FACE RECOGNITION USING ORTHOGONAL LOCALITY PRESERVING PROJECTIONS.

Dr. Ravish R Singh
Academic Advisor
Thakur Educational Trust
Mumbai, India.
ravishrsingh@yahoo.com

Ronak K Khandelwal
EXTC Engineering
L.R.Tiwari COE
Mumbai, India.
ronakkhandelwal2804@gmail.com

Manoj Chavan
EXTC Engineering
Thakur COE
Mumbai, India.
prof.manoj@gmail.com

Abstract: **In this paper a hybrid technique is used for determining the face from an image. Face detection is one of the tedious job to achieve with very high accuracy. In this paper we proposed a method that combines two techniques that is Orthogonal Laplacianface (OLPP) and Particle Swarm Optimization (PSO). The formula for the OLPP relies on the Locality Preserving Projection (LPP) formula, which aims at finding a linear approximation to the Eigen functions of the astronomer Beltrami operator on the face manifold. However, LPP is non-orthogonal and this makes it difficult to reconstruct the information. When the set of features is found by the OLPP, with the help of the PSO, the grouping of the image features is done and the one with the best match from the database is given as the result. This hybrid technique gives a higher accuracy in less processing time.**

Keywords: OLPP, PSO, higer accuracy.

I. INTRODUCTION

Recently, appearance-based face recognition has received tons of attention. In general, a face image of size $n_1 \times n_2$ is delineating as a vector within the image house $Rn_1 \times n_2$. We have a tendency to denote by face space the set of all the face pictures. Although the image house is incredibly high dimensional, the face space is typically a sub manifold of terribly low spatiality that is embedded within the close house. A common thanks to decide to resolve this downside is to use spatiality reduction techniques. The foremost standard ways discovering the face manifold structure embrace Eigen face, Fisher face [2], and Laplacianface [9]. Face illustration is basically regarding the matter of manifold learning [3] which is a rising analysis space. Given a group of high-dimensional knowledge points, manifold learning techniques aim at discovering the geometric properties of the information house, reminiscent of its geometer embedding, intrinsic spatiality, connected parts, homology, etc. notably, learning representation is closely regarding the embedding downside, whereas agglomeration is thought of as finding connected parts. Finding a geometer embedding of the face house for recognition is the primary focus of us in this paper. Manifold learning technique is classified into linear and non-linear techniques. For face process, we have a tendency to be particularly fascinated by linear techniques because of the thought of process complexness.

The Eigen face and Fisher face ways are too of the foremost standard linear techniques for face recognition. Eigen face applies Principal part Analysis [6] to project the information points on the directions of outside variances. The Eigen face methodology is bound to discover the intrinsic geometry of the face manifold once it's linear. Not like the Eigen face methodology that is unattended, the Fisher face methodology is supervised. Fisher face applies Linear Discriminate Analysis to project the data points on the directions optimum for discrimination. Each Eigen face and Fisher face see solely the global geometer structure. The Laplacianface methodology [9] is recently planned to model the local manifold structure. The Laplacianface are the linear approximations to the Eigen functions of the mathematician Beltrami operator on the face manifold. However, the idea functions obtained by the Laplacianface methodology are non-orthogonal. This makes it difficult to reconstruct the information. In this system we will implement OLPP with PSO both the techniques are explained as follows.

II. RELATED WORK

The following ways are typically accustomed that discover the faces from a still image or a video sequence.

A. Viola Jones Face Detection Algorithm

The Viola Jones object detection framework is that the initial object detection framework to produce competitive object detection rates in period of time planned in 2001 by Paul Viola and Archangel Jones. Albeit it are often trained to discover a range of object categories, it absolutely was motivated principally by the matter of face detection. This face detection framework is capable of process pictures very quickly whereas achieving high detection rates.

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Disadvantages: It takes very long coaching time, restricted head poses and we cannot find black Faces or grayscale images.

B. Local Binary Pattern (LBP)

This technique is incredibly effective to explain the image texture options. LBP has benefits akin to high-speed computation and rotation changelessness that facilitates the broad usage within the fields of image retrieval, texture examination, face recognition, image segmentation, etc. Disadvantages: It is a planned methodology isn't sensitive to little changes within the Face Localization, and victimization larger native regions will increase the errors. It is inadequate for non-monotonic illumination changes and is solely used for binary and gray pictures.

C. AdaBoost algorithm

It is a program for Face Detection Boosting is associate approach to machine learning which supports the concept of making an extremely correct prediction rule by combining several comparatively weak and incorrect rules. The AdaBoost algorithmic program is sensible boosting algorithmic program, and one in every of the foremost wide used and studied, with applications in various boosting algorithmic program to coach a classifier that is capable of process pictures quickly whereas having high detection rates.

Disadvantages: The result depends on the info and weak classifiers. The standard of the final detection depends extremely on the consistence of the coaching set. Each scale of the sets and the interclass variability are necessary factors required. Quite slow coaching. At every iteration step, the algorithmic rule tests all the options on all the examples which needs a computation time directly proportional to the scale of the options and examples sets. Weak classifiers too advanced ends up in over fitting. Weak classifiers too weak will cause low margins, and may conjointly cause over fitting.

D. SMQT options and SNOW Classifier technique

This technique consists of 2 parts. The first part is face luminosity. The operation of this part is being performed to induce component data of a picture and more enforced to detection purpose. The second part is detection. During this part, native SMQT options are used as feature extraction for object detection. The options were found to be able to take care of illumination and sensing element variation in object detection.

Disadvantages: If we tend to take into account color of the human skin colors varies less as compared to brightness. The bulk of the misses includes regions that contain terribly kind of like grey values regions that are present in a picture which could discover them as face.

III. OLPP

Laplacianface could be a recently projected linear methodology for face illustration and recognition. It is based on neighborhood protective Projection [10] and expressly considers the manifold structure of the face space.

Given a group of face pictures $\{x_1 \ldots x_n\} \subset R^m$, let $X = [x_1, x_2, \cdots, x_n]$. Let S be an identical matrix define on the information points. Laplacianface is obtained by finding the subsequent minimization problem:

$$u_o \; -a \quad m \quad \sum_{i=1}^{m}\sum_{j=1}^{m}(u^T x_i - u^T x_j)^2 S_i$$

$$= \arg\min u^T X \quad {}^T u$$

with the constraint

$$u^T X \quad {}^T u = 1$$

Where L = D − S is that the graph Laplacian [4] and $D_{ii} = \sum_j S_{ij}$. D_{ii} measures the native density around x_i. Laplacianface constructs the similarity matrix S as:

$$S_i = \begin{cases} e^{-\frac{|x_i - x_j|^2}{t}} & i. \; x_i \; i \; a \quad the \; p \; n \\ & n \quad hb \quad o \; x_j \; o \; x_j \; i \; a \\ & thr \; p \; n \quad n \quad hb \quad r. \; o \; x_i \\ 0, & o \; he \end{cases}$$

Here S_{ij} is really heat kernel weight, the justification for such selection and also the setting of the parameter t [3].

The objective perform in Laplacianface incurs a significant penalty if neighboring points xi and xj are mapped so much apart. Therefore, minimizing it's an endeavor to confirm that if xi and xj are "close" then *Yi* $(= a^T x_i)$ *and yj* $(= a^T x_j)$ are shut similarly [9]. Finally, the premise functions of Laplacianface are the Eigen's related to the tiniest eigenvalues of the subsequent generalized Eigen problem:

$$X \quad {}^T u = \lambda \quad {}^T u$$

XDX^T is non-singular when some pre-processing steps on X in Laplacianface, thus, the basis of functions of Laplacianface may be thought to be the eigenvectors of the matrix $(XDX^T)^{-1}XLX^T$ associated with the tiniest eigenvalues. Since $(XDX^T)^{-1}XLX^T$ isn't cruciform generally, the basis functions of Laplacianface are non-orthogonal.

Once the eigenvectors are computed, let $A_k = [a_1, \cdots, a_k]$ be the transformation matrix. Thus, the geometrician distance between two knowledge points within the reduced house is computed as follows:

$$d \quad (y_i, y_j) = \|y_i - y_j\|$$

$$= \|A^T x_i - A^T x_j\|$$

$$= \|A^T (x_i - x_j)\|$$

$$= \sqrt{(x_i - x_j)^2 A \quad {}^T (x_i - x_j)}$$

If A is an orthogonal matrix, $AA^T = I$ and also the metric structure is preserved.

IV. OLPP ALGORITHM

In this Section, we tend to introduce a unique mathematical space learning formula, referred to as orthogonal locality Preserving Projection (OLPP). Our Orthogonal Laplacianface formula for face illustration and recognition relies on OLPP. In appearance-based face analysis one is commonly confronted with the actual fact that the dimension of the face image vector (m) is far larger than the amount of face pictures (n). Thus, the m × m matrix XDX^T is singular. To beat this downside, we will first apply PCA to project the faces into a mathematical space while not losing any info and also the matrix XDX^T becomes non-singular.

The algorithmic procedure of OLPP is expressed below.

1. PCA Projection: We tend to project the face pictures x_i into the PCA mathematical space by abandonment the parts of zero eigenvalue. We tend to denote the transformation matrix of PCA by W_{PCA}. By PCA projection, the extracted options square measure statistically unrelated and the rank of the new knowledge matrix is up to the amount of options (dimensions).

2. Constructing the contiguity Graph: Let G denote a graph with n nodes. The i-th node corresponds to the face image xi. we tend to place a grip between nodes i and j if x_i and x_j square measure "close", i.e. x_i is among p nearest neighbors of x_j or x_j is among p nearest neighbors of xi. Note that, if the category info is obtainable, we tend to merely place a grip between two knowledge points happiness to constant category.

3. Selecting the Weights: If node i and j square measure connected, put

$$S_{i} = e^{-\frac{\|x_i - x_j\|^2}{t}}$$

Otherwise, place Sij = zero. The load matrix S of graph G models the native structure of the face manifold. The justification of this weight may be copied back.

4. . Computing the Orthogonal Basis Functions: we tend to define D as a diagonal matrix whose entries are column (or row, since S is symmetric) sums of S, Dii = PjSji. We tend to conjointly define L = D−S, that is named Laplacian matrix in spectral graph theory. Let be the orthogonal basis vectors, we define:

$$A^{(k-1)}=[u_1,\ldots\ldots\ldots\ldots,u_{k-1}.$$

$$B^{(k-1)} = \left[A^{(k-1)}\right]^{T} (X \quad ^{T})^{-1} A^{(k-1)}$$

The orthogonal basis vectors may be computed as follows:

• Work out a_1 because the Eigen vector of $(XDX^T)^{-1}XLX^T$ related to the littlest Eigen value.

• Work out a_k because the eigenvector of formula at center

$$M^{(k)}M^{(k)} = \{1 - (X \quad ^{T})^{-1} A^{(k-1)}[(B^{(k-1)})^{-1}[A^{(k-1)}]^{T}].(X \quad ^{T})^{-1} X \quad ^{T}$$

Associated with the small eigenvalue of M (k).

5. OLPP Embedding: Let WOLPP = [a1, ···, al], the embedding is as follows.

$x \rightarrow y = W^T x$

$W = W_{PCA} W_{OLPP}$

Where y could be an l-dimensional illustration of the face image x, and W is that the transformation matrix.

Particle Swarm Optimization:

In this section, we tend to explain a programming heuristic for dynamically scheduling advancement applications. The heuristic optimizes the price of task-resource mapping supported the solution given by particle swarm optimization technique. The optimization method uses 2 components: a) the programming heuristic as listed in rule one, and b) the PSO steps for task-resource mapping optimization as listed in rule a pair of. First, we'll provide a transient description of PSO rule.

$$v_i^{k+1} = w \; _i^k + c^2 r \, a \quad X^2 (p \quad _i - x_i^k) + c^2 r \, a \quad X (g \quad _i - x_i^k) \quad (6)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}, \quad (7)$$

Where

v_i^k	Velocity of particle I at iteration k
v_i^{k+1}	Velocity of particle I at iteration k+1
w	Inertia weight
c_j	Acceleration coefficients; j=1,2
$r \, a \quad _i$	Random number between 0 and 1; i=1,2
x_i^k	Current position of particle I at iteration k
$p \quad _i$	Best position of particle i
g	Position of best particle in a population
x_i^{k+1}	Position of the particle I at iteration k+1

V. PARTICLE SWARM OPTIMIZATION (PSO)

It is a swarm-based intelligence algorithm influenced by the social behavior of animals cherishes a flock of birds finding a food supply or a school of fish protecting themselves from a predator. A particle in PSO is analogous to a bird or fish flying through a search (problem) area. The movement of every particle is coordinated by a rate that has each magnitude and direction. Every particle position at any instance of your time is influenced by its best position and also the position of the most effective particle in an exceedingly drawback area. The performance of a particle is measured by a fitness worth that is drawback specific. The PSO rule is analogous to different biological process algorithms.

In PSO, the population is that the range of particles in a drawback area. Particles square measure initialized arbitrarily. Each particle can have a fitness worth, which is able to be evaluated by a fitness perform to be optimized in every generation. Each particle is aware of its best position pbest and also the best position so far among the whole cluster of particles gbest. The pbest of a particle is that the best result (fitness value) to date reached by the particle, whereas gbest is that the best particle in terms of fitness in a whole population.

Algorithm 2 PSO algorithm:

1. Set particle dimension as equal to the size of ready tasks in $\{t_i\}$ € T
2. Initialize particles position randomly from PC = 1,….,j and velocity $v_{i,}$ randomly.
3. For each particle, calculate its fitness value as in equation 4
4. If the fitness value is better than the previous best pbest, set the current fitness value to new pbest.
5. After step 3 and 4 all particles, select the best particle as gbest.
6. For all particles, calculate velocity using equation 6 and update their positions using equation 7.
7. If the stopping criteria or maximum iteration is not satisfies, repeat from step 3.

The algorithm is dynamic (online) as it updates the communication prices (based on the average communication time between resources) in every scheduling loop. It also recomputed the task-resource mapping so that it optimizes the cost of computation, supported this network and resource conditions. PSO: The steps within the PSO algorithmic rule are listed in algorithmic rule two. The algorithmic rule starts with random data format of particle's position and rate. During this downside, the particles are the task to be assigned and also the dimensions of the particles are the quantity of tasks during a workflow. The values assigned to an each dimension of particles are the computing resources in dices. Thus the particle represents a mapping of resource to a task. In our workflow every particle is five-D as a result of 5 tasks and also the content of each dimension of the particles is the computer resource assigned to it task. Let's say a sample particle might be delineated. The analysis of every particle is performing by the fitness function given in relative atomic mass. The particles calculate their rate victimization relative atomic mass. Half dozen and update their position according to relative atomic mass. Eq 7. The analysis is administered till the specified variety of iterations.

VI. IMPLEMENTATION

In this section of the paper the implementation of the projected technique that is OLPP with PSO is explained and also the implementation is explained.

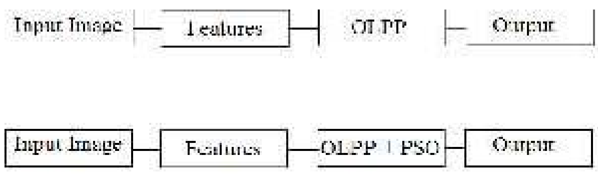

Fig.1. Flow of proposed system.

The figure on top of depicts the flow of the proposed system. As determined from the system there are two modules of the system. The primary part of the system solely Works with the OLPP system and also the second part of the system deals with the PSO and also the OLPP. Each of the systems are tested and also the result's given out by scrutiny each of them. There are multiple blocks within the system that are explained well as follows:

(1) *Input Block*: this is often the common and also the most initial block of the system. This part of the system accepts the input for the system. The input is any sort of image file that contains a face in it. The system can take the input from the native system and forwards it for the process. Let's say for a face lock, this part of the system can accept the image of the user he needs to examine for granting the access to him.

(2) *Features:* In appearance-based ways, vectorizes grayscale face pictures are typically used as coaching information to see a change to a lower spatiality area and model information neighborhood. Within the classification method of a replacement face sample, outliers might occur if the topic look isn't well painted within the coaching information (e.g., the individual seems with distinct facial features or pose). Therefore, we tend to discuss next a thin feature extraction technique that specializes in vital and discriminative locations of the face image. during this manner, most redundant face image pixels are discarded, whereas conserving relevant face details adore the eyes and eyebrows, creating it easier to handle variations in create and expression. A vectorial illustration of a face is obtained by concatenating color info within the locality of every biometric location on the face image (landmark), therefore this vectorial face illustration doesn't would like preparation to adapt to most poses and expressions since this selective sampling is tolerant to landmark location uncertainties. The thin facial

feature extraction theme was designed to be applied in high-resolution color face pictures that preserve fine details that offer helpful face discrimination information. On the opposite hand, the dense approach generally uses vectored grayscale down sampled face pictures. Considering P doable landmarks during a face image, typically it's not necessary to use all landmarks since they typically offer redundant info. Therefore, we tend to solely use the set of landmarks that offer the most effective face category discrimination, i.e., we tend to choose the most effective landmark topology. Finding the most effective landmark topology is computationally high-priced, since the quantity of mixtures of letter out of P landmarks offers a complete of Z =(P!/(P−Q)!) doable topologies.

A. PSO

It is a method implemented in varied applications so as to see associate optimum answer. It simulates the intelligent behavior of a bunch of birds moving from an area to their target. The birds regulate their rate and speed to succeed in the target in accordance to their own position also as neighbor's position closer to the optimum answer. Similarly, initial answers assumed are touched around during a search area logically following the PSO algorithmic program in accordance with the actual application and ranging varied parameters to succeed in the optimum solution. PSO learned from the situation and used it to resolve the optimization issues.

- In PSO, every single answer may be a bird within the search area termed as particles.
- At first, betting on the appliance a quest area is set consisting of variety of solutions.
- Every particle's initial position and rate is assumed.
- These particles are touched around within the search area in line with straightforward mathematical formulae over position and rate. Xi+1 are updated rate and position of every particle.
- Vi and Xi are previous iteration's rate and position severally of every particle.
- W is that the mechanical phenomenon weight.
- C1 and C2 are acceleration constants.
- Rand1 and rand2 are uniformly distributed random functions.
- pbest and gbest are personal best and international best positions of the particles.

Hence, pbest signifies the most effective position of specific particle until current iteration and gbest signifies the globally best particle nearest to the target.

VII. RESULTS

This section of the paper shows the result of the proposed system which is implemented and explained.

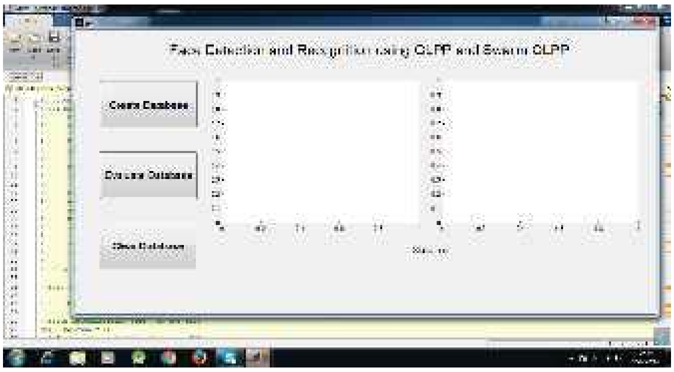

Fig.2. GUI of implemented system.

The above figure shows the GUI of the implemented system which contains multiple parts; on the left hand side there are few buttons which says Create Database, Evaluate Database and Clear Database. In the mid of the system there is a space for graphs of performance of the normal OLPP and the PSO OLPP.

Fig.3. Database Creation

The above figure shows the Database Creation. In this creation the image is taken as the input and the features of the face are calculated and the parts shown in the image are also calculated. In the figure the results of the face can be seen in the bottom part. All these are stored with a respective username. In this figure the image used is of a man.

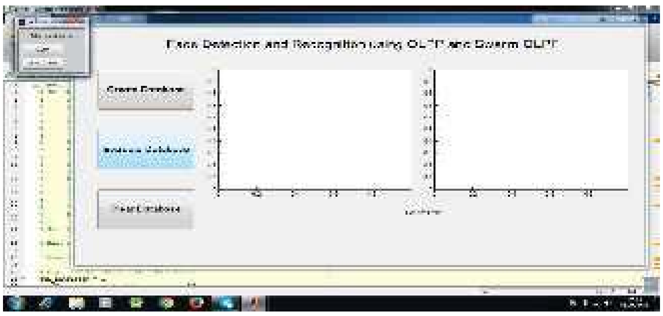

Fig.4. Database feature Evaluation

Once the database is created its evaluation can also be done with the help of two algorithms implemented that is first is the normal OLPP and the second is the OLPP with PSO. The outputs of the database are given out.

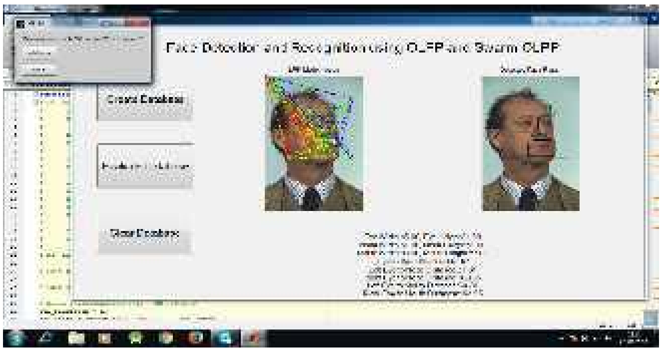

Fig. 5. Storing image with username

The above figure shows the saving part of the database. That is when the image is inserted and the image is created the image with the features and the username are stored in the database. As shown in the figure the image of the man is stores as 391 entries in the database.

Fig.6. System result with only OLPP

This is the evaluation phase of the image the image is inserted and is checked with the other entries of the database and if the match is found the match with the time required by the system is given out. Here in this figure a man's image is found by the system in 0.64 s. Only normal OLPP is used here. As seen in the figure the LPP or the distances and sizes of the face parts are taken into account and as observed the parts are best matched and their size is shown in the lower art of the image. In this system when only OLPP is applied the delay comes out to be 0.64s and the accuracy given is 80%.

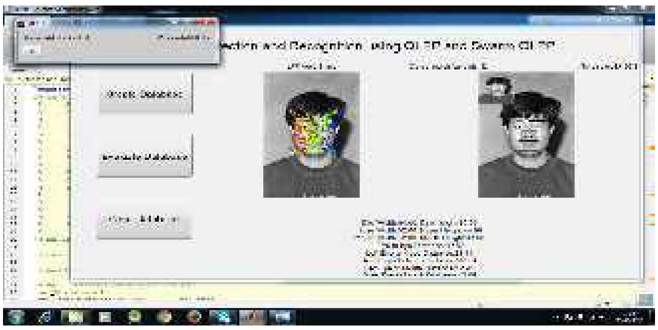

Fig.7. System Result with OLPP +PSO

To compare the timing and the efficiency the same image is taken as the input and the time required by OLPP + PSO to find the match is 0.0011sec which is much lesser than the normal OLPP. As observed from the figure when both the OLPP and PSO is applies the delay of the system decreases from approximately 0.63 seconds less, whereas when it comes to accuracy it is increased to 90%, which is a great number.

VIII. CONCLUSION

The proposed technique is much faster and gives efficient results with multiple types of face images. As seen in the result when only OLPP method is used the time required is much more then we use OLPP with PSO. Increasing time efficiency makes the system fast and uses less number of resources. As observed from the result same image is taken as the input for the OLPP and hybrid system, when the delay is calculated the delay takes approximately 90% less time than the normal OLPP, and the accuracy of the image is also increased, therefore the hybrid proposed method is better than the normal OLPP method.

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