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Comparison of Face Recognition Algorithms for Human-Robot Interactions

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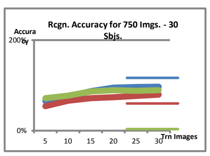
Graphical abstract



Abstract

Face recognition is a cornerstone of many robotic systems in which a robot has to identify and interact with a human being. Choosing a face recognition algorithm arbitrarily may not yield the best results for a researcher and may produce undermined results. In this paper we compare three widely used algorithms in terms of speed and accuracy. Such data can be very useful in choosing an algorithm for a particular task. The algorithms were applied to 36 different situations, and the results indicate the strengths, advantage and limitations of each of the three recognition methods in a certain setting.

Keywords: Algorithm comparison; eigen faces; face recognition; fisher faces; LBPH, OpenCV

■1.0 INTRODUCTION

During the past two decades, face recognition has gathered much interest, from applications in surveillance and security to research areas in robotics, such as human-robot interface (HRI). Many researchers have focused on improving the methods of face detection and recognition to enable correct recognition at the shortest possible time.

In searching for an optimum solution, a researcher is faced with many options in terms of methods, algorithms as well as the settings to obtain optimal performance for the face recognition job at hand. Choosing the correct algorithm and settings can be a time consuming matter and may not lead to optimum results in all situations. In [1] the authors compare PCA and LDA based algorithms using many different databases and conclude that although PCA has good performance using a small and large training set, and outperforms PCA in face images having different background, LDA outperforms PCA for computational efficiency.

In [2] PCA and LDA are compared with respect to noisy images. The paper used images affected by salt and pepper type of noise, and concludes that the performance of PCA is better than LDA for face images affected by the salt and pepper type of noise. In [3], the authors also compare PCA and LDA performance on a self-made face database of 10 subjects each with ten images showing a different facial expression in each image. The authors conclude that LDA has a better performance in comparison to PCA.

In this paper, an effort has been made to perform a more comprehensive comparison between PCA, LDA and LBPH face recognition methods in order to help fellow researchers reduce the time and effort taken in measuring the performance and comparing the different algorithms. This effort is carried out by running a set of 36 experiments to evaluate the three algorithms for face recognition, namely, the Fisher Faces (LDA), Eigen Faces (PCA) and Local Binary Patterns Histogram (LBPH). The results in this study will be valuable in understanding how well each of these algorithms behave in a certain situation compared to the other two and will give a guideline as to when and in what situation any one of those three may be used instead of the others.

The first two algorithms, Eigen face and Fisher face, are both appearance based approaches, while the LBPH algorithm is a feature based method. The Eigen faces algorithm uses the Principle Component Analysis (PCA) method. The Fisher faces algorithm uses Linear Discriminant Analysis (LDA) [4, 5], while LBPH on the other hand uses a local feature extraction approach [6].

To conduct the experiments, a program is written in C++ which makes use of the OpenCV set of libraries which include the three used in this study. OpenCV [7] is an open source collection of computer vision related libraries that comprise of hundreds of algorithms. OpenCV libraries can take advantage of multicore processors such as Intel. Intel Integrated Performance Libraries (IPP) consists of optimized routines in many algorithmic areas [8].

In order to choose a suitable database, the cropped Yale B database [9] which is obtained from the Extended Yale database [10] was chosen over many other available databases. This decision was made based on the following requirements:

a) The number of subjects should be over 25 to provide a good variety of subjects.
b) The number of images per subject must be over 60 to be able to use a large number of the images for training as well as a large number of the images for recognition.
c) The images need to be of a suitable size and resolution. Very low resolution may not result in accurate results and large pictures may take the system longer to train and recognize.

d) All the faces need to be cropped in order to accurately calculate the recognition time rather than spend time in detecting, extracting and resizing the face before doing the recognition process.
e) The pictures should all be of the same size, as this is a requirement for training the Fisher and the Eigen faces algorithms.
f) The subjects' pictures should be captured in different illumination conditions.

Since the role of color does not affect the performance of face recognition [11], the gray images in the chosen database suits the requirements of this study. All the aforementioned as well as being publically available added to the decision in choosing this particular face database.

2.0 THE APPROACH

In every experiment two phases were carried out: an algorithm training phase and a recognition phase.

2.1 The Training Phase

In the training phase a number of images were used to construct a matrix that would be later used to train the algorithm model. The matrix consists of images and corresponding labels. Each subject has its own label which will be later used to identify the subject which the image belongs to.

All the images must be of the same dimensions, otherwise an error will occur when training the algorithm model. The labels used must be unique for each subject in order to correctly identify the subject from the others.

Without doubt, the training time increases as the number of training images increase. This can be a problem if a system is depending on the Eigen faces or Fisher Faces algorithm in which case the algorithm model has to be retrained every time a new subject is added. The same is not true for the LBPH algorithm. In LBPH, a new subject can be added to the algorithm model and just update it with the images of the new subject.

2.2 The Recognition Phase

There are three tasks for face recognition [11]:

a) Face Verification: this is a sort of authentication for some systems such as logging in to a system using facial recognition.
b) Face Identification: in this type, the system compares a person's face against all the faces in the database, as the case in finding criminal suspects.
c) Face Classification: in this type, a person is classified as being a male/female or Asian/Caucasian/…etc.

In the conducted experiments, a special case of Face Identification took place. The system measured the speed and accuracy of identifying a person against images of the same person, while measuring the time taken and overall accuracy of identification.

3.0 EXPERIMENTAL SETUP

A set of 36 experiments were conducted. In each run, the training data was reset and the algorithm was retrained from the beginning to get accurate values of the time required for training using the number of training images for that particular run. The 25 recognition images were the same across all tests in order to maintain consistency across all experiments.

The full set of experiments was run twice, with the same settings and pictures in both runs, and then the results were compared. Although the recognition accuracies were the same in both runs of the experiments, there were slight differences between the training times as well as the recognition times in the two different runs. Table 1 shows a comparison between the values of the first and second run of the full set of experiments.

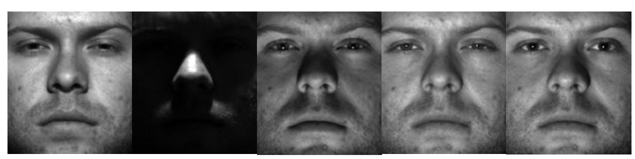
As can be seen from the table, the training times in the first run of the experiments are higher than the second run. There's no special reason. Both runs were conducted on the same laptop with the same source code and software, but on different nights. A third run of the experiment set was also carried out. The results were larger than those of experiment 2, but less than those of experiment 1.

The database used in conducting the experiment was the Cropped Yale B database. It contains 65 images of 38 subjects. The images' dimensions are 168x192 pixels. Some of the images, however, are totally black, so we settled for 59 images per subject, which is the lowest number of usable images for any of the subjects. Up to 30 images were used for training while 25 images were used for testing the recognition capabilities of each of the algorithms.

The dataset used for training and for recognition were both from the same database mentioned in the previous section. Even numbered images used for training, while odd numbered images were used for testing the recognition capability.

Figure 1(a) shows some even numbered images (2,4,6,8,10) and Figure 1(b) some odd numbered images (3,5,7,9,11) of one of the subjects:

(a) Even numbered images



(b) Odd numbered images

Figure 1 Images of one of the subjects used in the experiment

This particular setup was chosen to measure the algorithms' capabilities in recognizing different images of similarly illuminated nature rather than training them with images under a particular lighting condition and testing them with images under a different lighting condition. As can be seen from Figure 1, all the images, with the exception of image number 5 have similar illumination conditions.

Table 1 A comparison between the first and second run

				Experiment 1			Experiment 2		
Exp	**Sbj**	**TI**	**RI**	**FTT**	**ETT**	**LTT**	**FTT**	**ETT**	**LTT**
1	5	5	125	0.25	0.25	2.36	0.2	0.22	2.04
2	5	10	125	0.75	0.84	4.56	0.69	0.67	4.1
3	5	15	125	1.39	1.56	6.54	1.23	1.28	6.19
4	5	20	125	2.7	2.87	8.83	2.51	2.59	8.32
5	5	25	125	4.18	4.27	11.59	3.85	4.06	10.37
6	5	30	125	5.98	8.92	13.79	5.51	8.22	12.56
7	10	5	250	0.75	0.76	4.49	0.69	0.67	4.12
8	10	10	250	2.75	2.86	8.74	2.62	2.59	8.21
9	10	15	250	5.85	8.88	13.12	5.59	8.22	12.56
10	10	20	250	10.7	16.05	17.97	9.95	14.65	16.61
11	10	25	250	17.08	24.73	22.53	15.83	22.62	20.64
12	10	30	250	25.16	36.41	26.83	23.31	33.92	24.98
13	15	5	375	1.4	1.42	6.55	1.28	1.28	6.27
14	15	10	375	6.29	9.05	13.49	5.62	8.22	12.54
15	15	15	375	13.9	20.83	21.45	12.82	18.25	18.64
16	15	20	375	25.21	36.97	27.24	23.68	33.88	24.98
17	15	25	375	40.7	57.72	33.2	37.74	53.76	31.12
18	15	30	375	61.12	84.82	39.7	56.85	79.36	37.47
19	20	5	500	2.93	3.01	8.69	2.62	2.61	8.28
20	20	10	500	10.66	15.6	17.47	10.06	14.51	16.47
21	20	15	500	25.33	36.35	26.61	23.56	35.1	24.96
22	20	20	500	47.24	67.52	36.3	44.1	62.42	33.31
23	20	25	500	77.67	106.28	44.73	72.12	99.06	41.37
24	20	30	500	118.84	160.77	53.6	111.42	149.73	49.83
25	25	5	625	4.54	4.42	11.61	3.96	4.04	10.39
26	25	10	625	17.05	24.43	21.93	15.91	22.48	20.7
27	25	15	625	40.97	57.58	33.15	38.06	53.66	31.06
28	25	20	625	77.75	107.06	44.8	72.51	99.12	41.31
29	25	25	625	132.3	176.87	55.6	123.09	163.64	51.95
30	25	30	625	212.46	269.26	67.22	199.96	250.12	62.51
31	30	5	750	6.29	9.03	12.93	5.85	8.25	12.47
32	30	10	750	25.23	36.89	26.29	23.56	34.12	24.7
33	30	15	750	60.9	85.19	40.42	56.82	79.26	37.28
34	30	20	750	119.65	161.09	53.88	111.24	149.04	49.89
35	30	25	750	211.49	272.5	66.83	196.83	250.02	62.03
36	30	30	750	338.12	410.36	79.44	315.46	383.4	74.91

Hardware and Other Setting

The experiments were conducted on a laptop with the following specifications:

Processor: Intel i5 2410M @ 2.3 GHz
Memory: 4 GB DDR 3
Operating System: 64-bit Windows 7 Home Premium

The graphics memory and manufacturer may not be directly related to the performance of the algorithms as the CPU rather than the GPU was used to conduct the experiment, but they may be of interest to some researchers.

Other settings include: OpenCV version used was 2.4.3 and C++ was written and compiled using Visual Studio 2010.

■4.0 EXPERIMENT DATA

The experiment data is divided to three tables that show the differences between the algorithms in particular areas. Table 2 shows a comparison between the training times, while Table 3 shows a comparison between the recognition times, and lastly, Table 4 shows a comparison between the recognition accuracy of the three algorithms.

Abbreviations

The list below shows the heading abbreviations that are used in the data tables:

Exp :	The experiment number
Sbj :	The number of subjects
TI :	The number of images used in training the model
RI :	The total number of images the model tried to recognize in that particular run (25 images per subject)
FTT :	The time taken by the Fisher model to train
ETT :	The time taken by the Eigen model to train
LTT :	The time taken by the LBPH model to train
FTTPI:	Fisher Training Time Per Image
ETTPI:	Eigen Training Time Per Image
LTTPI:	LBPH Training Time Per Image
FRT :	The time taken by the Fisher model to recognize the pictures
ERT :	The time taken by the Eigen model to recognize the pictures
LRT :	The time taken by the LBPH model to recognize the pictures
FCR :	The number of images correctly recognized by the Fisher model
ECT :	The number of images correctly recognized by the Eigen model
LCR :	The number of images correctly recognized by the LBPH model
FRTPI:	Fisher Recognition Time Per Image
ERTPI:	Eigen Recognition Time Per Image
LRTPI:	LBPH Recognition Time Per Image
FWR :	The number of images wrongly recognized by the Fisher model
EWR :	The number of images wrongly recognized by the Eigen model
LWR :	The number of images wrongly recognized by the LBPH model

The following tables show the data obtained from conducting the experiments. In Table 2, the training times for the different algorithms are shown for experiments 1 to 36. These times were calculated as follows: the system clock was started just before the training instruction, and then stopped immediately after, and the difference in milliseconds was calculated.

Table 2 The training times for the different algorithms

Exp	Sbj	TI	FTT	ETT	LTT	FTTPI	ETTPI	LTTPI
1	5	5	0.25	0.25	2.36	0.05	0.05	0.47
2	5	10	0.75	0.84	4.56	0.07	0.08	0.46
3	5	15	1.39	1.56	6.54	0.09	0.10	0.44
4	5	20	2.70	2.87	8.83	0.13	0.14	0.44
5	5	25	4.18	4.27	11.59	0.17	0.17	0.46
6	5	30	5.98	8.92	13.79	0.20	0.30	0.46
7	10	5	0.75	0.76	4.49	0.15	0.15	0.90
8	10	10	2.75	2.86	8.74	0.27	0.29	0.87
9	10	15	5.85	8.88	13.12	0.39	0.59	0.87
10	10	20	10.70	16.05	17.97	0.54	0.80	0.90
11	10	25	17.08	24.73	22.53	0.68	0.99	0.90
12	10	30	25.16	36.41	26.83	0.84	1.21	0.89
13	15	5	1.40	1.42	6.55	0.28	0.28	1.31
14	15	10	6.29	9.05	13.49	0.63	0.90	1.35
15	15	15	13.90	20.83	21.45	0.93	1.39	1.43
16	15	20	25.21	36.97	27.24	1.26	1.85	1.36
17	15	25	40.70	57.72	33.20	1.63	2.31	1.33
18	15	30	61.12	84.82	39.70	2.04	2.83	1.32
19	20	5	2.93	3.01	8.69	0.59	0.60	1.74
20	20	10	10.66	15.60	17.47	1.07	1.56	1.75
21	20	15	25.33	36.35	26.61	1.69	2.42	1.77
22	20	20	47.24	67.52	36.30	2.36	3.38	1.82
23	20	25	77.67	106.28	44.73	3.11	4.25	1.79
24	20	30	118.84	160.77	53.60	3.96	5.36	1.79
25	25	5	4.54	4.42	11.61	0.91	0.88	2.32
26	25	10	17.05	24.43	21.93	1.71	2.44	2.19
27	25	15	40.97	57.58	33.15	2.73	3.84	2.21
28	25	20	77.75	107.06	44.80	3.89	5.35	2.24
29	25	25	132.30	176.87	55.60	5.29	7.07	2.22
30	25	30	212.46	269.26	67.22	7.08	8.98	2.24
31	30	5	6.29	9.03	12.93	1.26	1.81	2.59
32	30	10	25.23	36.89	26.29	2.52	3.69	2.63
33	30	15	60.90	85.19	40.42	4.06	5.68	2.69
34	30	20	119.65	161.09	53.88	5.98	8.05	2.69
35	30	25	211.49	272.50	66.83	8.46	10.90	2.67
36	30	30	338.12	410.36	79.44	11.27	13.68	2.65

Table 3 The recognition times for the different algorithms

Exp	Sbj	TI	RI	FRT	ERT	LRT	FRTPI	ERTPI	LRTPI
1	5	5	125	0.07	0.39	11.88	0.00	0.00	0.10
2	5	10	125	0.12	0.67	12.48	0.00	0.01	0.10
3	5	15	125	0.12	1.05	12.48	0.00	0.01	0.10
4	5	20	125	0.16	1.28	12.95	0.00	0.01	0.10
5	5	25	125	0.25	1.76	13.46	0.00	0.01	0.11
6	5	30	125	0.14	4.11	13.79	0.00	0.03	0.11
7	10	5	250	0.44	1.30	24.06	0.00	0.01	0.10
8	10	10	250	0.50	2.70	25.79	0.00	0.01	0.10
9	10	15	250	0.55	8.27	27.68	0.00	0.03	0.11
10	10	20	250	0.36	11.17	28.90	0.00	0.04	0.12
11	10	25	250	0.45	13.74	30.39	0.00	0.05	0.12
12	10	30	250	0.55	17.04	32.62	0.00	0.07	0.13
13	15	5	375	0.72	3.18	37.14	0.00	0.01	0.10
14	15	10	375	1.07	12.04	41.48	0.00	0.03	0.11
15	15	15	375	0.92	18.35	45.45	0.00	0.05	0.12
16	15	20	375	0.76	25.55	48.52	0.00	0.07	0.13
17	15	25	375	0.97	30.98	52.12	0.00	0.08	0.14
18	15	30	375	1.01	37.81	56.19	0.00	0.10	0.15
19	20	5	500	1.34	5.11	51.13	0.00	0.01	0.10
20	20	10	500	1.46	22.46	57.34	0.00	0.04	0.11
21	20	15	500	1.47	33.45	64.50	0.00	0.07	0.13
22	20	20	500	1.65	45.69	71.49	0.00	0.09	0.14
23	20	25	500	1.75	56.33	78.87	0.00	0.11	0.16
24	20	30	500	1.63	67.74	85.17	0.00	0.14	0.17
25	25	5	625	2.24	8.88	67.68	0.00	0.01	0.11
26	25	10	625	2.15	33.33	76.85	0.00	0.05	0.12
27	25	15	625	1.99	51.84	87.65	0.00	0.08	0.14
28	25	20	625	2.27	70.26	98.10	0.00	0.11	0.16
29	25	25	625	2.35	88.13	108.42	0.00	0.14	0.17
30	25	30	625	2.44	105.12	119.08	0.00	0.17	0.19
31	30	5	750	3.17	25.31	81.63	0.00	0.03	0.11
32	30	10	750	2.99	50.98	96.73	0.00	0.07	0.13
33	30	15	750	3.08	76.63	112.65	0.00	0.10	0.15
34	30	20	750	3.10	102.22	128.02	0.00	0.14	0.17
35	30	25	750	3.05	127.69	143.79	0.00	0.17	0.19
36	30	30	750	3.16	150.97	158.61	0.00	0.20	0.21

In Table 3, the recognition times for the different algorithms are shown for experiments 1 to 36. Again, the times were calculated by starting the system clock just before the recognition instruction, and stopped immediately after. The difference in time was then calculated in milliseconds. This was repeated once for every algorithm for every picture, and a variable for every algorithm kept track of the accumulated time. The FRTPI is zero for all experiments. This is because the time required for the Fisher faces Algorithm to recognition the face was less than 5 milliseconds (0.005 seconds), so when it was rounded up, it became zero.

Table 4 shows the number of correctly recognized images as well as the recognition time per image for experiments 1 to 36. The images to be recognized were 25 images per subject, so as the number of subjects increase, the number of recognition images increase.

Table 4 The number of correctly recognized images

Exp	Sbj	RI	TI	FCR	ECT	LCR	FCR%	ECT%	LCR%
1	5	125	5	97	89	112	0.78	0.71	0.90
2	5	125	10	109	100	113	0.87	0.80	0.90
3	5	125	15	112	108	120	0.90	0.86	0.96
4	5	125	20	118	114	124	0.94	0.91	0.99
5	5	125	25	120	114	124	0.96	0.91	0.99
6	5	125	30	119	114	124	0.95	0.91	0.99
7	10	250	5	173	147	205	0.69	0.59	0.82
8	10	250	10	209	175	208	0.84	0.70	0.83
9	10	250	15	224	200	227	0.90	0.80	0.91
10	10	250	20	236	209	239	0.94	0.84	0.96
11	10	250	25	240	214	239	0.96	0.86	0.96
12	10	250	30	239	215	238	0.96	0.86	0.95
13	15	375	5	275	217	287	0.73	0.58	0.77
14	15	375	10	305	248	292	0.81	0.66	0.78
15	15	375	15	328	282	324	0.87	0.75	0.86
16	15	375	20	350	292	339	0.93	0.78	0.90
17	15	375	25	360	301	338	0.96	0.80	0.90
18	15	375	30	360	310	340	0.96	0.83	0.91
19	20	500	5	331	282	380	0.66	0.56	0.76
20	20	500	10	397	336	397	0.79	0.67	0.79
21	20	500	15	433	368	437	0.87	0.74	0.87
22	20	500	20	470	375	447	0.94	0.75	0.89
23	20	500	25	480	389	441	0.96	0.78	0.88
24	20	500	30	483	400	446	0.97	0.80	0.89
25	25	625	5	414	343	460	0.66	0.55	0.74
26	25	625	10	463	419	487	0.74	0.67	0.78
27	25	625	15	544	457	539	0.87	0.73	0.86
28	25	625	20	591	468	551	0.95	0.75	0.88
29	25	625	25	605	481	544	0.97	0.77	0.87
30	25	625	30	607	498	554	0.97	0.80	0.89
31	30	750	5	492	404	536	0.66	0.54	0.71
32	30	750	10	560	495	580	0.75	0.66	0.77
33	30	750	15	656	538	647	0.87	0.72	0.86
34	30	750	20	711	554	668	0.95	0.74	0.89
35	30	750	25	722	574	657	0.96	0.77	0.88
36	30	750	30	727	594	669	0.97	0.79	0.89

The following graphs show a comparison between the three algorithms, Fisher, Eigen & LBPH in three areas. Figure 2 shows a comparison between the three algorithms in the time taken to train the algorithm model. The graph shows the training times for 5–30 training images per person in steps of 5. Figure 3 shows a comparison between the times taken to recognize 750 images of the 30 subjects.

Figure 4 shows a comparison of the recognition accuracy between the three algorithms as the number of training images increases. The recognition images were 25 images per subject which results in a total of 750 images for the 30 subjects. Figure 4 indicates the True Success Rate (TSR) [12] as given in the following equation:

$$TSR = \frac{No.of\ Persons\ Correctly\ Matched}{Total\ Number\ of\ Persons}$$

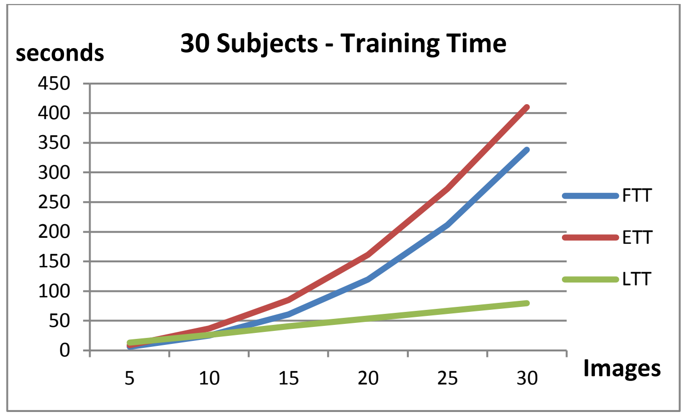


Figure 2 Training time comparison

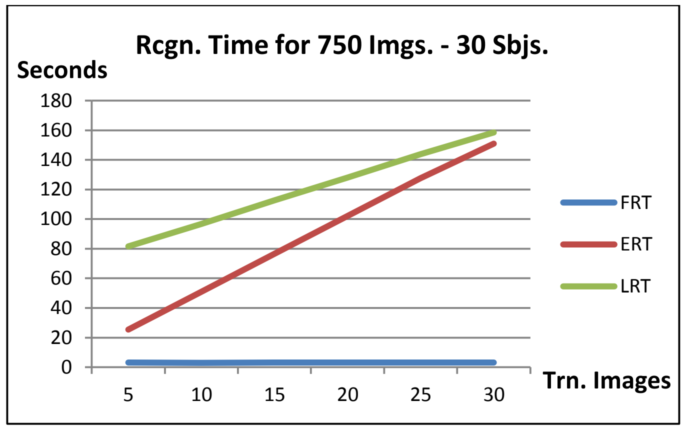


Figure 3 Recognition time comparison

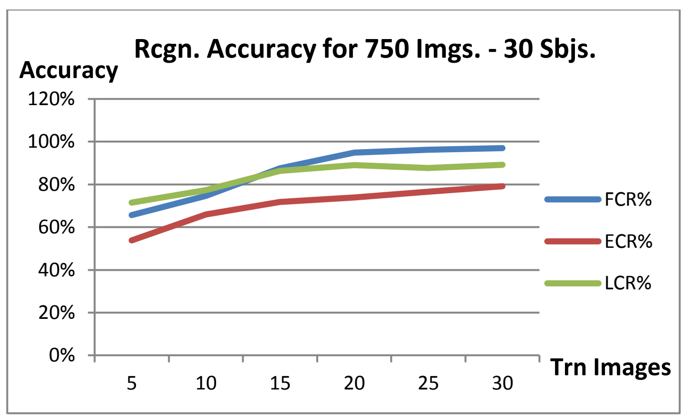


Figure 4 Recognition accuracy comparison

5.0 DISSCUSSION

From examining the experiments' results, we can be observed the training and recognition times are not fixed; they can fluctuate on the same computer as well as be longer or shorter on other computers depending on their processing power.

The images used show the subjects in different illumination conditions, however, they do not show different expressions for the subject.The training time per image increases as the number of training images increase. This means that training a system with a large number of images will take even more time. If, for example, the FTTPI for experiments 1 and 7 were compared, we find that the FTTPI for experiment 7 is triple the value of the FTTPI for experiment 1, when they should have been the same.

The recognition time per image also increases as the number of training images increase. This means that for a faster performance, one may need fewer images rather than more.

In Table 4, the recognition accuracy increases as the number of training images increase for the same number of subjects, however, the recognition accuracy drops as the number of subjects increase. By comparing experiments 6, 12, 18 and 24 we observe that the accuracy drops constantly. While the accuracy remains constant for 24, 30 and 36.

In Figure 2, the training time for the Fisher and Eigen models increases almost exponentially, while it increases somewhat linearly for the LBPH model. It can be clearly seen that as the number of images increase, the LBPH algorithm needs much less time than the other two algorithms. The LBPH algorithm also supports updating the database during operation, while the other two do not.

In Figure 3, the recognition time for the Fisher algorithm model remains almost constant and very much below the other two. This shows that using the Fisher algorithm for recognition has a big advantage in time over the other two. The slope angle of the Eigen faces algorithm is higher than the slope angle for LBPH, which means that if the number of training images were to increase further, then the LBPH algorithm would have outperformed the Eigen faces algorithm.

In Figure 4, we observe that the Fisher algorithm model achieves higher recognition accuracy than the other two models. If we take this fact, with the fact that the Fisher model is much quicker than the other two, this shows the superiority of the Fisher algorithm in these areas.

■6.0 CONCLUSION AND FUTURE WORK

A set of 36 experiments were run twice to measure the training time required, the recognition time taken and the recognition accuracy of three face recognition algorithms: Fisher faces, Eigen faces and Local Binary Pattern Histogram. There were slight differences between the times of the two runs, but the recognition accuracy was equal in both runs.

From the results, it was apparent that the LDA based Fisher faces algorithm is the fastest and most accurate in recognizing the subjects. However, it does not support updating the training set, and the same is true for the PCA based Eigen faces algorithm. The LBPH on the other hand supports updating the training set, and can therefore be used to incrementally increase the size of the database by learning new faces during operation. Since each one of the algorithms has its own strengths and weaknesses, there isn't a definite winner, but rather a more suitable choice depending on the researcher's requirement. It is expected that combining two or more face recognition algorithms may yield higher accuracy at a higher computational cost.

The currently used database shows subject in different illumination settings, future work may use other databases which comprise of images in which the subjects have different facial expressions.

It is also possible, for future work to test the algorithms by having them train and then try to recognize faces in video rather than still images.

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