Face Recognition Based on Geometric Features Using Support Vector Machines

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Abstract—**Face Recognition is among the most widely studied problems in computer vision and Pattern Recognition. Face has many advantages like permanence, accessibility and universality. It is still now not solved in literature. Several approaches are proposed to overcome with problems including; changing posed, emotional states, and illumination variation, etc. Geometric approaches which used as example distance between noses, eyes, mouth are still less efficient compared to holistic approaches. However, it provide and additional local information such as shape of local facial parts, face unit action, etc. The major problem of these approaches is to select the most relevant distances that can differentiate human faces. In this paper, we propose a bag of geometrical features based face recognition approaches using Support Vector Machines (SVM), Genetic Algorithm (GA) and minimum redundancy maximum relevance (mRmR) with Mutual Information Difference (MID) and Mutual Information Quotient (MIQ). Support Vector Machine Classifier (SVM) based on linear, radial basis function and multi layer Perceptron kernels is performed on the two benchmarks of facial databases ORL and Caltech Faces. Linear kernel based SVM classification using 10 selected distances by Genetic Algorithm (GA) ranks top the list of kernels conducted in our experimental study.**

Keywords-component; face recognition; linear SVM; genetic algorithm;mRmR

I. INTRODUCTION

Biometric is method used to recognize human identity based on morphological, behavioral and organic characteristics like fingerprint, iris, face, retina, palm and hand geometry, etc. Face is very important research field due to its wide range of its application in many context such as access control, portable media, time attendance systems, etc.

In this paper, face modality is used due to its simplicity and intuitiveness. Face is used by the human brain to recognize people. Face can be acquired at distance without user implication in recognition process, contrary to the fingerprint which has shown great efficacy.

Face recognition refers to techniques used for features extraction, features selection and features classification. Figure 1 gives the generic architecture of face recognition system.

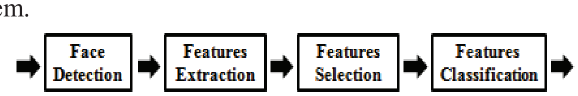

Figure 1. Generic architecture of face recognition system

Face detection is categorized in three classes since recently scientific works.

Face detection based on knowledge [1] which consists on definition of some rules like “symmetry of eyes”, “Region of Interest of eyes are darken than mouth and nose areas”, etc. Rules definition is the major drawbacks of these methods.

Face detection based on Template Matching [2]. Templates used for similarity measure are based essentially on Sobel edge detection [1], [2] of each facial part like eyebrows, eyes, nose and mouth. These approaches are limited by accessories such as eyeglasses, beard and moustache.

Face detection based on invariant features like the use of skin color segmentation [3] followed by some morphological operations to select right faces using width height ratio and area of the face.

Viola and Jones proposed [4] a robust approach for face detection based on harr-like features and cascade Adaboost classifiers. Viola and Jones algorithm is used in this paper for face localization in images form ORL and Caltech Faces databases.

Features extraction consists on new facial image representation with a set of characteristics computed by applying of different descriptors categorized in literature as shown in figure 2.

Features extraction approaches can be categorized in three families.

Holistic approach based on application of texture’s descriptors (as example expanded in many scientific proposed face recognition systems) like Gabor filter [5], Local Binary Pattern (LBP) [6] operators, SIFT [7], Zernike Moments [8] and SURF features [9] on the whole face.

Features based approaches which used geometrical distances [10] between facial parts. Many related works defined a set of distances measures and angles between eyes, nose, mouth and jaw.

Hybrid approach consists on the application of descriptors used in holistic approach but not on the whole image. Facial parts localization is much recommended in hybrid approaches to apply descriptor in modular way like modular PCA [11], modular LDA, modular Gabor and modular LBP.

Features Selection consists on choice of most relevant features which can differentiate human faces. The surveys comparison [12] of selection methods are multiple in literature. We note three families of features selections methods: Wrappers, Filters and Embedded techniques.

Wrappers methods use training set as a block box and the selection will be conducted by a prediction power computing.

Filters methods are based on cascade selections techniques to eliminate at each stage the worst features.

Embedded methods are based on learning of each feature in training set.

Features selection is an interesting component to succeed face recognition. Figure 3 illustrates categorization of some techniques used in literature for features selection performed in case of Pattern Recognition and Computer Vision fields.

Features classification is the last step in face recognition process. Many methods are offered in literature to validate the identity of users. There are three approaches of face classification.

Classification based similarities. It is the simplest method for classification which computes similarity between user to identify and users enrolled in database. It is based on measure similarity which can be based on many types of distances like Euclidian [7], Cosine, MahCosine [5], Hausdroff, etc.

Classification based on Probabilities. We compute in this case the probability of the membership of object to such class. In literature, authors used naïve Bayesian classifier [13] and Parzen classifiers.

Classification based on Decision Boundary. Many types of classifiers are used in literature to classify object. We note as example Neural Network [5], Binary Decision Tree, RBF, and Support Vector Machines [6], etc.

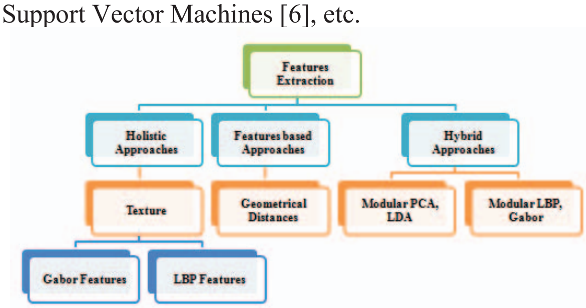

Figure 2. Categorization of popular features extrcation descriptors

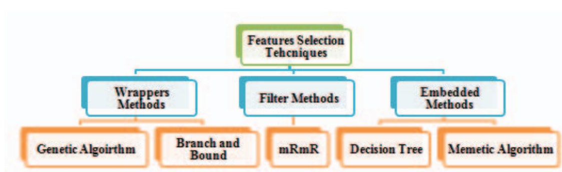

Figure 3. Categorization of popular features selection techniques

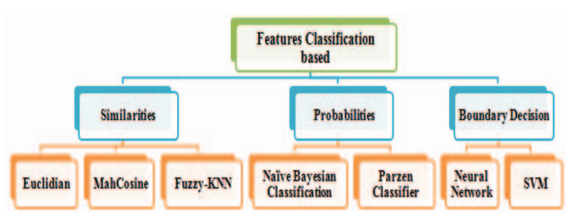

Figure 4. Categorization of popular features Classification techniques

To validate proposed approaches in scientific researches done on face recognition problems, many Face databases are used. There are many face databases in currently use. To make choice of database, comparison can be done based on some information like: Number of samples, Number of images per sample, changing illumination, changing pose, facial expression, eyeglasses, and aging. This table below presents popular face databases used in literature [11], [12].

TABLE I. SOME FACES DATABASES USED IN LITTERATURE

Databases	Number of Person	Databases Characteristics
ORL	40 10 images per person	Gray level images Resolution [112x92] Pose Changes
Caltech	26 10 images per person	RGB Color Image Resolution [592x896] Complex Background Changes illumination

Figure 5. Samples of Faces from ORL Database

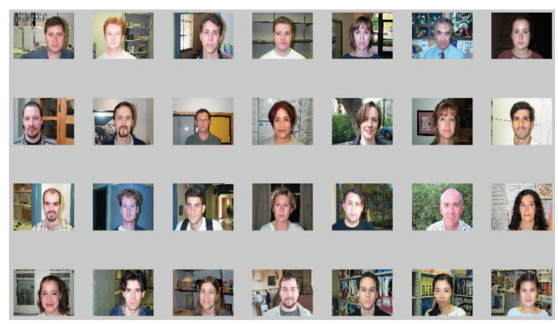

Figure 6. Samples of Faces from Caltech Faces Database

II. STATE OF THE ART

Table below summarizes some recent works done on face recognition systems to overcome with problems of changing illumination, posed, occlusion.

TABLE II. RELATED WORK ON FACE RECOGNITION APPROACHES TESTED ON POPULAR FACE DATABASES

Ref	Extraction Methods	Classification Methods	Database	Classification Accuracy
[7]	SIFT Features	Euclidian Distance	ORL	89.3%
		MahCosine Distance		93.7%
[8]	SURF Like Descriptros	Nearest Neighboors	ORL	97.7%
			Caltech	91.4%
[6]	LBP	KNN	Yale	78.5%

	Features		JAFFE	80%
[11]	Modular PCA	Confidence Projection Measure	ORL	92%
[5]	Gabor + PCA	MLP Neural Network	ORL	94.96%
			Caltech Faces	96.82%
			Faces94	96.84%
[13]	10 Distances using GA	Naïve Bayesian Classification	ORL	78.5%

III. Geometrical Features Based Face Recognition

Proposed approach based on geometrical distances contains five steps given in figure 5. We justified and detailed each technique used in next section.

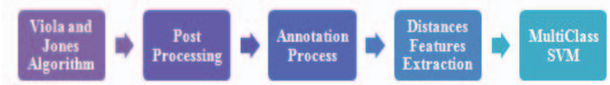

Figure 7. Proposed Geometric features based Face Recognition Architecture

A. *Face Detection using Viola and Jones Algorithm*

. Viola and Jones Algorithm [14] is based on Harr-like features obtained by computing of difference between black and white rectangles. 32 stages are defined for features classification to eliminate worst candidate region of facial part. Adaboost is used in cascade way to obtain in the end of all stages the right face detected as given in figure below where we performed Viola and Jones algorithm on two samples of faces from ORL and Caltech Faces Databases. All faces detected will be cropped and resizing into 120*120 resolutions.

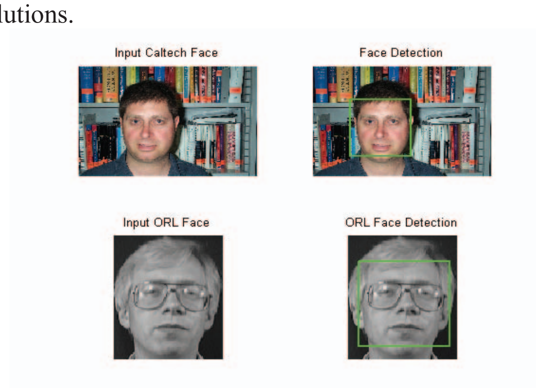

Figure 8. Face Detected on two samples of images form ORL and Clatech Faces using Viola and Jones Algoirthm

B. *Features Extraction using Geometrical Distances*

To prepare training dataset of geometrical distances of all images from the two facial databases ORL and Caltech Faces, we annotate all facial images using annotation process validated in [13]. Annotation process gives 33 points for each facial images detailed in table below.

Points	[X,Y] X	[X,Y] Y	Designation	Points Labels
1			Head Point	HP
2			Left End of Left EyeBrows	LELEB
3			High End of Left EyeBrows	HELEB
4			Right End of Left EyeBrows	RELEB
5			Lower End of Left EyeBrows	LoELEB
6			Center of Left EyeBrows	CLEB
7			Left End of Right EyeBrows	LEREB
8			High End of Right EyeBrows	HEREB
9			Right End of Right EyeBrows	REREB
10			Lower End of Right EyeBrows	LoEREB
11			Center of Right EyeBrows	CREB
12			Left End of Left Eye	LELE
13			High End of Left Eye	HELE
14			Right End of Left Eye	RELE
15			Lower End of Left Eye	LoELE
16			Center of Left Eye	CLE
17			Left End of Right Eye	LERE
18			High End of Right Eye	HERE
19			Right End of Right Eye	RERE
20			Lower End of Right Eye	LoERE
21			Center of Right Eye	CRE
22			Left End of Nose	LEN
23			High End of Nose	HEN
24			Right End of Nose	REN
25			Lower End of Nose	LoEN
26			Left End of Mouth	LEM
27			High End of Nose	HEM
28			Right End of Nose	REM
29			Lower End of Nose	LoEM
30			Center of Mouth	CM
31			Left End of Jaw	LEJ
32			Right End of Jaw	REJ
33			Lower End of Jaw	LoEJ

Figure 9. 33 points annotated Designation

To annotate ORL Faces database, we have imitate annotation rules used for AR Face Database.

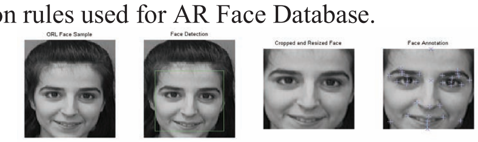

Figure 10. Annotation Process

Training dataset of geometrical distances is constructed by Euclidian distances measures defined in figure 10.

Distance	Description	Designation	Points used
D1	Height of Face	HF	{1,33}
D2	Distance between HP and CLEB	HP-CLEB	{1,6}
D3	Distance between HP and CREB	HP-CREB	{1,11}
D4	Distance between HP and HEM	HP-HEM	{1,23}
D5	Distance between HP and CRE	HP-CRE	{1,16}
D6	Distance between HP and CLE	HP-CLE	{1,21}
D7	Distance between HP and LoEM	HP- LoEM	{1,25}
D8	Distance between HP and CM	HP-CM	{1,30}
D9	Distance between HP and LEJ	HP-LEJ	{1,31}
D10	Distance between HP and REJ	HP-REJ	{1,32}
D11	Distance between HEN and LoEN	HEN-LoEN	{23,25}
D12	Distance between CLE and LoEN	CLE- LoEN	{21,25}
D13	Distance between CRE and LoEN	CRE- LoEN	{16,30}
D14	Distance between CLE and CM	CLE-CM	{21,30}
D15	Distance between CRE and CM	CRE-CM	{16,33}
D16	Distance between CLE and LoEJ	CLE-LoEJ	{21,33}
D17	Distance between CRE and LoEJ	CRE-LoEJ	{21,33}
D18	Distance between LoEJ and LEJ	LoEJ-LEJ	{33,31}
D19	Distance between LoEJ and REJ	LoEJ-REJ	{33,32}
D20	Distance between CRE and CLE	CRE-CLE	{16,21}

Figure 11. 20 Geomrtric distances used as input for features slections tecniques

C. *Features Selection Techniques usnig GA and mRmR Algorithms*

a) Genetic Algorithm (GA)

Genetic Algorithm used some operators based on probability distribution for features selection: selection, crossover and mutation. Operators are based on Fitness Function which guides relevant features selection. Parameters used for features selection based on GA in this paper are given in table below following work done in [12].

TABLE III. PARAMETERS USED FOR GA PERFORMING ON SUBSET CONSTRUCTED IN THE CASE OF ORL AND CALTECH DATABASES

Parameters	Values
Mutation rate	0.001
Crossover position	10
Selection method	Roulette Wheel
Fitness Threshold	0.97

b) minimum Redundancy maximum Relevance (mRmR)

minimum Redundancy maximum Relevance (mRmR) was proposed by Peng et al. [14] in 2005. It is based on Mutual Information (MI) computing. mRmR combines between two criteria: Features relevance and features redundancy . Mutual Information I between two features x and y is given by:

$$I(x,y) = \sum_{i,j} p(x_i, y_j) \log \frac{p(x_i, y_j)}{p(x_i)p(y_j)}. \quad (1)$$

The minimum Redundancy criterion is verified by WI.

$$\min W_I, \quad W_I = \frac{1}{|S|^2} \sum_{i,j \in S} I(i,j) \quad (2)$$

The maximum Relevance criterion is given by VI

$$\max V_I, \quad V_I = \frac{1}{|S|} \sum_{i \in S} I(h,i), \quad (3)$$

Two possible multi-objectives features selection is given based on Mutual Information.

Mutual Information Difference

$$\max(V_I - W_I). \quad (4)$$

Mutual Information Quotient

$$\max(V_I / W_I)$$

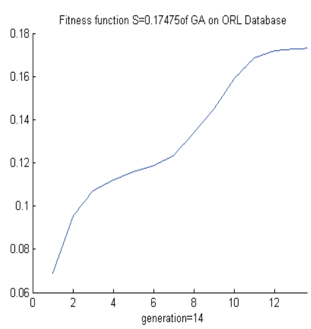

Figure 12. 10 Features selected with GA on ORL Database

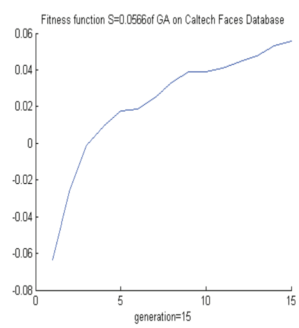

Figure 13. 10 Features selected with GA on Caltech Faces Database

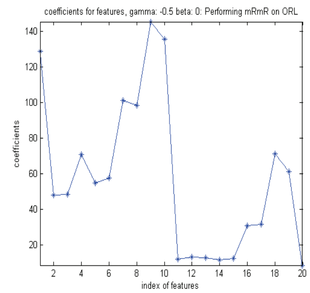

Figure 14. 10 Features selected with mRmR (Mutual Information Difference) on ORL Database

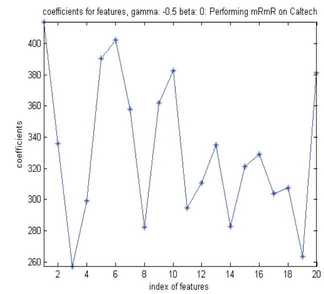

Figure 15. 10 Features selected with mRmR (Mutual Information Difference) on Caltech Faces Database

We present below tables that summarizes all outputs of each features selection techniques used for both ORL and Caltech Faces Databases.

TABLE IV. OUTPUTS OF FEATURES SELECTION TECHNIQUES PERFORMED ON ORL DATABASE

Feature Selection	10 Geometric Distances Selected
GA	D7, D11, D16, D2, D19, D18, D20, D10, D12, D4
mRmR (MIQ)	D8, D11, D4, D9, D16, D6, D7, D10, D2, D5
mRmR (MID)	D1, D4, D7, D8, D9, D10, D18, D19, D5, D6

TABLE V. OUTPUTS OF FEATURES SELECTION TECHNIQUES PERFORMED ON CALTECH FACES DATABASE

Features Selection	10 Geometric Distances Selected
GA	D20, D2, D16, D3, D1, D18, D7, D10, D19, D4
mRmR (MIQ)	D10, D2, D13, D3, D20, D4, D17, D11, D5, D18
mRmR (MID)	D18, D1, D6, D5, D10, D7, D9, D17, D15, D20

D. *Features Classification based mutticlass SVM*

SVM classification is very used in wide range of recognition systems. We found two models of multiclass SVM:

One versus all which is called also on versus the rest, it consists on constructing M binary SVM classifiers using a threshold to classify input image

One versus one which constructs M(M-1)/2 binary SVM classifiers. Input vector for test must be classified by all binary classifiers constructed.

The second opportunities of Multiclass SVM consust on the usefulness of Kernel functions. Many types are founded in literature. In our paper, we will use:

- Linear Kernel

$$K(x_i, x_j) = x_i^T \cdot x_j \quad (5)$$

- RBF Kernel

$$k(\mathbf{x_i}, \mathbf{x_j}) = \exp(-\gamma \|\mathbf{x_i} - \mathbf{x_j}\|^2) \text{ With } \gamma = 1/2\sigma^2 \quad (6)$$

- MLP Kernel

$$K(x, x_i) = \tanh\left(k x_i^T x + \theta\right), \quad (7)$$

IV. EXPERIMENTAL STUDY

It should be noticed that experimental process was made independently in the three databases. For each randomly split of data, we always get three partitions with the following percentages: 30% for training, 20% for validation and 50% for testing. A set of performance measures is used to obtain reported results. We used in this paper, multiple performance measures. Confusion Matrix is popular measure used to qualify supervised classification system. It shows percent of data which were correctly classified or incorrectly classified. It contains several performance indicators. Accuracy (Acc) percent gives the proportions of data correctly classified divided by all samples tested. $Recall_i$ or True Positive Cases (TP_i) is the proportions of cases correctly classified by class. Overall Recall is computed as follow.

$$Recall_i = TP_i/(TP_i + FN_i) \qquad (8)$$

$$Recall = 1/n * \sum Recall_i \quad \text{With n is number of classes}$$

$Precision_i$ or Positive Predictive Value (PPV) which gives the number of samples correctly classified divided by all samples classified. The overall Precision was computed as follow.

$$Precision_i = TP_i/(TP_i + FP_i) \qquad (9)$$

$$Precision = 1/n * \sum Precision_i \text{ ; n is number of classes}$$

F-score combines between Recall and Precision values in the harmonic mean as follow

$$F\text{-}Score = 2*(Recall * Precision) / (Precision + Recall) \qquad (10)$$

A. ORL Faces Database

TABLE VI. AVERAGE ACCURACY AND STANDARD DEVIATION USING GA ON ORL DATABASE

Test	SVM Classification		
	Linear	*RBF*	*MLP*
1	83.33	70.83	63.33
2	90.00	69.17	72.25
3	86.67	75.83	75.83
4	90.00	70.83	71.67
5	86.67	65.83	67.50
6	89.17	70.83	67.50
7	90.00	78.33	71.67
8	88.33	70.00	73.33
9	91.67	70.00	68.33
10	89.17	70.00	67.50
Average Accuracy	***88.50***	***71.67***	***70.25***
Standard Deviation	***2.3831***	***3.4960***	***3.6615***

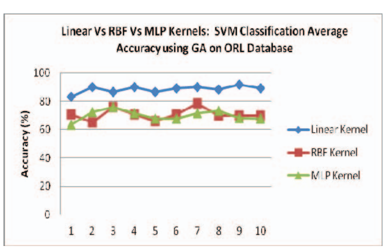

Figure 16. Kernels SVM Comparison on ORL Database using GA

TABLE VII. AVERAGE ACCURACY AND STANDARD DEVIATION USING MRMR (MID) ON ORL DATABASE

Test	SVM Classification		
	Linear	*RBF*	*MLP*
1	89.17	70.00	63.33
2	87.50	73.33	70.83
3	90.00	73.33	68.33
4	85.83	75.83	72.50
5	90.00	72.50	72.50
6	84.17	67.17	72.50
7	86.67	74.17	71.67
8	92.50	73.33	66.67
9	86.67	71.67	66.67
10	90.83	73.33	75.83
Average Accuracy	***88.33***	***72.66***	***70.08***
Standard Deviation	***2.5760***	***1.9563***	***3.7361***

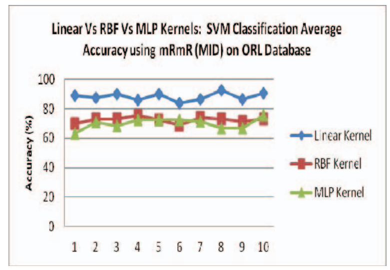

Figure 17. Kernels SVM Comparison on ORL Database using mRmR (MID)

TABLE VIII. AVERAGE ACCURACY AND STANDARD DEVIATION USING MRMR (MIQ) ON ORL DATABASE

Test	SVM Classification		
	Linear	*RBF*	*MLP*
1	90.00	78.33	70.83
2	87.50	73.33	64.17
3	90.83	80.00	68.33
4	87.50	74.17	65.83
5	85.83	75.83	77.5
6	88.33	75.00	65.83
7	91.67	72.50	77.67
8	83.33	77.5	67.50
9	89.17	70.00	79.17
10	88.33	75.83	70.17
Average Accuracy	***88.25***	***75.25***	***70.70***
Standard Deviation	***2.4359***	***2.9410***	***5.5055***

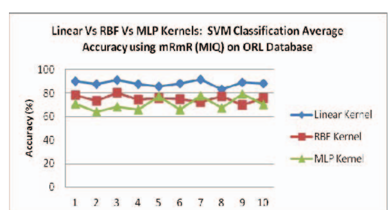

Figure 18. Kernels SVM Comparison on ORL Database using mRmR (MIQ)

B. Caltech Faces Database

TABLE IX. AVERAGE ACCURACY AND STANDARD DEVIATION USING GA ON CALTECH DATABASE

Test	SVM Classification		
	Linear	*RBF*	*MLP*
1	91.02	62.82	67.43
2	94.87	67.94	64.61
3	83.33	69.23	62.30
4	92.30	65.83	74.61
5	88.46	70.5	66.92
6	89.74	70.5	67.30
7	98.71	70.5	73.17
8	89.74	71.79	66.15
9	92.30	69.23	58.46
10	96.15	66.66	69.46
Average Accuracy	***91.66***	***68.33***	***67.04***
Standard Deviation	***4.3266***	***3.8792***	***4.7581***

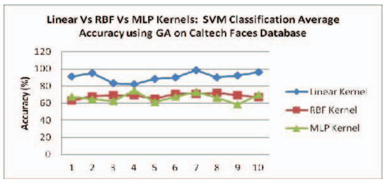

Figure 19. Kernels SVM Comparison on Caltech Database using GA

TABLE X. AVERAGE ACCURACY AND STANDARD DEVIATION USING MRMR (MID) ON CLATECH DATABASE

Test	SVM Classification		
	Linear	*RBF*	*MLP*
1	96.15	65.38	65.89
2	94.87	71.79	71.28
3	97.43	62.83	59.74
4	93.58	73.07	58.17
5	85.89	69.23	61.02
6	89.74	61.53	57.17
7	94.87	79.51	62.31
8	97.43	66.66	62.31
9	89.74	64.10	72.56
10	91.02	66.66	68.72
Average Accuracy	***93.07***	***67.18***	***63.92***
Standard Deviation	***3.8319***	***3.8792***	***5.4307***

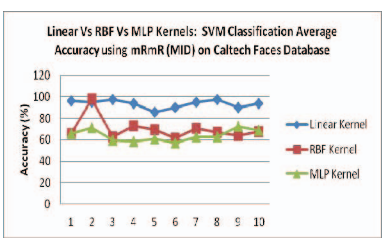

Figure 20. Kernels SVM Comparison on Caltech Database using mRmR (MID)

TABLE XI. AVERAGE ACCURACY AND STANDARD DEVIATION USING MRMR (MIQ) ON CALTECH DATABASE

Test	SVM Classification		
	Linear	*RBF*	*MLP*
1	91.02	70.51	61.02
2	92.31	64.10	68.72
3	97.43	66.66	66.15
4	93.59	67.94	67.61
5	92.31	71.79	74.74
6	89.74	67.95	72.46
7	91.02	70.51	73.90
8	87.18	71.79	70.87
9	89.18	67.95	65.89
10	93.74	67.95	70.87
Average Accuracy	***91.59***	***68.95***	***69.22***
Standard Deviation	***2.7827***	***2.4325***	***4.2020***

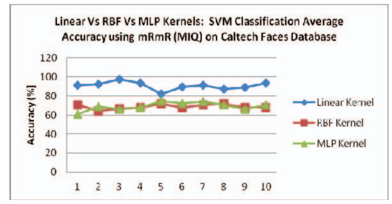

Figure 21. Kernels SVM Comparison on Caltech Database using mRmR (MIQ)

Linear Kernel based SVM classification ranks top the rest of performed kernel on the two benchmarks facial databases with different features selection techniques GA and mRmR.

The next step in our experimental study is to compare between tested features selection algorithms using linear SVM Classification.

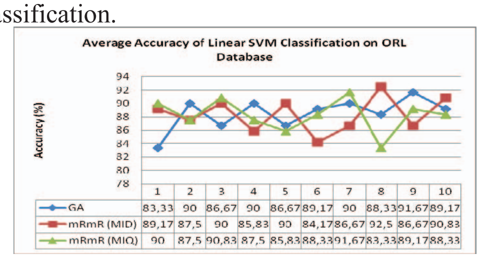

Figure 22. Comparison between Features selection algorithms on ORL Database using linear SVM classification

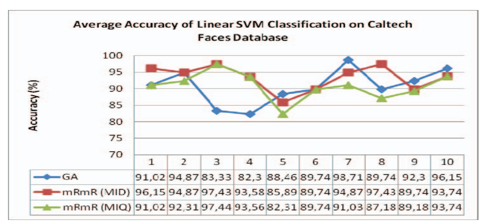

Figure 23. Comparison between Features selection algorithms on Caltech Database using linear SVM classification

We summarize in table below all average accuracy of geometrical based face recognition approaches using different kernel SVM for classification and the three features selection algorithms conducted on ORL and Caltech Faces Databases.

TABLE XII. AVERAGE ACCURACY AND STANDARD DEVIATION OF ALL PROPOSED GEOMETRICAL APPROACH FOR FACE RECOGNITION ON ORL AND CALTECH FACES DATABASES

Features Selection	Face Database	SVM Classification		
		Linear	***RBF***	***MLP***
GA	ORL	**88.50±2.3831**	71.16±3.4960	70.25±3.6015
	Caltech	**91.66±4.3266**	68.33±3.8792	67.04±4.7581

mRmR (MID)	ORL	88.33±2.5760	72.66±1.9563	70.08±3.7361
	Caltech	93.07±3.8319	67.18±3.8792	63.92±5.4307
mRmR (MIQ)	ORL	88.25±2.4359	75.25±2.9410	70.58±2.3547
	Caltech	91.79±2.7827	68.95±2.4325	69.22±4.2020

Proposed geometric based face recognition approaches have shown very competitive performance with holistic based approaches which gave in several scientific works the best performance on ORL and Caltech Faces as shown in table below.

TABLE XIII. CLASSIFICATION RATES COMPARISON OF PROPOSED APPROACH BASED ON GEOMETRICAL DISTANCES USING GA AND LINEAR SVM WITH SOME RECENT WORK BASED ON HOLISTIC AND FEATURES APPROACHES

Approaches	Classification Accuracy	
	ORL	*Caltech Faces*
GA + Linear SVM	**88.50±2.3831**	**91.66±4.3266**
GA + Naïve Bayesian Classification [13]	78.75%	-
Gabor + PCA + MLP NN [5]	94.96%	96.82%
SIFT + Euclidian Distance [7]	97.7%	91.4%
SURF + KNN [8]	89.3%	-

TABLE XIV. CLASSIFICATION PERFORMANCE: AVERAGE RECALL, PRCESION AND F-SCORE OF LINEAR KERNEL SVM AND GA PERFORMED ON ORL AND CLATECH FACES DATABASES

Faces Database	Classification Performance		
	Recall	*Precision*	*F-Score*
ORL	0.8985	0.9035	0.9009
Caltech Faces	0.9234	0.9459	0.9345

V. COCNLUSION AND PERSPECTIVES

Geometric approaches to facial recognition have not shown great efficiency in most scientific work. Researchers do not stop working on the geometric characteristics for many reasons. Essentially, they provide additional information about human identity. Examples include the shapes of parts faces like eyes shape, nose shape, and mouth shape defined in recent years as soft biometric traits that can be used to enhance performance of traditional biometric systems. In this paper, we proposed approaches to face recognition based on the geometric distances after the application of two popular soft computing techniques and pattern recognition: Genetic Algorithm and mRmR. The experimental results showed that these approaches tested with a linear SVM classification can be compared with holistic approaches recently developed. The high precision linear classification compared to other types of kernel can be justified by the linearity of facial geometric distances. The model one versus all tested does not found difficulty to separate linear samples of two bases: ORL and Caltech Faces. As future work, we intend to enhance performance of geometrical approaches with the integration of soft biometric traits like gender, age and ethnicity. All soft biometric traits mentioned in literature are not expensive in computing. As example, demographic soft biometric traits can be estimated or classified by the same techniques used in this paper without additional computing. That is the motivation towards integrating soft biometrics using geometrical approaches.

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