Angular Coherence Observation in Fingerprints and Lungs for Fingerprint Classification and COVID-19 Differentiation

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Abstract — Feature extraction and lung detection are critical phases for COVID-19 detection. Hence, the features by which normal lungs and abnormal lungs can be differentiated are significantly important. In this paper, the x-ray images are enhanced and the corresponding angles, coming from ribs, are extracted as the major features. According to the behavior of the angles, the image is bisected in order to evaluate each lung individually. The new definition of normal lungs is proposed so as to discriminate normal lungs from COVID-19 lungs. Considering the definition, the right and the left lungs are cropped from the main image. Subsequently, the Histogram of Oriented Gradient (HOG) features are extracted from the cropped images. Two neural networks with the same topology are trained by the features. First, one of the neural networks is trained by cropped images. Second, another neural network is trained by HOG features obtained from the cropped images. The simulation is performed by MATLAB and the database is comprised of 522 images and 96% accuracy is obtained. Furthermore, a novel method by which fingerprints are classified in eight categories is proposed in this paper. In fact, because of inevitable rotation, brought about during data acquisition procedure in fingerprints, the feature extraction procedure might be afflicted with the rotation. Hence, a new approach is suggested so that the rotation is rectified prior to the feature extraction process. From the enhanced images of fingerprints, the angles of ridges are calculated. According to the extracted angles, new points, called Origin Points, are mentioned as the origins around which decisive blocks are cropped. For each block, a Fourier series model is calculated so as to form a training data for the classifier. The classifier chosen is a Generalized Regression Neural Network (GRNN). FVC2004 is utilized for both training and test phases and 98.2% accuracy is achieved.

Index Terms — Angular Coherence, COVID-19 differentiation, Fingerprint Classification, Neural Network.

I. INTRODUCTION

The human body is the most complicated and mysterious phenomenon. The observations and discoveries stemming from the human body have been outstanding inspirations for engineers, culminating in creating new devices. Hence, scrutinizing the human body might assist experts to understand other phenomena better. In this paper, two parts of body, including fingerprints and lungs, are taken to be analyzed.

Fingerprints have been considered as reliable factors by which identification process can be carried out both precisely and fast. Unlike speech which can be imitated, fingerprints are unique even in twins with very close deoxyribonucleic acid (DNA). Although DNA is the most reliable device for identification, the data acquisition process is so demanding that the identification process might not be comprehensively finalized. In contrast, data acquisition process for fingerprints can be straightforwardly performed via sensors or scanners inserted in laptops, mobiles, and other devices which are both easily available and easily portable. When it comes to fingerprint classification, the first system introduced in 1905 was Henry system [1]. The system classified fingerprints in five main categories, including Tended Arch, Arch, Left-Loop, Right-Loop, and Whorl, demonstrated in Fig. 1.

![Fingerprints Classification](image-url)

One of the principal methods utilized at the first step of the classification process is enhancing images so as to enhance ridges quality [2]-[6]. The enhancement has been performed in order to eliminate unwanted parts such as scars on images or any distortion by using different types of filters [2]-[6]. The next step in all works is the feature extraction. Minutiae are unique and legitimate features which have been used for both classification and recognition procedure [7]-[11]. In addition, singular point detection and orientation
map extraction are proposed as other useful features [12]. Kernel smoothing feature is another feature utilized for training the classifier [13]. The final decision has been made by different classifiers, incorporating Artificial Neural Network (ANN), Fuzzy, and Hidden Markov Model [13]-[20]. Different techniques such as deep learning and back propagation have been used to improve the results [14]-[20]. One of the principal methods utilized at the first step of the classification process is enhancing images so as to enhance ridges quality [2]-[6]. The enhancement has been performed in order to eliminate unwanted parts such as scars on images or any distortion by using different types of filters [2]-[6]. The next step in all works is the feature extraction. Minutiae are unique and legitimate features which have been used for both classification and recognition procedure [7]-[11]. In addition, singular point detection and orientation map extraction are proposed as other useful features [12]. Kernel smoothing feature is another feature utilized for training the classifier [13]. The final decision has been made by different classifiers, incorporating Artificial Neural Network (ANN), Fuzzy, and Hidden Markov Model [13]-[20]. Different techniques such as deep learning and back propagation have been used to improve the results [14]-[20].

COVID-19 is a new virus with which the world is severely struggling. In fact, the world is afflicted with the virus economically, socially, emotionally, and psychologically. Hence, even a tiny new and useful information might alleviate the hard situation and pave the way for progress of other researchers in different fields. Many works have been performed to unravel the mystery of the new disease, incorporating deep learning and convolutional neural networks [21]-[28].

In this paper, the angular coherence existing in both fingerprints and lungs is demonstrated. Moreover, the pre-processing is proposed to enhance and rectify the rotation occurring in the fingerprints images. Therefore, the features extracted are rotation invariant factors. Next, a new approach is proposed to extract points behaving similarly in fingerprints. The points are called Origin Points. Therefore, the method generates features which are location-invariant. According to the number of Origin Points, a Fourier series model is created for each image. The model is considered as training data for training a Generalized Regression Neural Network (GRNN).

In addition, the angular coherence is the useful device for differentiating normal lungs from the lungs attacked by COVID-19. To fulfil the purpose, a novel approach is proposed to detect lungs and ribcages. Subsequently, a new perspective is proposed for normal lungs and the lungs attacked by COVID-19. Ultimately, two different neural networks are trained and tested by features extracted from the COVID-19 dataset.

II. PRE-PROCESSING

The pre-processing phase for fingerprints consists of five divergent phases, depicted in Fig. 2. The three main purposes should be fulfilled during the pre-processing phase, including rectification of rotation, enhancement, and extracting ridges’ angles. Initially, morphological process is performed with the intention of eliminating rotation, and the region of interest (ROI), shown in Fig. 3.

Owing to the fact that fingerprints are similar to ellipses, an equivalent ellipse is allocated to each image, illustrated in Fig. 3. The ellipse is filled so as to create a new object by which the rotation of the ellipse is calculated and then the rotation is rectified, demonstrated in Fig. 4.

![Image of pre-processing stages](Fig. 2. Pre-Processing Stage.)

![Image of pre-processing stages](Fig. 3. Pre-Processing (a): The Main Image (b): Morphological Process (c): Equivalent Ellipse.)
In order to calculate the rotation occurring in the image, the main ellipse is conceptualized as an ellipse which its main axis is perpendicular to the horizontal line crossing from the centroid of the ellipse.

As it can be observed in Fig. 5, the extracted ellipse from the image is rotated $\theta$ degrees. The length of the axis of the main ellipse is the same as the length of the image, which is equal to $R1\times2$. Furthermore, the length of the diameter of the rotated ellipse is $R2\times2$. By knowing that in a right triangle:

$$\frac{R2}{2} = \sqrt{K^2 + R1^2} \quad (1)$$

Then:

$$k^2 = \sqrt{R2^2 - R1^2} \quad (2)$$

In which:

$$\frac{R1_{\text{MAIN AXIS}}}{2} = \frac{\text{ELLIPSE LONGER DIAMETER}}{2} \quad (3)$$

$$\frac{R2_{\text{ROTATED AXIS}}}{2} = \frac{\text{ELLIPSE LONGER DIAMETER}}{2} \quad (4)$$

The rotation is given by:

$$\tan(\theta) = \frac{K}{R2} \quad (5)$$

$$\theta = \tan^{-1} \left( \frac{K}{R2} \right) \quad (6)$$

Once the rotation is rectified, the image should be enhanced. The useful method for enhancing fingerprint images is using Gabor filter which is utilized exactly the same to enhance both fingerprints and x-rays images [29], demonstrated in Fig. 6 and Fig. 7.

As it can be observed in Fig. 7, the belly, right side, and left side of the body create straight angles. Therefore, the first Region of Interest (ROI) is the region without any straight angles, depicted in Fig. 8. Once the straight angles are eliminated, the region is bisected in order to extract right and left lungs separately. In fact, it is observed that, specifically in images with COVID-19, the gray threshold of the right lungs is considerably different from the gray threshold of the left lungs. Thus, each one of the lungs should be evaluated individually.
III. ANGULAR COHERENCE

The angles of the lungs and ribcages are significant factors by which normal and abnormal lungs can be defined. Indeed, in this paper, a new definition and feature of normal lungs is explained. As it can be deduced from Fig. 7-b, the majority of the right lung, demonstrated in the left half of the picture because in the X-rays pictures the right lung is in the left part of the picture, consist of acute angles. Unlike the right lung, the left lung is comprised of obtuse angles. Hence, a new definition can be defined according to the behavior of the angles in the picture.

In order to illustrate the behavior of angles within the picture, the angles are divided into thirty degrees sectors, depicted in Fig. 9. It can be seen that in pictures with normal lungs, Fig. 9-e to Fig. 9-h, a logical coherence exists. In other words, the majority of the left part of the body consist of lines with 90 to 120 degrees. The right part of the body, on the other hand, consists of lines with 60 to 90 degrees. Furthermore, the right lung region commences with lines with 30 to 60 degrees. The left lung, however, starts with lines with 120 to 150 degrees. As it can be observed in Fig. 9, the right lung starts with lines with 30 to 60 degrees and continuous with lines with 0 to 30 degrees. The left lung, in addition, begins with lines with 120 to 150 degrees and continuous with lines with 150 to 180 degrees. Considering the aforementioned comments, the following definitions can be mentioned for both right and left normal lungs:

1-The right normal lung consists of lines with 30 to 60 degrees, which are adjacent to lines with 0 to 30 degrees, demonstrated in figure 9 with yellow and pink.

2-The left normal lung consists of lines, with 120 to 150 degrees, which are adjacent to lines with 150 to 180 degrees, demonstrated in figure 9 with white and dark blue.
When a lung is attacked by COVID-19, the coherence between angles in the lungs is deteriorated, demonstrated from Fig. 9-a to Fig. 9-d. The chaos is predicated upon the attacked regions in lungs. In fact, bleeding alters the grey threshold in the attacked areas. Therefore, the consistency of the normal lungs is sabotaged. In fact, the more progressive the disease is, the more chaos will be created.

Once the picture is bisected, the ROIs of both lungs are extracted according to the definitions and additional morphological process, depicted in Fig. 10. The cropped regions are utilized with the intention of training a neural network. The Histogram of Oriented Gradient (HOG) of the cropped regions is used for the purpose of training a different neural network.

Like lungs, the angular behavior of ridges is the principal factor by which a model can be created for each fingerprint. Pre-processing stage generates two images, incorporating orientation images and enhanced images. In order to evaluate ridges, the ridges in the orientation image are divided into nine different sectors and each sector is twenty degrees, shown in Fig. 11. A new point, called ORIGIN POINT, is proposed and defined so as to extract features around it. The origin point is the point around which all sectors exist. In other words, as it can be seen in Fig. 11, each sector is designated by a color and a point around which all color exist is an origin point. Therefore, the point which is close to all sectors is the origin point.

In this paper, fingerprints are classified in eight divergent classes, shown in Fig.11. Given the origin point, five different fingerprints exist. Fingerprints without any origin point, depicted in Fig. 11 (a). In fact, a point surrounded by all types of angles cannot be found in the image. Other classes are images with one origin point, Fig.11 (b) and Fig. 11 (c), two origin points, Fig. 11 (d), Fig. 11 (e), and Fig. 11 (f), three origin points, Fig. 11 (g), and four origin points, Fig. 11 (h).

The aforementioned points are the points around which the behavior of ridges categorizes fingerprints in eight classes. According to the number of origin points, an algorithm should be finalized with the intention of creating a Fourier model and training a Generalized Regression Neural Network (GRNN), demonstrated in Fig. 12.
Fig. 10. (a): The Normal Lung after Morphological Process (b): Cropped Image (c): HOG of (b) (d): The Lung with COVID-19 after Morphological Process (e): Cropped Image (f): HOG of (e)

Fig. 11. Eight classes (a): 0A, (b): 1L, (c): 1R, (d): 2L, (e): 2R, (f): 2W, (g): 3W, (h): 4W.
Once the origin points are localized, the number of Origin Points (NOR) is calculated. Subsequently, if NOR is zero, a Fourier series is calculated for the whole picture, given by:

\[
F(x) = a_0 + a_1 \cos x + b_1 \sin x + a_2 \cos 2x + b_2 \sin 2x + \ldots + a_8 \cos 8x + b_8 \sin 8x
\]

For instance, for a fingerprint without an Origin Point in Fig. 13, the Fourier series model is calculated and its coefficients are calculated in Table 1. In all types of fingerprints without an Origin Point the minority of ridges belongs to the ridges around ninety degrees, depicted in Fig. 11 and Fig. 13. Having been calculated from the angular behavior of ridges, a formula or model is created for the whole image.

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**IV. RESULTS AND DISCUSSION**

Fingerprints are conceptualized as images with heavy databases. Hence, the classifier has to be both fast and intelligent. Plus, owing to the fact that each fingerprint is modelled by Fourier series, the classifier has to be powerful for function approximation. The Generalized Regression Neural Network (GRNN) is a powerful network which is suitable for heavy databases and function approximation. In order to train and test the network, FVC2004 is utilized for both training and testing stages [30]. In fact, one hundred images are used to train the network and five hundred images are utilized to evaluate the network, demonstrated in Fig. 16. Spread parameter is very critical in designing a GRNN. In this work, the spread parameter is 0.99.
The performance of the network is analyzed when the spread is 0.1 and the result is not appropriate. The reason is that the GRNN uses radial basis function and the spread parameter determines the width of the function. Thereby, the lower the spread parameter is, the more suitable it will be for very close data. Hence, the larger it is, the more beneficial it will be for smoother function approximation. Therefore, because the features should be categorized according to their trend in general, the higher spread is considered. The performance of the system is compared to other work-of-arts in Table 2. The longest features are extracted when a fingerprint has four Origin Points. From the Fourier series formula, 180 points are calculated for each block cropped around the Origin Points. As a result, the length of the training data is $4 \times 4 \times 180 = 2880$ for 100 images. Therefore, the network has 2880 inputs. If a fingerprint has less than four Origin Points, then zeros are inserted in the features. In order to analyses the extracted features, decision tree is used to emphasize on critical regions, demonstrated in figure 17. The tree decides that $x_1$, $x_2$, $x_3$, $x_9$, and $x_{27}$, from region one, $x_{256}$, from region two, $x_{419}$, from region three, $x_{658}$, from region four, $x_{721}$, from region five, $x_{1294}$, from region eight, $x_{1441}$, from region nine, are critical features for classification. In the database, five fingerprints are 4W (four Origin Points and curly behavior of ridges), six fingerprints are 3W (three Origin Points and
curly behavior of ridges), sixteen fingerprints are 2W (two Origin Points and curly behavior of ridges), twenty three fingerprints are 2R (two Origin Points and the domination of obtuse angles), fourteen fingerprints are 2L (two Origin Points and the domination of acute angles), eleven fingerprints are 1R (one Origin Point and the domination of obtuse angles), fifteen fingerprints are 1L (one Origin Points and the domination of acute angles), and ten fingerprints are 0A (Zero Origin Point with minority of ridges with ninety degrees).

Fig. 16. The Designed GRNN.

\[ x_{721} < 0.5 \quad x_{721} \geq 0.5 \]
\[ x_{1} < 211.5 \quad x_{1} \geq 211.5 \]
\[ x_{2} < 16.5 \quad x_{2} \geq 16.5 \]
\[ x_{419} < 6.5 \quad x_{419} \geq 6.5 \cdot 0A \]
\[ x_{1294} < 15.5 \quad x_{1294} = 15.5 \]
\[ x_{1441} < 0.5 \quad x_{1441} \geq 0.5 \]
\[ x_{x_{9}} < 14 \quad x_{9} \geq 14 \quad 1R \]
\[ x_{256} < 11 \quad x_{256} \geq 11 \cdot x_{1441} < 1 \]
\[ x_{27} < 40 \quad x_{27} \geq 40 \quad 2W \]
\[ x_{658} < 2.5 \quad x_{658} \geq 2.5 \quad x_{3} < 12.5 \quad x_{3} \geq 12.5 \]
\[ x_{2W} \quad x_{2L} \]
\[ x_{2R} \quad x_{2L} \]

Fig. 17. The Decision Tree from the Features.

In order to differentiate normal lungs and lungs with COVID-19, two divergent Neural Networks are trained with different features, incorporating cropped images from the main picture and HOG features of the cropped images. When the regions of both lungs are achieved by the definitions, the regions are considered as the right and the left lungs. Consequently, the right lungs and the left lungs are compared indirectly. The networks designed for classifying the data are demonstrated in figure 18 and figure 19. The number of epochs for training the first network is 500.

TABLE II: Comparison of accuracy for fingerprint classification.
The HOG features are extracted by considering HOG cell size parameter to 4x4. The topology of the second network is the exact same as the first network with different number of input and epoch. In fact, the number of epochs for training the network with new features is 1000.

The dataset is comprised of 322 images with lungs with COVID-19 and 200 normal lungs [42-43]. Indeed, 222 images of images with COVID-19 and 100 images with normal lungs are utilized to train both networks. The performances of both networks are compared in table 3.

| Method              | Accuracy (%) |
|---------------------|--------------|
| [31]                | 98.69        |
| [32]                | 90.73        |
| [33]                | 95.84        |
| [34]                | 91.37        |
| [35]                | 97.2         |
| [36]                | 95           |
| [37]                | 99.02        |
| [38]                | 89.3         |
| [39]                | 90           |
| [40]                | 91.3         |
| [41]                | 97.4         |
| This Work           | 98.2         |

V. CONCLUSIONS

In this paper, a new technique is proposed for lung and ribcage detection. Plus, a new definition is proposed for lungs, according to the angular behavior of ribcage and lungs. In addition, a comparison is performed between the angular behavior of normal and abnormal lungs. Furthermore, new points called Origin Points are proposed to select regions which are decisive for fingerprint classification. The rotation of fingerprints is rectified in pre-processing stage, making features rotation-invariant. Plus, owing to the fact that all features are extracted from blocks cropped around Origin Points, the features are location-invariant either. A novel classification is proposed so as to classify fingerprints in eight different categories. For each cropped block a model is created by utilizing Fourier series and all features are concatenated to form a model for each fingerprint. Ultimately, GRNN is used to alleviate the classification process. The magical angular behavior is observed in both lungs and fingerprints. For the future studies, it might be more angular coherence in different part of the human body.

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TABLE III: The Performance of Both Networks for lung differentiation

| Topology of the Neural Network | Feature Utilized | Number of Epochs | Accuracy (%) |
|-------------------------------|------------------|------------------|--------------|
| 100-50-2                      | Cropped Images   | 500              | 91           |
| 100-50-2                      | HOG              | 1000             | 96           |

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