MULTI-OBJECTIVE DISTRIBUTION ROUTING OPTIMIZATION WITH TIME WINDOW BASED ON IMPROVED GENETIC ALGORITHM

C. CHEN †‡ and S. WU† ‡

† *Key Laboratory of Intelligent Robots, Wuhan Institute of Technology, Wuhan, Hubei, China*
3020732141@qq.com
‡ *School of Computer Science and Engineering, Wuhan Institute of Technology, Wuhan, Hubei, China*
381846433@qq.com

***Abstract*— In order to solve the shortcomings of the traditional genetic algorithm in solving the problem of logistics distribution path, a modified genetic algorithm is proposed to solve the Vehicle Routing Problem with Time Windows (VRPTW) under the condition of vehicle load and time window. In the crossover process, the best genes can be preserved to reduce the inferior individuals resulting from the crossover, thus improving the convergence speed of the algorithm. A mutation operation is designed to ensure the population diversity of the algorithm, reduce the generation of infeasible solutions, and improve the global search ability of the algorithm. The algorithm is implemented on Matlab 2016a. The example shows that the improved genetic algorithm reduces the transportation cost by about 10% compared with the traditional genetic algorithm and can jump out of the local convergence and obtain the optimal solution, thus providing a more reasonable vehicle route.**

***Keywords*— Logistics distribution; genetic algorithm; Vehicle Routing Problem with Time Windows (VRPTW).**

I. INTRODUCTION

Vehicle Routing Problem (VRP) (Braekers *et al.*, 2016) is an important combinatorial optimization problem, which is widely applied in the supply chain and logistics related fields. The problem is to design a set of routes that are arranged for each vehicle to meet specific requirements from different locations, which are restricted by constraints such as capacity constraints. VRP has many changes, among which Vehicle Routing Problem (Ghannadpour *et al.*, 2014; Iqbal, 2015) with Time Windows (VRPTW) is the most common one.

The VRPTW is usually described as a set of vehicles that start from the logistics center, deliver the goods to multiple customers and return to the distribution center after the vehicle has completed the delivery task (Slawñiski *et al.*, 2006). Each position and demand of customer are known and each car has the maximum load limit. The goods delivered to the customer must meet certain time limits, and a reasonable arrangement is required to optimize the function of the target. The research of this problem has attracted the attention of many scholars. It is an extension of the vehicle routing problem with load capacity constraints. This is a NP-Hard problem. The algorithm for solving the problem can be divided into the exact algorithm (Contardo *et al.*, 2014; Zheng *et al.*, 2015) and the heuristic algorithm (Reed *et al.*, 2014; Wu *et al.*, 2015a). However, with the increase of customer points, the scale of the problem increases exponentially, and the exact algorithm is difficult to obtain the optimal solution in the effective time. Therefore, heuristic algorithms are usually used to solve the common heuristic algorithms, such as ant colony algorithm (Baker *et al.*, 2013; Wu *et al.*, 2015a), genetic algorithm (Kumar *et al.*, 2015; Shaofei *et al.*, 2015), and simulated annealing algorithm (Yu, 2016). In recent years, due to the emergence of conditional constraint problems such as VRPTW, the traditional heuristic algorithm is prone to be unable to converge and fall into local optimality conditions. In order to solve and improve these problems, many scholars have done a lot of improvement work on heuristic algorithm (Bin *et al.*, 2015; Changdar *et al.*, 2016; Xu *et al.*, 2015; Wang *et al.* 2015; Yan *et al.*, 2017), which aims to improve the searching ability and convergence of the algorithm (Wang *et al.*, 2017).

In order to solve the VRPTW problem more effectively, an improved genetic algorithm is proposed in this paper. By changing the coding structure and cross mutation strategy of the algorithm, the convergence effect and the quality of the algorithm are improved. Simulation experiments verify the effectiveness and superiority of the improved genetic algorithm.

II. METHODS

A. Problem description

The basic VRP problem can be described as that vehicles starting from the distribution center must serve to complete all customer needs and then return to the distribution center. The purpose is to find a set of vehicle routes to meet these needs and restrictions at the minimum total cost (Hong *et al.*, 2017; Huang *et al.*, 2018). The above questions can be simply described as how to arrange the least vehicle and the total distance traveled (Yan *et al.*, 2017; Qin *et al.*, 2015).

The VRPTW problem can be defined as follows (He *et al.*, 2018; Yan *et al.*, 2018): Providing a set of points $V = \{0 \ldots N\}$, the vertex 0 is called the 'distribution center', and the others are called 'customers'. Vehicles with load bearing capacity are used to serve customers. Each customer needs $q_i > 0$ and time window $[\mathrm{e}t_i, \mathrm{l}t_i]$. The service time window constraint indicates that the vehicle should not arrive at the position of the customer earlier than the earliest time $\mathrm{e}t_i$ and not later than the latest time $\mathrm{l}t_i$. If the vehicle does not meet the time requirements of the service customer, a penalty cost, such as the delay fee, will be given accordingly.

B. Model Building

In this model, each customer can only be completed by a car in the time window$[\mathrm{e}t_i, \mathrm{l}t_i]$, The maximum load of each car is Q. The optimization goal is to determine the shortest route of the total route to meet all customer needs with the least transport vehicle (Wu *et al.*, 2017b). In order to simplify the problem, define the following symbols:

m: The number of distribution vehicles.
c_{ij}: The cost of customer i to customer j.
d_{ij}: The distance from the customer i to the customer j.
t_i: The actual time of the vehicle arriving at i.
$[\mathrm{e}t_i, \mathrm{l}t_i]$: The task time window of i.
q_i: The demand for goods of i.
Q: The Maximum load of vehicle.
s_i: The required service time of i.

$$\mathrm{P}(t_i) = \begin{cases} a(et_i - t_i), t_i < et_i \\ 0, et_i < t_i < lt_i \\ b(et_i - t_i), t_i > lt_i \end{cases} \quad (1)$$

$$x_{ijk} = \begin{cases} 1, k \ goes \ from \ i \ to \ j \\ 0, \text{otherwise} \end{cases} \quad (2)$$

$$y_{ik} = \begin{cases} 1, k \ completes \ i^{\prime} s \ task \\ 0, \text{otherwise} \end{cases} \quad (3)$$

The formula (1) represents the time penalty cost, and the formula (2) sum (3) is the decision variable. K presents vehicle, i and j represent the customers.

The multi-objective path planning problem with time windows and load constraints can be expressed as follows (Wu *et al.*, 2017a; Yu *et al.*, 2017; Yang *et al.*, 2017):

$$\mathrm{F} = \min(F_1 + F_2) \quad (4)$$

$$F_1 = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} C_{ij} \times d_{ij} \times x_{ijk} \quad (5)$$

$$F_2 = \sum_{k=1}^{m} P(t_i) \quad (6)$$

$$\sum_{i=1}^{n} q_i y_{ik} \leq Q, k = 1,2, \dots, m \quad (7)$$

$$\sum_{k=1}^{m} y_{ik} = 1, k = 1,2 \dots, n \quad (8)$$

$$\sum_{i=0}^{n} x_{ijk} = y_{jk}, j = 1,2, \dots, n, k = 1,2, \dots, m \quad (9)$$

$$\sum_{j=0}^{n} x_{ijk} = y_{ik}, j = 1,2, \dots, n, k = 1,2, \dots, m \quad (10)$$

$$\mathrm{e}t_i < t_i < lt_i \quad (11)$$

$$\sum_{j=0}^{n} x_{0jk} = 1, j = 1,2, \dots, n, k = 1,2, \dots, m \quad (12)$$

$$\sum_{i=0}^{n} x_{i0k} = 1, k = 1,2, \dots, m \quad (13).$$

The objective function (4) represents the sum of minimized costs, including distance cost and penalty cost against time windows. Equation (5) represents the distance cost. Equation (6) represents the penalty cost of vehicle against time windows. The constraint condition (7) is the weight limit of the transport vehicle. Constraint conditions (8) ensure that I is only allowed to be served by one vehicle. Constraint conditions (9) and (10) indicate the relationship between two decision variables. Constraint conditions (11) require each order of the customer to be served within a given time. Constraints (12) and (13) ensure transportation vehicles start and return to distribution centers.

C. Improved genetic algorithm design

Because the path planning problem with time window has multiple constraints, the traditional genetic algorithm cannot be well inherited when solving such problems, so it is easy to get poor solution and infeasible solution (Yu *et al.*, 2017; Yan *et al.*, 2017; Wang *et al.*, 2017). The purpose of this paper is to improve the coding, crossover and mutation of the algorithm with the aim of preserving excellent genes and increasing population diversity.

Constructing chromosomes by direct arrangement of client points (Yu *et al.*, 2017). Each of these genes represents a customer. Because there are certain restrictions on transportation vehicles, such as load limit, time window, and so on, and transportation vehicles must return to the distribution center, so we need to insert '0' in the customer sequence. So, '0' represents the distribution center. For example, sequence (0, 2, 5, 4, 0) indicates that the transport vehicle starts from the distribution center and visits the customer point 2, the customer point 5 and the customer point 4, then return to the distribution center. Therefore, each chromosome can represent multiple transport vehicles and routes. For example, chromosome "015027608490" represents three paths, the first one is 0-1-5-0, the second is 0-2-7-6-0, and the third one is 0-8-4-9-0.

The initial population is the beginning of genetic algorithm, and its composition has great influence on its evolution. According to the sequence of chromosomes, each demand for goods of the customer is allocated to the first vehicle in turn. When the maximum load of the car is greater than C_1, $C_2, C_3 \dots C_i$'s total weight and less than the total weight of C_1, $C_2, C_3 \dots C_i, C_{i+1}$, the substring (C_1, $C_2, C_3 \dots C_i$) represents the customer serving the first car.

Starting from C_{i+1} customers, repeat the above method, and second car can also get customers who need services (C_{i+1}, $C_{i+2}, C_{i+3} \dots C_{i+m}$). Finally, all the goods were loaded into the vehicle. In this way, chromosomes can be obtained continuously until they reach the initial population.

The goal of the model is to minimize the total cost, so the reciprocal of the objective function is used as fitness function. Due to the constraints of time windows and vehicle capacity, penalty factors need to be added, so the fitness function should be changed accordingly. For time window constraints, if it is a hard time window problem, when the arrival time is not within a given time window, the fitness function is set to infinity. If it is a soft time window, early arrival or late arrival can be allowed and punished accordingly. Using the roulette method to choose elites. The fitness value of each individual chromosome is calculated. One individual is selected each time, and N time is selected. The higher the fitness value, the larger the probability of being selected, which ensures the optimization effect of the algorithm.

Due to the conditional constraint of VRPTW problem, it is easy to produce infeasible solutions and inferior individuals by means of general crossover methods, resulting in poor convergence of the algorithm. In this paper, a maximum retention cross method is adopted to preserve the best genes as far as possible. Firstly, two paternal chromosomes were selected, and a gene segment was selected randomly as a cross reservation region, the initial sequence and length of this gene segment are the same. To avoid generation of infeasible solutions after gene deletion or duplication after crossing, the number of distribution centers contained in the gene segment must also be the same. Then, the two chromosomes separate the customer genes from the reserved regions in the chromosomes of each other to cover each other's non-reserved region and generate a pair of offspring chromosomes, such as Fig. 1:

Parent:

$P_1 = [0\ \boxed{1\ 7\ 5}\ 0\ 6\ 3\ 8\ 0\ 2\ 4\ 0]\quad \boxed{P_2} = [0\ 3\ 4\ 2\ 0\ 7\ 1\ 8\ 0\ 6\ 5\ 0]$

Children:

$C_1 = [0\ \boxed{4\ 2\ 7}\ 0\ 6\ 3\ 8\ 0\ 1\ 5\ 0]\quad \boxed{C_2} = [0\ 5\ 6\ 3\ 0\ 7\ 1\ 8\ 0\ 2\ 4\ 0]$

Figure 1. Example of cross operation.

In the process of evolution, in order to ensure the diversity of population, a probability of chromosomal variation has been set as P_m, the first gene in each chromosome of a chromosome does not produce variation. That is, the first customer of each vehicle path is unchanged. For every other gene I, a floating-point number Z_i corresponding gene i is generated randomly between 0~1. If $Z_i < P_e$, the gene is put into the gene bank Z, and a chromosome has been deleted.

Table 1. Customer point information.

Customer number	Coordinate (km)	Demanded (t)	Service Time (h)	Time window (h)
1	(3.6,5.7)	1.6	0.5	[3.6,11.5]
2	(14.2,11.9)	0.7	0.5	[2.5,6.3]
3	(17.3,12.5)	0.5	0.5	[4.6,11.2]
4	(10.8,8.7)	1.5	0.5	[4.2,8.4]
5	(7.2,9.5)	0.9	0.5	[4.3,9.9]
6	(5.1,9.7)	0.8	0.5	[6.4,12.6]
7	(0.9,10.7)	1.4	0.5	[6.9,11.9]
8	(6.4,17.0)	1.2	0.5	[0.8,6.1]
9	(7.3,19.1)	0.7	0.5	[2.8,6.5]
10	(16.1,15.7)	1.4	0.5	[3.5,9.1]
11	(14.3,15.2)	1.2	0.5	[5.2,11.3]
12	(1.8,15.7)	0.6	0.5	[2.4,7.1]
13	(9.1,7.2)	0.9	0.5	[0.0,6.0]
14	(2.5,13.7)	1.6	0.5	[5.4,10.6]
15	(7.0,11.0)	1.6	0.5	[3.1,7.5]
16	(18.5,7.2)	0.7	0.5	[6.7,12.2]
17	(13.9,4.7)	0.8	0.5	[7.3,13.7]
18	(14.0,17.7)	1.3	0.5	[7.1,11.7]
19	(9.3,6.0)	0.5	0.5	[4.9,8.8]
20	(2.5,6.0)	1.1	0.5	[6.5,12.5]

Otherwise, no variation is produced. After that, the genes in the Z are randomly inserted into the position of the first gene of any of the chromosomes in the chromosome, and then the vehicle is inserted to judge whether the vehicle is overloaded. If overloaded, the next chromosome is inserted into the next chromosome and again to judge whether the operation is overloaded until the genes in the Z are allocated, setting the maximum number of iterations as the terminating condition.

III. RESULTS AND DISCUSSION

Application of improved algorithm to solve the following path problem:

A logistics company provides distribution services for 20 customers, and all vehicles start from the distribution center. The coordinates of the distribution center are (5.4 km, 13.5 km).

The information of the 20 customers, as shown in Table 1, requires the arrangement of the appropriate number of vehicles and distribution routes to minimize the total cost of distribution.

It is known that the maximum load of each vehicle is 5T, the maximum driving distance is 50km, and the average speed in the transportation process is 30km/h, because the target is the distance cost. In order to unify the unit, the early and late penalties are determined to be 3km/h and 5km/h respectively.

The specific parameters of the algorithm are set as follows:

Population size	N = 100
Number of iterations	M = 200
Cross probability	$P_c = 0.75$
Mutation probability	$P_m = 0.1$
Generation gap	C = 0.9

The algorithm had been run 20 times on Matlab 2016a. The average total distance cost is 153.7km, the average distance is 122.4 km, the average penalty distance is 31.3km. The average iteration number of the optimal solution is 74 times. The optimal scheme is described as follows: Total distance cost = 144.5 km; Total distance = 118.7 km; Number of times = 70 times. So, both paths, that are random initial and the optimal one of the vehicle, are shown respectively in Figs. 2 and 3. Additionally, the optimization process is shown in Fig. 4.

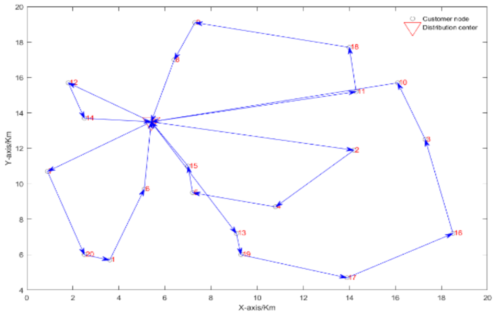

Figure 2. Initial vehicle path.

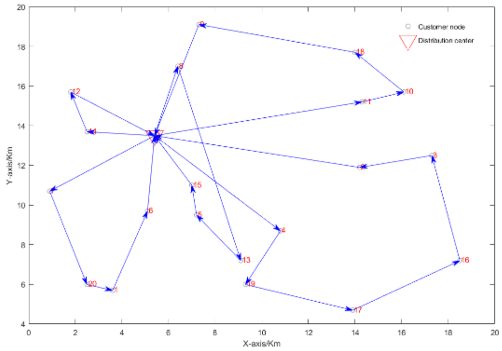

Figure 3. Optimal vehicle path.

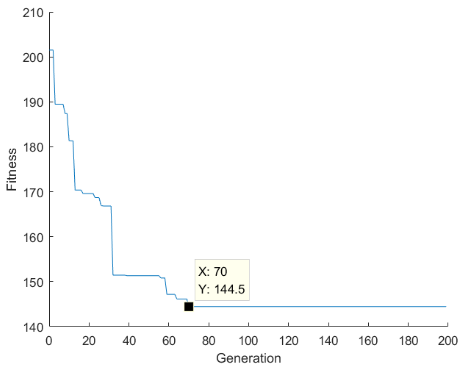

Figure 4. Algorithm optimization process.

Table 2. Comparison between IGA and GA.

Type	Optimal value /km	Worst value /km	Average value /km	Search success rate	Average iteration number
IGA	144.5	157.2	153.7	90%	73
GA	164.4	176.5	170.3	55%	71

In order to verify the superiority of the improved genetic algorithm (IGA), the traditional genetic algorithm (GA) is simulated. The results obtained from 20 times are compared with the improved genetic algorithm, and the statistical information is shown in Table 2.

From Table 2, when the traditional genetic algorithm is used to solve the optimal value, the quality of the solution and the global search ability are poor, and it is easy to get infeasible solutions and fall into local optimum.

The improved genetic algorithm maximizes the excellent gene segment in the crossover and mutation operation, improves the population diversity, makes the algorithm better than the traditional genetic algorithm in the quality of optimizing the optimization performance.

Compared with the traditional genetic algorithm, the improved genetic algorithm reduces the total cost of 9.7% transportation and achieves the goal of optimization. It further illustrates that the algorithm proposed in this paper has a great advantage in solving that kind of problems.

VI. CONCLUSIONS

This paper studies the problem of route optimization of logistics distribution, which not only considers the minimum path cost, but also regards the service time window with penalty and vehicle load limit, and thus establishes a more perfect vehicle routing problem model. A genetic algorithm is designed for the characteristics of the model. In order to verify the effectiveness and efficiency of the proposed genetic algorithm, a simulation experiment of the proposed algorithm is carried out in combination with an example. Experimental results show that the algorithm designed in this paper has better search ability and higher solution quality. Compared with the traditional genetic algorithm, it further proves the effectiveness and superiority of the algorithm.

ACKNOWLEDGEMENTS

This work was supported by Natural Science Foundation of Hubei Province of China (Grant No. 2018CFB681).

REFERENCES

Baker, E.K. and J.R. Schaffer, “Solution Improvement Heuristics for the Vehicle Routing and Scheduling Problem with Time Window Constraints”, *American Journal of Mathematical & Management Sciences*, **6(3-4)**, 261-300 (2013).

Bin, G.E., J.H. Han, W. Zhen, C. Lei and H. Yue, “Dynamic Hybrid Ant Colony Optimization Algorithm for solving the Vehicle Routing Problem with Time Windows”, *Pattern Recognition & Artificial Intelligence*, **28(7)**, 641-650 (2015).

Braekers, K., K. Ramaekers and I.V. Nieuwenhuyse, “The Vehicle Routing Problem: state of the art classification and review”, *Computers & Industrial Engineering*, **99**, 300-313 (2016).

Changdar, C., G.S. Mahapatra and R.K. Pal, “A modified genetic algorithm-based approach to solve constrained solid tsp with time window using interval valued parameter”, *International Journal of Operational Research*, **26(4)**, 398 (2016).

Ghannadpour, S.F., S. Noori, R, Tavakkoli-Moghaddam, and K. Ghoseiri, “A multi-objective dynamic vehicle routing problem with fuzzy time windows: Model, solution and application”, *Applied Soft Computing*, 14, 504-527.

He, Y., Y. Zeng and H. Chen, “Research on improved edge extraction algorithm of rectangular piece”, *International Journal of Modern Physics C*, **29(1)**, Document number: 1850007, (2018).

Hong, H. and Y. Shi, “Fast deconvolution for motion blur along the blurring paths”. *Canadian Journal of Electrical and Computer Engineering-Revue Canadienne de Genie Electrique et Informatique*, **40(4)**, 266-274 (2017).

Huang, Z., Y. Zhang and Q. Li, “Spatially adaptive denoising for X-ray cardiovascular angiogram images”, *Biomedical Signal Processing and Control*, **40**, 131-139 (2018).

Iqbal, S., M. Kaykobad and M.S. Rahman, “Solving the multi-objective Vehicle Routing Problem with Soft Time Windows with the help of bees”, *Swarm and evolutionary computation*, **24**, 50-54 (2015).

Kumar, S.N. and R. Panneerselvam, “A time-dependent Vehicle Routing Problem with Time Windows for e-commerce supplier site pickups using genetic algorithm”, *Intelligent Information Management*, **07(2)**, 181-194 (2015).

Qin, S., F. Yuan and L. Cheng, “Research on improving adaptive variable step length MPPT algorithm”, *International Journal of Sensor Networks*, **17(3)**, 139-145 (2015).

Reed, M., A. Yiannakou and R. Evering, “An Ant Colony Algorithm for the Multi-compartment Vehicle Routing Problem”, *Applied Soft Computing Journal*, **15(2)**, 169-176 (2014).

Slawñiski, E., V.A. Mut and J.F. Postigo, “Stability of Systems with Time-Varying Delay”, Latin American Applied Research, 36(1), 41-48 (2006).

Wang, C., D. Mu, F. Zhao and J.W. Sutherland, “A parallel simulated annealing method for the Vehicle Routing Problem with Simultaneous Pickup–delivery and Time Windows”, *Computers & Industrial Engineering*, **83(C)**, 111-122 (2015).

Wang, F. and Q. Zhang, “Systemic Estimation of Dam Overtopping Probability: Bayesian Networks Approach”, *Journal of Infrastructure Systems*, **23(2)**, Document number: 04016037 (2017).

Wu, Q., L. Wang and Z. Zhu, “Research of pre-stack AVO elastic parameter inversion problem based on hybrid genetic algorithm”, *Cluster Computing-The Journal of Networks Software Tools and Applications*, **20(4)**, 3173-3183 (2017a).

Wu, Q., Z. Zhu and X. Yan, “Research on the parameter inversion problem of pre-stack seismic data based on improved differential evolution algorithm”, *Cluster Computing-The Journal of Networks Software Tools and Applications*, **20(4)**, 2881-2890 (2017b).

Wu, S., "A Traffic Motion Object Extraction Algorithm", *International Journal of Bifurcation and Chaos*, **25(14)**, Article Number 1540039 (2015a).

Wu, S., W. Mingqing and Z. Yuntao, "Research on internet information based on agent algorithm", *Future Generation Computer Systems*, **86**, 598-602 (2018a).

Wu, S., W. Mingqing and Z. Yuntao, "Sewage information monitoring system based on wireless sensor", *Desalination and Water Treatment*, **121**, 73-83 (2018b).

Wu, Y., L. Amir and R. Jensen Jesper, "Joint Pitch and DOA Estimation Using the ESPRIT Method", *IEEE-ACM Transactions on Audio Speech and Language Processing*, **23(1)**, 32-45 (2015b).

Wu, Y., X. Pei and C. So Hing, "Utilizing Principal Singular Vectors for 2D DOA Estimation in Single Snapshot Case with Uniform Rectangular Array", *International Journal of Antennas and Propagation*, Document number: 681251 (2015c).

Yan, X., H. Liu and Z. Zhu, "Hybrid genetic algorithm for engineering design problems", *Cluster Computing-The Journal of Networks Software Tools and Applications*, **20(1)**, 263-275 (2017).

Yan, X., W. Gong and Q. Wu, "Contaminant source identification of water distribution networks using cultural algorithm", *Concurrency and Computation-Practice & Experience*, **29(4)**, Document number: UNSP e4230 (2017).

Yang, X. and Q. Wang, "A 2D numerical study of polar Yan, X., H. Liu and Z. Zhu, "Hybrid genetic algorithm for engineering design problems", *Cluster Computing-The Journal of Networks Software Tools and Applications*, **20(1)**, 263-275 (2017).

Yu, R., C. Ding and D. Zhang, "All-optical control of weak-light transport and Fano-like resonance using control-probe technique in a quantum-dot-pillar microcavity system", *Journal of Applied Physics*, **121(14)**, Document number: 144303 (2017).

Yu, S., J. Song and X. Hua, "Poissonian Image Deblurring Method by Non-local Total Variation and Framelet Regularization Constraint", *Computers & Electrical Engineering*, **62**, 319-329 (2017).

Yu, Z., H. Zhou and C. Li, "Fast non-rigid image feature matching for agricultural UAV via probabilistic inference with regularization techniques", *Computers and Electronics in Agriculture*, **143**, 79-89 (2017).

Received: December 15th 2017
Accepted: June 30th 2018
Recommended by Guest Editor
Juan Luis García Guirao