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FREEMAN CHAIN CODE ROUTE LENGTH OPTIMIZATION USING META-HEURISTIC TECHNIQUES FOR HANDWRITTEN CHARACTER RECOGNITION

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ABSTRACT

Chain code is used as representation for an image in form of sequence of directional codes along the border or structure line. Issue arises during its extraction when the line has branches and the sequence must be continuous; no restarting at any junction is allowed. This paper presents a chain codes extraction of Thinned Binary Image (TBI) from upper-case Centre of Excellent for Document Analysis and Recognition (CEDAR) dataset using Meta-heuristic techniques. There are six methods in Meta-heuristic techniques that called Differential Evolution (DE), Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Ant-Colony Optimization (ACO), Harmony Search Algorithm (HSA) and Simulated Annealing (SA). In the feature extraction, Freeman Chain Code (FCC) was used as data representation that uses 8-neighbourhood directions. However, the FCC representation is dependent on the route length and branches of the characters' node. These six methods are used to find the shortest route that consumed minimum computational time. The experimental result shows that the route length and computation time using DE, PSO, GA, ACO, HSA and SA. Comparing to five other techniques, the results revealed that SA has the shortest chain code length and lowest computational time with 1,856.13 and 0.07 second, respectively.

Keywords: freeman chain code, route length optimization, meta-heuristic algorithms, handwritten character recognition.

INTRODUCTION

FCC is proposed by Freeman, which encodes the direction travelled by the tracing agent in digit sequence. There are two types of neighbourhood available which are 4- and 8- neighbourhood, defining which neighbour is possible to reach from current position. For example, diagonal movement is possible for 8-neighbourhood while only cardinal direction is allowed for the former.

To extract the CC, first the direction is assigned with a unique label, usually starts with '0' for the north and '7' for north-west, in the case of 8-neighbourhood. Then, starting point of the tracer on the structure to be extracted is located. Finally, the tracer is to follow the structure border, possibly defined as at the boundary between foreground and background pixels, or at any unvisited pixel in case of TBI until it reaches back to its starting point (Nasien *et al*, 2015).

Handwritten character recognition (HCR) is the ability of a computer to receive and interpret intelligible handwritten input then analyzed to many automated process system (Nasien *et al*, 2010). The major problem in HCR system is the variation of the handwriting styles, which can be completely different for different writers (Patel and Thakkar, 2015). The objective of HCR is to implement computer assisted character representation that will allow successful extraction of characters from handwritten documents and to digitalize and translate the handwritten text into machine-readable text. However, after many years of intensive investigation and research, the main goal of developing character recognition system remains unachieved (Pithadia and Nimavat, 2015). Recently, interest in feature extraction and selection has been on the increase with the abundance of algorithms derived. These algorithms can be classified into two groups: heuristic and meta-heuristic techniques. Many heuristic algorithms have been proposed in the literature for finding near–optimal solutions (Somol *et al*, 2004; Mohamad *et. al*, 2015). Meta-heuristic comes from two Greek words are Meta and heuristic (Nasien *et al*, 2010). Meta is "higher" while heuristic means "to find or to discovery". Meta-heuristic algorithms are a stochastic optimization (optimization algorithm) which that to try to improve a candidate solution. A meta-heuristic goes beyond heuristic to draw on ideas and concepts from another discipline to help solving the artificial system being modelled (Jia and Lin, 2008). The aim of meta-heuristics is to perform the process searching with effective and efficient for the global optimum of a problem.

Isolated characters, especially Latin characters, usually contain branches on each character node, which causes difficulty to decide which direction would the traverse continues. Moreover, a revisit to previous visited node is often needed to visit all the nodes. A one continuous route is needed to solve this problem, which will cover all the nodes of the character image. This situation resembles Chinese postman problem where character branches and junctions translates to edges and nodes, respectively, and shortest possible route passing all edges is to be found (Nasien *et al*, 2015). Thus, FCC extraction techniques via meta-heuristics techniques are proposed. There were six meta-heuristic techniques that used in this paper includes DE, PSO, GA, ACO, HSA and SA. Knowing that the use of meta-heuristics techniques is to construct FCC is not widely explored and the existence of the length problem in representing and recognition characters of FCC.

This paper is divided to seven sections. Section 2 describes literature review. Section 3 describes structure of the algorithms. Section 4 describes problem formulations, Section 5 describes experimental settings, Section 6 describes experimental results and discussions and Section 7 describes conclusion

RELATED WORK

GA is one of the global optimization methods that belong to the family of evolutionary algorithms. GA explores the solution space through an artificial evolutionary process, i.e. recombination, mutation, and selection. The applications of GA have been used in several HCR problems. The genetic algorithm for feature selection for handwriting recognition has been discussed (Kao *et al*, 2007). A powerful method that enables 2D character image reconstruction from a feature space in optical character recognition by 2D shape morphing was proposed in (Iga and Wakahara, 2004). GA works with a set of individual solutions called population; it is natural to adopt GA schemes for Multi-objective Optimization problems so that one can capture a number of solutions simultaneously (Gupta *et al*, 2013)

DE was introduced by Storn and Price, 1996. It was developed to optimize real (float) parameters of a real valued function. Like GA, DE use similar operator: crossover, mutation and selection. Without characteristics of questions, DE can dynamically trace the current value to improve its searching strategy. The advantages of DE are fast convergence and using few parameters (Delvis and Selcuk, 2004). DE has been applied to solve image processing problems including image; reconstruction, thresholding, segmentation, classification and recognition (Kao *et al*, 2007).

PSO is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling (Kennedy and Eberhart, 1995). The system is initialized with a population of random solutions and searches for optima by updating generations. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. PSO also has been used successfully in image watermarking, data clustering, character recognition, image thresholding and recognition (Oliveira *et al*, 2002; Vehedi *et al*, 2007). Recent studies in University of Technology Sydney (UTS) have demonstrated the potential of PSO algorithms for solving pattern recognition and signal modeling problems including power wheelchair control, hypoglycemia detection, fall detection, gait analysis, and feature extraction from images. The PSO has also been reported to be a powerful tool in the field of data mining (Yuwono, *et al*, 2013).

ACO approaches have successfully been used in several HCR problems and it has not widely explored by researchers. An ant colony neural network model and applies in Lithology recognition and prediction was established in (Yuxiang and Qing, 2008). ACO approaches have successfully been used in several HCR problems and the thesis about it has not widely explored by researchers. Phokharatkul *et al.* (2005) presented a system of handwritten Thai character recognition, which is based on the Ant-minor algorithm (data mining based on Ant colony optimization). Zoning is initially used to determine each character then three distinct features of each character in each zone is extracted, which are head zone, end point, and feature code. All attributes are used for constructing the classification rules by an Ant-miner algorithm in order to classify 112 Thai characters. ACO approach was applied to the portfolio optimization mean–variance model. The problem of portfolio optimization is a multiobjective problem that aims at simultaneously maximizing the expected return of the portfolio and minimizing portfolio risk (Haqiqi and Kazemi, 2012).

To find the shortest route to cover all branches in a character image, metaheuristic algorithms are applied aiming to minimize solution length. The two methods, harmony search algorithm (HSA) (Geem *et. al,* 2001) and simulated annealing (SA) (Kirkpatrick *et. al*, 1983) have at least 13 years of history since their first debut, and have been applied in various fields such as routing problem (Wang *et. al,* 2015; Hoseini *et. al,* 2014), character segmentation (Potrus and Ngah 2012), network channel assignment (Chen and Chen, 2015) and civil engineering (Yoo *et al,* 2014). This paper collects the previously published result from (Arif *et al,* 2015) while applying the proposed method in (Nasien *et al,* 2015) to the same image database used by the former.

RESEARCH METHODOLOGY

Firstly, Problem Identification and Specification are specified in Stage 1. In this stage, the problems are the branches existed in TBI that may lead to multiple chain code extractions. Due to that, the shortest route must be found and to make sure that all the branches are covered.

In Stage 2, CEDAR dataset was chosen to be the input and tested. The size of dataset image is 50x50 pixels and only uppercase characters are used. The number of images tested is 126 (Table-1).

In Stage 3, thinning is performed to binarized input character in pre-processing stage with TBI as the output.

Then in Stage 4, FCC is selected to represent the character in feature extraction stage to be extracted from the TBI by using all six meta-heuristic techniques.

VOL. 10, NO 22, DECEMBER, 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

Finally in Stage 5, the desired output of shortest chain code route and computational time are obtained.

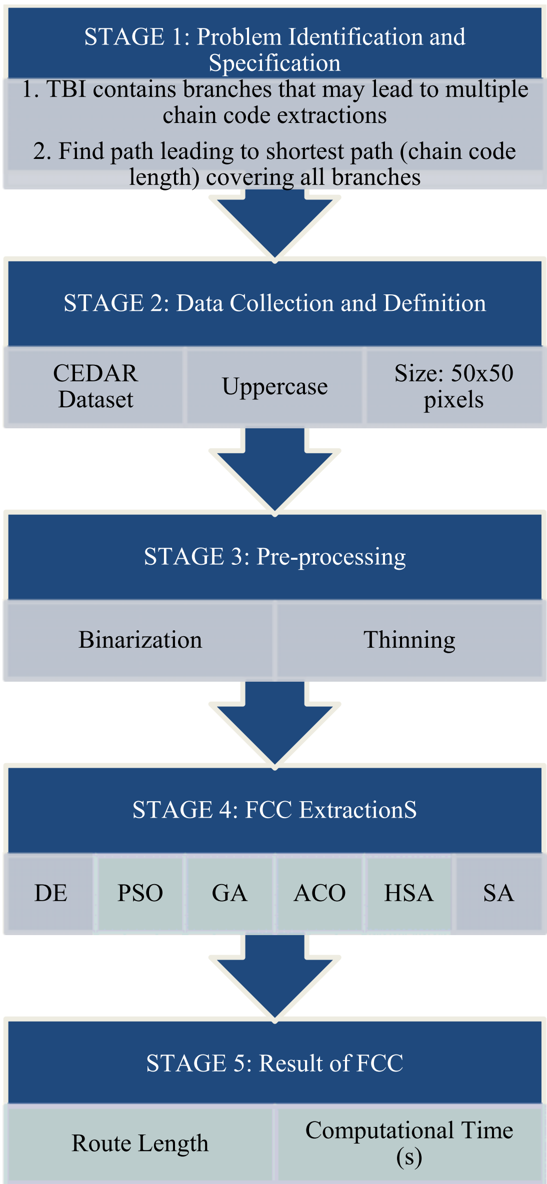

Figure-1. The process of FCC extraction using Meta-heuristic techniques

Table-1. Character image count in CEDAR dataset.

Characters	Image count
Q	3
I,P	4
A-H	5
J-O	
R-Z	
TOTAL	126 images

Figure-3 demonstrates a TBI with foreground (white) nodes and background (black) nodes. S is referring to starting node; travels to the above two nodes and stop and the branch. The node will travel to the right, come back, move to the left and finally to the end node (E). The chain code result is 001570.

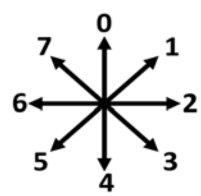

Figure-2. 8-Neighbourhood FCC.

FCC is used to encode the node travelled in the TBI and record it. In this work, 8-neighbourhood FCC is used as showed in Figure-2. Process of generating FCC from binary image can be modeled as problem of finding a route in a graph. Initially, the binary image is transformed into a digraph consists of vertices and edges. The vertices of the graph are taken from node that has only one or more than two neighbours. In turn, edges of the graph are come from nodes having exactly two neighbours connecting the vertices from before. The lengths are obtained from the total number of nodes between two vertices (Nasien *et al*, 2015).

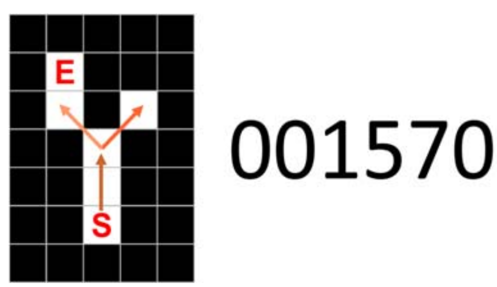

Figure-3. FCC extraction demonstration.

PROBLEM FORMULATIONS

As mentioned before, there are six meta-heuristic techniques will be tested to the character images? Below are the problem formulations for each technique.

Genetic Algorithm (GA)

Genetic Algorithm (GA) is one of the global optimization methods that belong to the family of evolutionary algorithms. GA explores the solution space through an artificial evolutionary process, i.e. recombination, mutation, and selection. The general pseudo-code of GA is depicted in Figure-6.

```
Step 1: START
Step 2: Input data and setting parameter values
Step 3: Generate random nodes
Step 4: Until Stopping criteria is achieved
Step 4.1 Generate offspring population
4.1.1 Select two parents randomly
4.1.2 Recombination
4.1.3 Mutation
4.2.4 Perform local search
Step 4.2 Selection
Step 5: END
```

Figure-4. Genetic algorithm pseudo-code.

For the execution several parameter values must be determined. The algorithm starts with randomly generated initial population then through recombination, mutation, and local search the offspring population is constructed. After that, the algorithm selects the best solutions which will survive for the next iteration. Algorithm stops with the predetermined number of iterations.

Differential Evolution (DE)

The proposed DE uses a real-value solution representation. It will be converted to a discrete solution representation using SPV (smallest position value) rule. Figure-4 shows the pseudo-code of proposed DE.

```
Step 1: START
Step 2: Input data and setting parameter values
Step 3: Generate random nodes
Step 4: Until Stopping criteria is achieved
        Step 4.1 Generate trial population
                4.1.1 Select four vector solutions
          randomly
                4.1.2 Create mutant vector Create trial
                      vector
                4.1.3 Apply SPV rule
          Step 4.2 Selection
Step 5: END
```

Figure-5. Differential evolution pseudo-code.

Initially, the proposed DE has several parameter values which must be determined. They are maximum number of iterations, number of population (n), factor number (F) and mutation rate (ρ). Initial population is randomly generated. The population consists of n solutions which take real-value representation which will then be converted to discrete representation using SPV. After that, the objective function for every solution in the population is calculated.

After the random selection of four solutions, the mutant vector is calculated. The equation for calculating the mutant vector is shown in Equation (1).

$$\text{Mutant Vector} = \text{Second Vector} + F * (\text{Third Vector} - \text{Fourth Vector}) \quad (1)$$

Then the component of trial vector is determined by provoking a random number. If the random number generated is less than the mutation rate, then the edge will be taken from mutant vector. Otherwise, it will be taken from the first vector. This procedure is repeated until all components of the trial vectors have been determined. After that, the trial vector is converted to discrete representation using SPV rule.

Following that, selection process is executed. In the selection process, the DE algorithm does not use the common pairwise selection between trial vector and first vector. Nevertheless, it selects n best solutions which will survive to the next iteration. This procedure is preferred to attain a collection of best solutions.

Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) uses collaboration among particles to explore the solution space. It updates its particle position using information from previous particle position, local best position, and global best position. The solution representation used here is real-value representation and will be converted to discrete representation using SPV rule. The

ARPN Journal of Engineering and Applied Sciences

implementation of PSO to generate the FCC is depicted in Figure-5.

```
Step 1: START
Step 2: Input data and setting parameter values
Step 3: Generate random nodes
Step 4: Until Stopping criteria is achieved
        Step 4.1 Generate next population
                 4.1.1 Calculate next velocity
                 4.1.2 Calculate next particle position
                 4.1.3 Apply SPV rule
                 4.1.4 Apply local search
        Step 4.2 Update local best and global best
Step 5: END
```

Figure-6. Particle swarm optimization pseudo-code.

Ant Colony Optimization (ACO)

The implementation of ACO to generate the FCC is depicted in Figure-7. Several parameter values must be determined. The algorithm iterates within three main components which are ant solution construction, local search procedures, and pheromone update. The algorithm termination depends on predetermined number of iterations. In addition, the proposed ACO algorithm keeps record about the best solutions already found.

```
Step 1: START
Step 2: Input data and setting parameter values
Step 3: Generate random nodes
Step 4: Until Stopping criteria is achieved
        Step 4.1 Ant-Colony Construction
        Step 4.2 Apply local search
        Step 4.3 Update pheromone value
Step 5: END
```

Figure-7. Ant-colony optimization pseudo-code.

Harmony Search Algorithm (HSA)

The HSA extraction algorithm process is summarized as pseudo code in Figure 8. Harmony memory (HM) contains route samples, sequence of nodes completing the graph tour, which will be reduced as short as possible throughout the process, ending after reaching maximum iteration count.

```
Step 1: START
Step 2: Input data and setting parameter values
Step 3: Generate random initial population
Step 4: Start HAS search with objectibe()-minimum
        path length
Step 5 Until stopping criteria is achieve
        Step 5.1 Improve a new harmony form
                 harmony memory
        Step 5.2 Update harmony memory
Step 6: END
```

Figure-8. Harmony search algorithm pseudo code.

Simulated Annealing (SA)

In order for SA to optimize the route to reach the shortest possible length, a baseline route needs to be constructed first. The route does not have to be in the lowest length at this point, thus randomized node sequence is enough as long a complete route is produced? Pseudo code of SA is shown in Figure-9.

```
Step 1: START
Step 2: Input data and setting parameter values
Step 3: Choose random node as starting point
Step 4: Until Stopping criteria is achieved
        Step 4.1 Select neigbouring route
        Step 4.2 Apply acceptance probability
                 Function
        Step 4.3 Update system temperature
Step 5: END
```

Figure-9. Simulated annealing pseudo code.

SA iterates on a single route sample sequentially as its processing flow. However, by having multiple route samples for a single image, parallel execution can be performed per sample, since the process does not interfere with other route samples. The shortest route among the samples then will be selected as the solution. Basic blocks for SA are neighbouring route selection, temperature control, and acceptance probability function. Each of the blocks is explained in subsections below.

Neighbouring route selection

A neighbouring route is defined as a route that is close or similar to current route in terms of node and edge sequence. Changing a random node in current route is enough in order to construct it. However, route continuity may be hard to maintain or resulting to longer route after reconnecting broken paths.

ARPN Journal of Engineering and Applied Sciences

Process temperature control

In nature, the dropping temperature shape resembles inverse exponent graph, which is how the shift is implemented here. The exact equation is shown below in Equation (2):

$$t = T_0 e^{\frac{i}{I}\ln\left(\frac{T_1}{T_0}\right)} \quad (2)$$

with t as temperature for current iteration, T_0 and T_1 for initial and final temperature, respectively. Finally, i and I are current iteration index and total iteration count, in that order.

Neighbouring route acceptance probability function

If the neighbouring route length is shorter compared to the current, the switch is done regardless of the probability value. Else, higher temperature and smaller length difference result in higher acceptance probability for the neighbour route. The function equation is given in Equation (3):

$$p = e^{-\frac{L_N - L_C}{t}} \quad (3)$$

where p is the acceptance probability value, L_N and L_C for length of neighbouring and current route, and t for current temperature.

Selecting shortest route as solution and chain code assembly

After temperature reaches the minimum at the end of iteration, shortest route from multiple samples is chosen based on their length. This step exists only if multiple route samples approach is used; resulting route is directly elected as solution for the single route sample.

Finally, a route solution is sequence of nodes and edges exist in the character structure. Following the sequence, chain code from each edge is combined to complete the representation of character image in chain code.

EXPERIMENTAL SETTINGS

In pre-processing stage, dataset used is CEDAR, limited to upper-case character class. The output of pre-processing stage is thinned binary image, which for CEDAR the size is 50 x 50 pixels. Thinned binary image from CEDAR is taken from Engkamat, (2005). During the experiment, several adjustments of parameter setting are used. The parameter values that were used in the proposed GA and ACO are show in the Table-2 while the proposed values for DE and PSO as shown in the Table-3. Parameter values for HSA and SA are shown in Table-4.

Table-2. The parameter used in DE and PSO.

DE	PSO
Maximum number of iterations 2000	Maximum number of iterations 200
Number of populations (n)= 100	Number of populations (n)= 100
Factor number (F) = 0.5	Inertia weigth (I) = 0.2
Mutation rate (ρ)= 0.9	Relative weight of local best (C_1)= 0.4
Maximum local search = 0	Relative weight of global best (C_2)= 1.6
-	Number of local searchs = 10

Table-3. The parameter used in GA and ACO.

GA	ACO
Maximum number of iterations 100	Maximum number of iterations 100
Number of populations (n)= 100	Number of ants (n)= 100
Mutation rate (ρ) = 0.3	Evaporation rate (ρ) = 0.3
Number of local searchs = 10	Number of local searchs = 10

Table-4. The Parameter Used in HSA and SA.

Maximum number of iterations 50	Maximum number of iterations 50
HM sample count 100	Sample count 20
HM selection rate=0.85	Temperature range 0.1-100
Pitch adjustment delta=1	-
Pitch adjustment rate=0.2	-

RESULTS AND DISCUSSIONS

Every algorithm tries to find a collection of good FCC solutions with its FCC length minimized. SA performed far better compared to other five techniques.

ARPN Journal of Engineering and Applied Sciences

The results are the lowest which are 1856.13 and 0.07seconds in terms of route length and computational time. This technique can be used efficiently in local search procedures. Compare to the nearest competitor which is HSA (Mohamad *et al*, 2015), lag in data transfer between device and host memory may be the reason of HSA poor performance. Table-5 shows the whole results of six meta-heuristic techniques.

Table-5. Comparison of the proposed algorithms based on route length and computation time.

Proposed algorithm	Route length			Average computation time (Second)
	Best	Average	Worst	
GA	2,318.04	2,334.63	2,349.73	1,144.58
DE	2,334.74	2,359.42	2,386.32	865.7
PSO	2,247.79	2,370.89	2,391.77	2,012.11
ACO	2,343.42	2,354.92	2,380.19	1,126.33
HSA	1,880.28	1,915.88	1,934.13	1.10
SA	1,856.13	1,889.45	1,912.93	0.07

CONCLUSIONS

This paper describes a solution for extracting shortest chain code for handwritten character image using six meta-heuristics techniques which are GA, ACO, DE, PSO, HSA, and SA. In order to find shortest route passing all edges, this situation resembles Chinese postman problem where character branches and junctions translates to edges and nodes. Comparing to five other techniques, the results show that SA has the shortest chain code length and lowest computational time. Temperature plays an important role in SA in determining the possibility of transferring from current to neighboring route. Similar with original annealing usage in metallurgy, cooling rate of the temperature need to be controlled to allow wide exploration of solution search space, while also converges to optimal solution at the end of iteration.

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