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RESEARCH ARTICLE

Autonomous Driving of a Guided Emergency Service Robot with Route Tracking Control

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ABSTRACT

This work presents a method for controlling the travel routes that tracked robots use to get around their environments. The algorithm utilized in model-predictive control could be implemented in a vehicle to make the vehicle capable of driving itself if an emergency arises. It is anticipated that soon, collaboration between edge clouds will become more commonly used to connect and control various pieces of rescue equipment. The Linear Model-Predictive Control algorithm, also known as LMPC, is an excellent choice for controlling the path that the rescue robots will take because it makes efficient use of the limited computational resources available and delivers accurate results in real-time. This makes it an excellent choice for controlling the rescue robots' route. Despite this, the driving conditions are hazardous, and there are significant shifts in how the road is curved at various points in this scenario. The level of accuracy that can be achieved when tracking a route with significant curvature variations is limited because only linearized feed-forward data can be entered into the LMPC. This places a restriction on the level of accuracy that can be achieved. The authors of this study suggest utilizing a preview linear MPC as a means of locating a solution to this problem and a means of addressing it. The test controller has had a simulation loaded into it that was created in MATLAB with the assistance of Simulink. Despite the significant variations in the curvature of the route, performance regarding route tracking was improved by utilizing the suggested strategy. This was possible due to more accurate route tracking.

Keywords: Autonomous robots, MatLab simulation, Model prediction control, Path tracking control, Wireless networks

Introduction

Mobile robotic platforms explore and observe dangerous environments, like natural disasters and military operations. Real-time audio and video streaming allow remote monitoring and body detection with these robots. Path drawing, collision avoidance, motion detection, object detection and tracking, and image processing need improvement.[1] Researchers have proposed several control strategies to enhance autonomous vehicle (AV) performance. Nonlinear model predictive control (NMPC) improves AV path tracking accuracy in low-speed and narrow spaces.[2] The Stanley algorithm, which calculates the front wheel angle based on the geometric relationship between the vehicle's pose and the reference path point, is also widely used for AV path tracking at low speeds and with small curvature changes.[3] The alternative path-tracking control method for AVs, model predictive control (MPC), performs better under complex road conditions.[4] AV safety depends on collision avoidance. Calculating the minimum distance between vehicle ellipses is one method. Control strategies can integrate this theoretical framework for collision avoidance.[5] Route optimization algorithms like Dijkstra's algorithm aid in efficient delivery scheduling and reduce administrative errors.[6] Learning-based control strategies are prevalent in robotics, especially for unknown disturbances. Linear quadratic regulator (LQR) control schemes are

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effective but limited by system constraints. As an alternative, learning model predictive control (LMPC) incorporates learning mechanisms to adapt to changing environments.[7] Path tracking for autonomous vehicles with four-wheel independent driving and steering capabilities presents unique challenges due to the complex dynamics of these systems. Several studies have proposed a novel controller for path-following based on yaw rate tracking, offering a more robust and efficient method for path-tracking in these vehicles.[8–10] Unified model predictive control (MPC) provides a framework for constrained vehicle path following and trajectory tracking. This strategy addresses feasibility issues and ensures safe and efficient AV operation by adding artificial variables to the optimization problem.[11–13] The stability and performance of AV control systems require robustness and disturbance compensation. Robust AV control widely uses sliding mode control (SMC), and to improve response time, transient performance, and robustness, integral variable structure SMC (IVSMC) is proposed. Nonlinear disturbance observers can estimate unknown disturbances without additional sensors.[14–16]

Because of their high mobility and ability to adjust to different types of terrain, researchers are looking into the possibility of using robots in rescue operations. In a potentially life-threatening rescue scenario, it can be difficult to set up a communication system that can be relied upon. Therefore, connecting and controlling rescue equipment through edge clouds is the way of the future 1. The rescue effort could be improved by employing a method for controlling mobile robots that is both straightforward and efficient. Therefore, having quick computation times for control values is advantageous for raising information sampling frequencies between the cloud's edges, which increases their ability to work together synergistically.

The use of LMPC is ideally suited for the route-tracking control of mobile robots that are used in rescue operations. Because it does not require a complex system model and can handle system state restrictions, a control system with MPC makes it possible to determine the best parameters in the domain of training time. It is possible because MPC can handle system state restrictions. MPC has several advantages over other algorithms, including LQR, Fuzzy, and SMC.[3,4] For instance, the LMPC uses model linearization to expedite the calculation of results compared to other forms of predictive control. Nevertheless, it is not an overly simple task, and the intended path's curvature frequently varies significantly. Because LMPC controller feed-forward information is linearized data, feed-forward information generated using linear forecast is inaccurate when there is a significant change in the curvature of the reference route.[6,7]

When used as a reference route, the controller of LMPC possesses a low level of tracking accuracy. Therefore, the configuration of the tracking rescue portable robot to follow a path of this kind is essential. To find a solution to this problem, there needs to be a sufficient amount of research done on LMPC-based route tracking control. However, this can be done by utilizing feed-forward-feedback controls, which will provide feed-forward information in the form of a preview to increase control precision in route tracking. For example, a route-tracking control system could be governed by a linear-quadratic regulator, also known as a preview LQR. Therefore, it can utilize a preview-fuzzy control approach for route tracking. The findings of these investigations demonstrate that feed-forward control is effective.

Given that other control methods, such as fuzzy control and LQR, did not have any benefits over LMPC when dealing with system restrictions, there is a need to investigate the hybrid path tracking/preview control approach. The possibility of utilizing LMPC to provide feed-forward information employing preview control was investigated.[7] Even though LMPC-based route tracking control relies heavily on longitudinal speed, it introduces a new method for minimizing longitudinal speed when steering. It is done so to maximize steering accuracy.

Linear quadratic regulator

The control LQR is well known in current optimal control theory and is frequently employed in various applications. Optimal control problems have characteristics such as minimizing a scalar function by adjusting controlled variables and constraints that must be continually met or after the optimization process. It is also distinguished by the horizon, which is potentially limitless but finite. For example, consider the system's discrete-time state-space model.[8]

Model predictive controller

MPC is called receding horizon control; it is a control method that provides appealing solutions for controlling limited linear or nonlinear systems, more recently, hybrid systems. MPC is an optimum control approach that obtains the control action by solving a limited, finite horizon optimal control problem for the plant's present state at each sampling period. For a predicted development of the system model across a finite horizon, the sequence of effective control inputs is determined. However, just the first control sequence element is used, and the system's state is assessed again at the next sampling time. This Receding Horizon Strategy (RHC) brings input into the system, allowing for correcting any modeling mistakes or system disruption.[9–11]

The controller for the LMPC is designed in MATLAB/Simulink simulation. Therefore, this routed mobile robot kinematics model may be used to create a controller of the LMPC prediction model:

$$\begin{cases} m = v\cos(\theta) \\ n = v\,sin\,(\theta) \\ \bar{\theta} = Z \end{cases} \tag{1}$$

Where $\bar{x} = m$ and $\bar{y} = n$.

A mobile robot planar motion center has an abscissa, heading angle (θ), and ordinates (x, y), respectively. Longitudinal yaw (Z) and velocity (v) are the terms for the measurement. Controller design information is here.[12,13] First, conduct Jacobean Linearization by performing the extension at point $\mathbf{x}_0(x_0, y_0, \theta_0, Z_0, v_0)$ using Eq. (1) and keeping the first-order term. After that, discretization may produce the discrete-time prediction model as follows:

$$m(t+1|t) = Am(t|t) + B\Delta K(t|t) \tag{2}$$

Where

$$m(t|t) = \begin{bmatrix} x(t|t) - x_0 \\ y(t|t) - y_0 \\ \theta(t|t) - \theta_0 \end{bmatrix} \tag{3}$$

$$\Delta K(t|t) = \begin{bmatrix} v(t|t) - v_0 \\ \\ Z(t|t) - Z_0 \end{bmatrix} \tag{4}$$

At time t, K denotes the i-th control input, m denotes the i-th predictive state, and T is the control cycle.

$$A = \begin{bmatrix} 1 & 0 & -Tv_0\,sin\,(\theta) \\ 0 & 1 & Tv_0\,cos\,(\theta) \\ 0 & 0 & 1 \end{bmatrix} \tag{5}$$

$$B = \begin{bmatrix} T\cos(\theta) & 0 \\ T\sin(\theta) & 0 \\ 0 & T \end{bmatrix} \tag{6}$$

The system parameters in the prediction and control horizons are H_p and H_c, respectively, The LMPC controller's prediction model is found in Eq. (8).

$$m(t+H_p|t) = A^{Hp}m(t|t) + A^{Hp-1}B\Delta K(t|t) + \ldots + A^{Hp-Hc}B\Delta K(t+H_c-1|t) \tag{7}$$

The system's future output can be shown as a matrix.

$$n(t) = \psi\ m(t|t)\ +\ \Theta\Delta K(t) \tag{8}$$

Where

$$n(t) = \{m(t+1|t), \ldots, m(t+H_c|t), \ldots m(t+H_p|t)\}$$
$$\Delta K(t) = \{\Delta K(t|t), \ldots, \Delta K(t+H_c-1|t)\} \tag{9}$$

$$\psi = [AA^2, \ldots, A^{Hc}, A^{Hp}] \tag{10}$$

Tracking objective points are tracked using linearized status information (m_{ref}), while control input increment and tracking error are tracked by weight matrices E and Q, respectively. The optimization process's objective function can be constructed as illustrated in Eq. (10).

$$J(m(t), \Delta K(t)) = \sum_{i=1}^{Hp} ||m(t+i|t) - m_{ref}(t+i|t)||_E^2 + \sum_{i=1}^{Hc} ||\Delta K(t+i|t)||_{\tilde{Q}}^2 \tag{11}$$

Because

$$m_{ref}(t|t) = \{x_{ref}(t|t) - x_0, y_{ref}(t|t) - y_0, \theta_{ref}(t|t) - \theta_0\} \tag{12}$$

There is a tracking objective point that is abscissa, heading angle and ordinate, x_{ref} (t|t), y_{ref} (t|t), θ_{ref} (t|t). When paired with constraints, route tracking control with mobile may be expressed the problem using quadratic programing.[12,17]

$$\min J(m(t), \Delta K(t)) = \frac{1}{2}\Delta K(t)^T N \Delta K(t) + G\Delta K(t) + C \tag{13}$$

It is possible to determine the increase of the input sequence in the control range.

$$\Delta K^* = [\Delta K^*(t|t), \ \ldots, \Delta K^*(t+Hc\,|t)]T \tag{14}$$

The following control cycle's input will be

$$K(t|t) = \Delta K^*(t|t) + K(t-1|t) \tag{15}$$

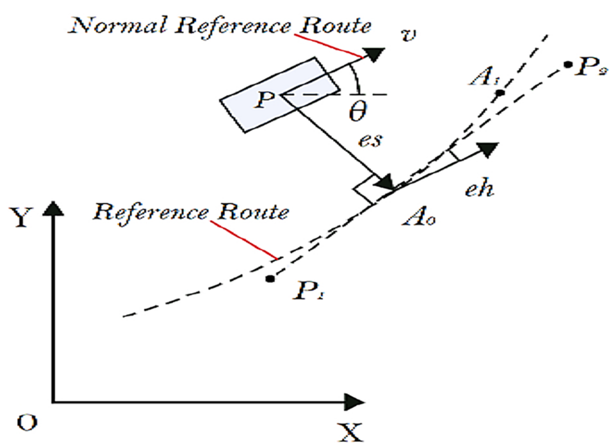

Fig. 1. The robot's reference path closest to its plane movement center.

Table 1. Parameters of robot through its moving.

The symbol	the meaning
A0	The intersection between point P and reference path at point A0
A0A1	The preview distance
P	Center of the robot
P1P2	The reference path's tangent line at point A0
es	The distance between the centers of the robot (P) to the nearest point of the center of reference path's A0 is known as displacement error (Lateral error).
eh	The difference between mobile robot's heading and reference path's direction at point A0 (Longitudinal error).

Mechanism for preview control

When a mobile robot goes far from the planned path, the closest places on this reference route to its plane motion center can be considered to be within a reasonable distance, as shown in Fig. 1. Table 1 illustrates all parameters at the mobile robot when is moving.[14–16]

The dynamics of a robot are typically separated into longitudinal and lateral motion. It is typically done to reduce the control tasks' complexity while the robot is being driven. The longitudinal behavior is frequently modeled by a simple system, whereas the lateral behavior is more complex.[18–20]

For example, the arc length ahead of the reference path's point A0, A1 will serve as the point of tracking the target and plugging its abscissa and ordinate into Eq. (11).

Verification of the simulations

The specifications of the computer used for the simulation are shown in Table 2. The controller's primary

Table 2. Specification of the standard computer.

Item	Specification
Computer Type	Laptop Lenovo z500
Processor	Intel(R), Core i7 QM CPU @ 2.10 GHz
Memory	12 GB, DDR3, 1600 MHz
Operating System	Windows 10 Pro, Arabic Edition
Simulation Software	MATLAB/Simulink R2018b

parameters are the prediction horizon, control horizon, and control cycle. The prediction horizon (H_P) and control horizon (H_C) are 25, and the control cycle (T) is 0.05 s, Curvature of the simulation's reference route is 0.2 m^{-1}.

The simulation

The findings are illustrated in Figs. 2 to 5. The Preview-LMPC offers a preview range of 0.7 m. In Fig. 2 the robot's path of travel is shown; when controlled by preview-LMPC, the path taken by the robot is nearest to the range of components in the illustration below. The yaw rate, as depicted in Fig. 3, represents the rate of change in the robot's heading

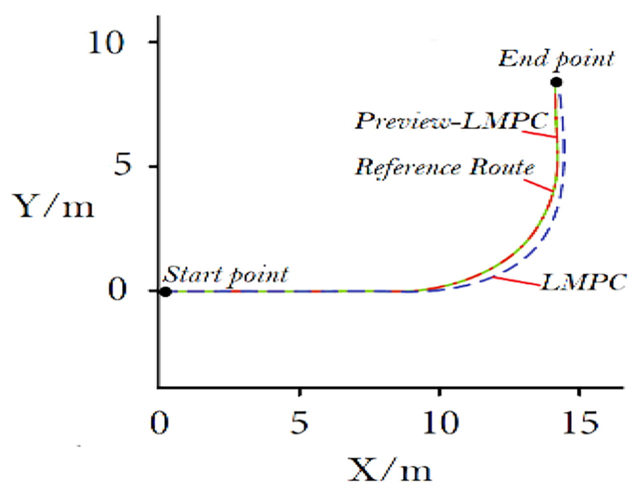

Fig. 2. Trajectories of simulations.

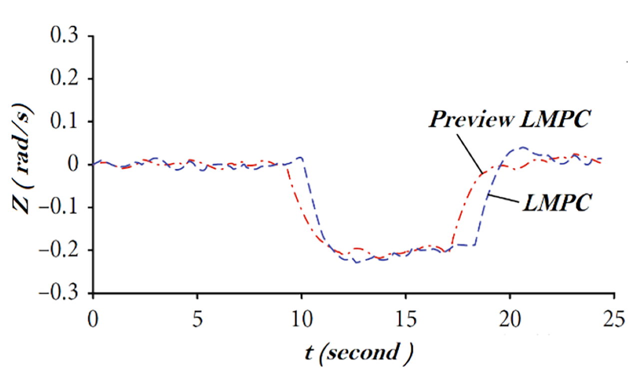

Fig. 3. The Yaw rate of simulation.

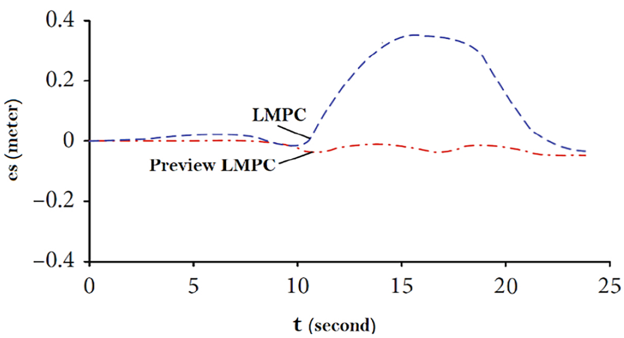

Fig. 4. The simulations displacement error.

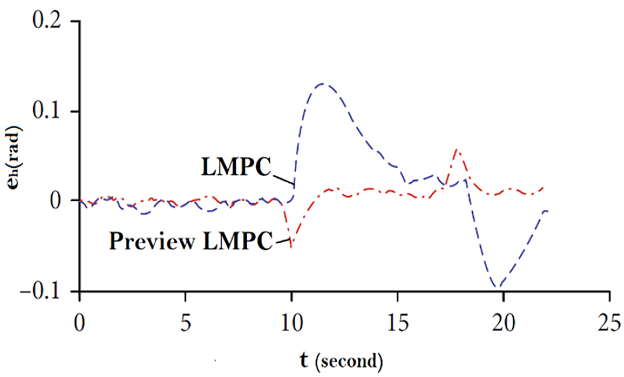

Fig. 5. The simulations heading error.

angle, indicating its turning speed. This parameter is crucial in path tracking control, as it precisely determines the robot's ability to follow a desired trajectory. By analyzing the yaw rate in simulations, researchers can evaluate the performance of path-tracking control algorithms in terms of their accuracy in following the desired path. The simulation results between 9 and 22 seconds in Fig. 3, with a large curvature under preview-LMPC, provide insights into the algorithm's effectiveness and help identify areas for improvement. However, preview control can improve the robot's track accuracy. Figs. 4 and 5 demonstrates dimensional erroneousness, respectively. To determine the robot's displacement and direction errors, it is necessary to compare the robot's tangent to reference the path's tangent and then subtract the result. Consider the following examples: the absolute movement LMPC error will be 0.3811 m.

Moreover, the absolute heading inaccuracy to LMPC will be 0.1072 rad respectively. So, the variables in the Preview-LMPC method stated have values of 0.031 m and 0.0456 rad, respectively. According to this method, by contrast, while comparing the error of maximum absolute movement to the LMPC, it was found that the highest absolute movement error is decreased by 89.24%. In comparison, the maximum value of absolute direction error is decreased by 57.46%.

Results and discussion

The preview of LMPC presents itself as a compelling choice for route tracking control of rescue mobile robots due to its ability to function effectively without the need for a complex system model and its tolerance for system state constraints. Simulation results obtained from the preview of LMPC reveal a remarkable reduction in both maximum absolute displacement and going error compared to LMPC without preview. Specifically, simulation data indicates an 89.24% reduction in maximum absolute displacement and a 57.38% reduction in going error. These performance improvements were achieved while traversing a reference route at one meter per second speed.

Conclusion

Using a strategy for controlling mobile robots that is simple and effective, the rescue effort may be improved. Thus, quick control value computation times are favorable for raising information sampling frequencies between the cloud's edges, increasing their synergistic ability. The route tracking control for rescuing mobile robots is well-suited to LMPC because it does not require a complicated system model and can handle system state restrictions.

MPC has several benefits over many other algorithms, including LQR, Fuzzy, and SMC. The LQR has low computational complexity and excellent robustness, making it easy to modify the parameters. Even though SMC is a reasonably reliable controller, its discrete-time performance still needs to be evaluated. MPC has a high computational complexity, but it has good performance, and it can handle constraints and include collision avoidance, all of which make this approach very appealing. For all these purposes, applications based on MPC algorithms to solve automated driving assistance tasks are still the subject of intensive research.

LMPC's reference route controller has low tracking accuracy. However, the tracking rescue portable robot must follow this path; LMPC-based route tracking control research needs to be improved. For example, feed-forward-feedback controls can increase route tracking control precision by providing feed-forward information via a preview.

The results of the preview of LMPC, as shown in simulation, LMPC's maximum absolute displacement and going error reductions are 89.24% and 57.38%

lower in simulation than those achieved by the LMPC without preview. Moreover, it was done on a reference route with a speed of 1 meter/s.

Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at Misan University.

Authors' contribution statement

S.T.A.A. conception, design, acquisition of data, analysis and interpretation. L.S.A.A. wrote and edited the manuscript with revisions idea.

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القيادة الذاتية لروبوت خدمة الطوارئ الموجهة مع التحكم في تتبع المسار

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المستخلص

يقدم هذا العمل طريقة للتحكم في مسارات حركة الروبوت المتعقبة. تقترح خوارزمية التحكم التنبئي في النموذج أنه يمكن استخدامها لتمكين الروبوت من قيادة نفسها في حالة الطوارئ. من المتوقع أن يصبح التعاون السحابية أكثر استخداماً لربط وتحكم في مختلف معدات الإنقاذ. تعد خوارزمية التحكم في النموذج التنبئي الخطي، والمعروفة أيضًا باسم LMPC، خيارًا ممتازًا للتحكم في مسار روبوتات الإنقاذ لأنها تستخدم موارد حسابية محدودة بكفاءة وتقدم نتائج قوية في الوقت الفعلي. على الرغم من ذلك، فإن ظروف القيادة معقدة، ويتغير انحناء الطريق بشكل كبير في هذا السيناريو. نظرًا لأنه يمكن إدخال بيانات التغذية الأمامية الخطية فقط في LMPC، فهناك قيود على الدقة التي يمكن تحقيقها عند تتبع مسار به اختلافات كبيرة في انحناءه. في هذه الدراسة، تم اقتراح معاينة MPC خطية كحل لهذه المشكلة من أجل معالجتها. يتم تحميل وحدة تحكم الاختبار بمحاكاة تم إنشاؤها في MATLAB باستخدام Simulink. لقد حققنا أداءً أعلى لتتبع المسار على الرغم من وجود اختلافات جوهرية في انحناء المسار باستخدام الاستراتيجية المقترحة

الكلمات المفتاحية: الروبوت،ت المستقلة، محاكاة MatLab، التحكم في التنبؤ بالنموذج، التحكم في تتب، المسار، الشبكات اللاسلكية.