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# Automatic Fingerprint Classification using Graph Theory

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***Abstract*—**Using efficient classification methods is necessary for automatic fingerprint recognition system. This paper introduces a new structural approach to fingerprint classification by using the directional image of fingerprints to increase the number of subclasses. In this method, the directional image of fingerprints is segmented into regions consisting of pixels with the same direction. Afterwards the relational graph to the segmented image is constructed and according to it, the super graph including prominent information of this graph is formed. Ultimately we apply a matching technique to compare obtained graph with the model graphs in order to classify fingerprints by using cost function. Increasing the number of subclasses with acceptable accuracy in classification and faster processing in fingerprints recognition, makes this system superior.

***Keywords*—**Classification, Directional image, Fingerprint, Graph, Super graph.

## I. Introduction

THE lines of fingertip that named fingerprints have three characteristics [1]:

- There are no similar fingerprints in the world.
- Fingerprints are unchangeable.
- Fingerprints are one of the unique features for identification systems.

Recognition procedure consists of retrieving fingerprints from database. Therefore in automatic recognition system, some characteristics of a fingerprint used in classification, are extracted [2]. Fingerprints are assigned to the predefined classes which make the recognition procedure more efficient, since each fingerprint must be compared with samples of one predefined class for matching.

As most of fingerprint recognition systems have large databases, comparing fingerprints with all their images takes long time and needs lots of computations. So today introducing new methods of classification with common fingerprints topology can be an efficient strategy for decreasing the number of comparing during recognition process. Therefore a good classification system can process fingerprints in short time and divide database to more non-overlapping classes.

A fingerprint consists of ridge lines which often run parallel, sometimes intersect or terminate. The points where ridge lines terminate or intersect are called minutiae [3]. Although minutiae are used by most of existing system for fingerprints comparison and matching, the automatic detection of minutiae cannot be accurate in noisy fingerprints [4]. For this reason minutiae are not used for reliable classification. In addition to minutiae, another characteristic of fingerprints which called singularities or singular regions (core and delta), are specified by ridge lines flow and often use in fingerprints classification [5], [6], [7] and [8]. Fig. 1 shows minutiae and singularities in fingerprints.

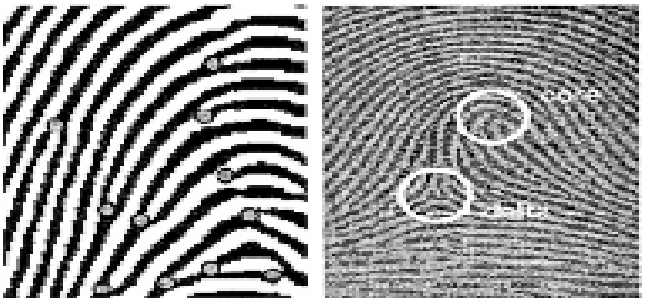


Fig. 1 On the left the minutiae and on the right the singularities of fingerprints including (core and delta) have been shown

One of the methodical classifications accepted by FBI (Federal Bureau of Investigation) has defined three classes that each class partitioned to two or more subclasses. So introducing new methods by increasing number of classes is important and leads to faster and more efficient fingerprint identification. In our method instead of singularities, directional image of fingerprint is used. Directional image is a discrete matrix which includes elements showing the dominant direction of ridge lines. Since directional image can include information in fingerprint model and compute on noisy fingerprint reliably, most of classification methods use it [1]. This paper at first step introduces new algorithm that uses directional image in fingerprint classification, then we compare the results with other methods.

## II. Computing and Segmentation of Directional Image

Directional image of fingerprint is a discrete matrix consists of elements that each one shows the direction of a pixel in main image. There are different methods in computing directional image. The method that used here is according to the algorithm introduced in [8] which computing directional field in fingerprint and the directional image is computed in eight directions. In forming super graphs and matching them that we talk about it later, as the number of quantified directions increases, comparing states also increase, so the speed of comparing decreases. For this reason directional image is quantified in four directions.

After making directional image, for controlling noise, the

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dominant direction in each 4x4 block is computed by using 4x4 local windows on each pixel of image. As result, the block directional image is formed and segmented to the homogeneous regions according to four directions. So each region includes elements with the similar direction and this leads to constructing the graph related to the fingerprint. In Fig. 2 the computed directional image in four and eight directions are shown.

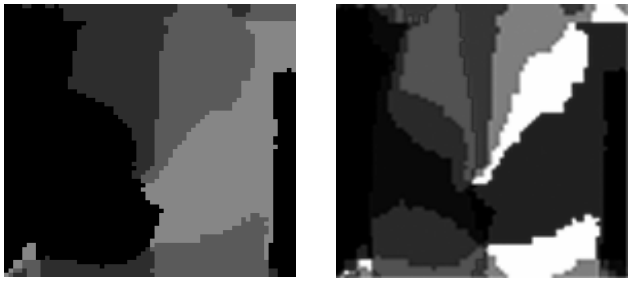


Fig. 2 The 4x4 block directional image related to the fingerprint has been shown in four directions on the left and in eight directions on the right

## III. Constructing Related Graph to the Fingerprint

The segmentation of block directional image is an optimum base for description fingerprints by using their related graphs. Each graph consists of some nodes and edges that connect nodes to each other. In mathematical approach a graph can be shown by G index including four parameters of G= (V, E, μ, υ) that V is the number of nodes, E is the number of edges, μ is the weight of nodes and υ is the weight of edges. Some information can be used in constructing the graph related to a fingerprint like: center of gravity of regions, the direction related to the elements of the regions, the area of regions, the phase difference between directions of two regions and the distance between centers of gravity and the perimeter of regions. So the related graph to the segmented directional image can be defined by different methods.

The graph defined in our method uses above information also, attributes a node to each region of segmented block directional image and devotes an edge to the common adjacent perimeter of two regions. The weight of nodes and edges are specified by some parameters. Here the area of regions in block directional image specifies the weight of nodes. Therefore each region of segmented image has a weight according to its area as in (1):

$$W_n = Area(R_i) \quad , \quad \text{i= 1, 2, 3, …, n} \qquad (1)$$

$W_n$ is the weight of nodes and $R_i$ is the specified region in block directional image. Also the weights of the edges are the function of three parameters like this:

1. Adj-p is the boundary of two adjacent regions linking with an edge.
2. Node-d is the distance difference between nodes that links by an edge.
3. Diff-v is the phase difference or direction difference between two regions of block directional image.

So the weight of an edge ($W_e$) can be calculated as in (2):

$$W_e = (Adj - p) \times (Node - d) \times (Diff - v) \qquad (2)$$

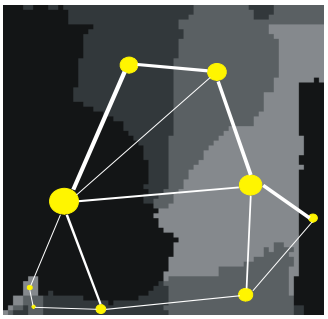


Fig. 3 The sample graph for segmented block directional image

In the sample of this graph in Fig. 3, the nodes are shown by dots in center of gravity of each region and their sizes are corresponding to their weight. Also the edges are shown by direct lines and their weight is proportional with the thickness of the lines.

## IV. Constructing the Super Graph Related to the Fingerprint

As probably there are some noises in an image of fingerprint, some regions with incorrect directions may appear in the segmented block directional image and cause to make incorrect nodes in them or edges in their adjacent regions during constructing their graphs and lead to some mistakes at the time of comparing and matching. In the other hand if we use graph for comparing, number of nodes and edges in an obtained graph may not be equal with its related class. Even if graph and sub-graph are compared with each other, extracting sub-graph from relational graph needs to consider many available states. So by increasing the number of states, there are many computations taking long time for their process. To solve this problem we combine the characteristics of a graph and model a super graph including a node for regions with similar directions that its coordinates is the center of gravity of nodes related to these regions of graph. The weight of node ($W_{sn}$) is equal to sum of the weights of nodes or areas of regions with similar directions as in (3):

$$W_{sn} = \sum_{i=1}^{n} Area \quad (R_i) \qquad (3)$$

$R_i$ includes regions with similar directions. The weight of edge ($W_{se}$) in super graphs is the function of distance between nodes of a super graph ($dis(sn)$) and sum of the adjacent perimeter ($Adj - p$) between two regions with different directions as in (4):

$$W_{se} = dis(sn) + \sum Adj - p(R_i, R_j) \qquad (4)$$

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According to definition of super graph, since the obtained block directional image has four directions, each fingerprint can be modeled by a graph with four nodes linked with three edges and specified weight which makes easier to compare fingerprints. In Fig. 4 the super graph related to the graph in Fig. 3 has been shown. Note that the parameters which used in comparing super graphs are too important.

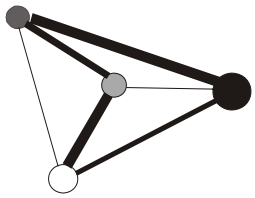


Fig. 4 The sample of super graph related to the graph in Fig. 3

## V. Matching Super Graphs and Classification

For classification of fingerprints by using their related super graphs, first we need some models from different classes that used as references for comparing. So we choose a fingerprint from each class as model according to the database, then the related super graph is constructed. Afterwards the obtained images compare and match with these models by using cost function. Therefore from the quantities of cost function that result from comparing obtained fingerprints with samples, the minimum value is chosen and used for classification.

After lots of searching on different functions and the results of them on classification, the best cost function for optimum classification is formed as in (5) which used two characteristics of super graph:

1. The sum of difference between nodes weights of obtained super graph and model super graph.
2. The sum of difference between edge weights of obtained super graph and model super graph.

Cost Function =

$$(\sum_{i}(W_{i.node}-W^{*}_{i.node}))\times(\sum_{j}(W_{j.edge}-W^{*}_{j.edge})) \qquad (5)$$

$W_{i.n}$ and $W_{j.e}$ are the node weight and edge weight of obtained super graph. $W^{*}_{i.n}$ and $W^{*}_{j.e}$ are the node weight and edge weight of model super graph. Each obtained fingerprint belongs to a specified class with minimum value of this cost function.

## VI. Result and Discussion

In Fig. 5 the algorithm procedure corresponding to our classification method has been shown. In this research 168 fingerprint images from a database belonging to 21 people are used for classification. In the other word each person has eight fingerprints in different situations. Since the fingerprints belong to 21 people, the maximum number of classes can be defined, are 21 that results the accuracy of 58/92%. Since some of these fingerprints are similar in their structures and can be considered in one class, the classification accuracy decreases for 21 classes. In the other hand the prior classification should have more classes and classify the samples with high correctness. So we should find acceptable range between two parameters of classification accuracy and number of classes. To do this by decreasing number of classes and combining them, the classification accuracy increases and by increasing the variety of samples structures, the number of classes increases. In our database nine kinds of structures can be found among fingerprints that other samples are similar with them, for example among 21 kinds of fingerprints in our database, seven of fingerprints belong to left loop class, three to right loop class, three to arc class, two to twin loop class and other fingerprints have their specified classes. Therefore in classification of different structures in nine classes, the resulted accuracy is 81/5%.

Resulted classification related to our database can be seen in Table I for nine classes. Since each person has eight fingerprints in different positions, one sample from them is considered as model.

## VII. Conclusion

In this paper a new structural approach to the fingerprint classification has been introduced by increasing number of classes. To do this, the directional image of fingerprints are computed and segmented to the regions with same directions, and then by constructing their graph, each fingerprint is modeled by related super graph. Comparing and matching super graphs according to the cost function will result to the classification. Other methods have the maximum of six classes by extracting singularities, but our method which considers structure of fingerprints for classification, can classify the fingerprints in nine non-overlapping classes. The possibility for increasing number of subclasses with high accuracy makes this method superior than others.

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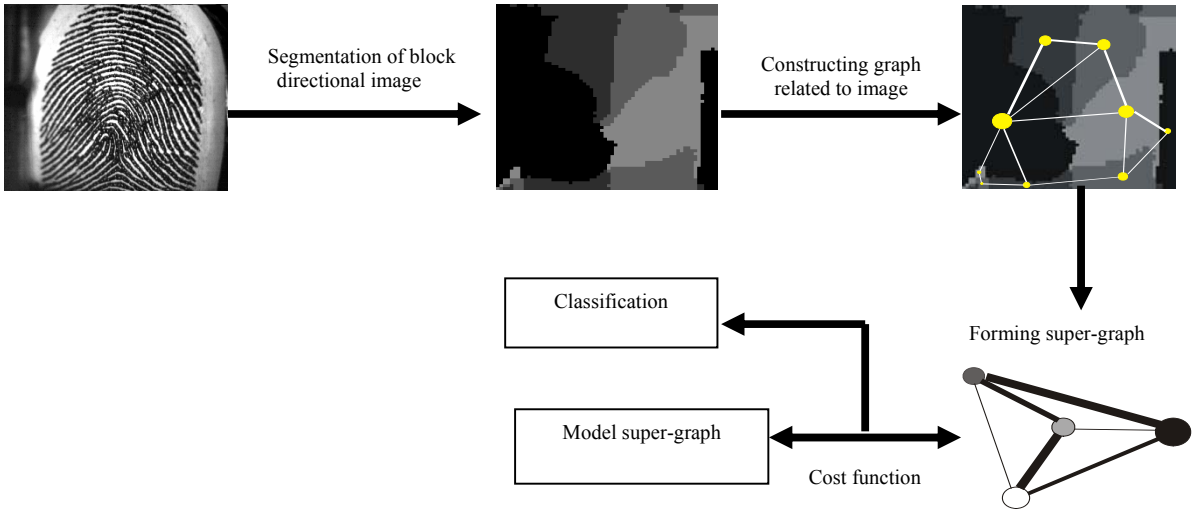



Fig. 5 The algorithm procedure corresponds to our classification method

TABLE I
THE RESULT OF CLASSIFICATION IN NINE GROUPS ON THE DATABASE CONSISTS OF 168 FINGERPRINTS

| | Number | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | Correctness |
|---|---|---|---|---|---|---|---|---|---|---|---|
| C1 | 24 | 23 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 95.8% |
| C2 | 56 | 1 | 45 | 2 | 1 | 0 | 0 | 0 | 6 | 1 | 80.3% |
| C3 | 8 | 1 | 0 | 6 | 0 | 1 | 0 | 0 | 0 | 0 | 75% |
| C4 | 8 | 0 | 2 | 0 | 4 | 0 | 0 | 0 | 2 | 0 | 50% |
| C5 | 16 | 0 | 0 | 1 | 0 | 15 | 0 | 0 | 0 | 0 | 93.7% |
| C6 | 8 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 100% |
| C7 | 8 | 1 | 0 | 0 | 0 | 0 | 0 | 7 | 0 | 0 | 87.5% |
| C8 | 24 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 18 | 0 | 75% |
| C9 | 16 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 62.5% |
| validity | | 88.4% | 76.2% | 66.7% | 80% | 93.7% | 88.9% | 100% | 69.2% | 90.9% | |

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