International Journal of Modern Engineering Research (IJMER)
www.ijmer.com Vol.2, Issue.1, pp-095-098 ISSN: 2249-6645

A Genetic Programming – DWT Hybrid Face Recognition Algorithm

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ABSTRACT
Increasing demand for a fast and reliable face recognition technology has obliged researchers to try and examine different pattern recognition schemes. But until now, Genetic Programming (GP), acclaimed pattern recognition, data mining and relation discovery methodology, has been neglected in face recognition literature. This paper tries to apply GP to face recognition. First Discrete Wavelet Transform (DWT) is used to extract features, and then GP is used to classify image groups. To further improve the results, a leveraging method is also utilized. It is shown that although GP might not be efficient in its isolated form, a leveraged GP can offer results comparable to other Face recognition solutions.

I. INTRODUCTION
Face recognition has become one of the most active research areas of pattern recognition since the early 1990s. In the past 20 years, significant advances have been made in design of successful classifier for face recognition [1]. However the diversity of the face patterns makes it difficult to create robust recognition systems and the complexity of the algorithms makes them hard to implement.

The wavelet transform has many unique features that have made it a popular method for the purpose of image processing and compression. The wavelet transform performs a high degree of decorrelation between neighboring pixels, and it provides a distinct localization of the image in the spatial as well as the frequency domain. This transform also provides an elegant sub-band framework in which both high and low frequency components of the image can be analyzed separately [2]. In this paper we used Discrete Wavelet Transform (DWT) for feature extraction. DWT coefficients are obtained by passing the image through the series of filter bank stages. The procedure of appropriate design of DWT and then selecting the low frequency approximation sub-band leads to improve the robustness of features space with respect to variation in illumination.

Genetic programming is an evolutionary algorithm methodology inspired by biological evolution [3]. Evolutionary algorithms create a population of abstract representations of candidate solutions, which is evolved using biology inspired operators such as selection, cross-over and mutation towards better solutions. In recent years, Genetic Programming and other evolutionary algorithms has been used in classification and pattern recognition problems [4-5], although to the authors' knowledge, Genetic Programming has never been used in Face Recognition domain.

In many applications, Genetic programming yields simplified symbolical representation of the underlying system it tries to model. This leads to efficient checking of a new sample [6]. On the other hand the complexity and the time needed to find such representation discourages its use in many applications.

Leveraging algorithms are a group of deterministic algorithms where a set of weak leaners are used to create a strong learner [7]. While it is not algorithmically constrained, most leveraging algorithms iteratively employ weak learners based on a distribution and combine them with weighting to form a final strong learner.

In this paper, Genetic Programming is utilized to classify face images which is applied to the extracted features. Using a training group, Genetic Programming discovers possible relationship between the extracted features, which is in turn used to classify new images. To improve results, a leveraging scheme is introduced, which employs Genetic Programming as a weak learner, and combine results of several Genetic Programming classifications as a single strong classifier.

The rest of paper is organized as follows: In section II and III, DWT and Genetic Programming are introduced respectively. Section IV presents the introduced algorithm, where Genetic Programming is used with and without leveraging. In section V, simulations are done on a selected face database and results are compared to previous studies.

II. DISCRETE WAVELET TRANSFORM
The Discrete Wavelet Transform (DWT) is used for feature extraction. Recall that the wavelet decomposition of an image is done as follows: In the first level of decomposition, the image is split into four sub-bands, namely HH1, HL1, LH1, and LL1, as illustrated in Fig 1. The HH1 sub-band gives the diagonal details of the image; the HL1 sub-band gives the horizontal features, while the LH1 represents the vertical structures. The LL1 sub-band is the low resolution residual consisting of low frequency components and it is this sub-band which is further split at higher levels of decomposition [8]. Fig 2 is an image from ORL Face Database with images obtained one-levelwavelet and after three-level wavelet transform respectively.

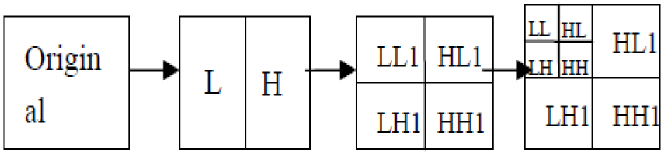

Fig.1. The process of decomposing a face image.

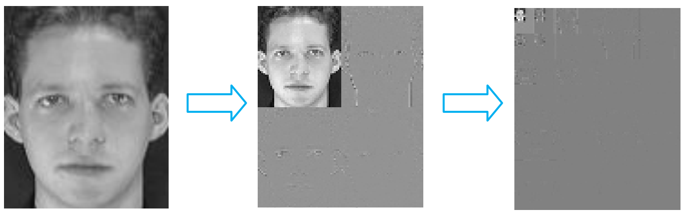

Fig.2. Original face image with figures after one-level and three-level DWT transform respectively.

III. GENETIC PROGRAMMING

Genetic programming is a methodology inspired by biological evolution to find equations, computer programs, analog circuits or in general any suitable structure for a predefined problem [6]. Genetic programming's general mechanisms are almost identical to genetic algorithms, as genetic programming is considered either a specialized form of genetic algorithms or an expansion of it [3]. Genetic programming is usually implemented similar to the following algorithm:

1. Create initial population. Individual solutions (called chromosomes) are usually generated randomly.
2. Evaluate the fitness of each individual in the population.
3. Select best-ranking individuals to reproduce.
4. Breed new generation through crossover and/or mutation (genetic operations) and give birth to offspring.
5. Repeat from step 2 until a termination condition is reached (time limit or sufficient fitness achieved).

Fig. 3 illustrates the general Genetic programming algorithm. Genetic programming's chromosome is traditionally represented by a tree structure, where each node can be function, operator, variable or constant number. Trees can be evaluated in a recursive manner, in which each node's operator or function is executed up on the results of its children's evaluation. Tree structure can easily represent a mathematical equation or a Turing complete program.

IV. CLASSIFICATION ALGORITHM

A. Using Genetic Programming

To classify a given dataset, it is usually enough to find a way for differentiating classes. Using genetic programming, this translates to finding a function which outputs a unique value for each different class:

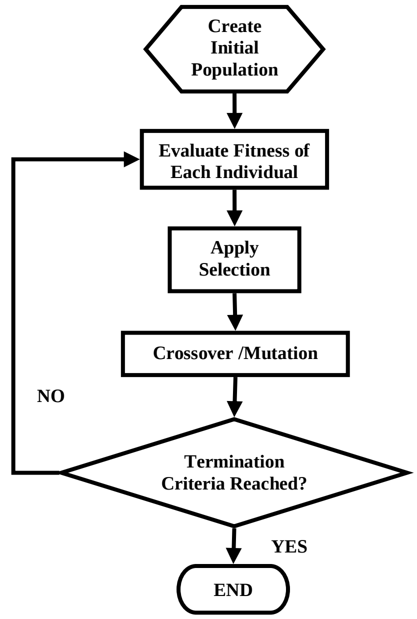

Fig. 3. Genetic programming's flowchart.

$$f(X)=\begin{cases}0 & X\in C_0\\ 1 & X\in C_1\\ & \dots\\ n & X\in C_n\end{cases} \qquad (1)$$

This is proven to be difficult. As a result, genetic programming is used to find a function per class that can discriminate only a certain class from others:

$$f_i(X)=\begin{cases}1 & X\in C_i\\ 0 & X\notin C_i\end{cases} \qquad (2)$$

This method creates *N* different functions for a total of *N* classes. Test images are tested one by one against the functions, and the first function to return a non-zero value is used to determine the image's class.

B. Leveraging Algorithm

Leveraging is a method of using multiple results to improve detection. A leveraging algorithm employs multiple weak classifiers to create a strong classifier. The following leveraging algorithm is used in this paper: Instead of using all training images as input, the whole group is partitioned to *k* different groups. Detector function $f_{i,j}$ is then obtained as a function which can detect class *i* from other classes in group *j*. To further improve the results of classification, algorithm above could be repeated *N* times. For a given image *X*, the following equation creates the results of classification:

$$C = \sum_{j,n} f_{j,n}(p) \times \frac{1}{1+\frac{1}{N} err_{j,n}} \tag{3}$$

where $f_{j,m}$ is result of nth iteration on the jth group, n is the iteration number from total N repetitions, and $err_{j,k}$ is sum of total errors for all images in the training group.

To determine a new image's class, all values acquired from (3) are compared. The class which yields the greatest C is nominated as the new candidate class. It should be noted that a threshold could be defined, as if the results of all classifiers for an image yield lower than a certain value, the image is certainly misclassified.

V. SIMULATION AND RESULTS

The algorithms were implemented in Python and then were tested on the ORL face image database [9]. The ORL database consists of 40 groups, each containing ten 112×92 gray scale images of a single subject. Each subject's images differ in lighting, facial expression and details (smiling/frowning, glasses/no glasses, etc.). Some sample images are displayed in Fig. 4.

Two set of images were created from the ORL database; For the Five-to-Five dataset, five random images of each group were selected for training while the others were used for testing. For the Leave-One-Out set, 9 images were used for training and the remaining image was kept for validation.

First Genetic Programming was tested without leveraging. To evolve the population, an Evolutionary Strategy (ES) of 1+λ with λ = 4 was chosen. Mutation rate was set to 15 percent. The selected function set was *{+, -, ×, <, >, MIN, MAX, AND, OR, NOT, CNST}* where Boolean operators first compare their operands with 0 and *CNST* returns a random constant floating point number in range of [-10, 10]. Inputs were chosen from all available DWT features. To limit algorithm time and prevent bloat, each chromosome's depth was limited to 25 and a maximum of 20000 iterations for each evolution was maintained.

To test the leveraged algorithm, algorithm was executed with the same parameters. Also the number of iterations was set to $N = 8$, while the set was divided to $k = 8$ different groups.

Table1 shows a few of discovered relationship functions for a set of pictures. It could be seen that the generated formulas are often simple while only depending on a few components and as a result have a relatively low computational overhead.

Results are brought in Table 2, where they are compared to Euclidean [10] and SVM classifiers. It is observed that Genetic Programming without leveraging has the worst results. On the other hand, Leveraged Genetic programming beats other methods in Five-to-Five. In leave-one-out the results are repeated for Genetic Programming, although this time Leveraged Genetic Programming fell %0.5 (one image in total of 40 images) short of SVM.

Fig. 4. Samples from ORL Face Database

To further investigate Genetic Programming's performance, number of partitioned class groups was changed and the results were brought in Table 3. It was observed that the further partitioning of the images increases recognition error, while decreasing k might mandates increase in time spent for Genetic Programming's evolution.

VI. CONCLUSION

Genetic programming is a general purpose search algorithm that can be utilized in classification problems. In this paper, Genetic programming was exploited to classify face images. The results showed that Genetic Programming alone is not suitable, as required time and computational overhead surpasses that of other methods, and also its recognition ratio is usually lower.

To improve results, a leveraging algorithm was applied to Genetic Programming. The leveraged Genetic Programming in combination with DWT feature extractor showed a good recognition rate, comparable to or in some cases even better than that of other methods.

It is shown that Genetic Programming produces results that usually have a simple structure and therefore a very low computational overhead. Once the system is trained, results can be computed quickly and with lower memory requirements. This might prove lucrative for embedded systems programmers, which have storage and processing constraints.

Table 1
Examples of Acquired Relationship Functions for Detecting Image Group1. *DWT[n]* is The Nth Value on DWT Vector.

No	*Function*
1	*(DWT[8]- MAX(DWT[15], DWT[7]))> DWT[11]*
2	*AND((DWT[2]< DWT[13]), MAX(DWT[3], 3))*
3	*(DWT[0]× NOT(DWT[5]))*
4	*(DWT[12]× (DWT[20]> (DWT[2]- DWT[18])))*

Table 2
Comparison of Different Algorithms' Recognition Rate

Method	Five-to-Five	Leave One Out
DWT+Euclidean distance	88%	90%
DWT+SVM	91%	93%
DWT+GP	64%	66.5%
DWT+Leveraged GP	92%	92.5%

Table 3
Effect of Number of Partitions in Leveraged Genetic Programming on Recognition Rate

Number of Partitions	Recognition Rate
2	89%
4	92%
5	92%
8	91.5%
10	90%

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