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Four Forklift Induced Docking Strategy Based on NMPC

Min WANG[1], Zhenrui CHEN
Department of Basic Education, Shandong Jiaotong University, Weihai, China

Abstract. The induced docking of automated forklift workshop between zones can solve the problem of manual cargo transportation in the current storage and sorting system, which is conducive to improving the transportation and efficiency of goods, programing the operation cycle, and guaranteeing the storage safety of goods. The docking route of four associated forklifts are planned. The route planning algorithm base on nonlinear model-predictive control (NMPC) is given by setting the objective function, constraints of forklift induced docking, and the multi-forklift docking induction strategy is realized. Kalman filtering is introduced into the prediction of forklift states and the analysis of docking results. The simulation results show that effective linkage can be realized between four forklifts to complete the forklift cargo docking transportation in the case of low uniform speed with preset obstacles, and the experimental data show the effectiveness and practical value of this strategy in forklift induced docking.

Keywords. Forklift docking, NMPC, route planning, Kalman filtering, transportation

1. Introduction

With the continuous improvement of the intelligent vehicles application range for storage and transportation, in addition to the study of simple path optimization problems for goal arrival, complex path optimization problems such as collision avoidance, tracking, docking, and multi-objective ones have become hot，Due to the complexity of the vehicle operating environment, path planning for autonomous vehicles has many difficult problems. In the docking process of intelligent warehousing goods transfer, the induced docking of autonomous forklifts in the zone is a key factor to improve the efficiency of warehousing and transportation. In recent years, route planning algorithms are developed efficiently and used widely. Hou proposed a trajectory planning and tracking strategy for unmanned ground vehicles (UGVs) navigating in environments with obstacles. The strategy aims to optimize trajectories while ensuring safe and efficient movement in the presence of obstacles [1]. MONOT introduced a lateral guidance system for automated vehicles utilizing multi-PID steering control and a look-ahead point reference. The system aims to improve lateral stability and tracking accuracy during autonomous driving [2]. Zhang presented a modified A* algorithm for optimizing the path of unmanned aerial vehicles (UAVs) considering radar detection and stealth requirements [3]. Metzler examined how the fidelity of prediction models affects vehicle stability control systems in explicit NMPC, with the objective of improving both

[1] Corresponding Author: Min WANG, wangmin@sdjtu.edu.cn.

accuracy and resilience [4]. Sivakumar proposed a multi-sensor fusion-based proactive anomaly detection method for robot navigation, aiming to ensure safe and reliable navigation by detecting and mitigating anomalies in real-time [5]. Belge introduced a metaheuristic optimization-based approach for path planning and tracking of drones during payload hold-release missions, aiming to optimize trajectories for efficient payload delivery and release [6]. Yang explored the application of particle swarm optimization (PSO) in solving the shortest path problem to improve path planning effectiveness in various applications [7]. Kumar introduced a hybrid approach that combines regression and adaptive particle swarm optimization, designed to enhance the efficiency and adaptability of humanoid robot navigation in challenging environments [8]. Tan introduced a novel adaptive intelligent method based on particle swarm optimization for planning surgical needle paths, with the goal of enhancing both the efficiency and precision of surgical procedures [9]. Fang introduced an advanced neural network-based model for vehicle dynamics, aimed at achieving superior performance in trajectory tracking control. Aiming to accurately predict vehicle dynamics to improve trajectory tracking and control effectiveness [10].

For the self-coordinated docking problem of four forklifts, this paper adopts the multi-forklift cooperative algorithm based on NMPC, the path of four forklift is controlled and optimized by establishing the four-vehicle motion model, the nonlinear constraints are designed, the positional information, the velocity-direction angles, and the distances between each other are predicted and tracked by the forklift model.

2. Forklift Dynamics Model

In the process of dynamics modeling design, two pair of forklift trucks is considered for induced docking problem, and one pair of pickup forklifts (F1, F2) is designed to dock another pair of storage forklift trucks (F3, F4) , as shown in Figure 1. Among them, (F1, F2) are pickup forklifts for unloading the goods on the vehicle, and (F3, F4) are storage forklifts for meeting the goods in F1, F2 and transferring them to storage for warehousing. the following assumptions of model are made.

a. Ignoring the in-situ steering system for forklift orientation, the model inputs are the coordinate position of the forklift and the velocity angle;

b. The role of aerodynamics is ignored;

c. The velocity changes at the start and termination of the forklift are ignored;

d. The multiple obstacles areas are disregarded.

The forklift model was simplified to longitudinal and transverse coordinates in the geodetic coordinate system, $\left(x_{f1},\ y_{f1},\ x_{f2},\ y_{f2},\ x_{f3},\ y_{f3},\ x_{f4},\ y_{f4}\right)$. V_{f1}, V_{f2}, V_{f3}, V_{f4} are the speeds of pickup forklifts and storage forklifts respectively, $\alpha_{f1}(\mathrm{t})$, $\alpha_{f2}(\mathrm{t})$ are the heading angle of two pickup forklifts. $\alpha_{f3}(\mathrm{t})$, $\alpha_{f4}(\mathrm{t})$ are the heading angle of two pickup forklifts. The velocity of the forklift is constant by assumption. The equation controlling the relative motion of the four objects can be written as the formula 1 to formula 12.

$$x_{fi}(t) = v_{fi} cos\alpha_i(t) \tag{1}$$

$$y_{fi}(t) = v_{fi} sin\alpha_i(t) \tag{2}$$

$$L_1' = v_{f3}\cos\varphi - v_{f4}\cos\sigma \tag{3}$$

$$L_2' = v_{f1}\cos\gamma - v_{f4}\cos\beta \tag{4}$$

$$S_1' = v_{f1}\cos\theta_1 - v_{f3}\cos\theta_3 \tag{5}$$

$$S_2' = v_{f2}\cos\theta_2 - v_{f4}\cos\theta_4 \tag{6}$$

$$(\alpha_{f3} - \varphi)' = (V_{f4}\sin\alpha_{f4} - V_{f3}sin\alpha_{f3})/L_1 \tag{7}$$

$$(\alpha_{f1} - \gamma)' = (V_{f1}\sin\alpha_{f1} - V_{f2}sin\alpha_{f2})/L_2 \tag{8}$$

$$(\theta_3 - \varphi)' = (V_{f1}\sin\theta_1 - V_{f3}sin\theta_3)/S_1 \tag{9}$$

$$(\theta_3 - \beta)' = (V_{f2}\sin\theta_2 - V_{f4}sin\theta_4)/S_2 \tag{10}$$

$$\alpha_{f1}' = C_1 \tag{11}$$

$$\alpha_{f1}' = C_2 \tag{12}$$

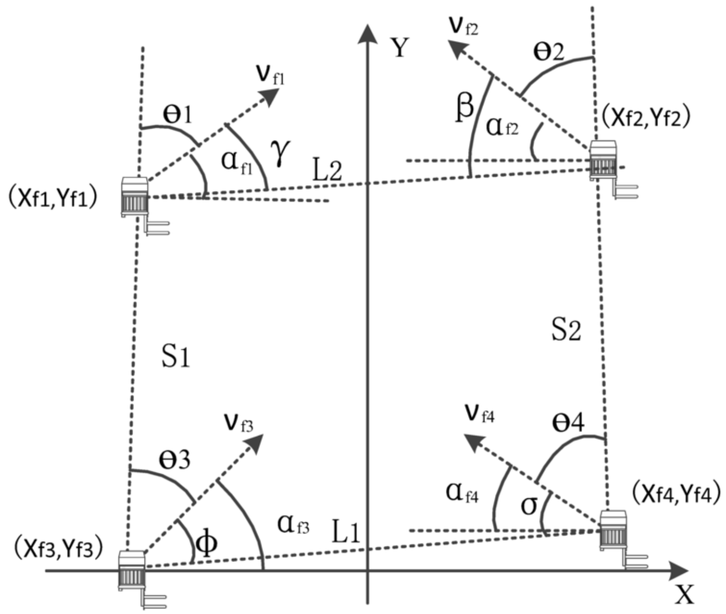

Figure 1. Forklift power model.

In the model, storage forklifts F3 and F4 track the trajectories of receiving forklifts F1 and F2, which are close to each other, inducing F3 and F4 to approach each other. By setting constraints and objective functions, the operating angles of the forklifts are constantly updated so that the forklifts can approach each other quickly. Here, the position data, velocity data, and target position data in the initial state data of the forklifts are free.

3. Solver Design

Nonlinear model predictive control is a control method based on a model, it is used to handle control problems of complex systems such as nonlinear, multivariable, time-varying and constrained conditions. NMPC predicts the system state and output for a period of time in the future, and based on this character, the optimal control input is obtained for system control. NMPC controller design consists of four parts: constraints, predictive model, objective function and solver. In the strategy of induced docking using

NMPC, improved NMPC controller is designed and the state of the model is predicted by Kalman filtering. The linkage objective function of the predictive model is designed.

3.1. Predictive Model

The path trajectories of the four forklifts are computed using an iterator, and the warehouse forklift approaches the receiving forklift via information induction. The main components of the controller are the motion model, as shown from formula1 to formula12, a nonlinear optimizer, an objective function, and physical constraints on the state and control. The EKF is used to predict the state of the receiving forklifts. Combining the method with state feedback helps to reprogram the control sequence to cope with the uncertainties involved in real-world systems. For accurate docking between the vehicles, it is necessary to minimize the distances $L_1$and L_2 between the receiving forklifts and between the storage forklifts, and minimize S_1 and S_2 to keep their velocity vectors within the docking range of the storage forklifts. During the iteration of the program, the prediction model is discretized and the setup iteration process is shown in formula14 and 15.

$$fu = f(X[i], U[i]) \tag{14}$$

$$X[i+1] = X[i] + fu * \Delta t \tag{15}$$

3.2. Constraints

In the design of the solver for forklifts, data constraints encompass various aspects including position, velocity, angular velocity, and others. Position constraints may involve the effective range of the forklift within the workspace and restrictions to avoid collisions or entry into restricted areas. Velocity constraints ensure the forklift moves within a safe range, such as limiting maximum speed to avoid hazardous operations or reducing speed to ensure stability of cargo. Angular velocity constraints are typically used to control the forklift's turning radius and stability, ensuring it doesn't lose control or overturn during turns. Other constraints may include acceleration limits, load capacity restrictions, and environmental conditions such as slope and coefficient of friction affecting the forklift's performance. Integrating these constraints requires a combination of mathematical modeling, optimization algorithms, and control strategies to ensure the forklift operates safely, stably, and efficiently. Here, Simple and basic constraints were given to the model, the rate of change of angular velocity was set in the range of $[-\frac{\pi}{4}, +\frac{\pi}{4}]$, the setting range of speed v_{fi} is $[0, 60]$km/h, The angle is set at $[-\pi, +\pi]$.

The advantage of these simple constraints lies in their clarity, making the problem-solving process more intuitive and manageable. They are not only easy to understand but also straightforward to implement, simplifying the design and implementation of corresponding algorithms or control systems. Furthermore, the simplicity of these constraints helps reduce complexity and enhance system stability by constraining the range of possible behaviors, thus lowering the risk of errors and instability. Therefore, these simple constraints effectively balance the complexity of the problem with the feasibility of solutions, providing a solid starting point for problem-solving.

3.3. Objective Function

The NMPC has better computational speed and computational accuracy for solving the nonlinear problem of vehicle motion process. Here, the distance relationship between the four vehicles is set to ensure the forklift paths are smooth, and at the same time, the induced docking accuracy between the forklifts is improved. The minimization of the NMPC control performance index function can be expressed as the formula (16), and $wi, i = 1...5$ are the weights. L_1 is the distance between the storage forklift, L_2 is the distance between the pickup forklift, S_1 is the distance between the storage forklift f1 and the pickup forklift f3, S_2 is the distance between the storage forklift f2 and the pickup forklift f4.

$$minOBJ = \int_t^{t+\Delta t} w_1 * L_1 + w_2 * L_2 + w_3 * S_1 + w_4 * S_2 \tag{16}$$

The objective function is designed to minimize the performance index of the NMPC system, aiming to optimize the distances and interactions among the four vehicles, ensuring smooth forklift paths and improving docking accuracy. By minimizing this objective function, the NMPC aims to optimize the overall performance of the vehicle motion process, balancing between smooth forklift paths and improved docking accuracy.

3.4. Solver

Based on the above constructed part, the NMPC control is transformed into solving the following nonlinear programming problem as shown in formula17, 18.

$$X = f\,(X, U, t) \tag{17}$$

$$\mathrm{U} \in [-\mathrm{U}, +\mathrm{U}] \tag{18}$$

Where $\mathrm{X} = \{x_{f1}, y_{f1}, x_{f2}, y_{f2}, x_{f3}, y_{f3}, x_{f4}, y_{f4}, L_1, L_2, S_1, S_2, \theta_1, \theta_2, \theta_3, \theta_4, \varphi, \sigma\}$ are the states, the control commands, denoted as $\mathrm{U} = \{u1, u2\}$, are calculated for the pickup forklifts. The range from -U to +U represents the minimum and maximum allowable values for the commands. The fuction $f(t, t + \Delta t)$ signifies the set of piece-wise continuous functions within the time interval $[t, t + \Delta t]$. Because the states of the storage forklifts are not directly observable by other storage forklifts, they are estimated using an EKF.

4. Docking Prediction Based on Kalman Filtering

Kalman filtering is a powerful mathematical tool used to estimate the future states of linear dynamic systems. By predicting the state of the forklift and updating the measurement results, the state of the forklift at the next moment is estimated. The core idea of Kalman filtering is to optimize the estimation of the state of the system by using a priori and a posteriori information.

Kalman filtering represents the state of the four forklifts as a vector. The vector contains information about the position, speed and direction angles of the forklifts. This vector is referred to as the state vector. The next state of the forklifts is predicted by using the motion model and the state estimation of the previous moment. The process of prediction consists of two main steps: the future state prediction and covariance estimation. The future state prediction utilizes the dynamic model of the forklift and previous state estimates to predict the next state of the system. Covariance estimation utilizes the state prediction and a noisy model of the forklift to predict the uncertainty of the forklift state. The new measurements are then used to update the predicted state estimates. The update involves two stages: computing the Kalman gain and revising the state estimate. The Kalman gain is determined by considering the covariance prediction and measurement noise models, indicating how much emphasis should be placed on the measurements when adjusting the state estimate. Updating the state estimate means to update the previous state estimate by using the Kalman gain and the measurements.

The forklift docking induction process is designed as follows.

Step1: initialize the starting position and velocity of the forklift, then create the state vector and covariance matrix.; Step2: predict the next state of the forklift by using the motion models of the receiving forklift and the storage forklift and the estimation of the previous state; Step3 is measurement model calculation. the state of forklifts on the sensor measurement distance and the angle of view information data, and the specific measurement model design is shown in the formula (19); Step4: by the formula of Kalman filtering, the results obtained from the measurement model are combined with the forecasted outcomes to derive the revised state estimate and covariance matrix; Step5: Repeat the steps from Step2 to Step4, in order to realize the continuous trajectory tracking.

$$measure = \begin{cases} \sqrt{\left(x_{f1}-x_{f2}\right)^2+\left(y_{f1}-y_{f2}\right)^2} \\ \sqrt{\left(x_{f3}-x_{f4}\right)^2+\left(y_{f3}-y_{f4}\right)^2} \\ \sqrt{\left(x_{f1}-x_{f3}\right)^2+\left(y_{f1}-y_{f3}\right)^2} \\ tan^{-1}\left(\frac{y_{f1}-y_{f2}}{x_{f1}-x_{f2}}\right) \\ tan^{-1}\left(\frac{y_{f3}-y_{f4}}{x_{f3}-x_{f4}}\right) \\ tan^{-1}\left(\frac{y_{f1}-y_{f3}}{x_{f1}-x_{f3}}\right) \end{cases} \tag{19}$$

The specific induced docking prediction algorithm flow is designed as follow.

Firstly, Forklift state initialization is performed. At the beginning of the induced docking, the starting position and speed of the forklift need to be determined and the state vector and covariance matrix of the four vehicles need to be established as shown in the power model. Here the state vector contains the initial position, velocity and angular velocity information of the forklifts, while the covariance matrix is used to represent the uncertainty of the state estimation.

Secondly, the next state of the forklift is predicted. The next state of the forklift is predicted using the forklift's motion model and previous state estimates. The motion model of the forklift can be determined from historical data, where it is assumed that the motion of the forklift is either a uniformly accelerated motion or a uniformly accelerated motion. Assuming that the state vector of the forklift at moment t is $x(t),$ the following equation (20) can be utilized for prediction.

$$x(t+1) = Arr\backslash cdot\ x(t) + C\backslash cdot\ col(t) + n(t) \tag{20}$$

where Arr is the state transfer matrix, C is the control matrix, $col(t)$ is the control vector, and $n(t)$ is the process noise to represent the uncertainty of the motion model.

The prediction of the covariance matrix can be calculated by the following equation (21).

$$Cov(t+1) = Arr \cdot Cov(t) \cdot Arr^T + N \tag{21}$$

Where $Cov(t)$ is the covariance matrix of the previous state estimates and N is the covariance matrix of the process noise, which is used to represent the uncertainty of the state estimates.

Thirdly, observation computation: the measurement model is utilized to compute the position of the forklift to obtain the measurement vector $z(t)$. The measurement vector contains the position information of the forklift.

Fourthly, updating: utilizing the formula of Kalman filtering, the measured state is combined with the predicted state to obtain an updated state estimate and covariance matrix. Specifically, the updating of the Kalman filter includes the following steps. The Kalman gain $G(t)$ is calculated, The Kalman gain $G(t)$ represents the weight of the measurement on the state estimate. It is calculated as in equation (22):

$$G(t) = Cov(t) \cdot H^T \cdot (H \cdot Cov(t) \cdot H^T + R)^{-1} \tag{22}$$

Where H is the measurement matrix for mapping the state vectors into the measurement space and R is the covariance matrix of the measurement noise for representing the uncertainty of the measurement results. During the validation process, the state vectors are updated using the Kalman gain and the measurement results, calculated as in equation 23. the covariance matrix is updated using the Kalman gain and the measurements, calculated as in equation 24.

$$x(t+1) = x(t) + G(t) \cdot (z(t) - H \cdot x(t)) \tag{23}$$

$$Arr(t+1) = (X - G(t) \cdot H) \cdot Cov(t) \tag{24}$$

Procedure two to procedure four are repeated to realize successive induced docking. In induced docking, some parameters need to be set, including the state vector, motion model, measurement noise, process noise and initial covariance matrix. State vectors such as forklift position, velocity and acceleration information can be set according to the specific application.

5. Experimental Data

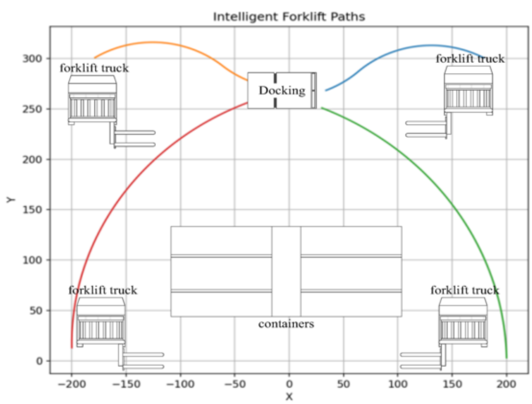

Figure 2. Smart forklift docking path.

The simulation experiments were performed using the CasADi Python library on a Windows 10 system with an Intel i7-10510U CPU and 8 GB of RAM. all simulations were performed in a time range of 0.5 s (a prediction horizon of 50 steps with a sampling interval of 0.05 seconds). The average computational time for each NMPC replanning step was 0.1 seconds. The weight parameters were set as $w1 = w2 = 25$, $w3 = w4 = 50$ for practical reasons regarding turn rate. Due to practical considerations of the turn rate, the angular velocity was limited to $-0.785 \leq \{C\_1, C\_2\} \leq 0.785$ rad/s.The speed of the warehouse forklift is set to $v_{f3}, v_{f4} = 50m/s$, The speed of the pickup forklift is set to $v_{f1}, v_{f2} = 25m/s$. As shown in the docking scenario in Figure 2, the curves in the figure are the forklift docking run paths predicted by the algorithm. This figure shows the initial state configuration $x_{f1} = 180$, $y_{f1} = 300$, $x_{f2} = -180$, $y_{f2} = 310$, $x_{f3} = -200$, $y_{f3} = 10$, $x_{f4} = 200$, $y_{f4} = 0$. In the simulation, the optimized path of docking does not change even if the speed changes, but the value of the initial angular velocity of the forklift has a greater influence on the tracking trajectory.

As depicted in Figure 3, the dashed line represents the desired detection path in reality, and the solid line is the planning path predicted by the model. The comparison of the fitted paths shows that the predicted planning paths can meet the needs of the actual problem when friction, environment and other complexities are not considered.

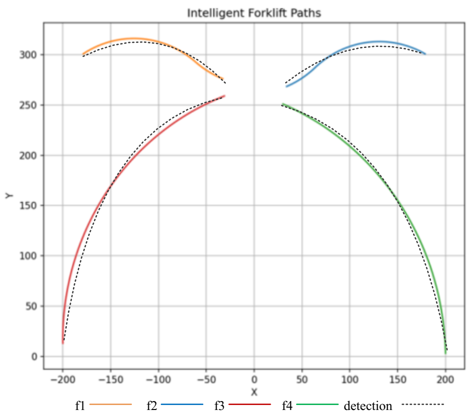

Figure 3. Comparison chart between detected and estimated values

6. Conclusion

The NMPC-based induction strategy is proposed for induced docking problem of four forklifts, the pickup forklift and storage forklift positions were analyzed by Kalman filtering, and the induced docking strategy was verified by program simulation. Numerical simulations verified the effectiveness of the program. The results show that the NMPC path planning strategy is able to satisfy the goal of multi-vehicle induced docking without considering the influence of the complex environment. In addition, the data of EKF and NMPC were well fitted and the estimation error was within the controllable range. The results of the study also support the strategy analysis.

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