A novel edge gradient algorithm for multiple mobile robots cooperative mapping in unknown environment

Huang Yiqing¹,², Wang Hui¹,², Wei Lisheng¹,², Gao Wengen¹,² and Ge Yuan¹,²

Abstract
This article presented a cooperative mapping technique using a novel edge gradient algorithm for multiple mobile robots. The proposed edge gradient algorithm can be divided into four behaviors such as adjusting the movement direction, evaluating the safety of motion behavior, following behavior, and obstacle information exchange, which can effectively prevent multiple mobile robots falling into concave obstacle areas. Meanwhile, a visual field factor is constructed based on biological principles so that the mobile robots can have a larger field of view when moving away from obstacles. Also, the visual field factor will be narrowed due to the obstruction of the obstacle when approaching an obstacle and the obtained map-building data are more accurate. Finally, three sets of simulation and experimental results demonstrate the performance superiority of the presented algorithm.

Keywords
Multiple mobile robots, cooperative mapping, visual field factor, edge gradient algorithm

Introduction
Mapping, localization, and path planning are three major tasks in robotic navigation. Autonomous mapping is one of the crucial and challenging problems for mobile robots.¹,² Currently, the simultaneous localization and mapping (SLAM) method is proven to be an effective technique for achieving self-localization and map construction simultaneously, which can be successfully applied to many robotics fields such as soil mapping on farms,³ monitoring of power lines,⁴ and online robot navigation system.⁵ In the last decade, many significant approaches in mobile robots localization and mapping have been performed. A fast algorithm of SLAM based on the ball particle filter is presented for mobile robot in the work of Jinwen and Qin,⁶ the proposed SLAM algorithm is verified by a series of simulation experiments and exhibited good performance.

To improve the localization accuracy in SLAM, an improved iterative extended Kalman filter is developed, which is used to estimate the mobile robot position. Then, a perception-driven hierarchical SLAM method that can be used.

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applied to search and rescue environments is presented in
the work of Hongling et al. However, mobile robot map
construction methods are divided into three methods:
geometrical, topological, and hybrid. A kind of topological
map is used to demonstrate modeling of indoor environ-
ment and a topological localization and mapping approach
is presented for mobile robots via human memory model.
However, most of reconstructed environment models only
include geometry information, which decreased the level of
robot autonomy in complex environment. The authors
developed a three-dimensional (3-D) reconstructed seman-
tic map using a RGB-D image sequence in the work of
Zhe and Chen. Further, an indoor positioning system is
developed by RGB-D mapping method and neural network
training algorithm in the work of Chun and Su, which can
improve the association result in the intelligent mobile
robot pose tracking and apply to multiple robots indoor
positioning system. Unlike the static environment in tradi-
tional research results, map construction in dynamic envir-
onments is more challenging due to the uncertainty of the
estimated state variables. A new mapping method is
presented for long-term mobile robot in dynamic indoor
environments in the work of Tomás et al. In addition,
by combining normal distribution transform technique and
occupancy mapping, a generic SLAM system based on
sensor independent graph is developed, which is suitable
for 2-D and 3-D mapping in dynamic environment. However,
robot mapping in outdoor environments has caused
extensive attention due to various uncertainties and
unknown disturbances, the authors consider the uncer-
tainties arising from multiple sources and a set—thetoric
algorithm is developed to realize real-time terrain mapping
for mobile robots in outdoor environments. Subse-
sequently, for a mobile robot in outdoor environments, a new
3-D SLAM technique with terrain inclination assistance is
presented by using iterative closest points (ICP) algo-
rithm. Nowadays, the elevation map becomes the most
popular map in outdoor robot navigation. An outdoor loca-
larization system is developed using the presented elevation
moment of inertia and Monte Carlo localization method in
the work of Tae-Bum et al. However, vision-based
SLAM method may fail to the application of outdoor
mobile robot navigation system due to image blur and
low-cost hardware. Thus, the authors proposed a novel
SLAM algorithm to solve the problem of low lighting, low
cameras, and perceptual change via visual place recogni-
tion technique. Accurate mapping in urban environments
is a crucial topic for autonomous robots. Based on a sparse
2-D map, the article proposed global localization technique
of 3-D point clouds, which is verified on the collected
large data sets in two different real environments. How-
ever, all of the above-mentioned SLAM algorithms are
built on the static environments assumption, which limits
the applications of these presented methods. Therefore, to
improve Red Green Blue-Depth (RGB-D) SLAM algo-
rithm in dynamic environments. The authors proposed a
novel RGB-D data-based motion removal method with a
freely moving RGB-D camera. Subsequently, an online
RGB-D data-based motion removal approach is proposed
and it is worth mentioning that the algorithm does not
require prior knowledge from moving objects.
In generally, multiple mobile robots can improve the
working capability and performance. Therefore, recently,
research on localization and mapping of multiple mobile
robots has become a hot topic. The authors focused on the
problem of unknown environments cooperative mapping,
which developed a new unified methodology and cooper-
ation architecture for heterogeneous mobile robots with
inexpensive sensing ability. The SLAM problem is inge-
niously decomposed into the recursive calculation. Sub-
sequently, a multiple mobile robots cooperative
localization and mapping method is proposed based on
hybrid dynamic belief propagation algorithm. However,
each robot can build a map to complete its assigned task
and multiple robots system can obtain the relative location
by a shared map. So, the author developed an effective map
construction method using a wave algorithm for a multi-
robot system. Also, each mobile robot takes an indepen-
dent task to avoid the problem of graphics redundancy in
multirobot system. The authors presented a decentralized
multirobot mapping and graph exploration approach with
collision avoidance. As multiple mobile robots mapping
systems play a critical role in many robotic applications,
distributed cooperative mapping techniques of multiple
mobile robots are required in unknown environment.
Note that the search efficiency of the above-mentioned
methods is relatively low for large and complex environ-
mental maps. Therefore, to increase the robustness and
efficiency in the problem of mobile robot mapping, the
unknown environment is divided into four quadrants and
we presented a cooperative mapping method using a novel
dge gradient algorithm. The proposed algorithm with four
different behaviors can effectively prevent multiple mobile
robots falling into concave obstacle areas. The main
contributions of the article are summarized as follows: (1) the
proposed edge gradient algorithm can be divided into four
behaviors, which can effectively prevent multiple mobile
robots falling into concave obstacle areas; (2) comparing
with the existing research results, in this article, a visual
field factor is constructed based on biological principles,
which make the obtained map-building data more accu-
rately; and (3) simulation and experiment results in real
environments verify the feasibility of the presented edge
gradient as an online cooperative mapping approach for
multiple mobile robots. The remainder of this article is
organized as follows. The second section describes mobile
robots model and problem formulation. The third section
presents the novel edge gradient algorithm. The fourth sec-
tion shows the results of simulation and experiment to
demonstrate the performance of the proposed algorithms.
The concluding remarks are given in the fifth section.
Mobile robots model and problem formulation

The current position of the robot is taken as the coordinate origin and the unknown environment is divided into four quadrants. Suppose each robot is equipped with ultrasonic and infrared sensors, the maximum sensing range is 5 m. The robot moves at a constant speed $v$. We can obtain the following motion equations of the robot at time $k + 1$

$$
x_{k+1} = f(x_k, y_k, v, \theta, \beta_1, \beta_2, \text{dr})
$$

$$
\begin{align*}
x_{k+1} &= x_k + v \times \cos \theta \times \text{dr} \\
y_{k+1} &= y_k + v \times \sin \theta \times \text{dr}
\end{align*}
$$

where $x_k$ and $y_k$ are the position coordinates at time $k$, $v$ and $\theta$ denote the velocity and the angle between the velocity direction and the abscissa axis, and $\text{dr}$ is sampling time.

As shown in Figure 1, the field of view of the robot can be described as follows

$$
\begin{align*}
\beta_1 &= \theta - \frac{\alpha}{2} \\
\beta_2 &= \theta + \frac{\alpha}{2}
\end{align*}
$$

where $\beta_2 - \beta_1 = \pi$ is angular field of view of the robot, $\alpha = \pi$.

A novel edge gradient algorithm

In this section, a novel edge gradient algorithm is proposed for multiple mobile robots cooperative mapping in unknown environment. The algorithm enables the robots to construct the environment map by collecting the relative coordinate information of the obstacle while exploring the unknown environment. The virtual coordinate axis is constructed to make the robots distinguish the difference between the obstacle and the edge of the obstacle, which plays an auxiliary role in constructing the map in the unknown environment. Also, the visual field factor is constructed based on biological principles. It is worth mentioning that the field of view of the robot can be adjusted adaptively by the developed visual field factor. We divide the virtual coordinate system into four quadrants from the starting point. Each robot starts to move along the X axis or the Y axis. During the construction of the environment map, the robot responsible for edge exploration maintains a safe distance from the edge of the obstacle, while the robot for obstacle exploration collects the detected nonedge obstacle information. The edge gradient algorithm can be divided into the following four behaviors: adjusting the direction of motion, evaluating the safety of motion behavior, following behavior, and obstacle information exchange.

Adjusting the movement direction

The behavior of adjusting the movement direction occurs only when the following two situations are encountered. One is that the next moment of the current state is no longer safe, the robot may hit the obstacle or the distance between the robot and the obstacle is lower than the safety distance, the other is that the obstacle is lost in the field of view of the mobile robot. Therefore, we developed four kinds of the motion direction adjustment strategies when $\theta = 0$, $\theta = \pi$ or $-\pi$, $\theta = \pi/2$, and $\theta = -\pi/2$, as shown in Figure 2.

In Figure 2(a) to (d), $\text{sgn}_A$ and $\text{sgn}_B$ are represented as the right and left sides of the moving direction of the mobile robot, respectively. $A_2A_1$ and $B_2B_1$ denote the original motion direction. $A_2A_1$ and $B_2B_1$ are the motion direction after adjustment. Suppose the coordinates of an obstacle are $p_k(x_k, y_k)$ and $p_{k+1}(x_{k+1}, y_{k+1})$ at time $k$ and $k + 1$, respectively. The vertical distance between the obstacle and the direction of the robot motion are $d_1$ and $d_2$. When $d_1 > d_2$, it indicates that the robot is constantly approaching the obstacle, and there is a possibility of collision. when $d < d$, the situation is reversed.

Therefore, a flag bit $\text{sgn}$ is defined as follows:

$$
\text{sgn} = \begin{cases} 
1 & d_1 > d_2 \\
-1 & d_1 \leq d_2
\end{cases}
$$

In this article, we design the following motion direction adjustment function

$$
\theta' = \theta + \text{sgn} \times \text{sgn}_{\text{flexible}} \times \frac{\pi}{2}
$$

In equation (5), $\text{sgn}_{\text{flexible}} = -1$ when the obstacle is on the left side of the movement direction, contrarily, $\text{sgn}_{\text{flexible}} = 1$.

Evaluating the safety of motion behavior

The mobile robot uses the infrared sensor and the ultrasonic sensor to determine the distance between the current position and the obstacle within the field of view. At the same time, the robot predicts the position of the movement direction at the next moment to determine whether the distance
between the position and the obstacle is safe. If it is not safe, adjust the angle of movement until the obstacle to be followed is still within the field of view. The flow chart for evaluating the safety of motion behavior is shown in Figure 3. Dist Barrier and save level denote the distance between obstacles and the safety distance coefficient between obstacles, respectively.

**Following behavior**

The basic principle of following behavior is that the mobile robot keeps the target obstacle in its field of view by adjusting the direction of motion and evaluating the safety of motion behavior. If the multiagent does not detect the obstacle information, it will move along the X or Y axis of the coordinate axis. When an obstacle is detected, it will judge whether it is an obstacle edge or an obstacle inside the edge according to the position of its coordinate axis. At the same time, the incremental position coordinates (Δx, Δy) are constructed to determine whether the intersection between obstacles is within the field of view, and if it is, it is stored as effective information.

**Obstacle information exchange**

Multiagent robots are numbered from agent 1 to agent 8. Agents with odd numbers (i.e. agents 1, 3, 5, and 7) perform unknown environment edge exploration tasks, and agents with even numbers (i.e. 2, 4, 6, and 8) perform internal obstacle bypass tasks. To quickly complete the map construction task of the four quadrants in the plane coordinate system, the agents are divided into four groups. The agent-robot responsible for exploring the edge of the obstacle is prone to detect obstacle information in other quadrants through a larger field of view, but the obstacle information has no effect on its task and it will be stored separately to maximize the efficiency of information usage. After receiving the obstacle information, the robot queries the obstacle information in the existing obstacle set and discards the information if it already exists; otherwise, it will be saved in a new obstacle set. Then, the obstacle information is sent to the corresponding quadrant, a circular area with the radius r is generated, which is used for a landmark to assist the path generation for the robot. When the robot completes the obstacle bypass and returns to the starting position, if all the circular areas of the received obstacle landmark are passed, the path is completely correct; otherwise, it indicates that there is still obstacle information that is not collected and the task needs to be executed again. The flow diagram of the presented edge gradient algorithm is shown in Figure 4.

**Simulation and experiment results**

In this section, we evaluate the performance of the proposed edge gradient algorithm by simulation analysis and real environment experiments.
Simulation results

Simulation experiments for multiple mobile robot cooperative mapping based on edge gradient algorithm are given in three different unknown environments. Figure 5 shows three different shapes obstacle environments which are constructed by linear programming method. Among the three different shapes obstacle simulation environments, we only place one obstacle in each quadrant for Figure 5(a) and (b) and simulation environments are relatively simple. Compared with Figure 5(a) and, more complex environment is considered in Figure 5(c). Eight mobile robots labeled as agent $i$ ($i = 1, 2, \ldots, 8$) are used for map construction. Suppose the speed of each agent-robot $v = 0.2$ cm/s. The intersection point between the obstacle and the field of view is used as landmark to generate a circular of radius $r = 1$.

Figure 6 demonstrates motion trajectories of eight mobile robots during map construction. The final map construction results in three different simulation environments are shown in Figure 7. As shown in Figure 7(a) to (c), the presented edge gradient algorithm can build highly precise map in unknown environment with complex shape concave or convex polygonal obstacles.

To demonstrate the superiority of the presented algorithm, simulation comparison results are given between our algorithm and the algorithm without the visual field factor. Actually, the reference algorithm used for comparison does not consider visual field in the process of map construction.

While a visual field factor is developed in our algorithm, which can improve the search efficiency of the algorithm. Figure 8(a) is a constructed simulation environment, Figure 8(b) and (c) are motion trajectories of the robots using the mapping algorithm without the visual field factor and the presented algorithm, respectively. In the second quadrant, we can clearly see that the iterative path obtained by our
method is shorter than the mapping algorithm without the visual field factor.

In this article, a visual field factor is developed based on biological principles. The mobile robots can have a larger field of view when moving away from obstacles, which can improve the search efficiency of the algorithm. Further, performance comparison results are given in Table 1 for the present algorithm and the mapping algorithm without considering the visual field factor. We can see clearly that the developed visual field factor improves the search efficiency.

**Experiment results**

In real environment experiments, the practicability and rationality of the edge gradient algorithm is demonstrated by a single robot. TurtleBot is used to test the performance of the presented method in unknown environment, which is robot operating system (ROS) standard platform robot. As shown in Figure 9, The TurtleBot is equipped with a 360

Figure 6. Eight robot paths in three different simulation environments.

Figure 7. Map construction results in three different simulation environments.
lidar for slam and navigation, single board computer, Open-source Control module for ROS (OpenCR) and sprocket wheels for tire and caterpillar.

As shown in Figure 10, the novel edge gradient algorithm is tested in two different real environments.

Table 1. Performance comparison.

| Method                               | The number of iterations | Path length (m) | Iteration time (s) |
|--------------------------------------|--------------------------|-----------------|--------------------|
| The algorithm without visual field factor | 65                       | 13              | 6500               |
| The presented algorithm              | 52                       | 10.4            | 5200               |

Figure 9. TurtleBot platform robot.

Figure 10. Two different real environments.
10(a) is an environment with carton obstacles and Figure 10(b) is a laboratory environment with some desks and chairs. The experimental parameters are the same as the multiple mobile robots parameter settings in previous section. Obstacles data in two real environments can be acquired by the sensors of TurtBot. Reconstructed maps can be obtained by Robots Operating System Visualizer (RVIZ) simulation platform. We can see the obstacle contour lines and the robot paths in Figure 11.

The fan-shaped area with arrows in the figure is formed by adjusting the angle of motion. The mobile robot gradually accumulates the odometer data errors due to the actuator errors. Therefore, we can see the motion path of the mobile robot is not a straight line and the robot has to adjust the direction of motion many times, which is different from the obtained simulation results by MATLAB 7.0 software. In experiment, based on the principle of extended Kalman filter, the position and attitude of mobile robot are tracked according to the environmental map information, and the real-time feedback compensation for the accumulated errors can be realized.

Conclusions
This article focuses on the problem of exploring an unknown environment and constructing a map by multiple mobile robots. A novel edge gradient algorithm is proposed to realize cooperative mapping of multiple mobile robots in unknown indoor environment. The proposed algorithm with four different behaviors can effectively prevent multiple mobile robots falling into concave obstacle areas. In order for map-building data to be more accurate, a visual field factor is constructed based on biological principles. Simulation and experiment results in real environments verify the feasibility of the proposed edge gradient as an online cooperative mapping and positioning method for multiple mobile robots.

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References
1. Lee JS, Yep NS, and Kyun CW. Robust RBPF-SLAM for indoor mobile robots using sonar sensors in non-static environments. Adv Robot 2011; 25(9-10): 1227–1248.
2. Wang J and Takahashi Y. SLAM method based on independent particle filters for landmark mapping and localization for mobile robot based on HF-band RFID system. J Intell Robot Syst 2018; 92(3-4): 413–433.
3. Jaime PF, Gould I, Duckett T, et al. 3-D soil compaction mapping through kriging-based exploration with a mobile robot. IEEE Robot Autom Lett 2018; 3(4): 3066–3072.
4. Dorit B, Nüchter A, Đakulović M, et al. A mobile robot based system for fully automated thermal 3D mapping. Adv Eng Inform 2014; 28: 425–440.
5. Jongdae J, Lee SM, and Myung H. Indoor mobile robot localization and mapping based on ambient magnetic fields and aiding radio sources. IEEE T Instrum Meas 2015; 64(7): 1922–1934.
6. Jinwen L and Qin S. A fast algorithm of simultaneous localization and mapping for mobile robot based on ball particle filter. *IEEE Access* 2018; 6: 20412–20429.

7. Hongling W, Zhang C, Song Y, et al. A perception-driven exploration hierarchical simultaneous localization and mapping for mobile robots adapted to search and rescue environments. *Adv Mech Eng* 2018; 10(3): 1–18.

8. Bacca B, Salvi J, and Cufi X. Appearance-based mapping and localization for mobile robots using a feature stability histogram. *Robot Auton Syst* 2011; 59: 840–857.

9. Zhe Z and Chen X. Building 3D semantic maps for mobile robots using RGB-D camera. *Intell Serv Robot* 2016; 9: 297–309.

10. Chun CL and Su KL. Development of an intelligent mobile robot localization system using Kinect RGB-D mapping and neural network. *Com Elect Eng* 2018; 67: 620–628.

11. Wong RH, Jizhong X, and Samleo LJ. A robust data association for simultaneous localization and mapping in dynamic environments. *Information-Tokyo* 2010; 13(6): 1869–1884.

12. Wang Y, Weidong C, and Jingchuan W. Map-based localization for mobile robots in high-occluded and dynamic environments. *Ind Robot* 2014; 41(3): 241–252.

13. Zhang H, Zaojun F, and Guilin Y. RGB-D simultaneous localization and mapping based on combination of static point and line features in dynamic environments. *J Electron Imaging* 2018; 27(5): 053007.

14. Tomiaš K, Fentanes JP, Santos JM, et al. FreMEn: frequency map enhancement for long-term mobile robot autonomy in changing environments. *IEEE T Robot* 2017; 33(4): 964–977.

15. Erik E and Gross HM. Generic NDT mapping in dynamic environments and its application for lifelong SLAM. *Robot Auton Syst* 2015; 69: 28–39.

16. Larry HM, Xiong Y, and Hogg RW. A portable, autonomous, urban reconnaissance robot. *Robot Auton Syst* 2002; 51(2): 163–172.

17. Tudor N, Gracias N, and Negahdaripour S. Efficient three-dimensional scene modeling and mosaicing. *J Field Robot* 2009; 26(10): 759–788.

18. Shrihari V, Ramos F, and Nettleton E. Gaussian process modeling of large-scale terrain. *J Field Robot* 2009; 26(10): 812–840.

19. Bo Z, Qian K, and Ma X. A set-theoretic algorithm for real-time terrain mapping of mobile robots in outdoor environments. *Int J Adv Robot Syst* 2013; 10: 392–405.

20. Xiaorui Z, Qiu C, and Minor MA. Terrain inclination aided three-dimensional localization and mapping for an outdoor mobile robot. *Int J Adv Robot Syst* 2013; 10: 76–84.

21. Tae-Bum K, Song JB, and Joo SH. Elevation moment of inertia: a new feature for Monte Carlo localization in outdoor environment with elevation map. *J Field Robot* 2010; 27(3): 371–386.

22. Michael M, Vig E, and Scheirer W. Vision-based simultaneous localization and mapping in changing outdoor environments. *J Field Robot* 2014; 31(5): 780–802.

23. Christian L and Wollherr D. Global localization of 3D point clouds in building outline maps of urban outdoor environments. *Int J Intell Robot Appl* 2017; 1: 429–441.

24. Yuxiang S, Liu M, and Meng MQH. Improving RGB-D SLAM in dynamic environments: a motion removal approach. *Robot Auton Syst* 2017; 89: 110–122.

25. Yuxiang S, Liu M, and Meng MQH. Motion removal for reliable RGB-D SLAM in dynamic environments. *Robot Auton Syst* 2018; 108: 115–128.

26. Ellips M, Jannati M, and Hekmatfar T. Cooperative mapping of unknown environments by multiple heterogeneous mobile robots with limited sensing. *Robot Auton Syst* 2017; 87: 188–218.

27. Jiuqing W, Bu S, and Yu J. Distributed simultaneous localization and mapping for mobile robot networks via hybrid dynamic belief propagation. *Int J Distrib Sens N* 2017; 13(8): 1–19.

28. Saitov D, Park J II, Jungwon C, et al. Effective map building using a wave algorithm in a multi-robot system. *Int J Precis Eng Man* 2008; 9(2): 69–74.

29. Sarat CN, Vachhani L, and Sinha A. Multi-robot graph exploration and map building with collision avoidance: a decentralized approach. *J Intell Robot Syst* 2016; 83: 503–523.

30. Yu NG, Yun-He Y, Ti L, et al. A cognitive map building algorithm by means of cognitive mechanism of hippocampus. *Acta Automatica Sinica* 2018; 44(1): 52–73.