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Simplifying Handwritten Characters Recognition Using a Particle Swarm Optimization Approach

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Abstract:

This manuscript considers a new approach to Simplifying Handwritten Characters Recognition based on simulation of the behavior of schools of fish and flocks of birds, called the Particle Swarm Optimization Approach (PSOA). We present an overview of the proposed approaches to be optimized and tested on a number of handwritten characters in the experiments. Our experimental results demonstrate the higher degree of performance of the proposed approaches. It is noted that the PSOA in general generates an optimized comparison between the input samples and database samples which improves the final recognition rate. Experimental results show that the PSOA is convergent and more accurate in solutions that minimize the error recognition rate.

Key words: Pattern recognition techniques, handwritten characters recognition, feature extraction, particle swarm optimization algorithm

Introduction

Pattern recognition is a science that helps develop "classifiers" that can recognize unknown instances of objects in different categories and classes. Pattern recognition techniques are used in a wide variety of areas such as commercial applications, engineering, business, medicine etc. (Litvin 1982; Davis and Lyall 1986).

Common examples include character recognition, the scanning of a printed page, natural language recognition, analysis of images taken from airplanes or satellites, and analysis of medical images in order to scan for abnormalities (Savas and Elden 2007; Ganapathy and Leong 2008). A particle swarm optimization algorithm (PSO) is used to solve many difficult problems in the field of pattern recognition (Poli, Kennedy, and Blackwell 2007; Eberhart and Kennedy 1995).

This manuscript investigates the application of an efficient optimization method (PSO) in the field of pattern recognition. PSOs solve optimization problems by simulating the social behavior of bird flocks (Omran 2004). Character recognition is one form of a pattern recognition process. A PSO algorithm starts with a random population initialization of particles in the search space. Unlike other evolutionary optimization methods, particles in PSO do not recombine genetic material directly between individuals during the search, but instead work on the social behavior of swarms. Therefore, the global best solution is found by simply adjusting the moving vector of each individual according to personal best and the global best position of particles in the entire swarm at each time step (generation) (hyma, Jhansi, and Anuradha 2010).

2. Related Work

Arabic handwriting recognition can be divided into the tasks of recognizing characters or numerals, individual words, and unconstrained text consisting of a sequence of an a priori unknown number of words. Recognition of characters and numerals is by far the simplest problem for which mature solutions have become available. The other two problems, word and word sequence recognition, are considerably more difficult and are still subject to research.

Handwritten character recognition in different languages, including Japanese, Hiragana, Katakana, Kanji, English alphanumeric and symbols emerged at the end of the 1960s (Impedovo, Wang, and Bunke 1997). The problem of handwritten characters recognition is a complex task due to variations among writers, such as style of writing, shape, stroke etc. Handwritten characters recognition, including both isolated characters and continuous text, has received intensive attention (Mantas 1986; Shridhar and Badreldin 1986). Character recognition is one form of a pattern recognition process. In reality, it is very difficult to achieve very high accuracy. Even humans will make mistakes when it comes to pattern recognition. Common techniques that are used for character recognition include the use of artificial neural networks and the feature extraction method (Mao and Jain 1995; Oja 1992).

Nowadays, the Evolutionary Algorithm (EA) has been successfully applied to find the solution to numerous problems in the pattern recognition domain. This technique uses biological evolution viz. reproduction, mutation, recombination and selection. The most common Evolutionary Algorithms now being used are Genetic Algorithm, Evolutionary Programming, Evolutionary Strategy, Genetic Programming, Particle Swarm Optimization, Artificial Immune, Ant Colony Optimization and Invasive Weed Optimization and Bee's Optimization (Dorigo, Birattari, and Stuzle 2006).

3. Particle Swarm Optimization Algorithm

The Particle Swarm Optimization algorithm (PSO) was originally designed by Kennedy and Eberhart in 1995. PSO is a population-based searching method which imitates the social behavior of bird flocks or fish schools. The population and the individuals are called a "swarm" and "particles", respectively. Each particle moves in the swarm with a velocity that is adjusted according to its own flying experience and retains the best position it has ever encountered in memory. The best local and global positions ever encountered by all particles of the swarm are also communicated to all other particles. The advantages of PSO are that there is neither mutation calculation nor overlapping. The popular form of particle swarm optimizer is defined in the following equations and in the flow chart in Figure (1) (Moraglio et al. 2008):

$$V_{id}(t+1) = W * V_{id}(t) + C_1 R_1 \left(P_{id}(t) - X_{id}(t)\right) + C_1 R_1 \left(P_{id}(t) - X_{id}(t)\right) \quad (1)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \qquad (2)$$

Where:
v_{id}: is the velocity of particle i along dimension d.
x_{id}: is the position of particle i in dimension d.
c_1: is a weight applied to the cognitive learning portion.
c_2: is a similar weight applied to the influence of the social learning portion.
r_1, r_2: are separately generated random numbers in the range of zero and one.
w: is the inertia weight.

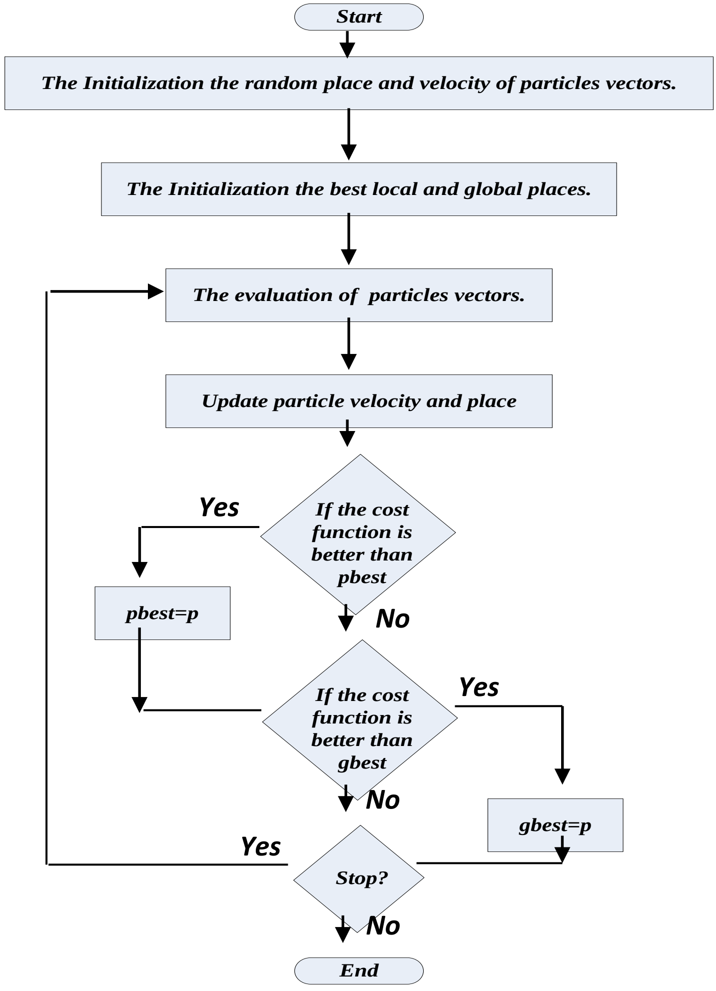


Figure 1: PSO Flow Chart.

4. Character Modeling

4.1. Normalization

There are many variations in the handwriting of different persons. Therefore, the process of normalization of characters is performed so that all characters can become of equal dimensions of the matrix. In this manuscript, characters are normalized into 18X18 pixel characters, and then we take every character from 2000 characters, locate the area for the character and calculate how many rows and columns after reading it as a matrix. Set out below are the steps of the normalization algorithm, explaining how the area of the matrix is located.

Normalization Algorithm:

1. The main program call location subroutine program.
2. Delete matrix elements of any character from the top until the first location contains the value 1, then stop the deletion operation and save this row in the variable c1
3. Delete matrix elements of any character downwards until the first location contains the value 1, then stop the deletion operation and save this row in the variable c2
4. Make new matrix, saving the matrix dimension as c1xc2
5. Rotate for new matrix by angle 900, repeat steps 2, 3, 4 and replace c1 by r1, c2 by r2 and save this matrix
6. Rotate saved matrix by angle 2700 until the character returns to original shape but its dimension is r2xc2
7. Save the resultant matrix to use it in the next processing mechanism, zooming in to the main program
8. Let the zero matrix of dimension 18x18 be called (w).
9. Read the result file from cut character called (m).
10. Apply zooming equation to obtain new value for matrix of dimension 18x18

    W(i , j)=m(ceil(i*c2/18),ceil(j*r2/18)
11. Save the matrix w with an area 18x18 in external file for future use (its shape to be larger and fixed)

    End

The above algorithm is applied to all characters, whether database or form characters to be recognized. Now, after the above steps, we may have prepared characters saved as a database and shapes required to be recognized by using the application of PSO.

4.2. Feature extraction

Feature extraction is used to look for properties or behavior of each character entrance and these properties are qualities with which to describe a particular character and distinguish it from another character. Algorithms can be used effectively in features extraction (Pradeep and Srinivasan 2010; Pradeep, Srinivasan, and Himavathi 2010). A diagonal feature extraction scheme for recognizing handwritten characters is proposed in this manuscript. Every character image of size 18X18 pixels is divided into 7 equal zones, each of size 4X4 pixels, which are analyzed and the features are formed. The features are extracted from each zone of pixels by moving along the diagonals of its respective 4X4 pixels. It is known that a feature represents the smallest set that can be used for discrimination purposes and for a unique image at this stage, the features of the characters that are crucial for classifying them at recognition stage are extracted. This is an important stage as its effective functioning improves the recognition rate.

5. Database and Experiment

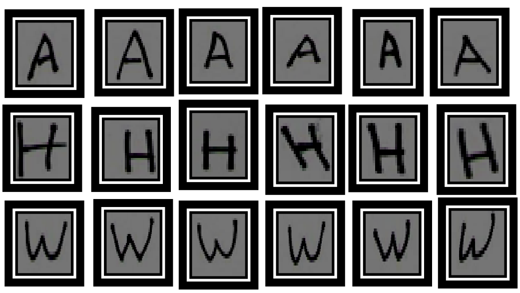
5.1. Database

A database is used for the scanned input of Handwritten English Characters in our experiments. The size of each character is 18X18 pixels after the normalization process. The database consists of 26 characters from A to Z, and each a separate file for each character. The Training Dataset consists of 2000 samples for characters (A-Z), 6X26 saved as database, and 2000 characters with different shapes as input samples. We use Matlab to extract the isolated handwritten character for each file. Some different shapes of English handwritten characters are shown in Figure (2).

Figure 2: Sample of English handwritten characters written by six different writers.

5.2. Experiments

In order to check the working of the approach proposed in this manuscript, we applied it in Matlab. Some different images after normalization and the features extracted values of the six English handwritten characters (A, H and W) from 2000 characters are shown in Figure (3 a and b).



(a)

[2.3852 2.5941 2.4299 2.6509 2.7164 2.3802]

[2.1190 2.1090 2.1040 2.1290 2.1340 2.1140]

[2.4699 2.4599 2.4449 2.4799 2.4849 2.4799]

(b)

Figure 3: (a) Some samples of images after normalization of characters (A, H and W) from 2000 English handwritten characters and, (b) the features extracted values.

The results obtained for the feature extraction values of the six different shapes of some input English handwritten characters are presented in Figure (4). This shows that the diagonal feature extraction provides greater recognition accuracy.

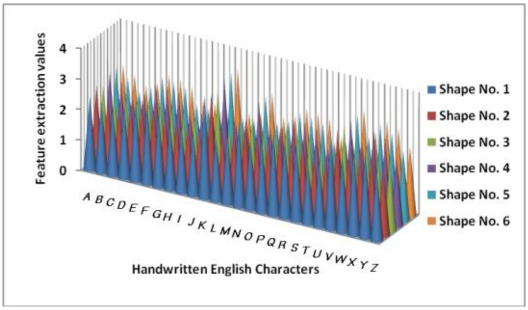


Figure 4: The variation of feature extraction values of six different shapes of some input English handwritten characters from 2000 Training Dataset characters.

The features extracted are given to the proposed approach, and similarly the features of other characters from A-Z are extracted and given for training. Table (1) shows the feature extraction results for some input English handwritten characters.

Table 1: Feature extraction results for some input characters from 2000 Training Dataset characters.

	Character	First value for shape1	second value for shape2	third value for shape3	Forth value for shape4	Fifth value for shape5	Sixth value for shape6
1	A	2.3852	2.5941	2.4299	2.6509	2.7164	2.3802
2	B	2.3097	2.2097	2.1597	2.4097	2.4597	2.4547
3	C	2.1144	2.1044	2.1094	2.1244	2.1194	2.1094
4	D	2.3244	2.3144	2.3094	2.3344	2.3394	2.3194
5	E	2.6016	2.5016	2.4516	2.7016	2.7516	2.5966
6	F	2.5435	2.4435	2.3935	2.6435	2.6935	2.5385
7	G	2.3684	2.2684	2.2184	2.4684	2.6184	2.3634
8	H	2.1190	2.1090	2.1040	2.1290	2.1340	2.1140
9	I	2.1061	2.0961	2.0911	2.1161	2.1211	2.1011
10	J	2.0681	2.0581	2.0531	2.0781	2.0831	2.0631
11	K	3.3418	3.2418	3.2368	3.4418	3.4468	3.4368
12	L	2.0713	2.0613	2.0563	2.0813	2.0863	2.0663
13	M	2.2618	2.3618	2.4118	2.1618	2.1118	2.0568
14	N	2.8177	2.7177	2.6677	2.9177	2.9677	2.8127
15	O	2.2142	2.2042	2.1992	2.2242	2.2292	2.2092
16	P	2.3417	2.3317	2.3267	2.3517	2.3567	2.3367
17	Q	2.6873	2.6773	2.6723	2.6973	2.7023	2.6723
18	R	2.5415	2.4415	2.4365	2.6415	2.6465	2.5365
19	S	2.5348	2.5248	2.5198	2.5448	2.5498	2.5298
20	T	2.0103	2.0003	1.9953	2.0203	2.0253	1.9053
21	U	2.1018	2.1118	2.1168	2.0918	2.0868	2.1968
22	V	3.1173	3.1073	3.1023	3.1323	3.1273	3.1123
23	W	2.4699	2.4599	2.4449	2.4799	2.4849	2.4649
24	X	2.8392	2.7392	2.6892	2.9392	2.9892	2.8342
25	Y	2.7737	2.7637	2.2587	2.7837	2.7887	2.7687
26	Z	2.2659	2.2559	2.2509	2.2759	2.2809	2.2609

6. Results and Discussions

Experiments were carried out on a database of English handwritten characters obtained as described in section 4.2. The input characters were grouped into 26 subsets. During each iteration, every subset was saved in different locations as, character A in locations from 1 to 6, character B in locations 7 to 12 and through to character Z in locations 151 to 156.

The input character was chosen as the test set and the process of transformation starts with a scanning of the matrix of any character of database (A). The matrix of required recognized character (B) was combined to form training set F(A, B). Row sizes (1 to 18) represent the map sizes in the horizontal directions and Column sizes (1 to 18) represent the map sizes in the vertical directions. Note that F(A, B) has four valid coordinates: (0,0), (0,1), (1,0) and (1,1). Then a simple operation is performed which replaces the value of matrix F(A, B) with the minimum among the four values obtained by adding the values of the matrixes A, B and normalizing the value of matrix F(A, B) corresponding to the matrix M, as in equation (3).

$$M = \sum_{i=1}^{18} \sum_{j=1}^{18} \begin{cases} 1 & \text{if } A(i,j) = B(i,j) = 1 \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

We then start to simplify the English handwritten characters recognition using a PSOA, as illustrated in Figure (5). The proposed approach of the PSO was implemented using Matlab software. The parameters used in the simulation are: the number of iterations is 500, the inertia weight is 0.7, and the weights applied to the cognitive learning and to the influence of the social learning portions are 1.5 and 1.6, respectively.

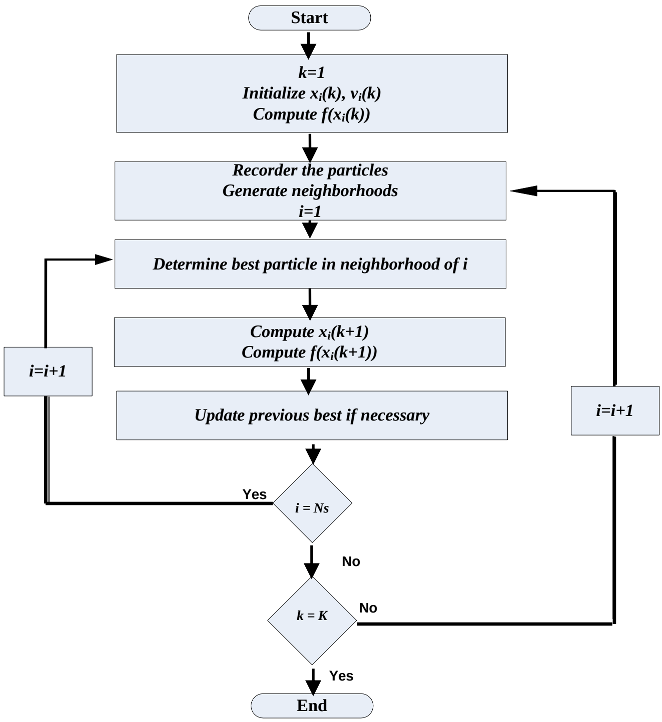
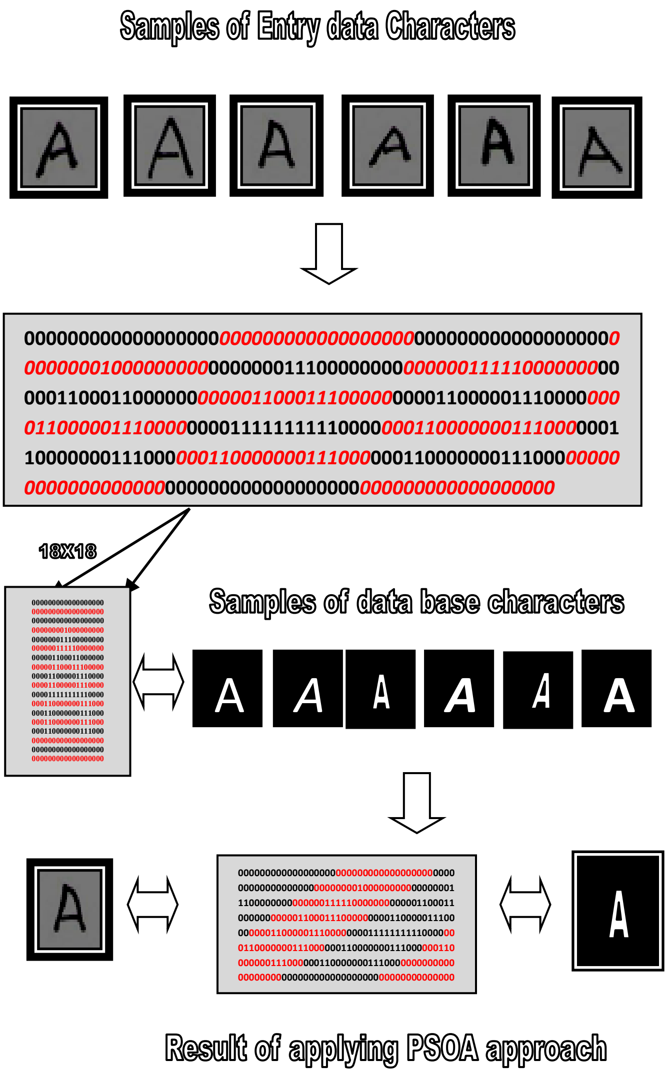
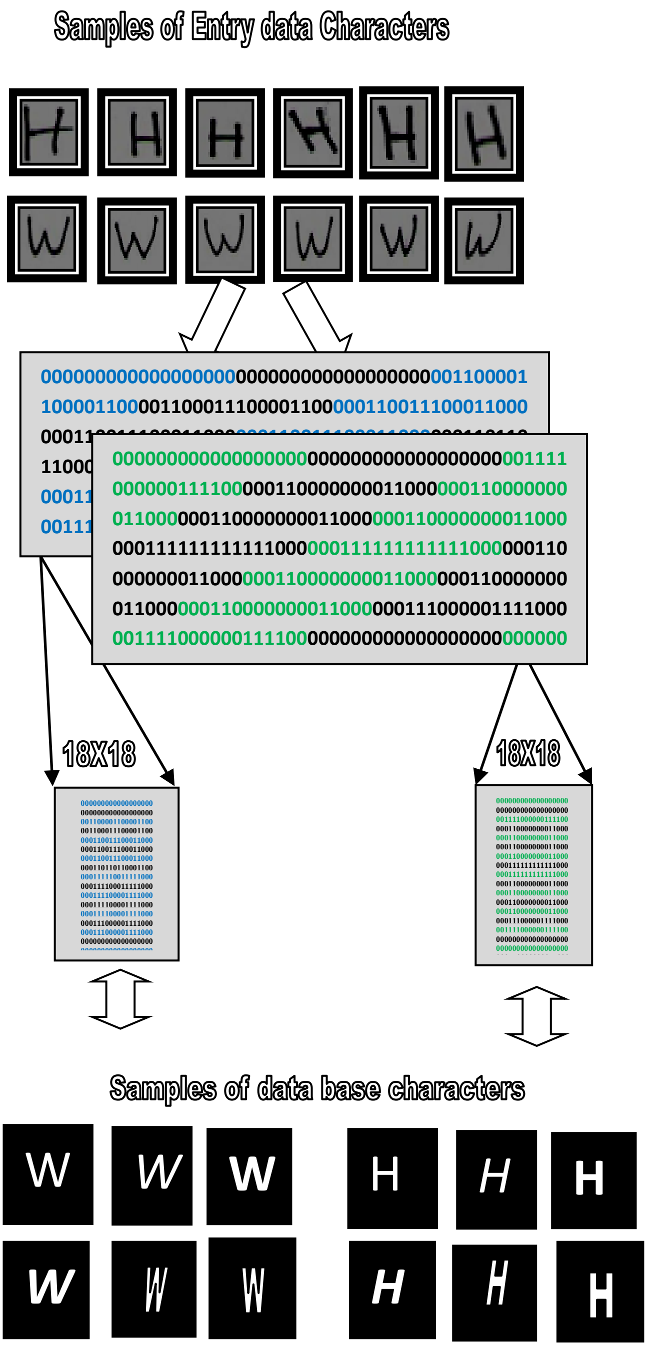


Figure 5: Proposed recognition approach flowchart of Handwritten English Characters.

In our proposed algorithm the particles are the entry data characters that exchange information and move to reach the lowest value of objective function as considered in the velocity update equation. Further, definitions of optimality are obtained via objective function, minimizing rate error recognition, and providing explicit solutions by choosing the smallest values of the entry English handwritten feature extraction. Figure (6) explains the application of the PSOA for the English handwritten chosen characters (A, H and W) from 2000 Training Dataset characters with six different shapes, and the result of applying PSOA.


Samples of Entry data Characters
000000000000000000000000000000000000000000000000000000
000000010000000000000000111000000000000001111100000000
000110001100000000000110001110000000011000001110000000
011000001110000000011111111110000000110000000111000001
100000001110000001100000000111000000110000000111000000000
0000000000000000000000000000000000000000000000000000
18X18
Samples of data base characters
A
A
A
A
A
A
A
Result of applying PSOA approach


Samples of Entry data Characters
0000000000000000000000000000000000001100001
1000011000011000111000011000001100111001100O
000000000000000000000000000000000000001111
000000111100000110000000001100000110000000
011000000110000000001100000110000000001100O
000111111111111000000111111111111000000110
000000011000000110000000001100000110000000
011000000110000000001100000111000001111000
001111000000111100000000000000000000000000
18X18
18X18
Samples of data base characters
W
W
W
H
H
H
W
W
W
H
H
H

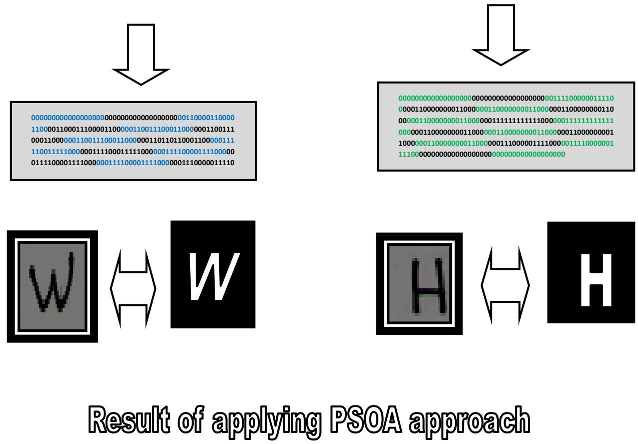


Figure 6: The application of the proposed PSOA on the six shapes of some input characters A, H and W.

Take each character from the above input characters, compute the matrix F(A, B) with characters of the database and after application of the PSOA, a Window appears containing the recognized characters and the value of F(A, B). The following Tables (2, 3) present the results obtained from testing our proposed approach on the English handwritten database. Our experiment results are illustrated in Figures (7 a and b), yielding recognition rates for 2000 English handwritten characters of about 93.39%. We have achieved major improvements by applying PSOA with a low rate of error recognition.

Table 2: Recognition results obtained from testing our proposed approach on English Handwritten database

	character	Writer1	Writer2	……	Writer 1998	Writer 1999	Writer 2000	No. of successes shapes for testing	No. of failed shapes for testing	Rate recognition %
1	A	1√	1√	……	1√	8√	1√	1987	13	99.35
2	B	2√	√2	……	2√	2√	5√	1985	15	99.25
3	C	3√	3√	……	7√	3√	3√	1994	6	99.70
4	D	4√	15√	……	4√	4√	4√	1987	13	99.35
5	E	2√	5√	……	5√	2√	5√	1981	19	99.05
6	F	6√	6√	……	6√	6√	5√	1992	8	99.60
7	G	7√	7√	……	7√	7√	7√	1995	5	99.75
8	H	8√	8√	……	8√	3√	13×	1589	411	79.45
9	I	9√	9√	……	9√	9√	1√	1996	4	99.80
10	J	10√	10√	……	10√	10√	10√	1857	143	92.85
11	K	11√	11√	……	5√	11√	11√	1811	189	90.55
12	L	12√	12√	……	12√	3√	12√	1896	104	94.80
13	M	13√	8√	……	13√	13√	13√	1980	20	99.00
14	N	14√	14√	……	14√	14√	8×√	1438	562	71.90
15	O	15√	15√	……	2√	15√	15√	1989	11	99.45
16	P	16√	16√	……	16√	16√	2√	1991	9	99.55
17	Q	15√	17√	……	17√	17√	17√	1985	15	99.25
18	R	18√	18√	……	18√	6√	18√	1734	266	86.70
19	S	19√	5√	……	19√	19√	19√	1838	162	91.90
20	T	20√	20√	……	16√	20√	20√	1899	101	94.95
21	U	21√	21√	……	21√	15√	21√	1848	152	92.40
22	V	22√	21√	……	22√	22√	22√	1921	79	96.05
23	W	23√	23√	……	23√	23√	13√	1769	231	88.45
24	X	24√	13√	……	24√	24√	25×	1482	518	74.10
25	Y	25√	25√	……	22√	25√	25√	1799	201	89.95
26	Z	26√	26√	……	26√	20√	26√	1821	179	91.05
	The average rate							1868	132	93.39

Table 3: Final recognition results obtained from testing our proposed approach

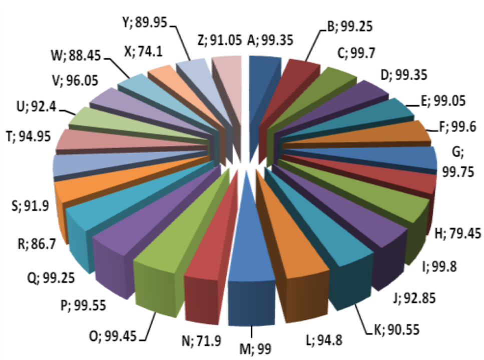
	No. of characters recognition	Rate recognition %	Rate recognition from 26 characters	Rate error recognition		No. of characters recognition	Rate recognition %	Rate recognition from 26 characters	Rate error recognition
1	2	99.35	7.692	0.262	12	1	99.00	3.846	0.202
2	2	99.25	7.692	0.302	13	1	71.90	3.846	7.816
3	1	99.70	7.692	0.060	14	1	99.45	3.846	0.111
4	1	99.05	7.692	0.192	15	1	99.55	3.846	0.090
5	1	99.60	3.846	0.080	16	1	86.70	3.846	3.068
6	1	99.75	3.846	0.050	17	1	91.90	3.846	1.763
7	1	79.45	3.846	5.173	18	1	94.95	3.846	1.064
8	1	99.80	3.846	0.040	19	1	92.40	3.846	1.645
9	1	92.85	3.846	1.540	20	1	96.05	3.846	0.822
10	1	90.55	3.846	2.087	21	1	88.45	3.846	2.612
11	1	94.80	3.846	1.097	22	1	74.10	3.846	6.991

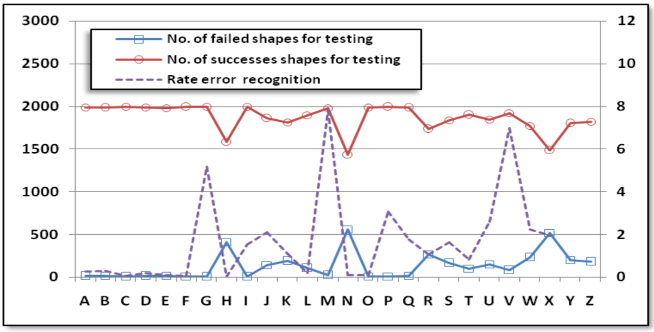
100%

93.39%

26

Figure 7: Experiment results from testing PSOA approach on English Handwritten database (a) recognition rates, (b) recognition value of number of failed, successes shapes from 2000 characters and rate error recognition.





Conclusions

In this present manuscript, the diagonal feature extraction method and an approach of handwritten characters recognition using the concept of particle swarm optimization algorithm (PSO) have been discussed. It is noted that the PSOA in general generates an optimized comparison between the input samples and database samples which improves the final recognition rate. The proposed approach has been tested with many handwritten English characters; a high recognition rate was recorded of 93.39%. Experimental results show that the PSO approach is convergent and more accurate in providing a solution to the problem.

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