Cluster Optimization Using Angle Oriented Fuzzy Rough Images

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Abstract

Angle Orientation is a renowned technique for Image Processing Applications. Several Authors discussed various methods for face recognition and matching. In this paper, the process of knowing the face using any angle-oriented image needs optimization in two levels namely micro-level optimization and macro level optimization. The evolutionary optimization technique is used to achieve micro level optimization and by providing parallel computation. By Using Rotational and Reduction procedure which leads to a macro-level optimization. To eliminate the unwanted angle-oriented images from input images identify the equivalent face using different angle-oriented images, Micro-level optimization is essential. Due to the volume, variety, and velocity characteristics of input angle-oriented images and huge volumes of images already stored in the database, macro-level optimization is required. The experimental results are compared with the angle-oriented images of different huge databases like MIT, FERET, Yale and College student's data for identification. For finding the reliability of failure rate, we used exponential failure rate model.

1. Introduction

Predictive data analytics and machine learning methods exposed as the pair of tools to save the day for most organizations currently. The impediment can apply both tools in which can drag influential approaching for storing the data. However, mainly a big data system requires identifying and storing of digital information. By using Machine-learning algorithms, it can optimize and expose new statistical patterns, which form the stamina of predictive analytics. With the huge data can begin analytics before beginning data scientists should make sure that predictive analytics fulfills their goals and is appropriate for the big data environs. As we are aware of that, in big data analytics we concentrate to study on Velocity, Volume and Variety of the angle-oriented image for our predictive analysis. The machine-learning tactic based predictive data analysis competence knowledge that makes use of machine learning move toward to gain an edge over the rest of the bazaar. Machine learning improvement is to discover the hidden patterns in unstructured data sets and uncover new information. However, building a complete data analysis and predictive data analytics plan entails big data and evolution Information Technology systems. The complete data analysis including the unwanted information from the collected data consumes lot of time and efforts to reduce the time and cost. An optimization criterion is to be adopted.

Optimization is a process of obtaining the best possible solution to the problem under consideration. It can be achieved by concentrating on choosing appropriate parameter i.e. minimum cost or maximum utility as of user choice. In our proposed application, one of the identified optimization problem is to compare various angles of images with various databases. In the recent research work, various approaches are used for identifying the suitable data by various forms to processing the data. By the very nature of recognition system, many duplicate data is generated by the training image in the application field area. To reach the objective, this concentrates on improving minimum iterations for angle-oriented recognition system using L-axial model. Using this approach, an angle-oriented recognition system, which can take various angles of images from the sensed data for comparing with the database image, is incorporated. The number of image data communications and receptions by duplicating the data at various levels of angle-oriented clusters are decreased. However, at the same time the timeliness must be known because of integrity constraint nature of detection system. So, decreasing the redundancy of the sensed data is concentrated by applying various optimization techniques to optimize the sensed data without losing the generality such that the quality of the transmitted data from the application field to the end user can be improved.

The rest of this paper is arranged as follows: Unstructured data Using Fuzzy Rough Set approach is discussed in Section 2. In section 3, the K-means Fuzzy Rough Angle Oriented Clusters in each cluster is calculated. Section 4 deals with the Hyper-Plane Process for Similarity Poses. Section 5 deals with Evolutionary Optimization for Reduction method. The details of proposed work and discussion of various parameters in which affect its performance of Rotation and Reduction Method discussed in Section 6.The experimental results highlighted in Section 7. Section 8 deals with the future perspective and conclusion.

2. Angle Oriented-Fuzzy Rough Sets

Initially, the input image is chosen and compared with the database image. If input image size is not similar to the database size, the input image is to be resized to match with the size of database image. We compare the pose of the database image in both input and database images. If the input image is not at an angle of 90^0 we can't compare the images; some authors Hafed and Levine [19] used eye coordinates techniques to recognize such an image. In this method, one can identify the feature images of the faces even though they are angle oriented. If the input image angle is other than 90^0 and then apply normalization technique such as geometric and illumination approach. Recognition of an image by using rotational axis is easy to achieve or recognize the face. If the input image rotates from horizontal axis to vertical axis, the face rotates anticlockwise and the face appears in which it is the same as the database pose, then the object is recognized. Similarly, when the input image rotates from vertical axis to horizontal axis, the face rotates clockwise and the face appears in which it is the same as the database pose, then the object is recognized. Therefore, if input image is Angle oriented the pose is changed, or angle is altered using rotational axis either Clockwise or Anticlockwise and then compared suggested by Jagan Mohan et al. [1], [6], [7].

As per Pawlak's renowned framework for the construction of lower and upper approximations of any Orientation given incomplete information, models have been extended in two ways:

1. Any set 'I' (Images), may be generalized to a fuzzy set in X, allowing that input images can belong to an Orientation (i.e., meet its characteristics) with varying degrees.
2. Instead of modeling elements indistinguishability, one may assess their similarity (input images are similar to a certain degree), represented by a fuzzy relation R. As a result, the input images are considered into classes with "soft" boundaries based on their similarity to one another.

Accordingly, the whole of input image (tuple) can be divided into two parts namely Anticlockwise and/or Clockwise methods proposed by Jagan Mohan, 2012 for each method can be two clusters $0^0 to 45^0$ and $45^0 to 90^0$ mathematically defined given below as follows

$$\sum_{\theta=0^0}^{45^0} \sin\theta + \sum_{\grave{e}=45^0}^{90^0} sin\theta$$

The entire tuple i.e., clockwise or anticlockwise are composed of the lower and upper approximations is called a rough set. Therefore, a rough set composed of two crisp sets, one representing a lower boundary of target **X** and the other representing an upper boundary of X.

$$\propto_p (x) = \sum_{\theta=0^0}^{45^0} \sin\theta + \sum_{\theta=45^0}^{90^0} sin\theta$$

When

$$\theta = 0^0, \sum_{\theta=0^0}^{45^0} Sin\theta = 0$$

$$\because lower\ approximation\ is\ empty$$

When

$$\theta = 90^0, \sum_{\theta=45^0}^{90^0} Sin\theta = 1 \ \because Upper\ approximation.$$

3. K-Means Fuzzy Rough Angle Oriented Clusters

Consider a set of Angle Oriented Fuzzy Rough Images whose feature vectors θ = (0^0, 1^0... 90^0) where each value in angles annotations is in n dimensions actual image vectors to find out the mean m_i of the angles based on image feature vectors in cluster K. Our aim to separate the n observations into K (<=n) sets S= {S_1, S_2 ...S_K} as a result, to reduce the variance within the angle-oriented cluster sum of squares. If the angle-oriented clusters are well alienated, then we can use a minimum distance using Tanimoto distance method for mean and variance calculated and classify the angle-oriented images. For example,θ in cluster S If $\| \theta - m_i \|$ approximates minimum distances for angle-oriented clusters. The cluster images are stated using Tanimoto distance method by Tanimoto et al. [17].

4. Hyperplane

Hyperplane is a familiar tactic for the classification of both linear and nonlinear data. Angle Oriented images data is an attribute such as in-degree, out-degree, level, incidence, and usefulness, etc. of angle-oriented clusters. Let 'W' be a set/cluster with the angle-oriented images cluster namely clockwise or anti-clockwise. In each cluster either clockwise or anticlockwise collection of Θ angles like [0^0-45^0], [46^0-90^0], denoted as {(P_1, I_1), (P_2, I_2)… (P_n, I_n)}, where P_i is a tuple of angle-oriented clusters images 'i' with related class label I_i. Each I_i can obtain one of two values either positive class (+1/Yes) or negative class (-1/No) as shown in Figure. For Angle-oriented images, set with two attributes/dimensions is an infinite number of separators can be drawn. This can be widespread to n – dimensions /attributes. This optimal separator is

known as Hyperplane. Hyperplane by way of a larger margin is more accurate than with smaller margin.

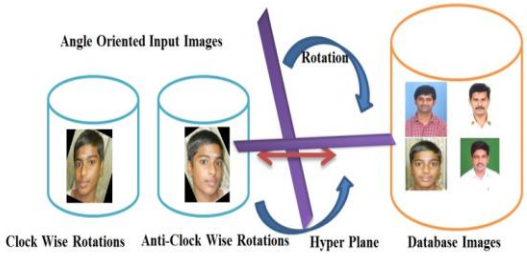

Figure 1. Hyperplane of Angle-Oriented Images

Initially, the input images have taken that are captured from input devices (user request image) and of these input images classification technique is applied i.e., image can be rotated into clockwise or anticlockwise and measure the feature extraction of each image which are stored into a local database W. The database I already consists of feature-extracted images. Now when a user passes a query image as an input then the hyperplane calculates the similarity between the query image and database image based on Tanimoto distance. The Hyperplane now moves the image that is having minimum distance by rotating either clockwise or anticlockwise to the database.

As we know that, to designate the use of hyper-planes, separate convex sets that does not intersect. Assume that 'W' and 'I' are two convex sets that do not intersect i.e., $I \cap W = \emptyset$. The input image set I is the collection of angle-oriented clusters of input images; 'W' has the collection of those database image set. Then $\exists a \neq 0$ and b such that $a^T x \leq b$ for all $x \in C$ and $a^T x \geq b$ for all $x \in W$. In this function, $a^T x - b$ is non-positive on I and non-negative on W. A separating Hyperplane exists for the sets 'I' and 'W' if and only if $\{x \mid a^T x = b\}$ is discussed by Stephen Boyd, (2004).

5. Evolutionary Optimization Method

Evolutionary Optimization is an effortless optimization method. This algorithm needs $(2^N + 1)$ points of which 2^N are angle-corner dots of an N-dimensional $(\text{hypercube})^2$ centered on the other point. All $(2^N + 1)$ function values are compared, and the best point is identified. In the next iteration that a further hypercube is produced roughly, this best point. At any iteration that is an improved point is not found then the size of the hypercube is reduced. This process maintains in anticipation of the hypercube becomes very tiny.

The algorithm consists of the following steps:
Input: A**ngle oriented images i.e.,** $\theta = 0^0 - 90^0$
Output: Equivalent Pose Image

1. Select an initial point$i=0$ and reduction size parameters Δ_i for all the values of 'i' angle-oriented image variables.
2. Choose a termination parameter Є. Set i^0.
3. If $\| \Delta \| < Є$, Terminate.
   Else, Create $2^{\text{Sin } \Theta}$ angle-oriented image points by subtracting 1from each θ variable $2^{\text{Sin } \Theta}$.
4. Compute the angle-oriented images at all $2^{\sin \theta}$ to find out the point having the minimum function value.
5. Select the best suitable image i.e., which has minimum θ value.
6. If $[\, 2^{sin0^0} - 1 < i < 2^{sin90^0} - 1]$, reduce size parameter $2^{\text{Sin } \Theta}$, go to Step 2.
   Else set i^0, go to Step 2.

Note: $i = 2^{\text{Sin } \Theta} - 1$, where $\theta = 0^0$ to 90^0,

$$\because 2^{sin0^0} - 1 < i < 2^{sin90^0} - 1,$$

$$\because (0 < i < 1).$$

From the above algorithm, if $i^0$is the present best point. At the end of simulation, i^0 becomes the obtained optimum point. It is clear from the algorithm that at most 2^N functions are evaluated in each level. Therefore, the necessary number of function evaluations rises exponentially with N.

6. Rotation and Reduction Procedure (R^2 Procedure)

With the intent of R^2 procedure need to have a sympathetic of how data is transformed as it executes in the Rotation and Reduction outline. The Rotational-Map and Reduction Procedure is described below: Initially, we split the entire angle-oriented input images into two major clusters as shown (in section 2) above angle-oriented fuzzy rough image cluster classification. This will distribute the process among all the rotational-based map nodes. Then, we demonstrate the various angles of images between 0^0-90^0 that is clockwise or anti-clockwise in each of the mapper and give angle-oriented image (1/Yes) to each of the images. The basis behind giving an angle-oriented image equal to 1/Yes is that every image occurs only once.

At this moment, a cluster (list of angles-value) will be created with a key, where the key is nothing-but the individual angles and its value is one. The mapping processes remainder the same on all the (nodes) images. After rotational based mapper phase, a partition process takes place where sorting and shuffling happens so that all the tuples with the same key are sent to the reduction process. Therefore, after the sorting and shuffling phase, in reduction process each reducer will have a unique angle in addition to a

list of images corresponding to Key-Value. Each reducer counts the angles, which are present in that list of values. As shown in Figure 1, reducer gets a list of images, which [1, 1] for the angle value. Then, it counts number of ones in the actual list and gives the final output. Finally, all the output of angle-oriented image cluster pairs are then collected and written in the output file.

7. Experimental Result

The standard databases are used for analysis of our angle-oriented recognition purposes. We use three variety of sampled data sets, the popular and standard datasets such as MIT, FERET and Yale in which are generally used as sample datasets for analyzing any research findings in the image processing and especially face recognition applications. Further, to have more insight into the functionality and the performance analysis of the developed angle-oriented recognition system we have synthesized the local database, apart from the above, covering all possible cases of the face angles that may appear before the recognition system in practical scenario. Our synthesized database named SRKR Engineering College Student Database consists of sample images considering the requirements to test most possible cases for which our system has to be subjected for analysis. We predict the possible angle orientations that may usually appear in a general face recognition system and synthesized our database accordingly. The synthesized image database used in our experiments consisting of 6000 anterior(frontal) images in which a randomly selected 243face images for experiment. Only few images from database are shown in below figures. These images deviate in facial expression and illumination. The face images (N x N) in the database were resized to 8 x 8 for angle-oriented experiment. The experiments were divided into two parts and have been performed for 10 persons preferred from the dataset.

In the first part, one sample per person is used in the training process and the numbers of test samples are generated per person with angles ranging between 0^0-90^0.The second part has ten samples for every individual and 0^0-90^0 orientations foreach person are used in testing process. Discrete Cosine Transform technique is used for recognizing the faces. Applying the angle orientation technique, we tested each input for all image angles ranging between0^0-90^0 (anti-clock or clockwise directions) of above database images and applied DCT based feature extraction method on the generated images of angle orientation system.

7.1. Clockwise Rotation

The portrayal of recognition system has major drawbacks such as to test the multiple scales, orientation etc. It is more difficult to incorporate solutions to all these problems in any single autonomous face recognition system. We hope our efforts in addressing these problems have given considerable contributions to solve these problems with our angle-oriented recognition system. The scope of this part of experiment in our work is to achieve the clockwise rotation in angle orientation technique. The tested sample images and the respective angle-oriented outputs for various images from various kinds of standard and synthesized databases as mentioned above are shown in Figure 2.

Figure 2. The first row is the Clockwise input images in the Test database while the second row shows Database Images of MIT, FERET, Yale and College Students

Figure 3. Mean values of the Database images

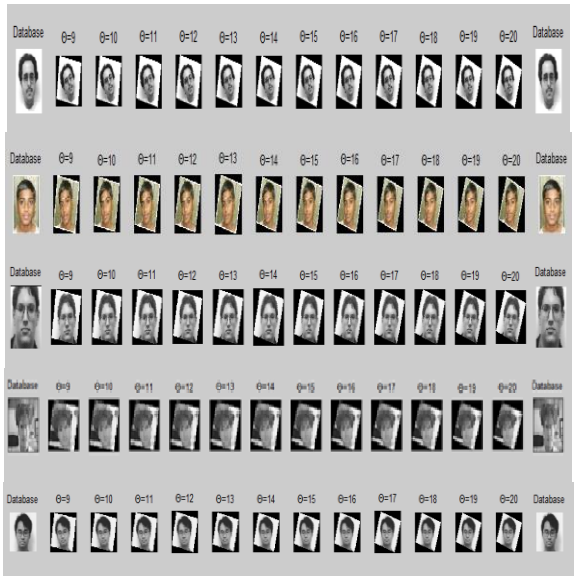

Figure 4. The first image is the database image, whiles the second and subsequent is the clockwise rotation of images of the same subjects with different scaling and orientation

Here, we considered the images with multiple orientations from three different databases and

generated the images with various angles between 0^0-90^0, which form an input data set for the clustering and classification part of our recognition system.

Various angles, i.e. between 0^0-90^0in the clock wise with different orientations, are shown in the above figures. The angle-oriented pose recognition system checks the availability of the image in the database. The resultant data of that person is displayed. The angle orientation technique is to handle the drawbacks mentioned in the above. These are addressed as two cases 1) various angles, i.e. 0^0-90^0, input image namely clockwise rotation with different scale of the poses. 2) Orientation problem can be solved to increase the reliability of the performance rate and compare with other scale (angle) changes.

7.2. Anticlockwise Rotation

The similar process as mentioned for the anticlockwise rotations in the above description of Figure 5 is again used for the recognition of the images, which are required to be rotated in anticlockwise direction to form an input dataset for the angle-oriented recognition system. The major drawbacks in the picture recognition system are to test the multiple scales, orientation. The anticlockwise rotation in angle orientation technique can also solve the above problems.

Figure 5. The first row is Anticlockwise input images in the Test database while the second row shows Database Images like MIT, FERET, Yale and College Students

Figure 6. Mean values of Database images

The anticlockwise rotations with different orientations i.e., 0^0-$90^0$are mentioned in the above. The angle-oriented pose recognition system checks user availability in the database. The resultant image of that person is displayed. To handle the drawbacks which are mentioned above we used angle orientation technique, which is addressed as two cases 1) various angles of input images i.e. 0^0-90^0 namely anti-clockwise rotation with different scale of the poses. 2) to improve the reliability of performance recognition rate to high and compare with other scale (angle) changes, we solve the orientation problem.

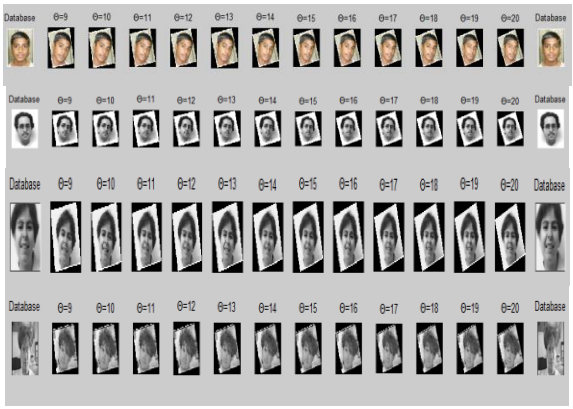

Figure 7. The first image is the Database image, whiles the second and subsequent is the Anti-Clockwise image of the same subjects with different scaling and orientation

7.3. Optimized Clockwise Angle-Oriented Images

Optimization is the selection of the best angle or pose image from Various Database images. This problem consists of maximizing or minimizing a real angle-oriented image function by systematically choosing input images from within an allowed set and computing the images of the image function. The generalization of optimization study and methods to other formulations constitutes a large area of applied mathematics and computing. More generally, optimization includes finding "best available" images of some objective given a defined domain (or input), including a variety of different types of objectives and different types of domains.

The above-mentioned datasets are considered for testing cluster optimization. The recognition rate is find-using DCT. The input image is taken as variables and it is considered as life random variables. The corresponding probability model fitted to the data is exponential. In the process of Clockwise or Anticlockwise model, take five poses out of 90 poses in input images in all the two clusters of 78 poses are recognize and 12 poses are unmatched and deduct them. Out of these 78 recognized poses only one pose can be like the database pose as per the normalization technique. It is noticed from the test results, to optimize 12.8% rate of recognition and 87.2% deviate to database poses. The exponential based angle-oriented fuzzy rough cluster images are used as modest model for cluster optimizations as failure times of recognition system. The exponential distribution is characterized by a constant failure rate, denoted by lambda (λ). T has an exponential distribution with rate lambda(λ) >0 if $P(T\leq t) = 1-e^{-\lambda t}$ for any nonnegative t. This function can be used to evaluate. For instance, for a failure rate =12.8the output is 0.9999.

8. Conclusion

This paper, we attempted for cluster optimization using angle-oriented fuzzy rough images. Two types of optimization techniques, micro and macro level are adopted. For micro level, parallel computation and for macro level R^2 procedure adopted. Reliability failure rate model for cluster optimization is used by considering the exponential failure rate model. The technique is tested on three types of databases and experimental results are mentioned. It is also used to optimize redundancy. The future perspective of this work is to compare the different databases with various failure rate models.

9. References

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