A Novel Distributed Approximate Nearest Neighbor Method for Real-time Face Recognition

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Abstract Nowadays face recognition and more generally, image recognition have many applications in the modern world and are widely used in our daily tasks. In this paper, we propose a novel distributed approximate nearest neighbor (ANN) method for real-time face recognition with a big data-set that involves a lot of classes. The proposed approach is based on using a clustering method to separate the data-set into different clusters, and specifying the importance of each cluster by defining cluster weights. Reference instances are selected from each cluster based on the cluster weights and by using a maximum likelihood approach. This process leads to a more informed selection of instances, and so enhances the performance of the algorithm. Experimental results confirm the efficiency of the proposed method and its out-performance in terms of accuracy and processing time.

Keywords Approximate Nearest Neighbor · Face Recognition · Clustering · Maximum Likelihood

1 Introduction

Face and Image Recognition are two important fields in computer science and mainly machine learning. Their relevance in the modern world requirements is presented as a case of human machine interaction. They also have many applications such as “Access Control and Security”, “Health-Care”, “Advertising”, “Criminal Identification”, etc. In all the aforementioned applications, there are several classes, some reference images for each class and one or more input images. The purpose of this type of problems is defining the most fitting class to the input image based on the acquired information from reference images.

The process of achieving this goal can be summarized as the following steps:

1. Extracting features from reference images
2. Training some algorithms using the reference images
3. Extracting features from the input image
4. Identifying the most probable class for the input image using the reference images.

In all machine learning problems, one of the most important and challenging steps is feature extraction. In face recognition and generally image recognition problems, this process is more challenging due to the effect of lighting and complex background variability and also variability of objects presented in images. There are many ways for feature extraction such as “SIFT” which was applied in [7], “SURF” applied in [9], and “HOG” applied in [11]. Based on the application, we can decide which one to use. After extracting the feature of all images, it is time to use machine learning algorithms to classify the input image. Face recognition is both important and challenging tasks especially in working with big data-set. Related to the type of algorithm used in this task, there may be a need to train the reference images. For example, one of the useful methods in face recognition problems is Neural Network that includes training phase. There is another type of algorithms that does not include this phase. These algorithms are called lazy

1 Scale Invariant Feature Transform
2 Speeded Up Robust Features
3 Histogram of Oriented Gradient
algorithms. One of the examples for this type of algorithms is the Nearest Neighbour algorithm. In these type of algorithms, due to the elimination of the training phase, test phase gets more important and more time-consuming. So one of the challenges in this form of algorithms is reducing the processing time. Finally, the output will be a class label assigned to the input image.

As mentioned before we can use many algorithms in the face and object recognition process, but some of them are more frequently used such as Deep Neural Network [13] or Support Vector Machine [3]. Although both of these algorithms are demonstrated to be efficient when the size of training set is large, they are not accurate enough in the problems with few reference images per each class [14]. Small training size problem is important in face recognition, because some times, we have only one reference image for each person [3]. In these type of problems, we can use the NN algorithms, but if the number of classes is large the total number of reference images will be large too. So considering all the reference images to choose the nearest one will be time-consuming. In these cases the algorithm will be so slow [3] and it won’t be real-time. Since in most of the face recognition applications, recognition process must be real-time, we use ANN [7] to make this process faster.

There are many ANN algorithms such as DEM [15] and ML-ANN [3] [7] which we will consider in section 2. They are both faster than the Nearest Neighbour algorithm, but yet there may be a time problem for large data, and that is because of the procedure of choosing the reference images to be considered. On the other hand, in both approaches choosing the instances in each iteration is based on the information acquired from considered images in previous iterations. So, information obtained from the considered images is highly dependent on the first instance, that is chosen randomly in both algorithms.

In this paper, we try to propose a faster algorithm using a clustering approach before starting the recognition process.

This paper is organized as follows. In section 2 we review the related researches and explain the ML-ANN algorithm in detail. The proposed method is described in section 3. The experimental results are presented and compared in Section 4. Finally, concluding remarks are given in Section 5.

2 Related Researches

In this section, we consider the various types of recognition methods and mainly NN algorithms and state where we prefer to use or not use them.

As mentioned in the previous section for datasets, which has few images per each class, we cannot use deep learning algorithms [10] or SVM [17] because of the lack of accuracy in these cases. In these types of problems, we can use NN algorithms. This type of algorithm can be divided into two classes: “Fast” and “Brute force”.

In the brute force search, we consider the distance between the input image and all the reference images and choose the nearest one to the input image. If the number of classes is high, the amount of total images is high, and therefore this algorithm will be time-consuming.

The method which we propose in this paper is a type of fast algorithms which has two main types: exact and approximate [3]. In the exact form we search for the exact nearest neighbor without considering all the images [3]. One of the most used methods between the algorithms in this form is the use of kd-tree [15]. By using this data structure, we can find the nearest neighbor just like how we use a binary search tree but with additional backtracking [3]. In backtracking, we eliminate some branches, and that is why we have speed up in this form of algorithms. We can use this data structure when the data is low-dimensional, but when our data is high-dimensional backtracking will not eliminate the branches, and so we will not have speed-up, and using this structure will not be efficient.

In the cases which the exact form does not work efficiently in, we can use approximate form. In this type of algorithms instead of searching for the exact nearest neighbor, we try to find the neighbor with the acceptable distance with the input image.

There are many types of ANN algorithms such as clustering the reference images and using a hierarchical tree [19] [15]. The nodes in each layer are the centroids of the lower layers. In each layer the nearest node is selected and so in the lower layer the images in approximate nearest cluster are considered. This algorithm is so fast but not much accurate [15].

There is another type of approximate algorithm which defines a threshold and searches for the neighbor with the distance lower than the threshold. In this form of the algorithm, there are two important factors which should be considered. The first one is how we define the threshold. For defining threshold, we use the type 2 error [8]. The other factor is the order which we check the reference images. It is so important how the reference

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4 Nearest Neighbor
5 Approximate Nearest Neighbour
6 Directed Enumeration Method
7 Maximum Likelihood Approximate Nearest Neighbor
8 You can see the procedure of defining the threshold in [15] in detail.
images are selected, and different selection procedures result in different ANN algorithms. One of the algorithms of this type is DEM [15]. In this form of the algorithm, we create a matrix of distances between all the reference images before starting the recognition process and use it in the whole process. In this method, the first instance is selected randomly, and the others are chosen based on their distances to the nearest considered instance. In each step, we select all the reference images which have a lower distance to the nearest considered image than the distance between the nearest considered image and the input image. This process terminated whether there is an instance which has lower distance with the input image than the threshold or the number of iterations cross the previously defined maximum number of iterations. The problem of this algorithm is that we select the images only based on their distances with the nearest considered image, and we do not use the information acquired from other considered instances. For solving this problem, we can calculate the likelihood for each reference image based on all the information we obtained from the considered images. This procedure is used in ML-ANN [3], which we explain in detail in the following.

### 2.1 ML-ANN Algorithm

Previously, we considered different NN algorithms and also stated the reasons we use ANN method. Here, we explain how ML-ANN algorithm works. Our goal in image recognition problem is finding the best fitting class for the observed input image. Assume all images, both reference images, and the input image, have the same width U and height V [3]. ML-ANN algorithm is based on using HOG [10] features and we also use these features in our proposed method. It should be mentioned that for an image of size U*V, we have N HOG features where N is the number of bins in the histogram for these features. After extracting the features, the learning algorithm is used. In ANN algorithms such as [15] and [3], first a threshold (ρ0) for the distance between the reference images and the input image is determined. Then, instead of searching for the nearest reference image, the algorithm searches for the acceptable reference image. A reference image that its distance to the input image is smaller than the threshold is acceptable. Such ANN algorithms terminate when an acceptable reference image is found and decide that the class of the input image is same as the class of this acceptable reference image.

So the termination condition for these algorithms can be formulated as follows [3]:

\[ W_r : \rho(X, X_r) < \rho_0 \]  \hspace{1cm} (1)

where X and X_r are the input and the selected reference images, respectively and ρ(.,.) denotes the distance function. In this paper we use the chi-square distance formulated as:

\[ \rho_{\chi^2}(X, X_r) = \sum_{i=1}^{N} \frac{(X_i - X_{r_i})^2}{X_i + X_{r_i}} \]  \hspace{1cm} (2)

where X_i is the ith HOG feature of the input image, and X_{r_i} is the ith HOG feature of the reference image. The first reference image to compare with the input image, is chosen randomly. If this image satisfies criterion [3] the process will be finished. Otherwise we should choose another reference image to compare with the input image, so, we have a queue of chosen reference images.

The order of images in this queue is of great importance. How to choose the next reference image is the main idea of the ML-ANN method [3]. As it comes from the name, it chooses the most probable reference image based on the reference images which has been checked before. Assume we have checked k reference images and now we want to choose the X_{k+1} [3]. Based on the Bayesian theorem and independence of the reference images from different classes, the maximal likelihood choice is obtained using the following formula [3]:

\[ r_{k+1} = \arg\max_{v \in \{1,...,R\} \setminus \{r_1,...,r_k\}} (p_v \prod_{i=1}^{k} f(\rho(X, X_{r_i})|W_v)) \]  \hspace{1cm} (3)

where x_{r_1}, ..., x_{r_k} are the first to kth considered reference images, p_v is the probability of the vth class to be the best fitting class, and \( f(\rho(X, X_{r_i})|W_v) \) is the conditional density of the distance \( \rho(X, X_{r_i}) \) if the hypothesis \( W_v \) is true (the class label of observation X is \( v \)) [3]. Since we use chi-square distance and we have \( U \times V \) matrix of histograms containing N number of bins, the output of the distance is a chi-square distribution, \( \chi^2 \). After approximating the chi-square distribution with normal distribution, \( f(\rho(X, X_{r_i})|W_v) \) can be computed as [11]:

\[
\frac{UV}{\sqrt{2\pi}(4UV\rho_{v,r_i} + 2(N-1))} \exp[-\frac{(UV(\rho(X, X_{r_i}) - \rho_{v,r_i}) - \frac{N-1}{UV})^2}{8\rho_{v,r_i} + \frac{4(N-1)}{UV}}]
\]

\[ \text{Figures 10} \]

You can see the process of the approximating the distribution and computing the \( f(\rho(X, X_{r_i})|W_v) \) in details in paper [3].

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9 Directed Enumeration Method
10 Histogram of Oriented Gradients

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\[ \text{Figures 10} \]
Similar to ML-ANN, before starting the recognition technique in detail.

more accurately. In the following, we will explain the process, we compute the matrix of distances between all reference images, and that’s what makes the algorithms faster. In the proposed method, besides creating this matrix, we cluster all the reference images:

$$r_{k+1} = \arg \min_{\mu \in \{1, \ldots, R\} - \{r_1, \ldots, r_k\}} \left( \sum_{i=1}^{k} \varphi_{\mu}(r_i) - \ln p_{\mu} \right)$$

(5)

where

$$\varphi_{\mu}(r_i) \approx \frac{(\rho(X, X_{r_i}) - \rho_{\mu,r_i})^2}{\rho_{\mu,r_i}}$$

(6)

In [3], it is assumed that the matrix of the distances between all reference images is computed before starting the recognition, so, there is no distance computation in selecting instances process, and the recognition process can be real-time. This approach encounters a problem, when the input image does not belong to any classes. For avoiding this problem, we define the maximum number of iterations, and whether there is no reference image satisfying the criterion [1] the process will be terminated.

3 Proposed Approach

Although ML-ANN [3] algorithm is the improved form of the DEM[15] method and works faster, but yet there may be a time problem for big data.

In ML-ANN method, each time a reference image is selected and the termination condition is checked for it. If this condition is not satisfied, the next reference image is selected. So, simultaneously working on more than one image is not possible in this method. We propose a method that can work on more than one reference image simultaneously, so, it has a good capability for parallelism and can be more useful in large scale data-sets.

Selecting reference images, in ML-ANN method is based on likelihood; however, selecting the reference images can be more consciously and so in this paper we are trying to propose a faster and more conscious method.

As mentioned in the previous section, calculating the likelihood of each reference image is based on the information acquired from previous selected images in the queue of reference images. Hence selecting the reference images is dependent on the first selected image, which is chosen randomly.

In our method, we combine the ML-ANN algorithm with a clustering algorithm to select the next instance more accurately. In the following, we will explain the technique in detail.

Similar to ML-ANN, before starting the recognition process, we compute the matrix of distances between all reference images, and that’s what makes the algorithms faster. In the proposed method, besides creating this matrix, we cluster all the reference images:

$$\forall X_r, \ r \in \{1, \ldots, R\}; \ X_r \in C_i, \ i \in \{1, \ldots, K\}$$

(7)

Where $C_i$ denotes the ith cluster and K is the number of clusters. Choosing K can be based on the number of classes. But K should be much less than the number of classes, i.e, each cluster consists of some classes. We use K-means algorithm in this paper.

Recognition process starts with creating a queue for each cluster and that is why the proposed algorithm can be run in parallel. Unlike the ML-ANN algorithm where the first instance is chosen randomly, in this algorithm we use the centroid of each cluster as a first instance added to each of queues to make them more distributed on the data-set:

$$\text{queue}_i = \{\text{Centroid}_i\}; \text{ for } i \in \{1, \ldots, K\}$$

(8)

After adding the centroids to the corresponding queue, the distance between the instances and the input image is calculated, and whether one of them is less than the threshold the algorithm will be terminated. Otherwise, we must select the next reference images from each cluster and add them to the corresponding queue. In this step, to make our method more efficient, we propose an approach to add different numbers of reference images to different queues. To make the reason more clear assume that the distance between the centroid of ith cluster and the input image is small (but not smaller than threshold) and the distance between the centroid of jth cluster and the input image is large. We can conclude that it is more likely that the input image belongs to ith cluster, and the classes inside this cluster compared with the jth cluster. So, to consider this important issue in our proposed method, we define a weight for each cluster that demonstrates the importance of that cluster. It should be mentioned that the weight of each cluster changes when new instances are added to the cluster queue. In other words, the weight of each cluster in each step computed based on the last version of its queue. The number of the selected instances for each cluster is based on the weight assigned to that cluster. So before choosing the next instances, the weights assigned to each cluster must be defined.

For calculating the weights, there are many procedures such as using the average distance between the selected instances in each queue and the input image, maximum or minimum distance, the average likelihood of each queue, etc. For the rest of the paper we use average distances to calculate the weights. At first, we calculate
the average of distances between the instances in each queue and the input image as follows:

\[ \forall j \in \{1, ..., K\}; \text{avg}(distance)_j = \frac{\sum_{i=0}^{k_j} p(X, X_{i})}{k_j} \quad (9) \]

Where K is the number of clusters, \( \text{avg}(distance)_j \) is the average of distances between instances in the jth queue and the input image, and \( k_j \) is the number of images in the jth queue. After that we select the maximum value between the average distances of each queue as formulated below:

\[ \text{max}\_\text{average\_dist} = \max_{j \in \{1, ..., K\}} \text{avg}(distance)_j \quad (10) \]

Then, we divide the maximum value by the calculated average distance (\( \text{avg}(distance)_j \)) for each queue and use the ceil of the obtained value for each queue as the weight assigned to that queue. This process is formulated in below:

\[ \forall i \in \{1, ..., K\}; \text{weight}_i = \left\lceil \frac{\text{max}\_\text{average\_dist}}{\text{avg}(distances)_i} \right\rceil \quad (11) \]

In this way, the weight assigned to the queue with maximum average distance is equal to one and the others get their value according to their average distance. As the average distance get smaller the weight get bigger.

After calculating the weights assigned to each queue, we must select the instances for the next iteration. For selecting the instances from each cluster in the next iteration we use the same procedure as the ML-ANN method with a little changes. The instances are chosen by using the criterion \[12\]. It should be mentioned that according to formula \[12\] to select the most probable instances for each cluster queue, we use all previously compared instances in all cluster queues.

\[ \forall j \in \{1, ..., NC\}; \quad r_{(k+1)_j} = \arg\min_{\mu \in \{r_1, ..., r_{NC}\}} \left( \sum_{i=1}^{K} \sum_{k_i} \varphi_{\mu}(r_{i}) - \ln p_{\mu} \right) \quad (12) \]

Where \( r_{(k+1)_j} \) is the index of the next selected instance from the jth cluster, \( k_i \) is the number of selected instances from the lth cluster in previous iterations, and the \( \varphi_{\mu}(r_{i}) \) is the value calculated by the criterion \[6\]. This process terminates, whether there is an instance satisfying the criterion \[1\] or the number of iteration exceeds the maximum iteration \[3\]. If there are more than one reference image satisfying the criterion \[1\] or the number of iteration exceeds the maximum iteration, we choose the nearest image between the considered images. This process helps us choosing reference images more consciously by letting us select instances from different clusters.

Due to the above explanation, the details of the proposed method described in algorithm \[1\] and the steps can be summarized as follows (the lines mentioned in these steps are due to the lines of algorithm \[1\]):

1. Cluster the dataset to K parts and consider one empty queue for each cluster: queue\(_i\); line: preliminary step
2. Add the centroid of each cluster to its queue; line: 5
3. Check criterion \[1\] for centroid\(_i\); \( i = \{1, ..., k\} \) if this criterion established go to step 9 else continue; line: 8
4. Calculate the weights based on the criterion \[10\]; line: 9
5. Check the number of iterations, if it exceeds the maximum number of iterations go to step 9 else continue; line: 11
6. Select the instances from each cluster using \[11\] and \[12\]; (The number of instances is based on the weights assigned to each cluster \[11\]); line: 13-19
7. Check the criterion \[1\] for each new instance, if the criterion is satisfied return the image; line: 20-21

Algorithm 1 Proposed Algorithm

| Data: input image X and reference images database \( \{X_r\} \) |
| Output: reference image which is nearest image to input image between considered images |

**Preliminary Step:** calculating the matrix of distances between all the reference images (\( P[i][j] = p_{r_i, r_j} \)) and clustering the reference images using K-means algorithm

1. **procedure** Image Recognition(input image X)
2. **initialize** an array for each cluster \( \triangleright \) queues[i]; the array which is assigned to the cluster number i
3. for i in range(0, NumberOfClusters) do
4. Assign distances[i] := 0 \triangleright \text{distances[i]; Contains the sum of the distances between the input image X and the reference images[i]’s reference images}
5. Add centroids[i] to the queues[i] \triangleright \text{centroids[i]: centroid of the cluster number i}
6. Assign dist := \( \rho(X, centroid[i]) \) \triangleright \text{distance measure: chi-square}
7. Assign distances[i] := distances[i] + dist
8. Check criterion \[1\] for all centroids
9. calculate each clusters weight
10. Assign iteration := 0
11. while iteration < \text{max\_iteration} or criterion \[1\] is not satisfied do
12. Assign iteration += 1
13. for i in range(0, NumberOfClusters) do
14. for j in range(0, weight[i]) do
15. calculate likelihood for all the images in cluster based on the criterion \[11\]
16. select the reference image with the maximum likelihood
17. Assign dist := \( \rho(X, centroid[i]) \) \triangleright \text{distance measure: chi-square}
18. Assign distances[i] := distances[i] + dist
19. Add selected image to the queues[i]
20. if selected image satisfies the criterion \[1\] then
21. return Selected-Image
22. update weights based on the distances and the criterion \[9\] \[10\] \[11\]
23. select nearest image to the input image between considered images
24. return Selected-Image
Preliminary Step:
As it came in algorithm

1. Start
2. Input Image
3. initializing a queue for each cluster
4. adding centroid of each cluster to corresponding queue
5. criterion is satisfied
6. return nearest image to the input image between the considered images
7. select one or more reference image from each cluster using the weights and formula
8. calculate the distances between new instances and the input image
9. criterion is satisfied or \( iter > \text{max}_{iter} \)
10. return nearest image to the input image between the considered images
11. update the weights using the criterion
12. iter++
13. stop

Fig. 1: Block diagram of proposed algorithm

8. Go to step 5
9. Return the nearest image between the considered images; line: 24

Previously, we used the pseudo-code to show how the algorithm works in the algorithm and the block diagram of the method comes in Fig. to provide the better view of the steps.
4 Experimental Results

In this section we conduct number of experiments on publicly available data-sets [21] and [22] to verify the performance of our proposed method[23]. You can see an instance from data-set [21] and [22] in Fig. 2a and 2b respectively.

The main focus of this paper is on the face recognition problems and so the experimental study is devoted to this form of problems [20]. In the experiment process, we evaluate the average recognition time and the accuracy for the different number of clusters and compare them with each other and brute force NN algorithm. It should be mentioned that the proposed algorithm is a general form of ML-ANN method. In other words, when we have only one cluster, the proposed method is same as ML-ANN. So, we use the results generated from running the proposed algorithm with one cluster as ML-ANN algorithm’s results in our comparison. (We also run the proposed method with two and three clusters in our testing process. In the following figures, we show ML-ANN algorithm with “ML-ANN”, which means the proposed algorithm with one cluster, and the proposed algorithm with two and three clusters with “D-ML-ANN-C12” and “D-ML-ANN-C13”.) For evaluating the average recognition time, accuracy, and the average number of distance computation, we implemented the algorithms in python language and used 2 data-sets for testing the algorithms. In this section, the main results are obtained by using the data-set [21]. It contains three groups of people, and each group includes at least 20 persons. The total number of people is 153 and there are 20 images per person, and all the images are in size of 180 × 200 and RGB color space. Although parallel programming makes the proposed algorithm faster, we did not use it in the experimental study.

As mentioned in the introduction section, we used the HOG [10] method to extract features and also used HOG Descriptor class from the OpenCV library with the properties used in [3]. You can find the transformed form of Fig. 2a and 2b in Fig. 3a and 3b respectively.

We used the KMeans class from the sklearn library to implement clustering. The number of clusters is based on the data-set.

We tested all algorithms setting the threshold equal to 0.083 and 0.085. We also used 50 images from each data-set as input images and by using average term we mean the average value of the results generated from testing these images.

Since the most time-consuming part of recognition is distance computation, at first, we consider the average

![Instance from data-set](image1)

(a) An instance from data-set [21]

![Instance from data-set](image2)

(b) An instance from data-set [22]

Fig. 2: instances from each data-set

![Transformed form of Fig. 2a](image3)

(a) Transformed form of Fig. 2a

![Transformed form of Fig. 2b](image4)

(b) Transformed form of Fig. 2b

Fig. 3: The result of implementing HOG transformation on each instance

12 We use the second data-set to make more valid conclusion
number of distance computation in each algorithm. The results come in Fig. 4a, 4b and 5a:

(a) Threshold = 0.085, Data-set: [21]
(b) Threshold = 0.083, Data-set: [21]

Fig. 4: Number of Distance Computation per maximum iteration

Both Fig. 4a and 4b demonstrate that there is a great decrease in number of distance computation by using the proposed approach.

It is clear from Fig. 5a that, as expected, the number of distance computation in NN method is much more than ANN approaches. So, in the Fig. 5a, we ignore the results of NN method.

Fig. 5b give the same information as Fig. 4a and 4b and it shows that proposed approach needs fewer distance computation in comparison with other ANN approaches.

In the following we have plotted the accuracy of each algorithm per each iteration. Fig 6b and 6a shows the results. As you can see in Fig. 6b and 6a, there is limitation for the accuracy and that is due to the defined threshold for the acceptable distance. If we decrease this threshold we will have more accurate outputs.
As it is evident in Fig. 6b and 6a when maximum iterations increases, the accuracy increases too but with the same value for the maximum number of iterations proposed algorithm is more accurate.

For getting more clear comprehension, we evaluated the minimum value of average number of distance computation for achieving specific accuracy. The results come in Fig. 7a and 7b.

The results plotted in Fig. 7a and 7b demonstrate that number of distance computations for achieving same accuracy is fewer than other algorithms. Please consider that even with the minimum number of distance computation the accuracy of proposed algorithm was higher than 0.1 with threshold equal to 0.085, and 0.5 with threshold equal to 0.083.

The other parameter which is so essential in our experimental study is average recognition time. The reason for considering the average number of distance computations, was analyzing the recognition time in the proposed method. Therefore we evaluated the average recognition time, and the results come in Fig. 8a, 8b, and 9.
Fig. 8: Average Recognition Time per each value for maximum iteration

(a) Threshold = 0.085, Data-set: [21]

(b) Threshold = 0.083, Data-set: [21]

Fig. 9: Average Recognition Time algorithm, Threshold = 0.085, Data-set: [21]

The comparison results were almost similar, and according to Fig. 10 and 11, the proposed method’s per-

Fig. 10: Minimum Value of the Average Recognition Time for achieving specific accuracy, Threshold = 0.083, Data-set: [22]

Fig. 11: Minimum Value of number of distance computation to achieve the specific accuracy, Threshold = 0.083, Data-set: [22]

14 Same as the first study because of the fact that different values for maximum iteration may result same accuracy we use the minimum term to illustrate the minimum number of distance computation resulting specific accuracy.
formance was quite better in the second study too.

5 Conclusion

This paper proposed a novel ANN method that is a generalized and distributed version of ML-ANN. In this way, we clustered the reference images and chose one or more instances from each cluster instead of selecting just one reference image from the whole data-set in each iteration. This process made selecting instances more consciously, and so enhanced the performance of the algorithm.

The improvement of the algorithm is indicated explicitly in the experimental study. It is evident from the experimental results that the proposed algorithm provides better results in terms of accuracy and processing time.

As previously stated, parallel programming will make the proposed algorithm even faster. Although we enhanced the algorithm’s performance in time and accuracy, we did not decrease memory usage. Hence the other way to improve the algorithm is finding a procedure to eliminate the usage of the distance matrix and so reduce the memory usage.

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