 70 \\ 23 & 38 & 22 & 45 & 46 \end{matrix}$$

All possible sequences (known as variants) should be checked to obtain optimal weighted value.

If $W_{i,\,i+1}$ = Binary bit for each pair of consecutive pixels comparison (i^{th} and $(i+1)^{th}$ pixels), where i represents position of the pixel in the variant's pixel sequence path and I_i represents intensity value of the i^{th} pixel, then

$$W_{i,i+1} = \begin{cases} 1, & if \quad I_{i+1} \geq I_i \\ 0, & otherwise \end{cases} \quad (2)$$

TABLE II. LOCATION-WISE SEQUENCE OF PIXEL SELECTION

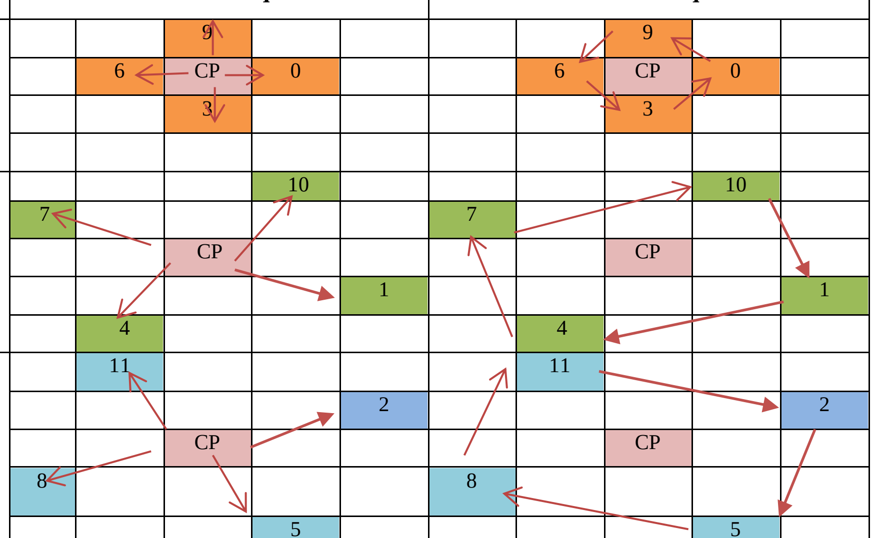
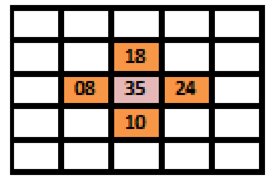
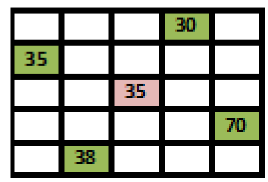
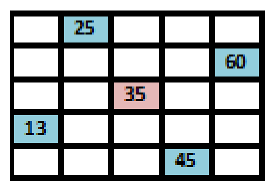
Pixel Group	Variant	Pixel Select Sequence	Pixel Select Sequence
			
PG-2	V-5...V-8		
PG-3	V-9…V-12		

TABLE III. MVSTP VARIANTS FORMATION

Variants no	Pixel Sequence	Pixel Position	Pixel Group
V-1	(35-24)(35-18)(35-08)(35-10) Then (24-18)(18-08)(08-10)(10-24)		PG-1
V-2	(35-24)(35-18)(35-08)(35-10) Then (24-10)(10-08)(08-18)(18-24)		
V-3	(35-24)(35-10)(35-08)(35-18) Then (24-18)(18-08)(08-10)(10-24)		
V-4	(35-24)(35-10)(35-08)(35-18) Then (24-10)(10-08)(08-18)(18-24)		
V-5	(35-70)(35-30)(35-35)(35-38) Then (70-30)(30-35)(35-38)(38-70)		PG-2
V-6	(35-70)(35-30)(35-35)(35-38) Then (70-38)(38-35)(35-30)(30-70)		
V-7	(35-70)(35-38)(35-35)(35-30) Then (70-30)(30-35)(35-38)(38-70)		
V-8	(35-70)(35-38)(35-35)(35-30) Then (70-38)(38-35)(35-30)(30-70)		
V-9	(35-60)(35-25)(35-13)(35-45) Then (60-25)(25-13)(13-45)(45-60)		PG-3
V-10	(35-60)(35-25)(35-13)(35-45) Then (60-45)(45-13)(13-25)(25-60)		
V-11	(35-60)(35-45)(35-13)(35-25) Then (60-25)(25-13)(13-45)(45-60)		
V-12	(35-60)(35-45)(35-13)(35-25) Then (60-45)(45-13)(13-25)(25-60)		

E. Weighted Value Calculation of Source Pixel using MVSTP Variants

Pixel group and MVSTP variant wise all possible weighted value calculation of source pixel (SP) is shown in Table IV. Calculations are shown with respect to matrix shown earlier with source pixel initial intensity value '35'.

TABLE IV. WEIGHTED VALUE CALCULATION OF SOURCE PIXEL USING MVSTP VARIANTS

Group No	**Variant No**	**Pixel Comparison**	**Binary Value**	**Decimal Value**
PG-1	V-1	(35-24)(35-18)(35-08)(35-10) (24-18)(18-08)(08-10)(10-24)	11111100	252
	V-2	(35-24)(35-18)(35-08)(35-10)(24-10)(10-08)(08-18)(18-24)	11111100	252
	V-3	(35-24)(35-10)(35-08)(35-18)(24-18)(18-08)(08-10)(10-24)	11111100	252
	V-4	(35-24)(35-10)(35-08)(35-18)(24-10)(10-08)(08-18)(18-24)	11111100	252
PG-2	V-5	(35-70)(35-30)(35-35)(35-38)(70-30)(30-35)(35-38)(38-70)	01101000	104
	V-6	(35-70)(35-30)(35-35)(35-38)(70-38)(38-35)(35-30)(30-70)	01101110	110
	V-7	(35-70)(35-38)(35-35)(35-30)(70-30)(30-35)(35-38)(38-70)	00111000	56
	V-8	(35-70)(35-38)(35-35)(35-30)(70-38)(38-35)(35-30)(30-70)	00111110	62
PG-3	V-9	(35-60)(35-25)(35-13)(35-45)(60-25)(25-13)(13-45)(45-60)	01101100	108
	V-10	(35-60)(35-25)(35-13)(35-45)(60-45)(45-13)(13-25)(25-60)	01101100	108
	V-11	(35-60)(35-45)(35-13)(35-25)(60-25)(25-13)(13-45)(45-60)	00111100	60
	V-12	(35-60)(35-45)(35-13)(35-25)(60-45)(45-13)(13-25)(25-60)	00111100	60

The source pixel’s initial intensity value is updated with decimal equivalent of the binary value which is calculated using Equation 3.

$$\left(avg\sum_{P=1}^{3}(avg\sum_{v=1}^{4} set \quad v) \right) \tag{3}$$

Where P=Pixel Group and v=variant number. Average of 4 variants for each pixel group is taken for each pixel group, so total 3 average values from 3 pixel groups are obtained. After that, again average value from those 3 average values is calculated, which is the optimal updated value of the corresponding source pixel. In the Table V, the comparative study between the minimum, maximum and the average optimal weighted values for the source pixel ‘35’ is shown. The original value of the source pixel is 35. Now if, the maximum value from all the 3 pixel groups is taken, then the optimal weighted value for ‘35’ will be 252. Maximum value makes the image bright (considering 255 means completely bright), for which distinct features can’t be identified. If, the minimum value from all the 3 pixel groups is taken, then the optimal weighted value for ‘35’ will be 56. Minimum value makes the image dark (considering 0 means total dark), for which also distinct features can’t be identified. Also, the algorithm won’t be able to detect the overlapping layer from the fingerprint. Thus, this can result in incorrect matching. The optimal weighted value can be calculated from the average value of every individual pixel group and that is 139.7 for ‘35’. Average value must always be intermediate value between maximum and minimum values. Thus, the image neither fades out nor becomes too dark. This average value calculation in turn will help the algorithms to detect and extract distinct features properly from image.

TABLE V. COMPARATIVE STUDY BETWEEN MAXIMUM, MINIMUM AND AVERAGE OPTIMAL WEIGHTED VALUES FOR THE SOURCE PIXEL ‘35’

Group No	Variant No	Decimal Value	Maximum of variants	Maximum of Pixel Groups	Minimum of variants	Minimum of Pixel Groups	Average Of Variants	Average of Pixel Groups
PG-1	V-1	252	252	252	252	56	252	139.7
	V-2	252						
	V-3	252						
	V-4	252						
PG-2	V-5	104	110		56		83	
	V-6	110						
	V-7	56						
	V-8	62						
PG-3	V-9	108	108		60		84	
	V-10	108						
	V-11	60						
	V-12	60						

MVSTP based fingerprint matching process steps are shown in Section 4.F. Initially, fingerprint image is taken as input and with respect to constraint of MVSTP, several 5×5 pixel grid area is selected. The center pixel within 5×5 pixel grid area is taken as source pixel whose value is going to be updated. Within 5×5 pixel grid area, 3 neighbour pixels from each left, right, top and bottom side of the source pixel are selected to have 12 neighbour pixels. Using those 12 neighbour pixels, 3 pixels groups of 4 pixels each are formed. For each pixel group, 4 variants are formed with 4 pixels present within that pixel group by changing their orientation. In each variant, consecutive two intensity values are compared to form 8-bit binary code which is then converted to decimal value. So, 4 decimal values are formed from 4 variants in a pixel group.

F. Steps of MVSTP based Fingerprint Matching Process

Step 1: Read query fingerprint image and stored fingerprint images.

Step 2: Divide each stored fingerprint images into candidate windows of query fingerprint image size.

Step 3: Implement local feature descriptor “Multi-Variant Symmetric Ternary Pattern (MVSTP),” on query fingerprint image and on all candidate windows formed from stored fingerprint images to extract features.

Step 4: As MVSTP works on 5×5 pixel reference grid image area (keeping source pixel at center of 5×5 pixel grid image area), then for each 5×5 pixel grid image area of query fingerprint image and of each candidate window, extract features by calculating binary value and corresponding decimal value using MVSTP.

Step 5: Generate histogram for each block with the updated weighted value (applicable for query fingerprint image and each candidate window).

Step 6: Marge all histograms to get one histogram (applicable for query fingerprint image and each candidate window).

Step 7: Compare (find distance) between each candidate window histogram with the original query fingerprint image histogram.

Step 8: Comparison gives recognition accuracy.

5. EXPERIMENTAL EVALUATION

The proposed algorithm MVSTP is tested on FVC 2004 database and a local database of fingerprint images. In the fingerprint matching process, initially fingerprint images are divided into a number of sub-regions of size 5×5 each and weighted decimal value of the source pixel which is present at the center of 5×5 grid area, is calculated by referring neighbour pixels within that grid area. The measurement of similarity is done by calculating similarity proximity with Euclidean distance between fingerprint pattern histogram and all possible candidate histograms formed from each image present in the image databases. A candidate window is selected based on the similarity score while it is compared with a threshold determined heuristically.

A. Image Database

FVC 2004 database [17] contains four different datasets: DB1, DB2, DB3 and DB4. The database contains 800 images. Eight different fingerprint impressions for every 100 individuals are taken with different rotational appearance.

Figure 7. Sample fingerprint images of the local database

The local fingerprint image database contains 100 fingerprint images. All images are with dimension of 248×338 pixels. Most images have little or no clutter. Here few sample images from the local database is shown in the Fig. 7.

B. Experimental Results and Comparison

The novel MVSTP generates 12 variants referring 12 neighbour pixels (3 pixels from each left, right, top and bottom side) with respect to a source pixel, from which pertinent variant will be selected. To calculate any source pixel's optimal weighted value, variant selection may not be same as all the variants have different pixel sequence path. This is because, pixel intensity values are different depending upon the image property.

Algorithm's performance is assessed on flexible number of samples with parameters – training percentage (ratio between the number of trained images and total number of database images) and matching accuracy becomes $\frac{(X-Y)}{X}\times 100\,\%$; where, X = database image number in total and Y= unmatched image number. For the fingerprint database, 20% training percentage means 20 numbers of fingerprint images are being trained.

C. Results on Fingerprint Images (Normal Type)

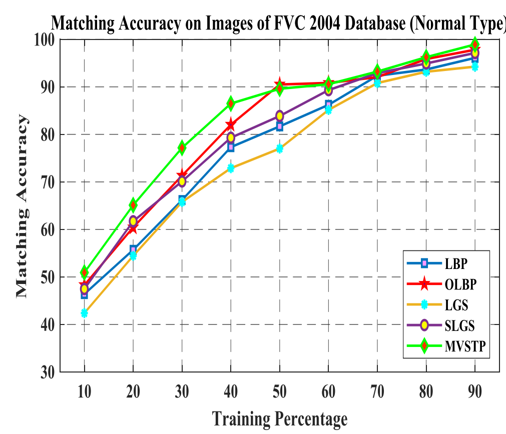


Figure 8. Fingerprint Matching Accuracies on Fingerprint Images (Normal Type) of FVC 2004 Database

Table VI shows evaluated experimental results on normal type images of FVC 2004 and local fingerprint image database. Fig. 8 and Fig. 9 show matching accuracy curves on FVC 2004 and local fingerprint image databases respectively and these demonstrate inter-acquaintance between training samples and accuracy of fingerprint matching. MVSTP has started with better accuracy compared to others and surpasses the performance of LBP, LGS and SLGS till the end for both the databases. In mid of the training percentage, OLBP has overlapping performance for local database and slightly better performance for FVC 2004 database compare to MVSTP. But, with higher training percentage, MVSTP completes with good note compare to others. Having more symmetricity in all directions and providing more variant options compared to LBP, OLBP, LGS and SLGS, MVSTP returns with better fingerprint matching accuracy.

TABLE VI. FINGERPRINT MATCHING ACCURACIES ON FINGERPRINT IMAGE (NORMAL TYPE)

Training Percentage	FVC 2004 Fingerprint Image Database					Local Fingerprint Image Database				
	LBP	OLBP	LGS	SLGS	MVSTP	LBP	OLBP	LGS	SLGS	MVSTP
10	46.39	48.28	42.39	47.47	50.92	47.23	49.12	43.27	48.35	50.44
20	55.70	60.43	54.44	61.71	65.10	56.54	60.27	55.32	62.59	64.62
30	66.17	71.30	65.77	70.10	77.16	67.01	71.89	66.65	69.68	75.68
40	77.31	82.04	72.88	79.29	86.48	76.54	80.63	73.76	78.87	84.75
50	81.68	90.49	77.01	83.86	89.6	80.91	88.08	77.73	83.44	88.87
60	86.21	90.82	85.14	89.31	90.55	85.44	90.55	85.86	88.89	89.82
70	92.34	92.05	90.80	92.89	93.21	92.02	91.78	91.77	92.58	93.86
80	93.65	95.86	93.18	94.92	96.24	93.33	94.09	94.55	94.61	96.89
90	96.10	97.81	94.25	97.13	98.92	95.78	97.14	95.22	96.82	99.12

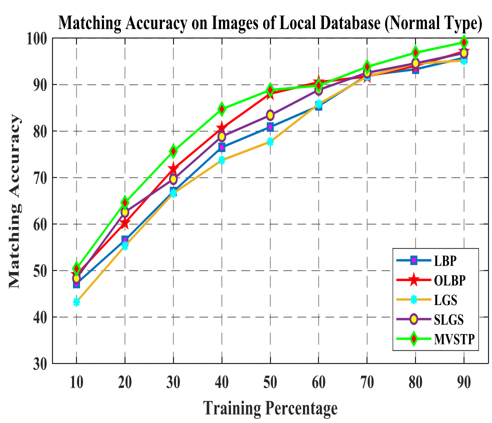


Figure 9. Fingerprint Matching Accuracies on Fingerprint Images (Normal Type) of Local Database

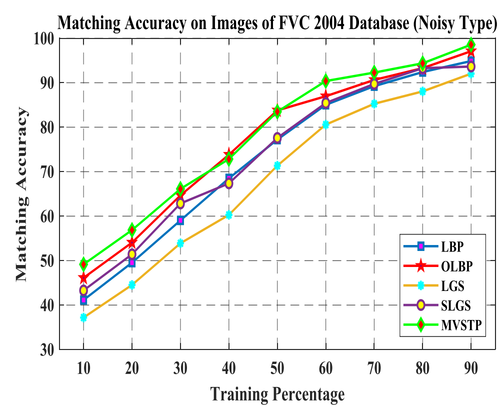


Figure 10. Fingerprint Matching Accuracies on Fingerprint Images (Noisy Type) of FVC 2004 Database

D. *Results on Fingerprint Images (Noisy Type)*

Performance of the algorithm on noisy image type, all fingerprint images of FVC 2004 and local fingerprint image databases, are made noisy by iid zero-mean Gaussian noise with noise level 100.

Fingerprint matching accuracies of LBP, OLBP, LGS, SLGS and MVSTP determined on images (converted to noisy type) of FVC 2004 and local fingerprint image databases with different training percentages delineated in Table VII. LGS remain far behind than others, whereas LBP and SLGS are competitive to each other, but OLBP is better performer than LBP, LGS and SLGS.

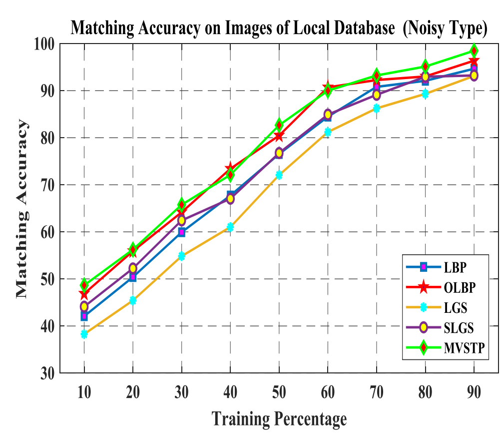


Figure 11. Fingerprint Matching Accuracies on Fingerprint Images (Noisy Type) of Local Database

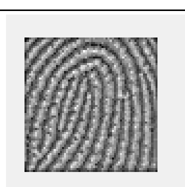
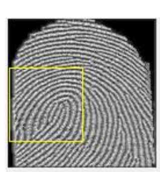
For FVC 2004 and local databases, MVSTP has very high fingerprint matching accuracy even with less training percentage and surpassing LBP, LGS and SLGS. Below 60% training percentage, OLBP come up as good competitor for MVSTP with overlapping performances but MVSTP has a very momentous persistent acceleration surpassing other methods to reach up to 100% accuracy. Matching accuracy curve with respect to fingerprint matching accuracy on FVC 2004 and local fingerprint image databases is figured in Fig. 10 and Fig. 11 respectively.

TABLE VII. FINGERPRINT MATCHING ACCURACIES ON FINGERPRINT IMAGE (NOISY TYPE)

Training Percentage	FVC 2004 Fingerprint Image Database					Local Fingerprint Image Database				
	LBP	OLBP	LGS	SLGS	MVSTP	LBP	OLBP	LGS	SLGS	MVSTP
10	41.15	46.13	37.20	43.30	49.16	42.08	46.87	38.27	44.11	48.65
20	49.55	54.07	44.54	51.43	56.87	50.39	55.91	45.42	52.23	56.23
30	59.05	64.68	53.91	62.85	66.13	59.92	64.17	54.84	62.43	65.75
40	68.50	73.82	60.28	67.37	72.84	67.73	73.41	61.02	67.05	72.11
50	77.21	83.78	71.35	77.59	83.49	76.54	80.47	72.07	76.75	82.66
60	85.04	86.97	80.58	85.44	90.38	84.47	90.70	81.20	84.91	89.99
70	89.23	90.63	85.27	89.73	92.28	90.81	92.26	86.24	89.12	93.23
80	92.41	93.28	88.05	93.27	94.37	92.09	93.01	89.32	92.96	95.12
90	94.88	97.09	92.04	93.64	98.56	94.66	96.37	93.12	93.23	98.48

E. Fingerprint Localization

TABLE VIII. LOCALIZATION USING MVSTP

Main Image	Updated Main Image
	
Pattern	Localization
	

Fingerprint localization means returning location of fingerprint detected on the image. Fingerprint pattern image is compared with candidate windows of stored fingerprint database images. If, fingerprint is found in any candidate window portion with high accuracy, then the image portion is localized, where that candidate window is originally present. In Table VIII, pattern localization using MVSTP is shown.

F. Time Complexity Analysis

This section presents time complexity analysis of pattern matching processes which are based on different local descriptors. Initial task is to form candidate windows of pattern fingerprint image size from query fingerprint image. If the size of a query fingerprint image is W×H pixels and the pattern fingerprint image size is p×q pixels, then the time complexity for candidate window formation would be O[{(W – p) + 1} × {(H – q) + 1}]. This is the time complexity for any pattern matching process. In addition, if M number of matched candidate windows are obtained, then best case time complexity would be O(M log M).

As feature extraction is one of the key part of pattern matching process, so the time complexity of pattern matching process mainly depends on feature extraction method used in the pattern matching process for feature extraction. Features are extracted from both pattern and candidate windows which are of pattern size (p×q pixels). Time complexity for feature extraction mainly depends on size of pixel grid used by local descriptor. LBP uses 3×3 pixel grid area, OLBP uses 3×3 pixel grid area (for radius = 1) and 5×5 pixel grid area (for radius = 2). LGS and SLGS use 3×4 and 3×5 pixel grid area respectively. Whereas, MVSTP uses 5×5 pixel grid area. The time complexity for LBP is O[{(p – 3) + 1} × {(q – 3) + 1}]. OLBP (radius = 1), has same time complexity like LBP. Time complexity for OLBP (radius = 2) would be O[{(p – 5) + 1} × {(q – 5) + 1}]. The time complexity for LGS is O[{(p – 3) + 1} × {(q – 4) + 1}]. The time complexity for SLGS is O[{(p – 3) + 1} × {(q – 5) + 1}]. The time complexity for MVSTP is O[{(p – 5) + 1} × {(q – 5) + 1}]. So, MVSTP and OLBP (radius = 2), having the best case time complexity compare to LBP, LGS and SLGS.

6. CONCLUSION

As a challenging field in the area of biometrics and computer vision, fingerprint analysis is one of the emerging techniques used for verification, identification and authentication of an individual identity. Fingerprint verification stage compares two fingerprints and recognizes whether they have same features or not, which means those fingerprints belong to the same person or not. In this paper, an attempt has been made to select distinct interest points and extract non-redundant informative relevant image features for developing better fingerprint matching system. MVSTP basically believes in updating the value of the source pixel to reflect the spatial relationship between source pixel and its neighbour pixels. MVSTP works with 5×5 pixel grid area for feature extraction, for that, MVSTP can handle minute image property variations efficiently and able to achieve higher percentage of matching accuracy even when fingerprint images are with slight orientation and partial appearance. It uses concept of candidate window to get a desired matrix for comparison and localization. For partial fingerprint matching, particular portion of the fingerprint image will be quested within other fingerprint image and if found, then that portion will be localized in the full fingerprint image. Additionally, reconstructed fingerprint image by MVSTP is much clearer than the other feature descriptor. This exemplifies, MVSTP is capable to extract distinct image features. Also, MVSTP is very robust to handle noisy images with higher fingerprint matching accuracy.

REFERENCES

[1] Rani P, and Sharma P, “A Review Paper on Fingerprint Identification System”, International Journal of Advanced Research in Computer Science & Technology, 2014, vol. 2, issue 3, pp. 58 – 60.

[2] Abdullah M.F.A.B, Sayeed S, Anbananthen K.S.M, Bashier H.K, Azman A, and Ibrahim S.Z, “Face recognition with Symmetric Local Graph Structure (SLGS)”, International Journal of Expert Systems with Applications, 2014, vol. 41, pp. 6131-6137. doi. 10.1016/j.eswa.2014.04.006.

[3] Chen L, Yang Y, Chen C, and Cheng M, “Illumination invariant feature extraction based on natural images statistics — Taking face images as an example”, IEEE Conference on Computer Vision and Pattern Recognition, Providence, RI, USA, 2011, pp. 681 – 688, doi. 10.1109/CVPR.2011.5995621.

[4] Kimhi A, “On the Tradeoff between Computational Simplicity and Asymptotic Properties in Multivariate Probit”, International Journal of Computational Economics, 1999, vol. 13, issue 1, pp. 93 – 101.

[5] Ayoob M.R, Mathusoothana R, and Kumar S, “Face Recognition using Symmetric Local Graph Structure,” Indian Journal of Science and Technology, 2015, vol. 8, issue 24, doi: 10.17485/ijst/2015/v8i24/80876.

[6] Rahim Md.A, Hossain Md.N, Wahid T, and Azam Md.S, “Face Recognition using Local Binary Patterns (LBP),” Global Journal of Computer Science and Technology Graphics & Vision, 2013, vol. 13, issue 4, version 1.0, ISSN: 0975-4172 & Print ISSN: 0975-4350.

[7] Abusham E.E.A, and Bashir H.K, “Face recognition using local graph structure (LGS),” Proceedings of the 14th International Conference on Human Computer Interaction, Lecture Notes in Computer Science, Orlando, FL, USA, 2011, pp. 169-175.

[8] Froba B, and Ernst A, “Face Detection with the Modified Census Transform,” 6th IEEE International Conference on Automatic Face and Gesture Recognition, Seoul, South Korea, 2004, pp. 91 – 96.

[9] Zhang L, Chu R, Xiang S, Liao S, and Li S.Z, “Face Detection based on Multi-block LBP Representation,” IAPR International Conference on Biometrics, Seoul, South Korea, 2007, pp. 11 – 18.

[10] Zhang H, Gao W, Chen X, and Zhao D, “Object Detection using Spatial Histogram Features,” Journal of Image and Vision Computing, 2006, vol. 24, issue 4, pp. 327–341.

[11] Yan S, Shan S, Chen X, and Gao W, “Locally Assembled Binary (LAB) Feature with Feature-centric Cascade for Fast and Accurate Face Detection”, In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Juan, Puerto Rico, USA, 2008, pp. 1 – 7.

[12] Aguilar G, Sanchez G, Toscano K, Salinas M, Nakano M, and Perez H, “Fingerprint Recognition”, In: 2nd International Conference on Internet Monitoring and Protection (ICIMP), Silicon Valley, USA, 2007.

[13] Kumar R, “Orientation Local Binary Pattern Based Fingerprint Matching”, International Journal of SN Computer Science, 2020, vol. 1, issue 2, article no. 67. https://doi.org/10.1007/s42979-020-0068-y.

[14] Imani M, Dougherty E.R, and Neto U.B, “Boolean Kalman filter and smoother under model uncertainty”, International Journal of Automatica, 2020, vol. 111, article no. 108609.

[15] Dixit U.D, and Shirdhonkar M.S, “Fingerprint-Based Document Image Retrieval”, International Journal of Image and Graphics, 2019, vol. 19, issue 2, article no. 1950008. https://doi.org/10.1142/S0219467819500086.

[16] Nanni L, and Lumini A, “Descriptors for image-based fingerprint Matchers”, International Journal of Expert System Application, 2009, vol. 36, issue 10, pp. 12414–12422.

[17] Cao K, and Jain AK, "Automated latent fingerprint recognition", IEEE Transaction on Pattern Analysis and Machine Intelligence, 2018, vol. 41, issue 4, pp. 788–800.

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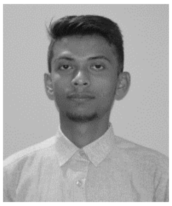

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