TRACKING OF MULTI-OBSTACLES WITH LASER RANGE DATA FOR AUTONOMOUS VEHICLES

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Abstract: Object tracking consists of estimating the trajectories and behaviour of objects, which will obviously play a role of the utmost importance in the future development of collision avoidance algorithms. This work tackles a group of modules that enlightens us on the positions and velocities of existing objects, in the visualisation area of a Laser Measurement System (LMS), using their scans. Scan processing is possible thanks to several modules (Segmentation, Static LMS and Moving LMS), which allow the tracking of several visible objects with the LMS, in a nutshell estimating their positions and velocities according to the same LMS, that can move and rotate.

Keywords: Tracking, Detection, Sensor, Kalman Filtering

1. INTRODUCTION

The matter concerning the tracking of objects and people assumes a paramount role in the understanding of the environment involving the vehicle (in order to control it) resulting in the safety of the vehicle itself, its passengers and other road users.

Research has been made in multi-objects tracking. In (Fod, et al., 2002) object tracking with a static sensor is performed. To improve tracking it’s useful to use cameras to determine the position and orientation of objects (Patric and Christensen, 2001). Tracking with a sensor in movement requires a new approach towards the issue stated in (Dietmayer, et al., 2001; Sparbert, et al., 2001; Fuerstenberg and Willhoeft, 2001; Fuerstenberg, et al., 2002).

This paper describes a tracking system constituted by the following modules: segmentation, static LMS and moving LMS. This system allows estimating the position and velocity of existing objects in the environment thanks to a number of scans provided by a laser measurement system (LMS).

2. SEGMENTATION

The goal here is to identify the limits of possible existing objects detected by the LMS and if so, to filter and provide additional information on the object in analysis. The main idea is to subdivide the readings obtained in each scan, into small sets of neighbouring points (segments), taking into account the proximity between two consecutive points of the scan.

A segment is, hence, a set of measurement values (points of the scan) close enough to each other that, due to their proximity, probably belong to the same object.

Segmentation criterion (based on (Dietmayer, et al., 2001)): two consecutive points, distant from the LMS, r_a and r_b, belong to the same segment as long as the distance between them fulfills the following expression:

\[ |r_a - r_b| \leq C_0 + r_{\text{min}} \frac{\sqrt{2} (1 - \cos(\phi))}{\cot(\beta) \cos \left( \frac{\phi}{2} \right) - \sin \left( \frac{\phi}{2} \right)} \]  

(1)

where \( r_{\text{min}} = \min \{ r_a, r_b \} \), and \( \phi \) is the angular resolution of the LMS. Angle \( \beta \) and constant \( C_0 \) are parameters of segmentation sensibility refinement (tuning). \( \beta \) was introduced to reduce the dependence of the segmentation with respect to the distance between the LMS and the object.
If $r_{min}$ is short the set of points defined by the $\beta$ angle is small and if it is high, the set of points defined by the $\beta$ angle is high. If $\beta$ is too short, some objects will not be detected (see Fig. 2-a). If $\beta$ is too high, then a segment can represent more than one object (see Fig 2-b).

After the subdivision of each scan in segments, a selection of several points of the segment (see Fig. 3) and the computation of the visible dimensions of the object take place.

3. TRACKING WITH SATIC LMS

3.1 Reference point choice

In order to retrieve a reliable tracking of the object, it is vital to define a certain point which can be easily identifiable in successive scans, corresponding to the same point in the object – this is a so called reference point. Through segmentation, the information regarding several points of each segment (farthest right, farthest left, minimum and angular medium) (Fig. 3) is gathered and it must be guaranteed that the movement of the reference point is compatible with, and adequately represents, the object’s movement.

The minimum point would be in principle a good candidate to represent the detected object motion behaviour, because it is always visible in the object. But two problems can arise (Fig.4):

1)-In particular situations of the object and of its faces position with respect to the LMS beams, the minimum point changes in the object face;

2)-The detected minimum point may not coincide with the real minimum point of the object, due to the existence of an angular aperture between consecutive beams of the LMS (see Fig.3).

If $C_0=0$, then $\beta$ gives the maximum absolute inclination with respect to the perpendicular to the dashed line $m$ (see Fig. 1), that an object’s face can have to belong to a segment. $m$ is the median line between the two consecutive LMS beams.
Fig. 5. Virtual displacement (Δx) of the medium point detected due to a rotational movement of the rectangular object.

The medium point corresponds to the medium angle of the detected object angular range (Fig. 3). This point is the one that better behaves in conformity with the movement of the object. However this point also presents the same problems as the minimum point. In particular, if a rectangular object describes a little rotation, the detected medium point changes in the object (Fig. 5).

Taking into account the minimum and medium point characteristics, a virtual point has been defined (x coordinate of the minimum point, y coordinate of the medium point). For the example illustrated in Fig. 5, the virtual point is the one that better represents the movement of the object (see Fig. 6). This is the segment reference point used in the objects tracking.

3.2 Segment-object pair identification

It is necessary to identify the segment-object pair in an unquestionable fashion taking into account the segment reference point.

Fig. 6. Virtual point (x coordinate of the minimum point, y coordinate of the medium point).

Fig. 7. Identification of the segment-object pair in polar coordinates. The interest region is a circle with a given radius R_i and centred in S_{ref}(k).

The estimated position (S_{ref}) of an object reference point at the current time instant k must be obtained (for this purpose a Kalman filter is used as described in Sec. 3.3).

Now the estimated position of each object and the segments' reference points of the present scan are known. Based on the S_{ref}(k) of each segment, an interest region is defined, in which the search of existing objects will be performed, searching for the match of segment S_{ref}(k) (see Fig. 7). Suppose that several potential objects are found. The one with most similar dimensions (defined by the points: farthest right, angular minimum and farthest left) to the segment (object boundary detected) in consideration is chosen.

A problem arises when object reference point occlusion occur. To detect situations of object occlusion, it is determined if the object reference point will be behind of any other or out of the measurement zone of the LMS in the next scan. In such situation two options are possible: 1) object velocity update will be frozen, or 2) at least an indication of how velocity reliability is given.

3.3 Object kinematics model

This subsection describes the velocity estimate. To perform this estimate, a Kalman Filter containing a kinematics model of the object (white noise acceleration model (Kohler, 1997)) is used. The motion is considered to be the superposition of an ideal basic motion with, for example, constant velocity and white noise. The white noise illustrates the acceleration that is time varying. The discrete time state equation of this kinematics model with sampling period \( h = t_i - t_{i-1} \) is given by (2)
\[
\begin{bmatrix}
    s_{k+1} \\
    v_{k+1}
\end{bmatrix} =
\begin{bmatrix}
    1 & h \\
    0 & 1
\end{bmatrix} \begin{bmatrix}
    s_k \\
    v_k
\end{bmatrix} + w_k
\]
\[
y_k = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix}
    s_k \\
    v_k
\end{bmatrix} + e_k
\] (2)

where \( s_{k+1} \) and \( v_{k+1} \) are the position and the velocity, respectively, in the instant \( k+1 \), \( w_k \) is the vector (considered white noise, in this model) that represents stochastic data with respect to the acceleration, \( y_k \) is the output of the model and finally, \( e_k \) is the observation error. The model described above is applied independently to the \( x \) and \( y \) coordinates, with separated Kalman Filters speeding the calculus. A special attention was drawn to the process and noise covariance matrices values for use in the Kalman filter. The filter covariance matrices are chosen similarly to (Kohler, 1997). The covariance matrix \( Q_k \) of process noise error is

\[
Q_k = Q_0 = \frac{a_{\text{max}}^2 h}{6} \begin{bmatrix} 2h^2 & 3h \\ 3h & 6 \end{bmatrix}
\] (3)

where \( a_{\text{max}} \) is the spectral amplitude of the white noise and \( \Delta t \) is the sampling period. Since the acceleration is identified as white noise, \( a_{\text{max}} \) is the maximum amplitude of the object’s predictable acceleration. This matrix may be applied for any filter models with translational motion of constant velocity and random acceleration. If \( Q \) is high (\( Q \) with high values), it means that the system model is able to follow high changes. Objects with different kinematics properties are modelled using different values for \( a_{\text{max}} \).

Since the model described by (2) is applied independently to the \( x \) and \( y \) dimensions, the two involved measurement error covariances are the following scalars: \( R_x = \sigma_{\epsilon_x}^2 \) and \( R_y = \sigma_{\epsilon_y}^2 \).

Apart from the LMS sensor range measurement error, the variances \( (\sigma_{\epsilon_x}^2, \sigma_{\epsilon_y}^2) \) also incorporate the error due to the angular aperture between beams (see Fig. 4).

The initial Covariance Matrix \( P_0 \) of the estimation error is:

\[
P_0 = \begin{bmatrix}
    \sigma_{\epsilon_x}^2 & \sigma_{\epsilon_{xy}}^2 \\
    \sigma_{\epsilon_{xy}}^2 & \sigma_{\epsilon_y}^2
\end{bmatrix}
\] (4)

where \( \sigma_{\epsilon_x}^2 \) is the variance of the position estimation error; \( \sigma_{\epsilon_{xy}}^2 \) and \( \sigma_{\epsilon_y}^2 \) are the cross variances of the position and velocity estimation errors; \( \sigma_{\epsilon_y}^2 \) is the variance of the velocity estimation error.

Fig. 8. Referential transformation between two reference frames which represent two different positions of the LMS.

4. TRACKING WITH A MOVING LMS

Since the LMS is to be used in an automobile vehicle that may rotate and/or translate, it is imperative to consider the movement of the LMS in the tracking of the objects. In fact when performing a Kalman filtering update cycle all the variables involved (including present and next state) must be expressed in the same reference frame. This problem can be solved using the transformation matrix that relates the present state variables (expressed in frame \{B\}) with the previous state variables (expressed in frame \{A\}), as depicted in Fig. 8.

So, if the coordinates \( (^A x, ^A y) \) of a point in the frame \{A\}, are known, then, its coordinates \( (^B x, ^B y) \) in frame \{B\} are given as follows:

\[
^B x = (^A x - \Delta x) \cdot \cos \theta + (^A y - \Delta y) \cdot \sin \theta
\]
\[
^B y = (^A y - \Delta y) \cdot \cos \theta - (^A x - \Delta x) \cdot \sin \theta
\] (5)

where vector \( (\Delta x, \Delta y) \) represents the position of frame \{B\} with respect to, and expressed in, frame \{A\}. \( \theta \) is the angle of rotation from frame \{A\} to frame \{B\}. The velocities will have to be projected to this new system of axes too:

\[
^B v_x = ^A v_x \cdot \cos \theta + ^A v_y \cdot \sin \theta
\]
\[
^B v_y = ^A v_y \cdot \cos \theta - ^A v_x \cdot \sin \theta
\] (6)

4.1. Data flow

Several modules constitute the tracking architecture each one with an associated model. The block diagram in Fig. 9 describes the relation between the several models.
The following objects were used: cardboard boxes, placards, a SCOUT robot, etc. The knowledge of all the objects' behaviour, including the LMS observation model, made possible the programming of the experiment with the moving LMS in simulation. In both experiments, the angular resolution of the LMS was configured to 0.5° and the reach to 8 m (indoor).

5.1. Real environment experiments

As an example is presented a real experimental environment, in which it is intended to track a person and a cardboard box placed on top of the Scout robot (Fig. 10). The following values have been used in the experiment:

\[ a_{\text{max}} = 80 \text{m/s}^2 \]
\[ h = 0.2135 \text{s} \]
\[ R_s = R_a = 400 \]
\[ P_o = \begin{bmatrix} 30 & 50 \\ 50 & 200 \end{bmatrix} \]
\[ Q_o = Q_0 = \begin{bmatrix} 20.76 & 145.86 \\ 145.86 & 1366.4 \end{bmatrix} \] (7)

The tracking algorithm was applied, taking into account the scans of the environment. Fig. 11 presents the velocity vectors of the two tracked objects, the identifying numbers of the objects (2 is a person and 3 is a cardboard box placed on the Scout robot) associated to the magnitude of the velocity in km/h.

Fig. 12 compares the real velocity with the estimated velocity of the cardboard box using respectively, the Scout robot's odometric data and the tracking values.

5. EXPERIMENTS

Experimental results regarding two different types of environment are reported: a real experiment and a simulation using Matlab. In the real life environment the algorithm's performance was tested with a static LMS providing scans at a rate of approximately 5 Hz.

Fig. 10. Picture of the experimental environment with the scout robot carrying a white cardboard box.

Fig. 11. Graph regarding a specific instant of the experience. We can observe that the object n°3 (cardboard box) moves at 0.937 m/s in the direction of the third quadrant; object n°2 (person) moves at 0.833 m/s in the y-axis direction. The dashed line represents the trajectory followed by the cardboard box.
If the magnitude of the real velocity is zero, the orientation of the velocity vector is also zero. Between time intervals 47 and 57, an error occurs because of the following situation: when the object moves close to the LMS, there is a face that becomes temporarily invisible producing an oscillation on the reference point. The estimate of the velocity vector orientation does not have any meaning when the velocity is zero (or close to zero) as we can see near the time instant 10.

5.2. Simulated environment

The simulator used allows the creation of vehicles of various forms and dimension and the programming of its movements. It also includes the possibility of using a laser sensor similar to the LMS. This subsection presents a simulating experience, where the vehicle that carries the LMS (A) moves at the constant velocity of 8.333 m/s (30 km/h) from left to right and another vehicle (B) moves in the opposite direction with the same velocity. Using the scans of the LMS taken from the Simulator, the tracking algorithm was applied. On the right hand side of Fig. 13, the objects detected by the LMS, with their respective velocities are represented. Object B is the car moving in the opposite direction. Objects U and L are the upper and lower walls respectively. Using the tracking algorithm presented in this paper the velocity of vehicle B is estimated with reasonable accuracy.
6. SUMMARY AND CONCLUSIONS

An object-tracking algorithm was developed in which the sensor itself (LMS) can be placed on a moving vehicle. It includes a kinematics model that can be adapted to the type of object detected. In order to do this, a more robust object classification is paramount. Previous knowledge on the type of the environment in addition to the increase of the rate of data acquisition are some of the developments being carried out which can improve the tracking system performance.

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8. REFERENCES


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