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NEW IMPROVEMENT ON ADAPTIVE PATH FOLLOWING CONTROL FOR MULTIPLE-POPULATIONS GENETIC ALGORITHM ADOPTED IN TRACKED VEHICLE

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Abstract. *Crawler mechanisms have the advantage of high-speeding and stable locomotion on uneven terrain. Therefore, such vehicles have been applied in many areas, including those used for search and rescue. Tracked mechanism is a high-tech product. One of the difficulties in the vehicle researching is the issue of path tracking. Numerous of control methodologies have been proposed before, yet limits to some simple paths, such as circle or straight line. In this paper, a control scheme involving complicated curve following is proposed to adapt vehicle to more intricate environment. Within the control structure, a novel method named curve fitting method (CFM) is issued to match the targeted route. Then, a multi-parameter adaptive control algorithm (MPACA) is further constructed based on conventional genetic algorithm (GA). This intends to automatically adjust the vehicle's speed parameters according to the changing route. However, some surveys show that GA is hard to be used to follow the transition area (TA) perfectly and this situation becomes more serious if many transition areas (TA) exist in the curve. Due to this phenomenon, multiple-populations genetic algorithm (MPGA) is applied to realize MPACA instead. Two simulations tested on typical routes which contain TA demonstrate the performance of CFM, MPACA and MPGA in the adaptive tracking sphere and the simulation tests are displayed in Section 4.1. At the end of this paper, a practical validation has been done in an open space of Shanghai University. This will be detailed in part 4.2.*

Keywords: Tracked vehicles, Adaptive path following control, Curve fitting method (CFM), Multi-parameter adaptive control algorithm (MPACA), Transition area (TA), Multiple-populations genetic algorithm (MPGA)

1. Introduction.

Crawler vehicles operate with low energy consumption and offer large advantages for the locomotion of vehicles because of their large contact areas, which allow them to be suitable to bumpy grounds. Therefore, such mechanisms are always employed in many robotic vehicles for "search and rescue" applications in disaster areas, such as collapsed buildings, underground stairs, or wide cracks in the ground. Path tracking is one of the research focuses of crawler vehicle. In the tracking field, some scholars have supplied a few simple following methods before. However, while the tracked vehicle encounters a practical application, the simplex and single path following tactic might lead to a runaway of the vehicle which is a fatal error on spot.

Some previous research directions as sliding mode control [1], predictive trajectory tracking [2] and feedback linearization control [3] have been the most promising tactics in the trajectory following realm.

Among these, sliding mode control is generally considered as a particularly major approach to path following. It is also a basic knowledge of the strategy given in this paper and will be involved in Sections 2.1 and 2.2.

Depend on a basic theory of the tracked vehicle's motion in [4], a work of [5] succeeded to some extent as it considered the slip estimation compensating for the effect of slippage. Extensive research from [6] is required to detect the slippage ratio and modify the action of vehicle to correct itself from deviations. Inspired by the work of [5], adaptive slip estimation was put forward on [7] using an adaptive least square estimator.

However, all researches mentioned above just structure strategies based on simple curve. None of them can work in a complex route environment.

Apart from the research mentioned above, a lot of scholars try to improve the mobility of tracked vehicle in any other respects. For example, paper [8] tries to solve the problems of the vehicle control at high-speed control and low-speed control by developing a five degree-of-freedom (DOF) steering model of a tracked vehicle. At the same time, handling behavior during non-stationary motion is studied as well. These exactly help to understand the interactions between terrain factors and vehicle characteristics during steering. In the aspect of material application, a novel vehicle with segmented rubber tracks has been studied in [9]. The special segmented rubber helps to minimize income losses that result from downtime and maintenance costs, then a better performance on a low-bearing capacity peat will be gained. In paper [10], some typical optimal algorithms has been used to improve the function of vehicle. Some researchers even attempt to make some dynamic analysis like authors of [11] and this trial partially solved the prediction problem of the tractive performance on the soft terrain. Similarly, a relevant work is also presented in [12]. Wong [13] was the first to solve the problem of major design features on the mobility of tracked vehicles over snow. A good discussion from [14] explores the robust point stabilization issue of a tracked mobile robot in the presence of track slipping, which can be treated as model perturbation that violates the pure nonholonomic constraints. Based on the classic terramechanics, a closed-form wheel-soil interaction model was derived by quadratic approximation of stresses along the wheel-soil interface from a research hosted by University of Michigan in [15]. Through this model, an approach to tracing the deformable terrain is acquired. Paper [16] developed a kinematic modeling scheme to analyze the skid-steered mobile robot. On the basic of the analysis of the kinematics of the skid-steer mobile robot, the research revealed the underlying geometric and kinematic relationship between the wheel slip and location of the instantaneous rotation center. Furthermore, some scholars in [17] put up and experimentally verified the dynamic model of a skid-steered wheeled vehicle for general planar (2-D) motion and for linear 3-D motion. This study is a significant extension in the robotic motion field.

Although these researches offer important various directions to improve the mobility, an effective tracking algorithm which aims at the real complex curve has not been developed yet.

Considering the current situation, it is obvious that a method which can offer accurate following of complex routes will improve the performance greatly. Thus this paper proposes a novel Curve fitting method (CFM) and a Multi-parameter adaptive control algorithm (MPACA). CFM is used to fit the curve to some straight lines and makes the basic tracing tactic showed in Section 2 suitable for some basic curves and the MPACA intends to adjust the parameters according to the real environment route. For the first time, we choose the genetic algorithm (GA) as the optimization algorithm to accomplish

MPACA. However, GA fails to optimize the parameters when many transition areas (TA) exist in the curve. TA refers to the area that owns transition point in the curve. It means that the curve changes the direction within TA in the defined coordinate system. For example, area near the inflection point and the pole in a curve is actually a typical TA. Multiple-populations genetic algorithm (MPGA) is one of the most popular algorithms which can sharply decrease the possibility of prematurity through the scheme of multiple populations and the tactic of communication between each population. Thus, MPGA will serve for realizing the MPACA instead of the conventional GA at the end of the strategy. It should be noted that the trace in the paper was completely constructed and recorded in the storage of the mechanism before vehicle moves. Section 2 of this paper involves kinematic of vehicle and a theory of CFM. Afterward, MPACA is put forward in Section 3. At the same time, a contrast between the conventional GA and the novel MPGA used in tracking sphere will be detailed in this section. Effectiveness of the strategy including CFM, MPACA with MPGA will be proved to be correct with some simulating contrasts conducted on several complicate tracing experiments in Section 4.1. Finally, a real experiment has been finished and showed in part 4.2.

2. **Theory of CFM.**

2.1. **Kinematic.**

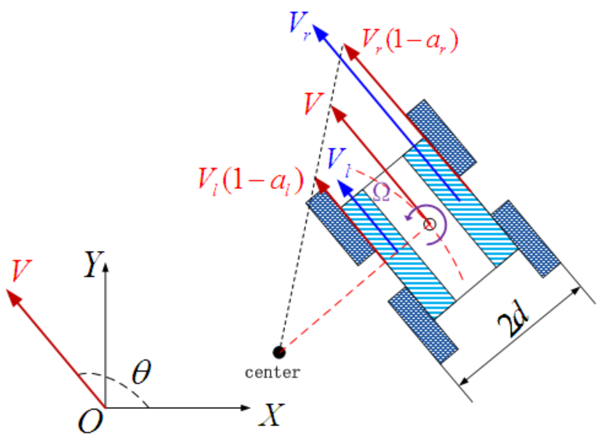


FIGURE 1. Kinematic of a skid-steered tracked vehicle

Kinematic Equation (1) [4] would be adopted in this paper,

$$\begin{cases} \dot{x} = \frac{V_r(1-a_r)+V_l(1-a_l)}{2}\cos\theta \\ \dot{y} = \frac{V_r(1-a_r)+V_l(1-a_l)}{2}\sin\theta \\ \dot{\theta} = \frac{V_r(1-a_r)+V_l(1-a_l)}{2d} \end{cases} \tag{1}$$

where V_l and V_r denote the theoretical left and right track velocity, respectively, which could be calculated from angular velocities and the radii of the pitch circles of the track's sprockets. $2d$ represents the tread and a_l, a_r are slip ratios defined as,

$$\begin{cases} a_l = \frac{V_l - V_l'}{V_l} \\ a_r = \frac{V_r - V_r'}{V_r} \end{cases} \tag{2}$$

Here V_l' and V_r' represent the absolute velocity of the left and right tracks, respectively. If no slippage occurs, the absolute velocity equals to the theoretical velocity ($V_l' = V_l, V_r' =$

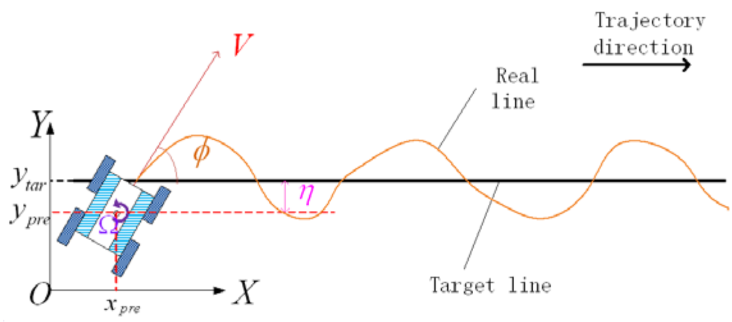


FIGURE 2. Image of basic following theory

V_r), and the above Equation (1) result in the conventional kinematics of wheeled mobile robots.

2.2. **Basic following theory.** Showed in Figure 2, tracing procedure would be described as follows:

a) Judge the coordinate of vehicle $P(x_{pre}, y_{pre})$ by odometry with encoder and gyro [4], and therefore the distance η between vehicle's geometrical center and targeted line will be achieved. Figure 2 illustrated that,

$$\eta = y_{tar} - y_{pre} \tag{3}$$

b) Measure the present angular velocity Ω with gyro. After that, compute the orientation angle-ϕ between vehicle body's position and the target line.

$$\phi = \Omega * T_0 + \phi_{org} \tag{4}$$

where ϕ_{org} and T_0 are the original orientation angle and sampling time, respectively.

c) Define the next angular acceleration by,

$$\left(\frac{d\Omega}{dt}\right)^{ref} = -k_\Omega \Omega - k_\phi \phi - k_\eta \eta \tag{5}$$

where k_Ω, k_ϕ, k_η are control gains.

Afterward, a new angular velocity will be achieved by,

$$\Omega_{next} = \Omega + \left(\frac{d\Omega}{dt}\right)^{ref} * T_0 \tag{6}$$

d) Then slip ratios will be required,

$$\frac{a_l}{a_r} = -sgn(V_l, V_r)\sqrt{\left|\frac{V_r}{V_l}\right|} \tag{7}$$

a_l, a_r can be obtained by two conditional equations, namely (1)-(3) and (7). We get V_r and V_l from encoder, while $\dot{\theta}$ in (1)-(3) was gauged by the gyro.

e) Finally, the speeds of two tracks can be acquired,

$$\begin{pmatrix} V_{rnext} \\ V_{l\,next} \end{pmatrix} = \begin{pmatrix} \frac{1}{1-a_r} & \frac{d}{1-a_r} \\ \frac{1}{1-a_l} & \frac{-d}{1-a_l} \end{pmatrix} \begin{pmatrix} V_{des} \\ \Omega_{next} \end{pmatrix} \tag{8}$$

As showed above, the speed of the vehicle – V_{rnext}, $V_{l\,next}$ have been decided, considering slippage effect. V_{des} is the expected speed of vehicle in the equation above.

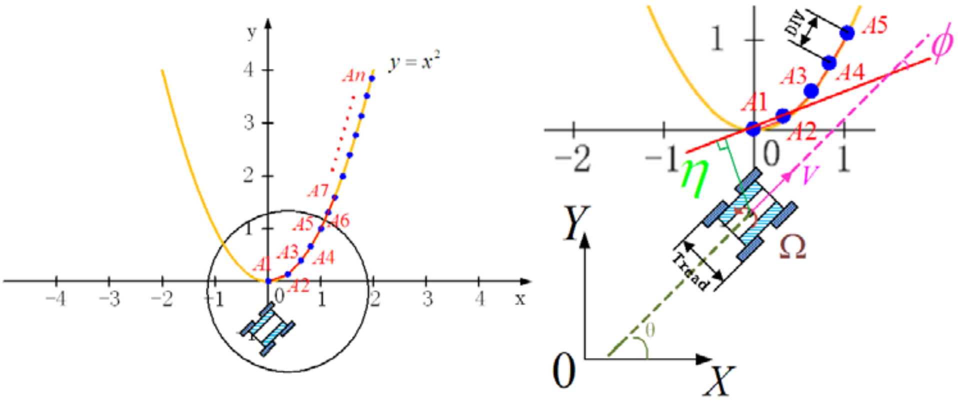


FIGURE 3. CFM in function of $y = x^2$

2.3. **CFM.** To follow a curve, this paper develops an extensive way named CFM. CFM is able to transform the curve tracking to basic following strategy in Section 2.2.

We will descript the method-CFM based on the function ($y = x^2$) as follows. 1) Divide the curve into n segments, namely, $Fit(A1, A2, A3, \ldots, An) = (y = x^2)$. It means that we are inclined to fit the curve by n straight lines which comprise $(A1, A2, A3, \ldots, An)$; 2) The strategy aims at the straight line which contains $(A1, A2)$ and attempts to trace it on the basis of the basic following theory given in Section 2.2; 3) Change the target line to $(A2, A3)$ once $x_{pre} > x_{A2}$ and go on following the straight line joined by $(A2, A3)$; 4) Repeat the steps 2) and 3) until the vehicle finishes the task.

It is obvious that if we divide the curve intensive enough, a very similar profile would be gained. However, overmuch division might lead to a serious time delay. This even affects the movement of vehicle. Thus, a recommended distance (DIV) of 10cm is given here.

It also should be noted that the principle to change the target line in step 3), $x_{pre} > x_{A2}$, is not unique. A proper principle should be chosen according to the specific condition.

2.4. **Verification.** This part will verify CFM over a simulation on Matlab. Initial statements are listed as follows: 1) The target line is set as $Target = \{y = x^2 | x \in (0, 5)\}$, namely a point conic $y = x^2$ with the domain of $(0, 5)$; 2) Original coordinate of the vehicle is $(x_0, y_0) = (0, 0.5)$; 3) Both speed of the left and right track is 1m/s, which stands for $(V_r, V_l) = (1\text{m/s}, 1\text{m/s})$; 4) Initial angular velocity is $\Omega = 1\text{rad/s}$; 5) Angular acceleration $\left(\frac{d\Omega}{dt}\right)^{ref} = 0.5\text{rad/s}^2$ is set as 0.5rad/s^2; 6) Orientation angle ϕ between vehicle body's position and the target line is 45°; 7) Sampling time T_0 is set as 0.01s; 8) Tread of the vehicle is $Tread = 2d = 0.24$m; 9) A desired speed of vehicle V_{des} is 1m/s; 10) DIV, which is the distance between two division points, is 10cm. The result of the experiment is showed as follows.

This experiment is finished according to the content in part 2.3. Figure 4 showed that, except for some deviations inside the rectangle, the tracing is excellent on the whole. Few deviations occur, because the curve of second order is smooth enough. It can be seen that CFM is effective to a normal, smooth curve. By the way, area surrounded by rectangle is called the adjustment area and this argument will be given in part 3.1.

3. Adaptive Tracing Method.

3.1. **Conventional MPACA.** The former section has successfully traced a curve as hereinbefore described. Nevertheless, these curves are too simple to be applied in practice.

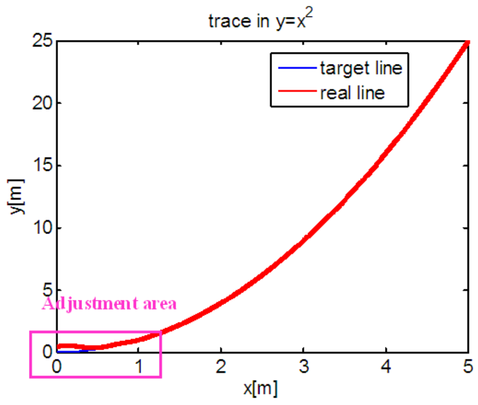


FIGURE 4. Simulation result on CFM in function of $y = x^2$

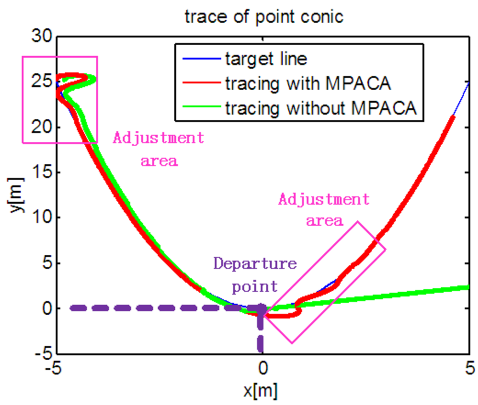


FIGURE 5. MPACA experiment on function of $y = x^2$

Here, a solution of adaptive tracing named MPACA will be put forward. An experiment to follow $Target = \{y = x^2 | x \in (-5, 5)\}$ is about to be set up to explain this issue.

In this experiment, two different schemes are separately applied to finish the task. Result of the experiment is showed as Figure 5. While the green line operates with the steps in original Section 2.3, the red one runs with MPACA.

The same initial conditions were taken in Figure 5. It can be observed that, Figure 5 (green line) indicated that the sphere of $x \in (-5, 0)$ could be tracing successfully. However, once the vehicle passes the departure point $(0, 0)$, it went away. It means that CFM is actual weak in adaptability to some complex routes. This makes the value of CFM decrease seriously.

There actually exist some reasons contribute to the inefficiency of the vehicle's self-adaption.

In fact, the inappropriate of the control gains in (5) causes the failure in the tracing. In most complicated routes, a single group of parameters is far from enough to complete the following mission. Taking the quadratic function for example, a group of parameters – $[k_\Omega, k_\phi, k_\eta]$ was suitable for the first half of the route, whereas the parameters could not meet the bottom half. So, the vehicle lost its way after passing the original point and failed to trace the route.

To solve the problem above, a solution named MPACA will be applied to adapt the changing route based on conventional GA for the first time.

A case curve of second order is showed in Figure 5. Procedures of MPACA are given as follows: 1) Make use of GA to optimize the parameters which could be suitable for the top half, namely the part $x \in [-5, 0]$. By this, we develop the first group of parameters – $para1 = [k_{\Omega 1}, k_{\eta 1}, k_{\phi 1}]$; 2) The vehicle starts to move once the first parameters are obtained. While moving, vehicle should search the second group of parameters – $para2 = [k_{\Omega 2}, k_{\eta 2}, k_{\phi 2}]$ at the same time, which will be adopted in the bottom half of the route; 3) Replace $para1$ with $para2$ as soon as vehicle passes the departure point showed in the figure above and continues to follow the route remained; 4) Employ $para2$ as the control gains until the vehicle arrives at destination.

It could be seen in Figure 5 (red line) that two different sets of parameters have been applied in each stage instead of a single one. By this means, it is successful to adjust control gains according to the changing route and employ the right parameters to trace the given route.

Two rectangles highlighted with pink color in Figure 5 should be paid close attention to. These refer to adjustment area that contains several deviations. Generally speaking, two factors contribute to these deviations. The first one is the inherent inertia of substance. Once a new set of parameters is utilized, vehicle will keep its original operative status for a while for its inertia. As a consequence, deviation forms inevitably. And the more important factor is the defect of the optimal algorithm-GA. GA has its natural premature drawbacks. This issue will be solved in part 3.2 and part 3.3 with MPGA.

3.2. **Theory of MPGA.** In the content above, GA is employed to realize MPACA. However, according to the experiment displayed in Figure 7 (left), GA is unable to achieve a desirable result. The experiment will be detailed in Section 3.3. In fact, GA is not the most suitable algorithm for sure. GA is a highly concurrent, random, self-suitable, global optimized algorithm that imitates the natural selection of organic sphere. It is widely used in areas such as machine learning, pattern recognition. Nevertheless, there exists a fatal defect in GA-premature phenomenon. Quite a lot of factors like the improper migration fraction, unsuitable population size, contribute to this defect.

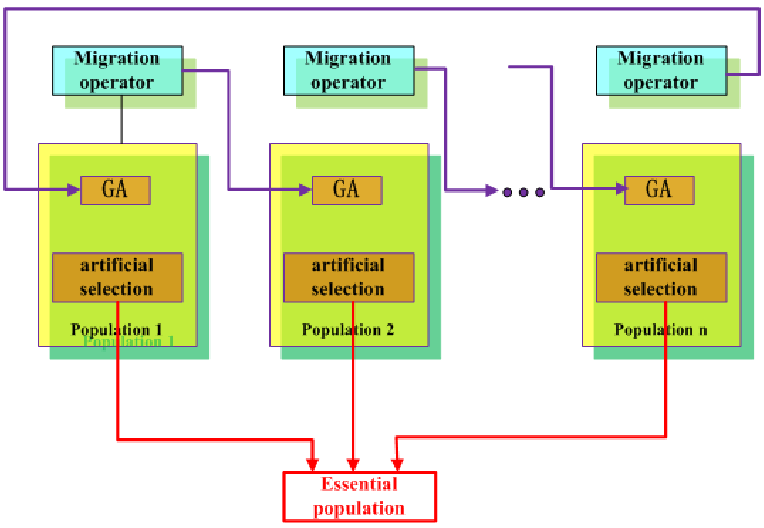


FIGURE 6. Composition of MPGA

Another algorithm named multiple-populations genetic algorithm (MPGA) can be used to replace the standard GA. It breaks the limiting of single population. At the same time, communication is established between several populations. Then, we can choose a best individual manually from each population. Eventually, a global set of optimized parameters will be achieved.

MPGA overcomes the prematurity of normal GA and increases the computing efficiency. This algorithm employs a potential solution to a specific problem on a chromosome-like data structure and applies recombination operators to these structures in such a way as to preserve critical information. MPGA are often viewed as function optimizers, where genetic algorithm imposes no influence on the function optimization.

A brief composition of MPGA is displayed in Figure 6. Several populations constitute the major frame of MPGA. Each population achieves the best individual via the standard GA. Then, each population can exchange information through Migration operator. After a couple generations of evolution, an essential population could be acquired. Finally, once the stop criteria met, the algorithm chooses a best individual as the output from the essential population.

3.3. **Tracing through MPGA.** The tactic put forward in Section 3.1 is actually able to trace some practical curves. However, a complicated curve with several TA introduced in part 1 is hard to be followed for the prematurity of GA. At the same time, delay is actually serious if GA serves as the adaptive algorithm.

To explain this issue, one more experiment is held and showed in Figure 7. Lemniscate has several typical TA in each direction displayed in Figure 7 with green dotted rectangle. So Lemniscate is chosen as the experimental route to distinguish the effect between GA and MPGA.

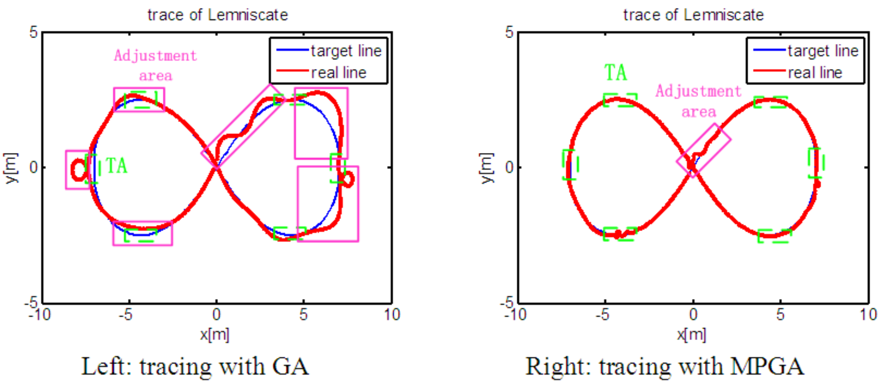


FIGURE 7. MPACA experiment on a lemniscate

TABLE 1. Summary of running time from a lemniscate

Curve	A lemniscates tracing	
Adaptive algorithm	GA	MPGA
Running time	3.4min	1.5min

Figure 7 (left) runs with GA. It can be seen that deviations are indeed severe, especially in the pink region. The pink region is exactly the adjustment area that mentioned in part 3.1. As we described in Section 3.1, it is the imperfection of optimization algorithm that leads to the terrible deviations.

From another side, it can be found that adjustment area has a similar area with TA. Adjustment area is indeed closely related to TA. In fact, it is the TA triggers optimization algorithm updating optimal parameters. As a consequence, deviations and adjustment area form once the new optimal parameters employed.

Actually, it is the prematurity of GA that leads to these awful biases. With the prematurity, GA is not able to find a group of global optimal parameters, but runs with a local optimal one instead. As a result, the local optimal parameters make the tracking imperfect and the serious deviations occur in adjustment area. For the same reason, GA spends dozens of time to search the parameters that meet the demand of stopping criteria. In this event, it takes 3.4min to finish the tracing showed in Table 1 (GA).

On the other hand, a significant contrast is provided in Figure 7 (right). This one runs in a same condition with the former one. It is apparently that vehicle follows the established route well without grievous error. Observe TA framed by green dotted rectangle carefully, little adjustment area can be found. As a matter of fact, for the reason of the inherent inertia illustrated in part 3.1, adjustment area is more or less existent.

The reason why this experiment so successful is that MPGA avoids prematurity smoothly and therefore achieves a set of global optimal parameters. A set of global optimal parameters keep the vehicle running along the trace closely without too much adjustment. At the same time, effects of "Multiple-populations" broaden the scope of search greatly and then improve the search efficiency. Through this method, a quick search of 1.5min is achieved in Table 1 (MPGA).

4. **Experimental Validation.**

4.1. **Simulation validation.**

Figure 4, Figure 7 and Table 1 have proved the validity of CFM, MPACA and the algorithm – MPGA. In this section, some more complex experiments will be set to validate the significance of the whole strategy further. The tracked vehicle (Figure 8) which is going to be considered as a test case is made by Shanghai University (SHU).

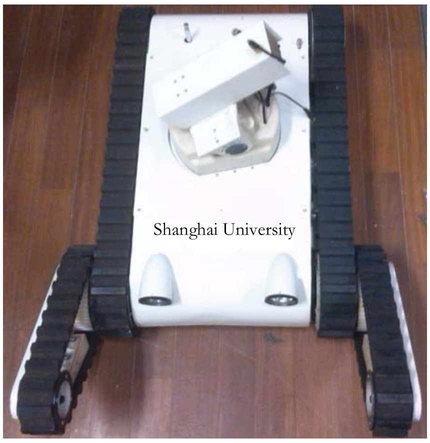
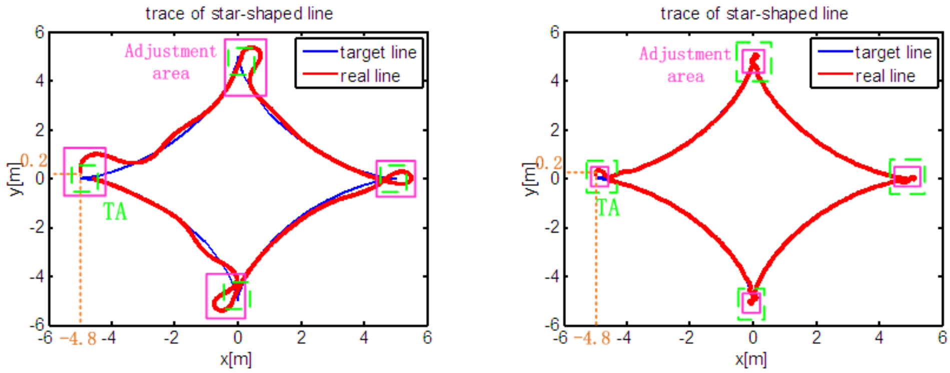


FIGURE 8. Tracked vehicle made by SHU

What follow in the passage are two cases. A star shaped line tracing will be given firstly. Then, this paper tests a much more complicated similar shaped line to explain the influence of TA. We choose these two curves, because both of them comprise several TA. So the whole strategies including CFM, MPACA and MPGA can be demonstrated perfectly. At the same time, a fore-and-aft comparison between these two experiments can be held. As a result, influence of TA to the tracing is fully exposed.

Experiment result of the first one is displayed in Figure 9 and Table 2. Initial situation is expressed as below: 1) The target line is set with a polar equation $Target = \{x = \cos\theta + (1/3) * \cos(3\theta), y = \sin\theta + (1/3) * \sin(3\theta)\}$. Wherein θ is the polar angle; 2) Original coordinate of vehicle is $(x_0, y_0) = (-4.8, 0.2)$; 3) Both speed of the left and right track is 1m/s; 4) Initial angular velocity is $\Omega = 1$rad/s; 5) Angular acceleration $\left(\frac{d\Omega}{dt}\right)^{ref^2}$ is set as 0.5rad/s^2; 6) Orientation angle ϕ that between vehicle body's position and the



Left: tracing with GA   Right: tracing with MPGA

FIGURE 9. MPACA experiment on a star-shaped line

TABLE 2. Summary of running time from a star-shaped line

Curve	Star-shaped line	
Adaptive algorithm	GA	MPGA
Running time	4.8min	2.2min

target line is 45°; 7) Sampling time T_0 is set as 0.01s; 8) Tread of the experiment vehicle is $Tread = 2d = 0.24$m; 9) Desired speed of vehicle V_{des} is 1m/s; 10) DIV, distance between two division points, is 10cm.

From one hand, Figure 9 shows that each test can trace established curves on the whole. It means that CFM is effective in tracing a curve as we said in Section 2.

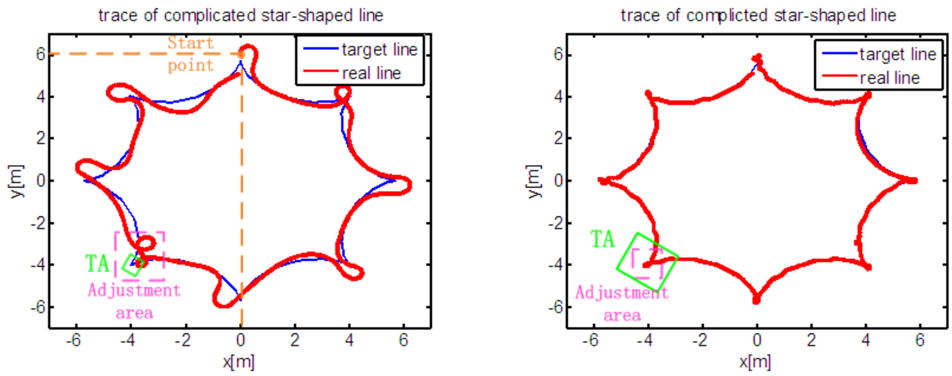
On the other hand, it is obvious that four TA lied in the given route displayed with green rectangles. Compare two pictures in Figure 9. The left one contains widespread adjustment areas showed with pink rectangles. Turn to the right one, it can be seen that fractional adjustment areas exist within pink rectangles. Apart from this, operation time of GA is twice than that of MPGA as Table 2 showed. Factors that result in this difference have been detailed in Section 3.3. That is because the premature characteristic of GA makes the tracing with a set of local optimal parameters not a global one. Yet MPGA works exactly with a global one instead.

The second example is a more complicated curve showed in Figure 10 and Table 3. This experiment sets the initial situation as below: 1) The target line is set as $Target = \{x = \cos\theta + (1/7) * \cos(7\theta), y = \sin\theta + (1/7) * \sin(7\theta)\}$, which is a polar equation. Wherein θ is the polar angle; 2) Original coordinate of vehicle is $(x_0, y_0) = (0, 6)$; 3) Both speed of the left and right track is 1m/s; 4) Initial angular velocity is $\Omega = 1.3$rad/s; 5) Angular acceleration $\left(\frac{d\Omega}{dt}\right)^{ref^2}$ is set as 0.7rad/s^2; 6) Orientation angle ϕ between vehicle body's position and the target line is 120°; 7) Sampling time T_0 is set as 0.01s; 8) Tread of our experiment vehicle is $Tread = 2d = 0.24$m; 9) The desired speed of our vehicle V_{des} is 1m/s; 10) DIV, the distance between two division points, is 10cm.

It can be confirmed again that CFM works well in curve tracing in Figure 10.

There are apparently eight TA in the route (only a single TA is drawn to simply the graph). It can be seen that a similar result with Figure 7 and Figure 9 is achieved. At the same time, time consuming of MPGA also keeps less than half of that of GA.

What is more, there is still another side need to be noticed. Compare Figure 9 (left) and Figure 10 (left), we can find that following become harder along with the number of



Left: tracing with GA Right: tracing with MPGA

FIGURE 10. MPACA experiment on a complicated star shaped line

TABLE 3. Summary of running time from a complicated star shaped line

Curve	A complicated star shaped line	
Adaptive algorithm	GA	MPGA
Running time	7.1min	3.2min

TA increasing. So, it is really necessary to employ an efficient algorithm like MPGA to complete the following task.

4.2. **Practical validation.** As Figure 11 showed, a practical validation has been finished in an open space of Shanghai University. Coordinate system of the experiment is set as Figure 11 (right).

Left Right

FIGURE 11. Vehicle running test

There were two groups of tests in the experiment. One was finished based on GA, whereas the other one was adopted by MPGA. Our research team chooses a most typical data from multiple tests of each group and displays them in Figure 12.

Experiment method. An 8m × 8m open space was chosen as the experimental site as Figure 11. Trajectory data of an epicycloid was input into the storage of vehicle before. Encoders and INS with GPS were installed in vehicle to measure the real time accurate location of vehicle. Experiment data was stored in a CF card while running. After the motion is completed, our research team read the data from CF card and displayed it with a matlab figure.

Result analysis. Figure 12 (left) shows the experimental data based on GA. We can see that, vehicle was barely able to follow the trajectory within the range of $x \in (-4.5, 4.3)$.

After that, GA failed to search out a proper set of parameters. As a consequence, vehicle ran beyond the boundary of the spot and had to be stopped manually in the location of $(x, y) = (8, 2)$. Turn to Figure 12 (right), vehicle achieved the optimal parameters through MPGA. Parts of TA in the route have been displayed with green ellipse and there always some deviations inside the adjustment areas which were caused by TA. Although some deviations exist in the experiment, vehicle followed the track very successfully. From the figure, a largest bias of 0.4m happened in the scope of $x \in (-4.8, 5.2)$. This is actually an acceptable bias. On the other hand, running with MPGA spent 4min and 27 seconds to complete the whole task. A great contrast has been put at Table 4 that it took the vehicle 4min and 13 seconds without fulfilling half of the journey if the conventional GA is employed instead.

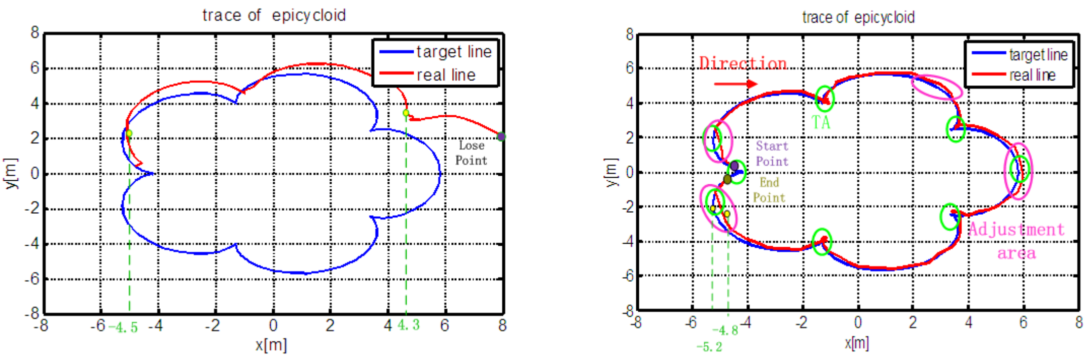


FIGURE 12. Experiment result

TABLE 4. Running time of the experiment

Curve	Epicycloid	
Adaptive algorithm	GA	MPGA
Running time	4min, 13 seconds (Lose)	4min, 27 seconds

Experiment conclusion. According to the experiment above, CFM can be proved to be effective from each test. However, a single CFM is absolutely insufficient. Optimization algorithm is needed to realize the MPACA strategy. The conventional GA is inefficient and poorly one. Yet, MPGA has been validated an effective and efficient algorithm in the experiment.

5. **Conclusions.** In this paper, a novel scheme is proposed for tracked vehicles trajectory following. Within the control, a basic tracking theory is adopted from [4]. Based on the theory, an original curve tracking tactic named CFM is put forward in this paper. To adapt to more practical route, a MPACA strategy which is adopted to improve adaptability via adjusting control gains to a proper value is proposed after CFM. For the first time, conventional GA is used as the optimization algorithm to realize MPACA. However, according to our test, a curve with numerous of TA is hard to be followed smoothly. So, a more suitable algorithm named MPGA is employed to execute MPACA instead. In the validation section, some contrasting simulations are carried out to prove the effectiveness of CFM and MPGA used in MPACA. Finally, a real experiment is held in Shanghai University and displayed in Section 4.2. It has been demonstrated that the strategy including CFM, MPACA and MPGA used in vehicle adaptive following is absolutely effective and practical.

In our research, following experiment is still limited to a plane environment. Our research team will extend it to the 3D environment in the near future. This is one of our important research projects for the future.

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REFERENCES

[1] J. M. Yang and J. H. Kim, Sliding mode control for trajectory tracking of nonholonomic wheeled mobile robots, *Robotics and Automation, IEEE Trans.*, vol.15, no.3, pp.578-587, 1999.
[2] M. Seyr and S. Jakubek, Mobile robot predictive trajectory tracking, *Proc. of the 2rd International Conference on Informatics in Control, Automation and Robotics*, pp.112-119, 2005.
[3] G. Oriolo, A. De Luca and M. Vendittelli, WMR control via dynamic feedback linearization: Design, implementation, and experimental validation, *Control Systems Technology, IEEE Trans.*, vol.10, no.6, pp.835-852, 2002.
[4] J. Y. Wong, *Theory of Grond Vehicles*, John Wiley & Sons, 1978.
[5] D. Endo, Y. Okada, K. Nagatani and K. Yoshida, Path following control for tracked vehicles based on slip-compensating odometry, *Proc. of IEEE/RJS International Conference on Intelligent Robots and Systems*, San Diego, CA, USA, pp.2871-2876, 2007.
[6] A. S. Badwe, R. D. Gudi, R. S. Patwardhan, S. L. Shah and S. C. Patwardhan, Detection of model-plant mismatch in MPC applications, *Journal of Process Control*, vol.19, no.8, pp.1305-1313, 2009.
[7] M. Burke, Path-following control of a velocity constrained tracked vehicle incorporating adaptive slip estimation, *Proc. of Robotics and Automation, IEEE International Conference*, pp.97-102, 2012.
[8] B. Janarthanan, C. Padmanabhan and C. Sujatha, Lateral dynamics of single unit skid-steered tracked vehicle, *International Journal of Automotive Technology*, vol.12, no.6, pp.865-875, 2011.
[9] A. Rahman, A. K. M. Mohiuddin and A. Hossain, Performance measurements of a tracked vehicle system, *International Journal of Automotive Technology*, vol.12, no.4, pp.503-512, 2011.
[10] B. Zhang, H. Zhu, J. Luo, S. Xie and H. Li, Adaptive path following control for tracked vehicles based on genetic algorithm, *ICIC Express Letters, Part B: Applications*, vol.4, no.3, pp.815-823, 2013.
[11] W. Y. Park, Y. C. Chang, S. S. Lee, J. H. Hong, J. G. Park and K. S. Lee, Prediction of the tractive performance of a flexible tracked vehicle, *J. Terramech*, vol.45, nos.1-2, pp.13-23, 2008.
[12] P. Servadio, Applications of empirical methods in central Italy for predicting field wheeled and tracked vehicle performance, *Soil and Tillage Research*, vol.110, no.2, pp.236-242, 2010.
[13] J. Y. Wong, Development of high-mobility tracked vehicles for over snow operations, *J. Terramech*, vol.46, no.4, pp.141-155, 2009.
[14] B. Zhou, J. Han and X. Dai, Backstepping based global exponential stabilization of a tracked mobile robot with slipping perturbation, *Science Direct Journal of Bionic Engineering*, pp.69-76, 2011.
[15] Z. Jia, W. Smith and H. Peng, Fast analytical models of wheeled locomotion in deformable terrain for mobile robots, *Robotica*, vol.31, pp.35-53, 2013.
[16] J. Yi, H. Wang, J. Zhang, D. Song et al., Kinematic modeling and analysis of skid-steered mobile robots with application to low-cost inertial-measurement-unit-based motion estimation, *IEEE Transactions on Robotics*, vol.25, no.5, pp.1087-1097, 2009.
[17] W. Yu, O. Y. Chuy, Jr. E. G. Collins and P. Hollis, Analysis and experimental verification for dynamic modeling of a skid steered vehicle, *IEEE Transactions on Robotics*, vol.26, no.2, pp.340-353, 2010.