Plate Recognition Using Fuzzy Noise Removal and Opposition-based Micro-Differential Evolution

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Abstract—Automatic plate recognition of vehicles is of great importance in route management systems. Especially that such systems require real-time algorithms to perform the plate recognition task as soon as possible. In this paper, a new plate recognition system based on a fuzzy noise removal technique and the opposition-based micro-differential evolution (OMDE) algorithms is presented. Since population-based algorithms are mostly working based on a large population size, which results in a high computational cost, the micro-population-based algorithm require a very small population size and as a result, less computational cost. However, due to lack of diversity in such algorithms, the idea of opposition-based learning is utilized to enhance the diversity in the search procedure. By employing the template matching method, the digits and alphabets are easily extractable from plate image. Performance evaluation of the proposed system shows that this system is capable of identifying the vehicle’s plate with high quality in route management systems.

Keywords—micro-differential evolution, plate recognition, opposition learning, template matching.

I. INTRODUCTION

Automatic license plate recognition systems play an important role in intelligent transportation systems and management design, such as automatic toll collection, traffic law enforcement, parkinglot access control, and road traffic monitoring [1]. Such systems try to recognize the plate number of vehicles. These systems are mostly working based on the image processing systems, such that by processing black and white or color image of plates try to perform plate recognition in a reliable and real-time manner. Population-based algorithms are state-of-the-art methods to deal with large-scale, high dimensional, non-linear, non-convex, and combinatorial problems, to mention some. The differential evolution (DE) algorithm is one of such algorithms, which presents a higher performance over other EAs because of its simplicity, effectiveness, and lower number of control parameters [3]. Over the past decade, because of its high performance, DE has been widely used to solve global optimization problems in various engineering and science fields, such as image thresholding [2] and global optimization [3].

The main idea of OBL is the simultaneous consideration of an estimate and its corresponding opposite estimate (i.e., guess and opposite guess) in order to achieve a better approximation for the current candidate solution. By considering opposite individuals during opposition-based population initialization and generation jumping, OBL was successfully applied to DE to solve well-known benchmark problems [9], noisy problems [8], and large scale problems [7]. In this paper, in this paper, a new plate recognition system based on the opposition-based micro-differential evolution (OMDE) algorithm is proposed. In this approach, the OMDE is utilized as an image thresholding method to distinguish the numerical and alphabetical objects in the plate image from the background and other unnecessary objects. After extraction of numerical and alphabetical elements, the simple but efficient template matching method is used to recognize the elements. Finally, the recognized elements are printed on a screen as the identified plate number.

The rest of paper is organized as follows: A review on DE algorithms, with micro and opposition approaches are provided in Section II. In Section III, the proposed plate recognition system is presented and described in details. Performance of the proposed system is then evaluated in Section IV. Finally, the paper is concluded in Section V and some further research challenges are introduced.

II. A REVIEW ON DIFFERENTIAL EVOLUTION

In this section, a review on DE algorithm, micro-differential evolution (MDE) algorithm, and the idea of OBL is presented.
A) Differential Evolution:
DE is an effective population-based optimization algorithm which can be utilized to solve an optimization problem formalized as follows.

\[
\text{Minimize}\ f(x), \quad x = [x_1, x_2, \ldots, x_D] \in \mathbb{R}^D \\
\text{Subject to} \quad g_i(x) \leq 0, i = 1, 2, \ldots, p
\]  

where

\[ x_i^{(L)} \leq x_i \leq x_i^{(U)}, \quad i = 1, 2, \ldots, D \]

and D is the dimension of the problem, \( p \) is the number of constraints, and \( x_i^{(L)} \) and \( x_i^{(U)} \) indicate the lower and upper bounds of the variable \( x_i \), respectively. DE operates through four stages, described below, in order to find the desired optimal solution.

1) Population Initialization: This initiates the search towards the global optimum by having \( NP \) number of population, \( D \) dimensional, uniform randomly generated candidate solutions which are known as initial parameter vectors. Since each parameter vector is subject to change over a limited number of generations (G), it is customary to denote the \( i \)th parameter vector of \( G \)th generation as:

\[ x_{i,G} = [x_{i,1,G}, x_{i,2,G}, \ldots, x_{i,D,G}] \]  

where \( G = \{0,1,2,\ldots,G_{\text{max}}\} \) and \( G_{\text{max}} \) indicates the maximum number of the generations. During the initialization stage, a component of a parameter vector \( x_{i,j,0} \) is initialized according to the following equation:

\[ x_{j,j,0} = x_{j}^{(L)} + \text{rand}_{i,j}(0,1) \times (x_{j}^{(U)} - x_{j}^{(L)}) \]

where \( j = 1, 2, \ldots, D \) and \( \text{rand}(0,1) \) generates a uniform random number in \([0,1]\).

2) Mutation Operator: A mutation operator generates a vector known as a donor vector \( x_{d} \) for each parameter vector in the current population identified as a target vector. Although there are variant DE-mutation schemes [4, 5], the classical version is given as:

\[ x_{d} = x_{i,j,0} + F(x_{i+1,j,0} - x_{i-1,j,0}) \]

where \( F \) is the amplification factor which typically lies in the interval \([0,2]\).

3) Crossover Operator: By shuffling a donor vector with its associated target vector to enhance the potential diversity of the population, this phase results in a vector known as a trial vector \( u_{i,0} \) defined as follows:

\[ u_{j,i,0} = f(x) = \begin{cases} v_{j,i,0}, & \text{if } \text{rand}_{i,j}(0,1) \leq Cr \text{ or } j = \text{rand}_{i,j} \\ x_{j,i,0}, & \text{otherwise} \end{cases} \]

where \( \text{rand}_{i,j}(0,1) \) is the \( j \)th uniformly distributed random number generated for the \( i \)th trial vector, \( Cr \in (0,1) \) is a constant crossover rate, and \( \text{rand}_{i,j} \in \{1,2,\ldots,D\} \) is a random integer number, where ensures \( u_{i,0} \) inherits at least one component from \( V_{i,0} \).

4) Selection: Finally, this step leads to a new generation \((G+1)\) which is derived by having made the selection either to retain the old solution \( x_{i,G} \) or introduce a new candidate solution \( u_{i,0} \) instead. For a minimization problem, it is defined as follows:

\[ x_{i,G+1} = \begin{cases} u_{j,i,0}, & \text{if } v_{j,i,0}(x_{i,G}) \leq f(x_{i,G}) \\ x_{j,i,0}, & \text{otherwise} \end{cases} \]

Figure 1. The idea of opposition-based learning by considering a point and its corresponding opposite in a one, two and three dimension space [2].
**B) Opposition-based Differential Evolution**

The idea of opposition learning in DE algorithm is implemented in the initial population generation and in the generation jumping steps. The OBL considers a point and its opposite in a N-dimensional space, Figure 1. The following steps present the initial population opposition procedure for the DE algorithm.

1) Initialize the population randomly.
2) Calculate opposite population as
   \[ OP_{i,j} = a_i + b_j - P_{i,j} \]  \hspace{1cm} (8)
   For \( i=1,..,NP \) and dimension \( j=1,..,D \).
3) Select \( NP \) fittest individuals from the set \( \{PUOP\} \) as the initial population.

In the generation jumping stage, the opposite of current population is computed as

\[ OP_{i,j} = \text{Min}^D_j + \text{Max}^D_j - P_{i,j} \]  \hspace{1cm} (9)

![System architecture](image)

**III. PROPOSED PLATE RECOGNITION SYSTEM**

The proposed system architecture is presented in Figure 2. As it is demonstrated, after capturing the plate image and calling it from the data center, the image pre-processing using fuzzy logic based noise removal technique is conducted on the image [11]. Then the OMDE thresholding algorithms is applied on the image to distinguish the numbers and alphabets from rest of image. By extracting the numbers and alphabets, the template matching object recognition is performed to finally understand the contents of plate.

Population-based algorithms are capable of searching the problem landscape and find the solutions. Particularly in situations where the problem type is not linear with low dimensions. Standard version of population-based algorithms are utilizing a set of individuals to look for optimal solution. However, since number of agents is large and also the problems are complex, the problem solving procedure takes a long time and is computationally heavy. The micro-population size algorithms utilize a small number of individuals in the population. However, due to lack of diversity, performance of such algorithms is not as well as large-size populations. Therefore, other techniques are required to enhance diversity of such algorithms.

The idea of opposition-based computing, not only considers the individuals, but also uses the opposite of individuals to search the problem landscape. In this way, this method can increase the diversity in the search procedure of a micro-population-based algorithm. In this way, the algorithm risk to experience stagnation or trapping in local optimal places is much lower. The same idea is used in the OMDE algorithm

The pseudocode of the OMDE algorithms is presented in Algorithms 1, where different steps are presented in Section II. The optimization model for a \( M \times N \) plate image with a corresponding threshold value such as \( B(T) \in [0,1] \), where \( T \) is the threshold value, is defined the following minimization model

\[ f(T) = \sum_{i=1}^{M} \sum_{j=1}^{N} |I_{i,j} - B(T)_{i,j}| \]  \hspace{1cm} (10)

In this model the objective is to minimize the dissimilarity between the input plate image and the threshold image [2]. The template matching procedure simply compares each detected element with the set of templates that are available in the systems memory and based on the best match, it picks up the corresponding number or alphabet.

**IV. PERFORMANCE EVALUATION**

In this section the parameter setting for the simulations are presented and the performance of the proposed systems is evaluated and discussed.

**A) Parameter Setting**

In experiments, a set of different plates in different angles of photo shooting are collected. The parameter setting of OMDE is considered as in Table I.

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**Algorithm 1. OMDE thresholding**

- Random opposition-based population initialization, \( P_0 \)
- Objective Function Calculation for the Generated Initial Opposition-Based Population
- \( \textbf{while} \) (satisfying termination criteria) \( \textbf{do} \)
  - For each population member
    - Mutation
    - Crossover
    - Selection
- \( \textbf{EndFor} \)
- Opposition-based Generation Jumping
- \( \textbf{End while} \)
- Thresholding input image with the found optimal value of thresholding level, \( T_{op} \)

where \( \text{Min}^D_j \) and \( \text{Max}^D_j \) represent the minimum and maximum values of the variable \( j \) \([10]\).
Table 1. Parameter setting for experiments.

<table>
<thead>
<tr>
<th>No.</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Population Size</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>Amplification Factor</td>
<td>0.9</td>
</tr>
<tr>
<td>3</td>
<td>Crossover Probability Constant</td>
<td>0.9</td>
</tr>
<tr>
<td>4</td>
<td>Mutation Vector</td>
<td>DE/rand/1/bin</td>
</tr>
<tr>
<td>5</td>
<td>Maximum Number of Function Calls</td>
<td>200</td>
</tr>
</tbody>
</table>

B) Performance evaluation

Performance of the proposed systems is evaluated on a number of Iranian plates. The performance results are compared with the Otsu method for better understanding. As it is presented in Figure 3, performance of the proposed system using the OMDE algorithms is visually similar and in some cases better than the Otsu method.
Another measure to analyze performance of the OMDE algorithm, is its number of function calls versus the cost of optimization model in Eq. (10). The cost is normalized in [0,1] and the algorithm is run for 30 individual runs and then averaged. As it is demonstrated in Figure 4, the algorithm converges to the minimized difference in 57 number of function calls.

V. CONCLUSION AND FURTHER CHALLENGES

In this paper, a new system design for automatic plate recognition is proposed. In this system, the opposition-based micro-differential evolution (OMDE) algorithms is used to apply thresholding on image. The digits and alphabets are extracted using a simple but efficient template matching method.

The proposed algorithm can be developed by enhancing the diversity of OMDE algorithm to minimize the function with fewer number of function calls. Also, utilization of other intelligent techniques such as fuzzy controller is interesting to be examined.

References


