Fast 3D Extended Target Tracking
using NURBS Surfaces

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Abstract—This paper proposes fast and novel methods to jointly estimate the target’s unknown 3D shape and dynamics. Measurements are noisy and sparsely distributed 3D points from a light detection and ranging (LiDAR) sensor. The methods utilize non-uniform rational B-splines (NURBS) surfaces to approximate the target’s shape. One method estimates Cartesian scaling parameters of a NURBS surface, whereas the second method estimates the corresponding NURBS weights, too. Major advantages are the capability of estimating a fully 3D shape as well as the fast processing time. Real-world evaluations with a static and dynamic vehicle show promising results compared to state-of-the-art 3D extended target tracking algorithms.

I. INTRODUCTION

Target tracking is an essential requirement for enabling autonomous driving. For instance, the autonomous vehicle has to react to other dynamic objects, e.g., cars or pedestrians. Typically, the estimated kinematic values are Cartesian position and velocity, and the most common approach is the small-target-assumption or point target tracking. Here, the target is the source of only one measurement per time-step. One exemplary application is radar-based air surveillance.

However, for safe navigation in autonomous driving the shape or extent of a target cannot be neglected. Moreover, with the upcoming of high-resolution LiDAR sensors, e.g., the Velodyne HDL-64, a dense point cloud is available. Generally, this implies several measurements per target. In these cases, the small-target-assumption cannot be used anymore. Therefore, at first, group target tracking approaches have been developed [1]. Every target generates spatially distributed measurements around the target, where the group consists of multiple sub-objects, e.g., edges or corners. These sub-objects are tracked together as a group with common motion [2].

This paper utilizes extended target tracking (ETT), where the target is the measurement source of a changing number of generally noisy and spatially distributed measurements [2]. ETT is a nonlinear estimation problem, where the, potentially time varying, extent of the target has to be recursively computed [2]. As mentioned in [2], ETT is often falsely equated with contour tracking in computer vision, where the complete contour of the target can be extracted of a RGB image. Contrarily, in ETT the target shape has to be estimated over time through a sparse set of measurements.

Common research in ETT deals with two-dimensional estimation in the x-y plane. This paper operates with a rather dense 3D point cloud of the Velodyne-HDL64, where the 2D approximation does not hold. Therefore, we propose a full three-dimensional estimation of the target’s extent using the well-known NURBS surfaces [3] as shape model. NURBS surfaces originate from the geometric modeling community and are the building-block for accurate computer aided design models. An exemplary result of estimating a NURBS surface with the proposed method is shown in Figure 1.

Our main contributions are:

• A full 3D estimation of the target’s extent while estimating the dynamics of the target
• A fast method where only the scaling of a pre-defined NURBS surface is estimated
• A second method which additionally estimates the weights of the NURBS surface, for more accurate shape estimation
• Both methods show real-time capability and are evaluated on real-world data against state-of-the-art

II. RELATED WORK

An extensive overview of group target tracking is given by [1], whereas [2] is a comprehensive ETT publication. There exists a vast variety of shape models in ETT. Prominent examples are sticks [4], [5] and rectangles [6]. Moreover, a frequently used approximation is an ellipse. There are several approaches for ellipse modeling like Gaussian inverse Wishart [7] or random matrix theory [8].

Another class are the star-convex shapes. The authors of [9] were one of the first to estimate arbitrary star-convex shapes by random hypersurface models (RHM). In this work...
scaled versions of ellipses and circles as base representation of the RHM have been used. The authors extended their work to arbitrary shapes by using level-set RHM [10] for general polygon trackers. An additional method for star-convex shapes are Gaussian processes (GP), which have been utilized for many applications, e.g., [11], [12]. Up to now, only a small number of publications has dealt with the 3D case. Recently, an extension for 3D GPs has been published [13]. Furthermore, [14] estimates the 3D objects by using transformed planes, whereas [15] estimates the 3D vehicle contour in LiDAR measurements.

B-Splines are a compact representation for a wide variety of shapes and they are, for instance, used for road estimation [16], [17]. Additionally, there exist spline-based methods for tracking extended targets [18], [19], [20]. [20] is the closest method to ours. The authors model the target extent with a Cartesian 2D B-Spline curve. For tracking vehicles, they estimate non-uniform scaling parameters in \( x \) and \( y \)-dimension for static targets. Contrarily, this paper uses a NURBS surface model to estimate a 3D target extent as well as the dynamics of the target. Furthermore, [20] only evaluates on simulated data opposed to our real-world evaluations.

### III. Extended Target Tracking

To track an extended target, the standard state space model has to be augmented. For instance, a shape model has to be specified to find the corresponding measurement source at the target’s surface to the noise corrupted measurement. Let \( x_k^d \) be the additional kinematic parameters of a process model and \( x_k^s \) be the shape part of the state. Furthermore, \( m_k \) be the Cartesian center and \( \psi_k \) the orientation of the extended target. Then, the augmented state vector is defined as follows:

\[
x_k = (m_k \psi_k \ x_k^d \ x_k^s)^T
\]

#### A. Dynamic Model

The following standard Gaussian dynamic model is chosen:

\[
x_k = f(x_{k-1}, v_{k-1}, u_{k-1}), \quad v_{k-1} \sim \mathcal{N}(0, Q_{k-1}),
\]

where \( Q_{k-1} \) is the process noise covariance and \( u_{k-1} \) is the input. In general, the input is not known and therefore, it is approximated as Gaussian noise with \( u_{k-1} \sim \mathcal{N}(0, C_{k-1}) \).

In this work we applied the constant curvature and velocity (CCV) [21] model as we deal with vehicles. Hence, it follows \( x_k^d = (v_k c_k) \) with velocity \( v_k \) and curvature \( c_k \). Furthermore, \( u_k \) is defined as \( (\dot{v}_k \ \dot{c}_k)^T \).

#### B. Shape Representation

In general, an extended target is the source of a set of \( n_y \in \mathbb{N} \) noise corrupted measurements \( Y_k = \{y_{kl}\}_{l=0}^{n_y} \). The relation between measurement source \( z_{kl} \) and corrupted measurement is modeled as:

\[
y_{kl} = z_{kl} + w_{kl}, \quad w_{kl} \sim \mathcal{N}(0, R_{kl}),
\]

where \( R_{kl} \) is the corresponding measurement noise covariance. Associating \( y_{kl} \) to its generating measurement source \( z_{kl} \) is not a trivial task. Therefore, the level-set of [10] as shape representation is chosen. Let \( d(x_k, z_{kl}) \) be a shape function. Then, the level-set for the level \( c \in \mathbb{R} \) is defined by [10]:

\[
\mathcal{L}_d(x_k, c) = \{ z_{kl} \mid d(x_k, z_{kl}) = c \}.
\]

Clearly, the target shape boundary is given by \( \mathcal{L}_d(x_k, 0) \). Moreover, the set of all \( z_{kl} \) inside the shape is given by:

\[
S_d(x_k) = \{ z_{kl} \mid d(x_k, z_{kl}) \geq 0 \}.
\]

#### C. Measurement Model

It is a challenging task to calculate and associate the corresponding level-set \( \mathcal{L}_d(x_k, c) \) to every measurement source \( z_{kl} \). However, with Level-Set RHMs of [10] the explicit level-set does not have to be computed as Level-Set RHMs model the target extent with a randomly distributed scaling of the maximum level. Let \( \alpha_{kl} \sim U(0, 1) \) be an uniformly distributed scaling factor and \( d_{\text{max}}(x_k) = \max_{z \in S_d(x_k)} d(x_k, z) \) be the upper bound of the shape function, which is the maximum level. Then, it follows with Equation (3) and \( \alpha_k \cdot d_{\text{max}}(x_k) = d(x_k, y_{kl} - w_{kl}) \) the measurement equation of one measurement [10]:

\[
0 = \alpha_k \cdot d_{\text{max}}(x_k) - d(x_k, y_{kl} - w_{kl})
\]

Hence, the current state, scaling factor and measurement are mapped to the pseudo-measurement 0, which is the level for the shape boundary.

It is a common approach to model the likelihood of each measurement \( p(y_{kl} \mid x_k) \) conditionally independent, which is described by the following likelihood of all measurements:

\[
p(Y_k \mid x_k) = \prod_{l=0}^{n_y} p(y_{kl} \mid x_k).
\]

This implies order independence of the incorporated measurements. However, while sequentially updating the posterior of a Bayesian estimator with nonlinear measurements, the order of the measurements, potentially, changes the outcome [10], [22]. Therefore, we apply all measurements at once with the following stacked measurement equation:

\[
g(x_k, Y_k, w_k, \alpha_k) = \left( g(x_k, y_{kl}, w_{kl}, \alpha_{kl})^T \right)_{l=0}^{n_y}
\]

\[
R_k = \text{diag} \left( R_{k1}, \ldots, R_{kn_k} \right),
\]

\[
w_k \sim \mathcal{N}(0, R_k),
\]

where \( \alpha_k = (\alpha_{kl})_{l=0}^{n_y} \). Modeling \( p(Y_k \mid x_k) \) with \( g(x_k, Y_k, w_k, \alpha_k) \) we get order independence.

#### D. Inference

Due to the high non-linearity of the measurement model as well as the presence of multiplicative noise, the Unscented Kalman Filter (UKF) [23] is applied. The UKF is a sampling based Bayesian state estimator.
weights according to their corresponding Gaussian curvature as well as the weights of the NURBS surface. Consequently, with \( \hat{\omega} \), the measurement source in target coordinates in similar fashion to [24]. Let \( \hat{S}_k(u,v) \) and \( S_k := S_k(u,v) \). Then, \( I \) and \( II \) are defined as [25]:

\[
I = \begin{pmatrix}
S_k^{(u)}, S_k^{(u)} \\
S_k^{(v)}, S_k^{(v)}
\end{pmatrix} \quad \text{and} \quad II = \begin{pmatrix}
S_k^{(u)}, N_k \\
S_k^{(v)}, N_k
\end{pmatrix},
\]

where \( N_k = S_k^{(v)} \times S_k^{(u)} / \| S_k^{(v)} \times S_k^{(u)} \|_2 \) is the normal vector and exemplary \( S_k^{(u)} \) the partial derivative with respect to \( u \). It follows the Gaussian curvature \( K_G(u,v) \) of the surface patch corresponding to \( (u,v) \) with [25]:

\[
K_G(u,v) = \frac{|II|}{|I|},
\]

where \( |B| \) denotes the determinant of a matrix \( B \). Hence, the dynamic model for one of the state's weights is defined as follows:

\[
\omega_k^{ij} = \omega_k^{ij+1} + \nu \cdot \frac{K_G(u,v)}{\max(u,v) \in U \times V K_G(u,v)} + v_k^{ij-1},
\]

where the Gaussian curvature at the surface point is normalized through the maximum Gaussian curvature of all surface points. Furthermore, \( v_k^{ij} \) is the additive Gaussian process noise of weight \( w_k^{ij} \) and \( \nu \) is a damping factor.

2) Method 2 (M2): In this method, only the scaling factors are estimated. Therefore, set \( \omega_k^{ij} = 1, \forall k \) and \( i = 0, \ldots, n_u, j = 0, \ldots, n_v \). Then, the reduced shape-part of the state is:

\[
x_k = \left( s_k^x, s_k^y, s_k^z \right).
\]

### B. NURBS Shape Function

In this section we define the shape function, which is based on the NURBS surface and used in the measurement model. But first, the closest surface point \( S_k(u,v) \) to a measurement source in local coordinates \( \tilde{z}_k \) has to be found. The chosen criterion is the angle difference \( \angle (S_k(u,v), \tilde{z}_k) \), as we deal with dynamic and star-convex targets like cars. For non-convex targets this could be easily extended with the minimum distance criterion of [10], [20]. Therefore, the parameter tuple \( (\tilde{u}, \tilde{v}) \) corresponding for the surface point \( S_k(\tilde{u}, \tilde{v}) \) is calculated through:

\[
(\tilde{u}, \tilde{v}) = \arg \min_{(u,v) \in U \times V} \angle (S_k(u,v), \tilde{z}_k).
\]

Another premise of the shape function is the mahalonobis distance \( m(x_k, \tilde{z}_k) \), which is defined as:

\[
m(x_k, \tilde{z}_k) = \sqrt{(\tilde{z}_k - S_k(\tilde{u}, \tilde{v}))^T \cdot R_{kl}^{-1} \cdot (\tilde{z}_k - S_k(\tilde{u}, \tilde{v}))}
\]

It follows the NURBS shape function as the signed mahalonobis distance:

\[
d(x_k, \tilde{z}_k) = \begin{cases} m(x_k, \tilde{z}_k), & \text{if } \tilde{z}_k \in S_k(x_k) \\ -m(x_k, \tilde{z}_k), & \text{else} \end{cases}
\]
V. RESULTS

The proposed methods are evaluated in real-world scenarios. They are recorded with a roof-mounted Velodyne HDL64-
S2 at our institute’s autonomous car. Ground truth data is
obtained through an equipped inertial navigation system (INS)
sensor at the target. Video footage can be found online.1

Performance evaluations are done against state-of-the-art
methods, as 3D Gaussian-processes (3DGP) [13] and the 2D
cartesian B-Spline method of [20] (2DBS). Furthermore, we
compare against a simple point tracking approach (PT) [26],
where the bounding box center as well as their dimensions are
estimated. The segmented point clouds of the target vehicle
are provided from the method of [27], [28]. During the
scenario, different occlusions (only the back or one side can
be seen) of the segmented vehicle and segmentation errors,
e.g., falsely associated ground plane points, occur. Moreover,
the bounding boxes of the PT approach are obtained with
[29]. The chosen number of points in the scenarios are a
compromise between better estimation results and faster run
time.

A. Scenario 1: Static Object

The goal of this scenario is to estimate the correct shape
of a static vehicle. Therefore, the static vehicle is recorded
from every side by driving around it multiple times. As
measurements, we randomly sample 50 laser points of the
segmented object and its 2D convex hull. Figures 3a and 3b
illustrate the object’s point cloud sampling.

1) Initialization: For M1, we initialize all weights \( \omega_0 \)
and scaling factors \( s_0 \) to 1. The damping factor for regularization
is set to \( \nu = 0.001 \). Moreover, shape covariances are set
to \( Q_{w,ij} = 0.1 \forall i,j \) and \( Q_{w,s} = Q_{a,s} = 10^{-7} \).
Furthermore, we use \( n_u = 7, n_v = 4 \) with cubic basis splines,
which means: \( p = q = 3 \). The red surface in Figure 4a shows
the initial configuration of M1’s NURBS surface.

M2 has the same initial scaling factors, and shape
covariances for the scaling factors as M1. However, we use
quadratic basis splines \( (p = q = 2) \) and less control points
\( (n_u = 5, n_v = 4) \). The initial surface of M2 can be seen
in the upper half of Figure 4b. 3DGP is set up with 60 control
points, which can be seen in the upper side of Figure 4c.
The hyper parameters of 3DGP are the variance of the mean value
\( \sigma_r \), the prior variance \( \sigma_f \) and the length scale \( l_{gp} \), which are
set to \( \sigma_r = 0.5, \sigma_f = 2 \) and \( l_{gp} = \pi/20 \). 2DBS is initialized
with 20 control points as in the original paper. We have tried
the method with different parameter settings. However, 2DBS
seems to be unable to estimate 3D point data as it does not
cope for measurements inside the closed B-spline curve.
The simple point tracking approach is initialized with the first
detected bounding box, which is shown in Figure 4d as the
red bounding box.

Covariances for input noise are set to \( C_v = 10^{-4} \) and
\( C_c = 10^{-4} \). The input noise for velocity and curvature is set
to small values as we do not expect movements of the target.

B. Scenario 2: Dynamic Object

In this scenario, the shape of a dynamic vehicle has to be
estimated alongside its dynamics, e.g., Cartesian position and
velocity. Furthermore, 20 laser points are randomly sampled
from the segmented object’s point cloud and its 2D convex
hull, as can be seen in Figures 3c and 3d.

1) Initialization: Here, for all methods the initial shapes
and most of the parameters are the same as in scenario 1.
Only the input noise is set to \( C_v = 0.2 \) and \( C_c = 0.05 \), whereas
\( Q_{w,ij} = 0.01 \forall i,j \).

2) Evaluation: Figure 5 shows the estimates of the static
vehicle at every time step \( k \). It can be seen that our methods
generate better or comparable results in every tested quantity.
Moreover, Table I supports this conclusion. Furthermore,
Table II shows that, except for SP, M2 is the fastest version
with only 3.1 ms per time step, followed by M1 with 18.8 ms.
3DGP needs 118.7 ms with 50 measurements. Hence, it is
not real-time capable with that many measurements.

C. Limitations of the Approach

In the evaluation and development of this approach, we
discovered that a fix process noise for the shape states has
difficulties with a large error in the initialization of the velocity

### TABLE I: The root mean squared errors for velocity \( \mathcal{E}_v \), area \( \mathcal{E}_A \),
Cartesian position \( \mathcal{E}_{pos} \) and orientation \( \mathcal{E}_\psi \) of the static scenario.

| Method | \( \mathcal{E}_v \) | \( \mathcal{E}_A \) | \( \mathcal{E}_{pos} \) | \( \mathcal{E}_\psi \) |
|--------|----------------|----------------|----------------|----------------|
| M1     | 0.100          | 0.617          | 0.308          | 0.029          |
| M2     | 0.027          | 1.433          | 0.393          | 0.041          |
| 3DGP   | 0.095          | 5.789          | 0.304          | 0.026          |
| SP     | 0.168          | 1.253          | 0.436          | -              |

### TABLE II: Comparison of the mean run time with 20 points \( \bar{T}_20 \)
and 50 points \( \bar{T}_50 \) and bounding box \( \bar{T}_b \) as measurements.

| Method | \( \bar{T}_{20}[\text{ms}] \) | \( \bar{T}_{50}[\text{ms}] \) | \( \bar{T}_b[\text{ms}] \) |
|--------|----------------|----------------|----------------|
| M1     | 6.5           | 18.8          | -              |
| M2     | 3.0           | 3.1           | -              |
| 3DGP   | 32.5          | 118.7         | -              |
| SP     | -             | -             | 0.8            |

1https://youtu.be/1tL3UrLhAUE
state. On the one hand, with a low process noise the velocity will be correctly estimated but the shape estimation needs more cycles to converge. On the other hand, with a high process noise the shape estimation has a fast convergence, but the velocity state needs more cycles to converge. Another limitation of M2 is that only approximately cuboid shaped objects like vehicles, persons and bicycles can be estimated.

VI. CONCLUSION

This paper proposed a novel 3D shape model, based on NURBS surfaces, for simultaneously estimating an extended target’s unknown 3D shape and dynamics. It has been shown that the estimation capability is above or comparable to state-of-the-art ETT approaches. Evaluations have been done in real-world scenarios with a high-resolution 3D LiDAR, which is a popular sensor of autonomous cars at research institutes. Furthermore, the proposed methods have shown real-time capability with the fastest method’s mean run-time of 3.0 ms. Future work will focus on applying it to multi-target tracking scenarios as well as adaptive process noise for the shape part to account for wrong state initialization.

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The area of the estimated shapes is defined as the product of the length and width of the encasing rectangle. Furthermore, one time step $k$ is 100 ms.

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