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Collision Avoidance Method with Nonlinear Model Predictive Trajectory Control

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Abstract:
The automatic navigation systems are able to control the tractor and even the implement without human interaction. However, if there is no device to recognize obstacles on the field, a human driver is still needed to ensure that the tractor does not collide with anything, like electricity poles.

In this research, the collision avoidance method was built on top of the existing experimental navigation system which is able to control both the tractor and the towed implement with the help of true MIMO controller. The existing navigation algorithm is based on the Nonlinear Model Predictive Control (NMPC) which is modified to support path tracking. The augmentation of the collision avoidance to the NMPC was inspired by the potential field method. The proposed solution does not increase the computational cost of the original NMPC.

The collision avoidance method was tested and was proven to work in real environment at driving speeds less than 3.5 m/s. The obstacles were detected with a 2D laser scanner which was mounted in the front of the tractor. The obstacle detection was also found to be sufficiently accurate to current application.

Keywords: Laser scanner, object detection, NMPC, path tracking, tractor-implement navigation

1. INTRODUCTION

Automatic steering systems are commonly used in agriculture nowadays and there are many commercial solutions available (Farm Journal Inc., 2011). Different navigation methods have also been widely researched in the past years. The focuses in the researches have usually been on either path tracking or path planning methods. With these methods, the tractor is able to realize complete agricultural operations on the field. However, the driver or operator is still needed to monitor the system and to ensure that the tractor does not collide with anything.

There are in agricultural field, however, few researches about collision avoidance methods, for example Noguchi et al. (2004) and Vougioukas (2007).

Noguchi et al. (2004) have developed a concept of a master-slave system for farm operations. In the concept, there are two different algorithms for the slave tractor or robot: GOTO algorithm and Follow algorithm. In the first one the tractor moves to predefined location and in the latter one follows the master that is operated by the human. The slave monitors the master position constantly through a radio link. The risk index is calculated based on the current position of the master and the slave. The risk index indicates a potential risk of collision. Two actions are used to prevent collisions if the risk is too high: speed reduction and pathway correction. The simulations were used to prove the functionality of the system.

Vougioukas (2007) has used the Nonlinear Model Predictive Control (NMPC) method to control the position of the vehicle. Moreover, the collision avoidance was included into the controller by using additional cost from distance sensor readings. The controller was able to follow a predefined path as well as avoid collisions with static obstacles. The functionality was again proven with simulations.

Generally, the collision avoidance methodology is a widely studied research area. The methods can be divided roughly into two categories, although some of the methods can be used in both situations. The first category is collision free path planning algorithms. The second one is more reactive real time obstacle avoidance methods. Widely used methods from the second category are for example Potential Field method (Tilove, 1990), Vector Field Histogram (Borenstein, 1991) and Velocity Objects (Fiorini and Shiller, 1998).

The Potential Field Method creates an artificial repulsive force field around the obstacle and an artificial attractive force at the goal. The direction of the movement is chosen based on the artificial potential field.

In the Vector Field Histogram a set of candidate directions are created and the best one that is closest to the goal is chosen. The candidate directions are created according to the probability of obstacle density in every direction. If the density is below a certain threshold, the movement to that direction is allowed.

The Velocity Objects uses candidate velocities rather than only directions. The selection of the new velocity is done in the velocity space, where also obstacles velocities are added.
Furthermore, also kinematic and dynamic constraints can be taken into account in the set of candidate velocities in velocity space.

In the context of the agriculture, the field is usually quite static; the electricity poles, wells, bugholes and large rocks are more or less stationary. If all obstacles are known beforehand, the route could be designed beforehand with a suitable coverage path planning method. One such method is for example Oksanen and Visala (2009). However, there might be a situation where an obstacle is known to be in the field but the position is not mapped yet. For example there is some moving object (animal, human or another machine) or the original map was imperfect. In these situations, there has to be some device to recognize these obstacles and a method to recalculate the route or simply to stop the navigation before the collision. In Finnish fields the most common obstacle is an electricity pole and therefore the attention is on pole type obstacles.

2. TEST CONFIGURATION

The collision avoidance system was built on top of the existing experimental navigation system described in detail in Backman et al. (2012a). In this research study, the test configuration is similar, a tractor with a towed implement with steerable drawbar. However, another tractor was used and the positioning devices were updated. The vehicle that was used in the current research is shown in Figure 1.

The tractor was Valtra T132 modified to support ISOBUS Class 3 commands. ISOBUS Class 3 commands make the tractor remote controllable (steering, speed, hydraulics, PTO and rear hitch) through the CAN-bus.

The heading measurement was based on Fiber Optic Gyro (FOG). All positioning devices (FOG, IMU and RTK-GPS) were now packed together in a compact box which was mounted on the top of the cabin. The improved heading estimation is described in detail in Backman et al. (2013).

There was also a device to recognize the obstacles on the field. In this research, the obstacles are considered to be mainly I-type electric poles that are not close to each other. In Figure 1, the laser scanner is shown in front of the tractor. The scanner scans the front area of the tractor horizontally and the electric poles and other high objects are in sight of the scanner.

The underlying navigation system is based on Nonlinear Model Predictive Control (NMPC) that was modified to support path tracking. The path tracking method is described in Backman et al. (2012a).

The reference path of the navigation is planned constructively. First, the driver drives the whole field around or the field boundaries are loaded from the file. After that, the field is driven around certain amount of times in order to make enough space for the headland turnings. Finally, the middle area is processed by driving to and fro along the longest edge using predefined turning patterns. The distance to the adjacent driving line is always kept constant. The path planning is described in detail in Backman et al. (2012b).

3. METHODS

The collision avoidance problem can be divided into two different subproblems: detecting the obstacle and bypass the obstacle. In this chapter, the obstacle detection method is described first. Then the modified path tracking algorithm is explained, where the collision avoidance is included.

3.1 Obstacle detection

The obstacle detection is based on a 2D laser scanner (SICK LMS221). The scanner is mounted in the front of the tractor and it scans the front area horizontally. The raw measurement consists of 181 distance measurements with one degree resolution. The raw measurements are at first transformed into Cartesian coordinates.

Figure 1. The test configuration; the laser scanner is mounted in the front of the tractor and positioning devices are on the top of the cabin.

Figure 2. Obstacle detection from laser scanner data (black dots). The red circle represents the clustered measurements and blue circle is the previous position of the associated obstacle.
The obstacles are detected from the transformed measurements using clustering method. The whole clustering process is illustrated in Figure 3. The initial positions for the clusters are gained from the set of known obstacles. The cluster initial position is added if known obstacle is in sight of the scanner. In Figure 2, the blue cross represents the center of the known obstacle and the initial cluster center.

The clustering is based on modified nearest neighbour algorithm. First, all the measurements are passed through one by one and the closest existing cluster for every measurement is searched. If the distance to the closest cluster is in permitted limits, the point is associated with the cluster and the cluster position is updated according to the equation:

\[
\begin{align*}
    x_{\text{cluster}} &= \frac{C \cdot x_{\text{cluster}} + x_{\text{meas}}}{C + 1} \\
    y_{\text{cluster}} &= \frac{C \cdot y_{\text{cluster}} + y_{\text{meas}}}{C + 1}
\end{align*}
\]

where \( x_{\text{cluster}}, y_{\text{cluster}} \) is the old position of the cluster center, \( x_{\text{meas}}, y_{\text{meas}} \) is the measurement and \( C \) is the number of measurements associated with the cluster before the current measurement. In Figure 2, four adjacent scanner measurements are clustered together and marked with a red circle.

If the distance to the closest cluster is not within the allowed limits, a new cluster is created.

After all the measurements are associated with some cluster, the numbers of associated measurements of the clusters \( C \) are reduced to one and the clustering is repeated. The process is continued until all measurements are associated with the same cluster as in previous iteration or the maximum number of iterations is reached.

After clustering the measurements, the clusters are matched back to the known obstacles. All obstacles that are in sight of the laser scanner are gone through again. The closest cluster of each existing obstacle is searched and associated. The positions of the associated obstacles are updated with the same equation as the cluster positions (Eq. 1). If there are new clusters, i.e. the cluster was not the closest one of any existing obstacle, new obstacle candidate is created. In Figure 2, the cluster marked with a red cross and a circle, is associated with a known obstacle marked with blue color.

An additional visibility counter is also updated. If the obstacle is in sight of the scanner and it is seen, the visibility counter is increased, otherwise the counter is decreased. When the obstacle is seen a predetermined number of times, the recognition is considered to be reliable. In turn, if the obstacle is not seen although it should been, the recognition is unreliable and the obstacle is removed from the set of known obstacles.

![Figure 3. The clustering algorithm](image-url)

### 3.2 Collision avoidance

As described earlier, the path tracking method is based on the Nonlinear Model Predictive Control (NMPC) method. In the NMPC, the control values are calculated so that the given cost function is minimized:

\[
\hat{u}^*(t_k \cdots t_{k+N}) = \underset{u}{\arg\min} J(t_k)
\]

where \( \hat{u}^* \) is the sequence of the optimal control values at time \( t_k \) and \( J \) is the cost function. In this case, the cost function is defined in the following way:

\[
J(t_k) = \sum_{j=1}^{M} \left[ \sum_{i=1}^{M} \left[ x(t_k+j|t_k) - r_s(t_k+j) \right]^2 \right] Q + \sum_{j=1}^{M} \left[ u(t_k+j|t_k) - u_s(t_k+j) \right]^2 R_1 + \sum_{j=1}^{M} \left[ \hat{u}(t_k+j|t_k) \right]^2 R_2
\]

where \( M \) is the prediction horizon size, \( x(t_k+j|t_k) \) is the predicted state for the future time \( t_{k+j} \) at the time \( t_k \), \( r_s \) is the reference trajectory for the state and \( r_u \) is the reference trajectory for the controls. In the function, \( Q, R_1 \) and \( R_2 \) are symmetric positive semi-definite weighting matrices.
The constraints of the optimization problem are obtained from the system model \( f(x,u) \), and the constraints of the states and control values as:

\[
\begin{align*}
  x(t_{k+j+1}|t_k) &= f(x(t_{k+j}|t_k), u(t_{k+j}|t_k)) \\
  u(t_{k+j+1}|t_k) &= u(t_{k+j}|t_k) + \hat{u}(t_{k+j}|t_k)T,
\end{align*}
\]

\[ x_{\text{min}} \leq x(t) \leq x_{\text{max}}, \forall t \in (t_k, t_{k+M}) \]

\[ u_{\text{min}} \leq u(t) \leq u_{\text{max}}, \forall t \in (t_k, t_{k+M}) \]

\[ u_{\text{min}} \leq \hat{u}(t) \leq u_{\text{max}}, \forall t \in (t_k, t_{k+M}) \]

where \( x_{\text{min}} \) and \( x_{\text{max}} \) are the minimum and the maximum values of the states, \( u_{\text{min}} \) and \( u_{\text{max}} \) are the minimum and the maximum values of the control values and \( u_{\text{min}} \) and \( u_{\text{max}} \) are the minimal decreases and the maximal increases of the control values.

There are different ways to include the object avoidance into the NMPC. One way is to add additional constraints to the state values. Another way is to add an additional cost from the obstacles or simply to modify the reference trajectory to go past the obstacle.

In this research, the modification of the cost function was chosen. The underlying path tracking cost function is not changed nor the reference trajectory, but the cost from state is modified. This is because of the calculation capacity and the possibility that the obstacles could move.

Original cost from the tractor position is:

\[
J_{(x_R,y_R)}(t_{k+j}|t_k) = \|x_{(x_R,y_R)}(t_{k+j}|t_k) - r_{(x_R,y_R)}(t_{k+j})\|_Q^2
\]

When the reference trajectory \( r_{(x_R,y_R)} \) is near an obstacle, it cannot be followed without colliding to the obstacle. Therefore it is irrelevant to keep the cost from the reference trajectory. Instead a cost that makes the vehicle drive past the obstacle should be added. The area where the original cost is changed to the avoiding cost is illustrated in Figure 4.

\[
\delta = \begin{cases} 
\pi - |\theta - \atan2(\text{OV})|, & \text{if } |\theta - \atan2(\text{OV})| < \frac{\pi}{2} \\
0, & \text{otherwise}
\end{cases}
\]

where \( \theta \) is the current heading angle and \( \atan2(\text{OV}) \) is the direction of the obstacle. By using this coefficient and nominal avoiding distance \( D \), the distance from the obstacle to the edge of the avoided area can be calculated according to the equation

\[ \varepsilon = (r + \delta \cdot D) - |\text{OV}| \]

where \( |\text{OV}| \) is distance between the obstacle and the vehicle and \( r \) is the radius of the obstacle. The used variables are shown in more detail in Figure 5.

Figure 5. Calculation of the distance from the obstacle to the edge of the avoided area inside the avoided area.

The calculated distance to the edge of the avoided area is used in the cost function, when the obstacle is inside the avoided area or the obstacle is closer to the avoided area than the vehicle is to the original reference trajectory.

Using these definitions, the cost from the tractor position is changed to:

\[
J_{(x_R,y_R)}(t_{k+j}|t_k) = \begin{cases} 
\|\varepsilon\|_Q^2, & \text{if } \Psi \\
\|\Delta x_{(x_R,y_R)}\|_Q^2, & \text{otherwise}
\end{cases}
\]

where \( \Delta x_{(x_R,y_R)} \) is the original distance to the reference trajectory:

\[
\Delta x_{(x_R,y_R)} = x_{(x_R,y_R)}(t_{k+j}|t_k) - r_{(x_R,y_R)}(t_{k+j})
\]

and \( \Psi \) is the boolean value whether the cost from the obstacle is used or not:

\[ \Psi = \varepsilon > 0 \vee -\varepsilon < |\Delta x_{(x_R,y_R)}| \]

Together with the cost from the position, also the cost from the heading angle is changed to:
\( J_{(\theta)}(t_k) = \begin{cases} ||x_{(\theta)}(t_{k+1}) - \theta_{ref}||_Q^2, & \text{if} \Psi \\ ||x_{(\theta)}(t_{k+1}) - r_{(\theta)}(t_{k+1})||_Q^2 & \text{otherwise} \end{cases} \) \tag{11}

where the new reference angle is calculated according to:

\[ \theta_{ref} = \text{atan}2(OV) \pm \pi/2 \] \tag{12}

In the above equations, the cost is calculated only from one obstacle. If there are multiple obstacles inside the avoided area, the one with the largest value of the \( \varepsilon \) is chosen. The same methods are also used for the cost from the trailer position.

4. RESULTS AND DISCUSSION

In this research, a plastic tube with foam covering was used as an artificial obstacle (Figure 6). The size and shape are equivalent to the electricity pole. As the obstacles are considered to be mainly electricity poles, the maximum distance from the measurement point to the cluster center in clustering algorithm was set to 0.3 m. The maximum iteration time in clustering was set to 10 iterations. The obstacle was considered to be confident, if it was seen 20 times and the detection counting was stopped when the obstacle had been seen 300 times. This means that the obstacle recognition takes at least 267 milliseconds and the obstacle that is considered to be very reliable has to be in sight of the scanner and not associated to any cluster at least 4 seconds until it is removed.

The obstacle avoidance method was tested with tractor alone navigation and with combined tractor-implement navigation. In the tests, the speed was varied from 2 m/s to 3.5 m/s.

Over all, the recognition of the obstacles was very reliable and accurate. In Table 1, the standard deviations of the recognized pole positions and also the maximum deviations from the mean values are listed. The standard deviation was below 10 cm and the maximum deviation was below 50 cm at all tested speeds.

<table>
<thead>
<tr>
<th>Speed [m/s]</th>
<th>2</th>
<th>2.5</th>
<th>3</th>
<th>3.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>std [m]</td>
<td>0.07</td>
<td>0.08</td>
<td>0.07</td>
<td>0.04</td>
</tr>
<tr>
<td>max [m]</td>
<td>0.30</td>
<td>0.39</td>
<td>0.48</td>
<td>0.20</td>
</tr>
</tbody>
</table>

In Table 2 the minimum distance to the pole and the size of the gap in the tractor alone navigation are listed. The minimum distance to the pole was about the same that it was set to be. In Figure 7 it can be seen that the avoidance maneuvers are smoother with higher speeds and the deviation from the original path is longer. This is because the dynamic restrictions are taken into account in the NMPC controller. These lead to larger gaps at higher speeds than those at lower speeds.

<table>
<thead>
<tr>
<th>Speed [m/s]</th>
<th>2</th>
<th>2.5</th>
<th>3</th>
<th>3.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>minimum distance [m]</td>
<td>3.2</td>
<td>2.9</td>
<td>3.0</td>
<td>2.9</td>
</tr>
<tr>
<td>The size of the gap ([m^2])</td>
<td>25.6</td>
<td>31.5</td>
<td>26.9</td>
<td>39.7</td>
</tr>
</tbody>
</table>

With the settings above, the obstacle was recognized and added to known obstacles about 8-10 meters ahead of the tractor. For this reason the nominal avoiding distance \( D \) was set to 6 meters in tractor-alone navigation and 8 meters in combined navigation. This means that the minimum allowed distance between the tractor and the obstacle was 3 meters and between the trailer and the obstacle 4 meters.
With the combined tractor-implement navigation, the collision avoidance was tested with nominal working speed. In this research, the nominal working speed was considered to be about 2.5 m/s which is typical for seeding applications. In Figure 8 two different collision avoidance maneuvers with towed implement are illustrated. The worked areas are depicted as gray, the unworked areas are depicted as black and overlapping areas are depicted as light gray. The size of the unworked area on the left of Figure 8 is 28.9 m² and on the right is 31.5 m². The size of the overlapping area on the left of Figure 8 is 17.8 m² and on the right is 32.4 m².

![Figure 8. Worked area in tractor-implement navigation with collision avoidance.](image)

5. CONCLUSIONS

In this research, a collision avoidance method with Nonlinear Model Predictive Control was developed.

The collision avoidance was divided into two different subproblems: detecting the obstacle and avoiding the obstacle.

The obstacles were detected from the 2D laser scanner measurements with the help of a clustering algorithm. There was also a list of recognized obstacles, which reduced false positive and false negative recognitions. Over all, the recognition of the obstacles was very accurate. The standard deviation of the recognized pole positions was below 10 centimeters at all tested speeds.

The obstacle avoidance method was built on top of the existing experimental navigation system. Because the computational capacity was already exhausted, the form of the original NMPC was left unchanged. An artificial avoided area was created, where the obstacles are not allowed to be. If there is an obstacle inside the avoided area, the cost from the path is changed to cost from the obstacle. The obstacle avoidance was proven to work at speeds lower than 3.5 m/s.

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