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Recognition of Human Faces through Genetic Algorithm

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Abstract

The objective of this work is to develop a system of automatic recognition of faces by means of a Genetic Algorithm (GA), applying to an archive with images of faces human, one differentiated technique that has as entered the coefficients, resulted of the calculation of the Discrete Cosine Transform - DCT. Through these coefficients the Euclidean distances between the images are calculated as which becomes possible to find the faces desired.

Keywords: Recognition of Faces, Genetic Algorithm, Discrete Cosine Transform.

1 Introduction

There are many complex factors that make the recognition of human faces automatically, because of the difficulties in processing the images are unpredictable, often presenting different lighting conditions, facial expressions, climatic conditions and other obstacles that hinder the extraction of features.

This work proposes the use of Genetic Algorithm (GA) for the identification of people through images of faces from the coefficients generated by the Discrete Cosine Transform (DCT) on each image.

2 Genetic Algorithm

Genetic Algorithms (GA) are search and optimization methods inspired by the mechanisms of evolution of living beings [3]. The basic principle of operation of genetic algorithms is to consider as a possible solution to the problem a "individual" of a "population" which will "evolve" with each iteration or "generation". In each generation individuals are selected to form a new population [2]. The selection mechanism takes into account the fitness of each individual so that the probability $\boldsymbol{p_i}$ of an individual $\boldsymbol{i}$ can be selected for reproduction proportional to the value of its fitness [4]. This probability can be calculated by the equation:

$$p_i = \frac{f_i}{\sum_{j=1}^{TamPop} f_j}$$

Where $\boldsymbol{f_i}$ is the fitness of individual, ***TamPop*** is the number of individuals in the population and $\boldsymbol{f_j}$ is fitness cumulative population.

Fig.1 shows the structure of a GA.

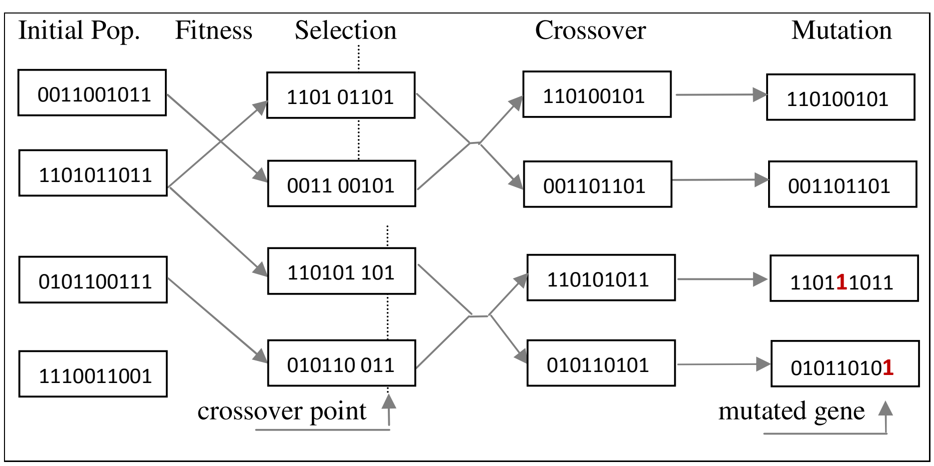

Figure 1: Basic structure of a Genetic Algorithm

3 Materials

It used a Dell laptop CPU with 1:40 GHz, 2.2 GB memory, Microsoft Windows XP operating system and programming language Matlab 7.0.1(2009a). The image archive consisted of 120 individuals and each individual is called class [1].

4 The use of DCT coefficients

Each image file has the size of 200 rows by 180 columns. It divided each in 550 submatrices of 8 rows by 8 columns. From each submatrix removed four coefficients resulting in a vector of 2200 coefficients. Thus each image is now represented by a row vector of 2200 elements, called feature vector G.

Figure 2 shows a representation of the 120 classes, and each class contains 20 poses the same person. Figure 3 represents one pose of the one class. Figure 4 is a subpose Y and Figure 5 represents the feature vector G.

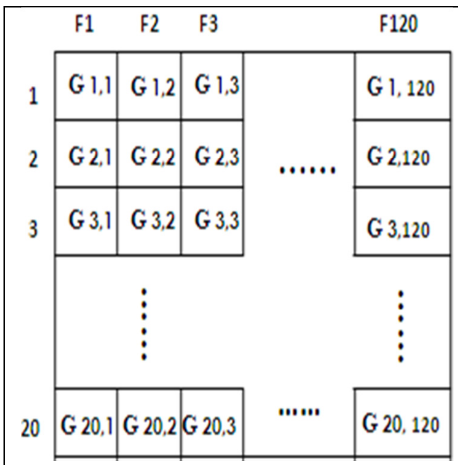

Figure 2: Representation of the 120 classes, each class contains 20 poses

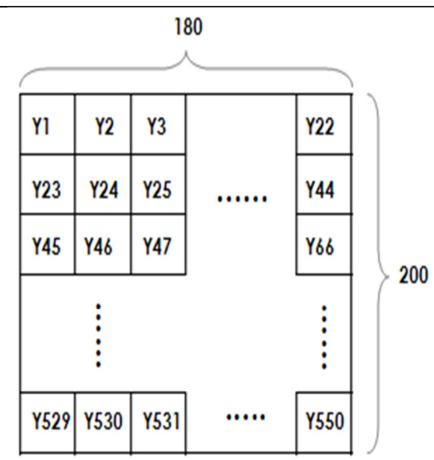

Figure 3: Represents one pose of the one class

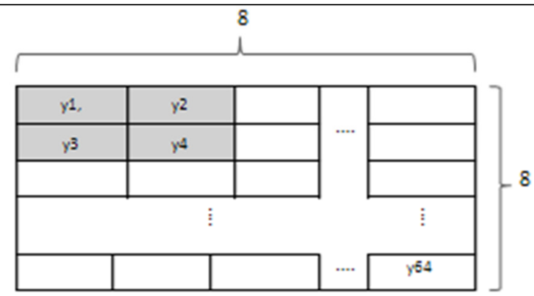

Figure 4: Represents one subpose Y basis to construct the feature vector of 2200 coefficients DCT

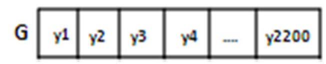

Figure 5: represents the feature vector G

5 Implementation of GA

The system implementation according to the structure of GA was made using the following parameters: Initial population with 50 individual, rate crossover of 10%, rate mutation of 2% and 100 the number of generation.

6 Processing GA

The GA compared the query image with the characteristics of each class along the shortest Euclidean distance, which represents better fitness.

In the experiment were used groups 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110 and 120 class and the GA is performed for the following variations:

1. Trained the GA with 19 poses and acknowledged with 1 pose.
2. Trained the GA with 18 poses and acknowledged with 2 pose.
3. Trained the GA with 17 poses and acknowledged with 3 pose.

To training with 10 poses and recognize with 10 other poses.

7 Experimental Results

Table 1 and Table 2 show the results of this experiment.

The variables in the tables are:

CP = Change Processing
NPT= Number of Poses used in Training
NPR= Number of Poses used in Recognition
PAR= Parameters

AC = Accuracy rate in percentage
TT = Training Time in seconds
RT = Recognition Time in seconds

Table 1: Face recognition result considering 2200 DCT coefficients, 5 to 60 classes

CP	NPT	NPR	PAR	Classes						
				5	10	20	30	40	50	60
1	19	1	AC	100	100	100	100	100	100	100
			TT	344.21	688.9	1336.8	2081.38	2464.43	3291.65	4145.8
			RT	0.0427	0.24	0.28	2.17	3.38	3.87	5.670
2	18	2	AC	100	100	100	100	100	100	100
			TT	310.48	540.1	1249.5	1729.95	2518.66	2967.20	3763.5
			RT	0.0858	0.47	1.72	2.30	6.93	8.42	10.995
3	17	3	AC	100	100	100	100	99.4507	99.2109	94.44
			TT	283.07	560.8	1084.6	1692.65	2178.82	2694.77	3376.3
			RT	0.1206	0.65	2.30	6.08	9.16	11.04	16.018
4	16	4	AC	100	100	100	99.2109	98.6316	99.2109	99.16
			TT	267.56	480.9	994.95	1566.00	1995.14	2387.34	3135.4
			RT	0.1565	0.83	3.30	7.57	13.13	13.72	21.032
5	15	5	AC	100	100	100	99.2109	99.2109	99.0811	99.33
			TT	230.80	452.0	852.65	1368.09	1727.30	2159.76	2668.7
			RT	0.1923	1.03	4.10	9.89	15.76	17.59	25.612
6	14	6	AC	100	100	100	99.0811	98.6316	99.2109	99.16
			TT	202.50	383.4	813.59	1112.56	1623.64	1815.45	2320.7
			RT	0.227	1.22	4.78	12.72	18.77	19.34	29.688
7	13	7	AC	100	100	100	99.4507	99.0212	99.0212	98.57
			TT	178.38	360.2	567.22	1083.74	1241.88	1688.78	2047.8
			RT	0.259	1.37	5.37	13.05	21.82	23.31	33.946
8	12	8	AC	100	100	100	99.2109	99.5605	99.0212	99.37
			TT	154.77	224.5	636.79	903.62	1278.24	1578.61	1845.7
			RT	0.2873	1.52	6.10	14.31	25.61	24.74	37.66
9	11	9	AC	100	100	100	96.9137	99.4806	98.7615	99.25
			TT	133.21	275.8	406.45	828.49	1073.83	1316.18	1546.7
			RT	0.3166	1.70	6.70	14.91	26.70	28.46	41.26
10	10	10	AC	100	100	98.382	99.2109	99.3807	99.3807	99.33
			TT	116.30	223.0	475.25	564.86	954.47	1185.54	1323.7
			RT	0.3751	4.03	7.20	21.20	28.77	37.47	44.445

Table 2: Face recognition result considering 2200 DCT coefficients, 70 to 120 classes

CP	NPT	NPR	PAR	Classes					
				70	80	90	100	110	120
1	19	1	AC	100	100	100	100	100	100
			TT	4586.5	5343.1	5896.0	6512.17	7262.52	8214.03
			RT	7.50	10.71	13.00	15.23	17.24	21.868
2	18	2	AC	99.600	99.880	99.880	99.4806	98.9712	99.58
			TT	4281.7	4818.7	5371.3	5836.06	6786.67	7471.31
			RT	13.97	19.25	24.19	29.88	36.42	42.813
3	17	3	AC	99.400	99.400	99.430	99.5406	99.6804	99.44
			TT	3811.9	4413.4	4860.9	5319.84	6079.36	6795.408
			RT	21.79	24.96	30.04	38.10	53.94	62.790
4	16	4	AC	9.5805	99.560	99.600	99.5805	99.6504	99.79
			TT	3444.2	4000.8	4319.7	4753.98	5461.10	6192.184
			RT	26.82	37.13	46.04	52.67	69.44	82.182
5	15	5	AC	9.3008	99.560	99.210	99.5106	99.5106	99.66
			TT	3040.2	3572.9	3872.4	4296.366	4729.74	5321.69
			RT	34.85	48.97	56.37	69.95	84.07	100.022
6	14	6	AC	9.2509	99.250	99.428	99.2109	99.2109	99.44
			TT	2658.2	3172.8	3411.7	3965.68	4297.77	4674.31
			RT	41.27	51.92	66.80	82.56	101.96	118.010
7	13	7	AC	99.260	99.260	98.921	98.9712	98.9712	99.166
			TT	2376.0	2763.6	3021.0	3426.61	3698.95	4118.89
			RT	46.29	59.99	75.73	92.62	112.83	134.015
8	12	8	AC	98.631	99.560	99.560	99.2509	99.2509	99.58
			TT	2087.6	2440.6	2679.9	3049.80	3131.75	3580.16
			RT	50.21	67.12	85.33	104.76	133.73	150.556
9	11	9	AC	99.400	99.011	99.011	98.9712	98.9712	98.88
			TT	1798.6	2072.4	2297.2	2684.31	2806.77	3110.193
			RT	56.74	74.33	92.41	110.64	138.27	163.55
10	10	10	AC	99.131	99.131	99.210	99.1810	99.1810	98.916
			TT	1479.7	1792.0	2018.8	2265.68	2480.11	2655.69
			RT	68.85	79.98	110.99	124.80	157.52	175.791

Figures 6 through 9, are shown the resulting graphs of this experiment. primarily relating to the accuracy rates, then the time of training and recognition, and then, the evaluation of the class 120 is shown (fitness).

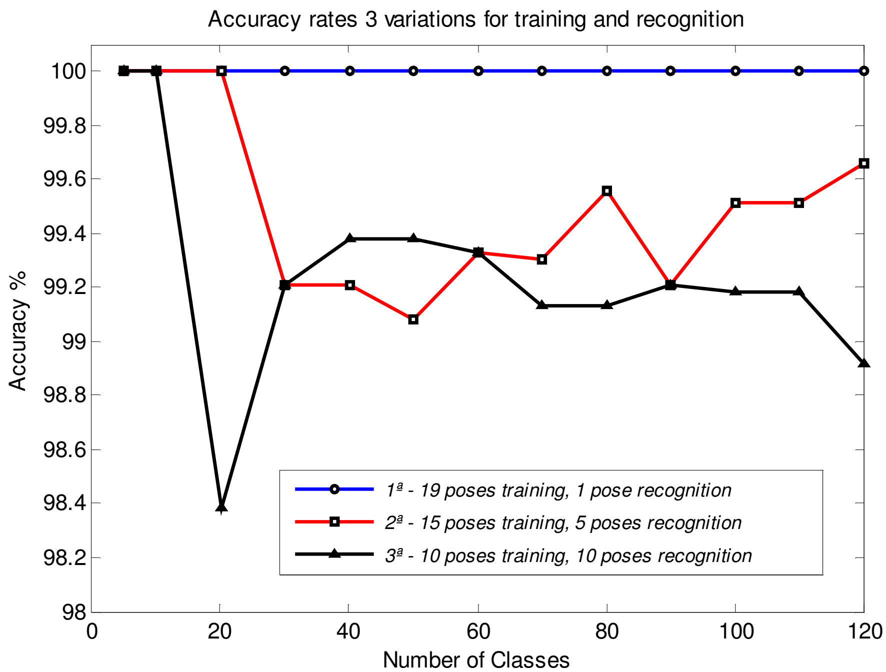

Figure 6: Accuracy rate in relation to the number of classes

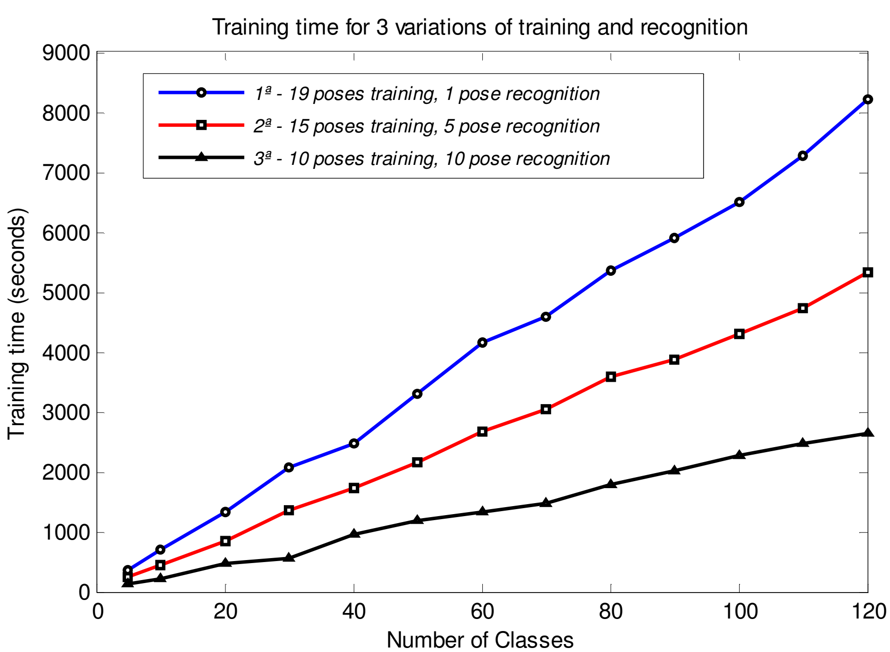

Figure 7: Training time in relation to the number of classes

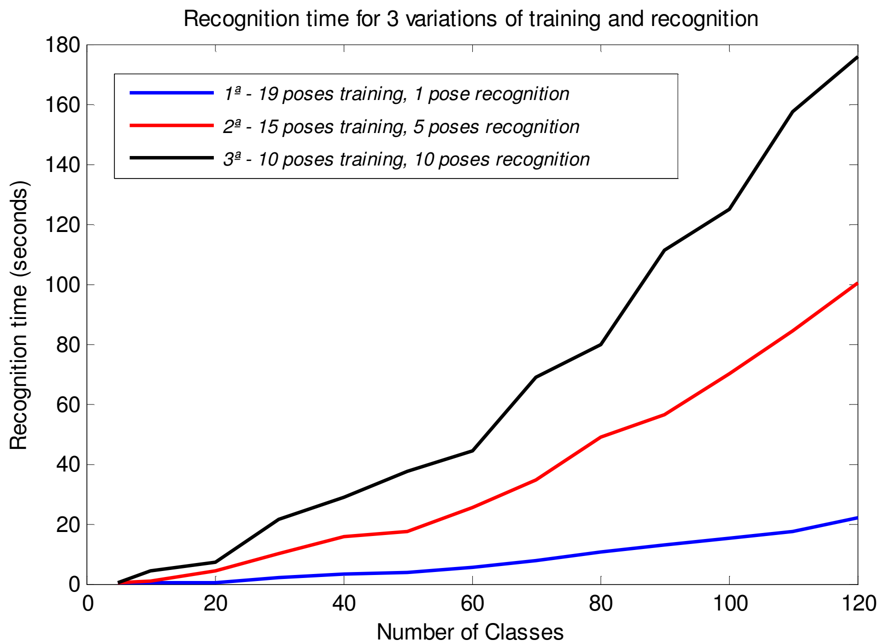

Figure 8: Recognition time in relation to the number of classes

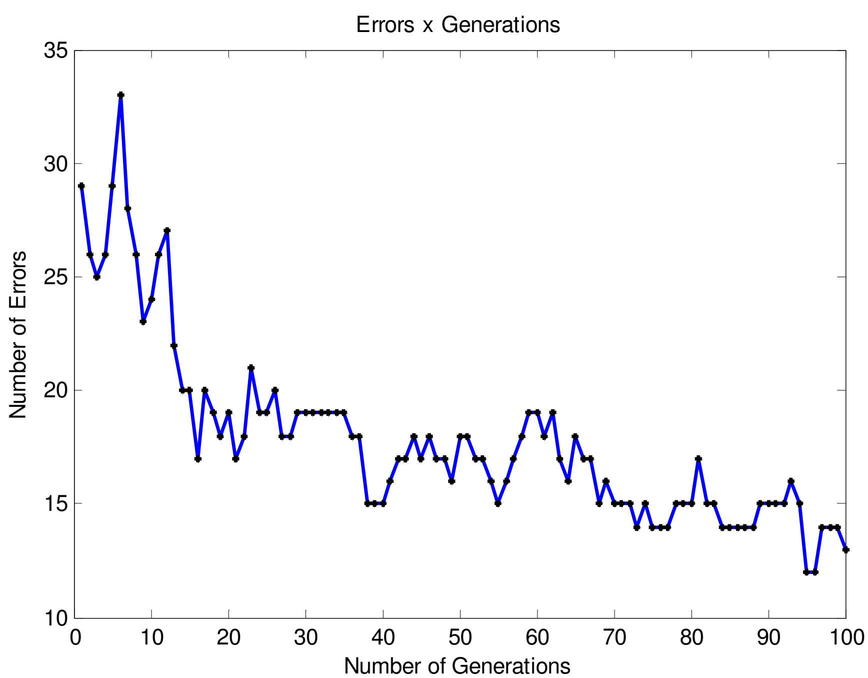

Figure 9: Errors in relation to the number of generations

The accuracy rates decreases because the greater the number of images whose characteristics were compared with the characteristics of the individual tests, the more likely confuse the algorithm to approximate the individual response, or becomes to select variables with worse regression.

8 Conclusion

When it comes to recognition of a person is the most natural way to do it by the facial image. A set of poses (face images) aggregates distinguishable characteristics and with which it becomes possible to uniquely identify. The challenge for researchers is to find methods that perform this task efficiently. Thus, this study demonstrated the evolutionary techniques of Genetic Algorithms that using the Euclidean distances generated an instrument of image retrieval based on a variation of facial gestures and variations in illumination of images. The results demonstrate robustness of this technique to differentiate between the experiences to freely manipulate the number of DCT coefficients. Other results appear to vary the parameters used in this work. Based on the presented results we can conclude that this article gave contributions to the fields of Evolutionary Computation in Computer Vision, showing a new approach for identifying people.

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