Laser-Based Target Tracking using Principal Component Descriptors

Michael Burke
Mobile Intelligent Autonomous Systems
Council for Scientific and Industrial Research
Pretoria, South Africa
Email: michaelburke@ieee.org

***Abstract*—The reliable detection and tracking of general objects is required by many field robotics applications, where autonomous agents need to navigate between and interact with dynamic targets in unstructured environments. This paper presents an approach to the detection and tracking of both moving and stationary objects in a forward-facing laser scan. Traditional approaches use geometric primitives to detect and model specific targets. A more general target descriptor taking object location and size into account is presented here, using principal component analysis to extract these features. Kalman filtering using a white noise acceleration model is implemented to track objects, with extensions to the target motion model provided in order to account for laser scanner motion. Results presented show that the proposed system tracks targets effectively over a wide range of challenging situations.**

I. Background and Introduction

Field robotics applications frequently require that objects surrounding a robotic platform be tracked and detected. In environments where manoeuvring objects are likely to be present, knowledge of these objects' trajectories can be used to improve navigation and collision avoidance systems. The detection of objects is also required prior to any meaningful interaction with them.

Specific objects can be recognised relatively easily using vision-based techniques, but these techniques experience difficulties in extracting accurate target position measurements. A better measure of a target's position is obtained through LIDAR (Light Detection and Ranging). LIDAR units are capable of determining distances to objects at long range, with high accuracy. LIDAR units are also able to operate in conditions under which vision systems traditionally fail, such as under extreme lighting.

The laser-based target tracking problem has received much attention in robotics literature, with numerous approaches proposed. Early approaches to laser-based target tracking only considered moving targets, which were detected through scan matching [1]. Scan matching is a relatively simple approach by which consecutive scans are aligned and compared, with differences assumed to be caused by a moving object.

Unfortunately, it is noted in [2] that scan matching suffers from numerous problems. Scans can not be compared directly, as the perceived shapes of moving objects change over scans. This occurs as new points become visible and previously visible returns are occluded. Instead, a fixed reference point on objects is required if target motion is to be detected. As a result, most laser-based object detection algorithms involve a pre-processing stage, in which scans are grouped into segments, each containing potential objects of interest. Information relevant to the detected objects of interest is then extracted so that the motion of the objects can be determined.

Geometric primitives are used in [3] to describe the properties of object segments. Initially, object segments are obtained by jump-distance classification, a process where a scan is separated into segments based on the distance between scan points. Thereafter, circles, arcs and linear regions are detected in each scan segment and used to determine likely segment matches in subsequent scans.

The geometric primitives of [3] are also applied to the problem of leg detection, for human target following, with a segment classified as legs if two arcs or circles are located close to one another. Human tracking is of particular interest in field robotics applications, as knowledge of the locations of humans is extremely important for the purposes of safety. Unfortunately, target detection in this manner is not robust, as one of the legs is often occluded, and the size of detected segments varies, depending on the distance to the target. Attempts to improve upon approaches such as this have been made in [4]. This approach attempted to bootstrap a laser detection system with visual information, obtained through facial detection. The technique marked uncertain detections, such as cases where only a single, leg-like object was detected, for visual clarification, and relied on visual tracking to detect false detections.

A far more robust method of classifying object segments in laser scans was proposed in [5]. Here, supervised learning was applied to the problem of building a classifier for the detection of people. Their approach used AdaBoost to create a strong classifier by combining a set of weak classifiers. Their classifier consisted of 14 measurements or features extracted from object segments. These incorporated both geometric and statistical properties.

[5] trained the classifier on labelled data in three different environments and found that the strongest features operating in all the environments were the radius and jump distances. This effectively means that the classifier was making decisions based predominantly on the size of targets and the distance to other segments. Similar results were obtained in [6], which

compared a variety of classifiers based on the 14 features of [5] in the context of pedestrian detection. A better classifier, which uses AdaBoost to train a classifier using a probabilistic part-based model of geometric laser primitives in conjunction with omnidirectional images, was proposed in [7].

Although the design of target specific classifiers can potentially produce a high detection rate, it does so at the expense of generality and may not be the best approach when targets are not clearly defined. In these scenarios, a better approach would be to attempt to detect and track objects of interest, rather than classifying them.

A generalised approach to tracking movable objects, which uses point matching to locate observations in a map of existing objects, was proposed in [8]. Unfortunately, this approach requires that a map of the environment be maintained, and that scans are closely matched, prior to object labelling.

Tracking of moving objects is of great desire in the context of simultaneous localisation and mapping (SLAM), where these targets can interfere with map building and should be removed before mapping takes place. This problem is termed SLAM with Detection and Tracking of Moving Objects (SLAM + DATMO). [9] propose a solution to this problem, where moving objects are detected in a scan, associated with those previously detected by comparing geometric primitives, and tracked over time. An interacting multiple model estimator (IMM) is used to find motion models for the objects and combined with multiple hypothesis tracking to predict the motion of these objects.

One of the most common techniques of object tracking makes use of Kalman filtering. [10], [11] and [12] all use a set of independent Kalman filter variants to track the position of moving targets. The work of [12] modelled the moving objects with constant linear acceleration and constant rotational velocity, while that of [10] used white noise acceleration velocity models.

This paper presents an approach to laser-based target detection and tracking. A generalised tracking system is used, with the goal of tracking all potential objects visible in a scan, and not just a specific target. Since this work aims to detect and track any object visible in the laser scan, no target specific geometries or motion models are assumed. If required, a secondary sensor more suited to discriminating between targets can be used in conjunction with the laser tracking to select and track a target of interest.

The paper is structured as follows. Section II describes the proposed approach to laser-based detection and tracking, with details of descriptor extraction and the Kalman filter tracking. This is followed by experimental results and conclusions in section III.

II. Methodology

A. System Overview

An overview of the entire target tracking process is presented here, to better describe its operation. Each iteration of the system commences with the arrival of a new scan. The new scan is then segmented and a descriptor extracted for each scan segment.

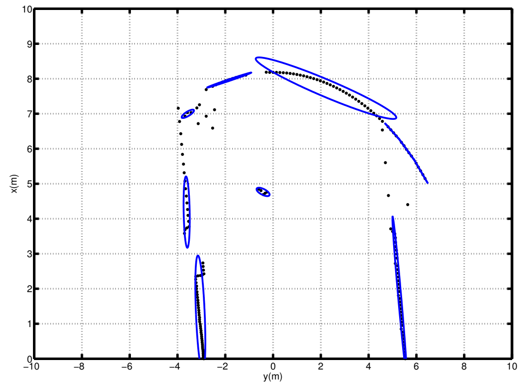


Fig. 1: A sample laser scan with detected ellipse overlay. The laser scanner returns are marked as black points. Note that the principal component ellipse requires at least 2 points to be calculated, so segments of less than two points are discarded.

The location of previously detected segments are predicted in the current scan's coordinate frame and matching segments located. The states of matched segments are updated, based on the current measurement. If a segment is not matched, it is labelled and enrolled as a new target.

A search through existing targets is conducted to find and combine any segments that share the same label. This assists in handling situations where objects coalesce. During this search, targets that have not been detected for a period of time greater than some threshold T are removed from the list of tracked targets.

B. Extraction of Segment Descriptors

Input scans are pre-filtered using a median filter, in order to remove salt and pepper noise. Thereafter, scans are divided into segments through jump-distance classification. This involves a simple pass over the laser data, separating segments if the distance between adjacent scan points is greater than some threshold.

Four properties or features of each segment are then concatenated into a four tuple segment descriptor. The work of [5], which involved training a classifier to recognise human targets using numerous extracted features, showed that the strongest features (features on which classification decisions were primarily based) were radius and jump distances. Intuitively, this means that classifier decisions should be based primarily on the location and size of point clusters, rather than on any particular geometric primitives.

These findings inspired the features used in the segment descriptor. The first two features of a segment are the positions of the segment's centroid, measured in 2D space, relative to the forward facing laser scanner. The choice of centroid coordinates as features ensures that segment location plays a role in segment matching. The last two features in the descriptor are the magnitudes of the principal components of the points in a segment and aim to capture information relating to segment size.

Principal component analysis (PCA) is a dimensionality reduction technique that transforms data into a coordinate system in which the largest variances in the data lie on coordinate axes termed principal components. Mathematically, the principal components of a set of observations are related to the eigenvalues and eigenvectors of its covariance matrix.

In the case of two-dimensional laser point data, the principal axes correspond to the major and minor axes of an ellipse encircling the points and so represent a good measure of the size of a segment. Figure 1 shows how ellipses obtained through principal component analysis neatly encompass scan segments. The ellipse is a good model of object size as it can be shown to cover almost all of an object's points, when the principal components are suitably scaled.

It should be noted that the ellipse does not model the shape of objects, but rather the size. As a result, the information obtained for non-linear point distributions, where the principal component ellipse does not always follow the contours of an object, is still relevant and can be used for matching.

Only the magnitude of the principal components is of interest, since ignoring direction allows for a certain amount of rotational invariance in the matching process.

C. Kalman Filter Tracking

Once the descriptors of segments in a scan have been extracted, they need to be associated with matching segments in preceding scans. This requires an update of the position features in the descriptors of previously detected segments, to account for potential motion of the segments. This is accomplished by means of Kalman filter tracking.

The Kalman filter is briefly explained here, in the context of laser-based target tracking. The Kalman filter consists of two stages, prediction and update. A prediction of a previous segment's position is made, based on a motion model, and then updated, based on the extracted descriptor of an associated segment. The predicted state $\hat{\mathbf{x}}_{k|k-1}$ and predicted covariance $\mathbf{P}_{k|k-1}$ is given by

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_k \hat{x}_{k-1|k-1} + \mathbf{B}_k \mathbf{u}_k \tag{1}$$

$$\mathbf{P}_{k|k-1} = \mathbf{F}_k \mathbf{P}_{k-1|k-1} \mathbf{F}_k^T + \mathbf{Q}_k, \tag{2}$$

with $\mathbf{F}_k$ the linear system update and $\mathbf{Q}_k$ the process noise covariance matrix. $\mathbf{B}_k$ takes the influence of any controls, $\mathbf{u}_k$, into account. Given a measurement $\mathbf{z}_k$, the measurement and covariance residuals are

$$\tilde{\mathbf{y}}_k = \mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{x}}_{k|k-1} \tag{3}$$

$$\mathbf{S}_k = \mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^T + \mathbf{R}_k, \tag{4}$$

with $\mathbf{H}_k$ the linear measurement model and $\mathbf{R}_k$ the measurement noise covariance matrix. Then, the updated state and covariance estimate are given by

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \tilde{\mathbf{y}}_k \tag{5}$$

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_{k|k-1}. \tag{6}$$

Here, $\mathbf{K}_k = \mathbf{P}_{k|k-1} \mathbf{H}_k^T \mathbf{S}_k^{-1}$ is the optimal Kalman gain for a linear system.

Using these equations, the operation of the Kalman filter is easily understood. First, a prediction of the system state is made, assuming zero-mean noise is present. An estimate of the uncertainty in this prediction is made by combining previous uncertainty, propagated through the model, with that introduced through control action and that of the model itself. A measurement is made and the uncertainty in prediction combined with the uncertainty in measurement. Finally, a revised state estimate is obtained by an uncertainty weighted combination of prediction and measurement.

D. Prediction Models

As general targets are tracked in this work, no explicit motion models can be defined ahead of time. For this reason, a constant velocity, white noise acceleration motion model is used to account for the motion of segments. Four states are of interest in this model, the 2D position and velocities of an object, measured relative to a forward facing laser scanner. The state vector will be denoted by $\mathbf{x} = [x, y, \dot{x}, \dot{y}]^{\mathrm{T}}$. Using this model, the system update equations are given by:

$$\mathbf{F}_k = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{7}$$

with Δt the sampling time. The white noise acceleration model assumes that object velocities are subject to Gaussianly distributed noise with zero-mean and variance σ_a^2. This means that the process noise covariance, $\mathbf{Q1}$ is written as

$$\mathbf{Q1} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \otimes \begin{bmatrix} \sigma_a^2 & 0 \\ 0 & \sigma_a^2 \end{bmatrix}. \tag{8}$$

The symbol $\otimes$ represents the Kronecker product, which is used for compact notation throughout this paper, in the interests of brevity. Note that $\mathbf{Q1}$ is not time varying, so has no subscript k.

If the laser scanner is stationary, the prediction model of (7) and (8) is sufficient to compensate for most target motions and the association of segments for the update stage of the Kalman filter can proceed. In the case of a moving laser scanner, however, additions to the white noise acceleration motion model are required.

E. Extension to Moving Platforms

Assuming that the laser scanner is mounted on a moving platform and that the translational and rotational velocity of the laser scanner is known, the white noise motion model can be extended in the following manner. Recall that the goal is to predict the position of a segment in a current scan in order to assist in the segment matching process. Assuming that the velocities of the laser scanner remain constant between scans, a previous scan can be brought into the current scan's coordinate frame by means of a translation and rotation.

Initially, previously detected objects are translated by an approximation of the motion of the laser scanner,

$$\begin{bmatrix} t_x \\ t_y \end{bmatrix} = \begin{bmatrix} \frac{v_k}{\omega_k} \sin\theta_k \\ \frac{v_k}{\omega_k} (1 - \cos\theta_k) \end{bmatrix}. \tag{9}$$

Here, $\theta_k = \omega_k \Delta t$ is the angular rotation of the laser scanner, resulting from its rotational velocity, ω_k. v_k represents the translational velocity of the laser scanner between scans, with Δt the time between scans.

Unfortunately, the velocities of (9) are never known perfectly, so uncertainty is present in this translation. This uncertainty in translation can be incorporated into the process noise covariance matrix as follows. It is assumed that the translational and rotational platform velocities are subject to zero-mean Gaussian noise with variances σ_v^2 and σ_ω^2 respectively.

This is denoted by writing $v_k = v_{ak} + \epsilon_v$ and $\omega_k = \omega_{ak} + \epsilon_\omega$. Here, subscript a represents the actual variable while ϵ denotes the zero-mean Gaussian noise. Substituting in (9), and linearising through Taylor expansion provides

$$\begin{bmatrix} t_x \\ t_y \end{bmatrix} \approx \begin{bmatrix} \frac{v_{ak}}{\omega_{ak}} \sin\theta_{ak} + \epsilon_v \frac{\partial t_x}{\partial \epsilon_v} + \epsilon_\omega \frac{\partial t_x}{\partial \epsilon_\omega} \\ \frac{v_{ak}}{\omega_{ak}} (1 - \cos\theta_{ak}) + \epsilon_v \frac{\partial t_y}{\partial \epsilon_v} + \epsilon_\omega \frac{\partial t_y}{\partial \epsilon_\omega} \end{bmatrix}. \tag{10}$$

(10) has the desirable property of separate system and noise terms. Hence, setting the random noise variables to zero provides the translation equations. This property also allows the system covariance update to be calculated as the sum of the system covariance and the noise covariance passed through the system model.

Given a linear system $\mathbf{Y} = \mathbf{TX}$, the transform of the mean and covariance of Gaussian random variables passed through the system is given by $\mathbf{E}[\mathbf{Y}] = \mathbf{TE}[\mathbf{X}]$ and $\mathbf{Cov}[\mathbf{Y}] = \mathbf{TCov}[\mathbf{X}]\mathbf{T}^{\mathrm{T}}$ respectively. Therefore, the system covariance update equation is $\mathbf{C} = \mathbf{T}_u \mathbf{C}_u \mathbf{T}_u^{\mathrm{T}} + \mathbf{T}_x \mathbf{C}_x \mathbf{T}_x^{\mathrm{T}}$. Here, subscript x represents system contributions and subscript u, noise contributions.

It can now be easily shown that

$$\mathbf{T}_u = \begin{bmatrix} \frac{\partial t_x}{\partial \epsilon_v} & \frac{\partial t_x}{\partial \epsilon_\omega} \\ \frac{\partial t_y}{\partial \epsilon_v} & \frac{\partial t_y}{\partial \epsilon_\omega} \end{bmatrix}, \quad \mathbf{C}_u = \begin{bmatrix} \sigma_v^2 & 0 \\ 0 & \sigma_\omega^2 \end{bmatrix} \tag{11}$$

where,

$$\frac{\partial t_x}{\partial \epsilon_v} = \frac{1}{\omega_k} (\sin\theta_k) \tag{12}$$

$$\frac{\partial t_x}{\partial \epsilon_\omega} = \frac{v_k}{\omega_k} \left(-\frac{\partial t_x}{\partial \epsilon_v} + \Delta t \cos\theta_k \right) \tag{13}$$

$$\frac{\partial t_y}{\partial \epsilon_v} = \frac{1}{\omega_k} (1 - \cos\theta_k) \tag{14}$$

$$\frac{\partial t_y}{\partial \epsilon_\omega} = \frac{v_k}{\omega_k} \left(-\frac{\partial t_y}{\partial \epsilon_v} + \Delta t \sin\theta_k \right) \tag{15}$$

Unfortunately, this system is not valid for $\omega_k = 0$. In this case the translation equations become

$$\begin{bmatrix} t_x \\ t_y \end{bmatrix} = \begin{bmatrix} v_k \Delta t \\ 0 \end{bmatrix} \tag{16}$$

and

$$\mathbf{T}_u = \begin{bmatrix} \Delta t & 0 \\ 0 & 0 \end{bmatrix}. \tag{17}$$

The knowledge of uncertainty in the translation of objects is incorporated into the object state update equations, by summing the uncertainty due to translation with the process noise $\mathbf{Q1}$ to give

$$\mathbf{Q}_k = \left(\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \otimes \mathbf{T}_u \mathbf{C}_u \mathbf{T}_u^{\mathrm{T}} \right) + \mathbf{Q1}. \tag{18}$$

The translation itself is included in the target state update equations by simply shifting the positional estimates in the white noise acceleration model by the estimated translation,

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_1 \hat{x}_{k-1|k-1} + \begin{bmatrix} t_x & t_y & 0 & 0 \end{bmatrix}^{\mathrm{T}}, \tag{19}$$

while the predicted covariance remains that of (2).

The incorporation of translation into the Kalman filter framework does not correct any error in laser scanner rotation. The rotation of the laser scanner still needs to be corrected for by rotating the estimates of target object velocity and position into the current laser scan's coordinate frame. This requires another iteration of the prediction phase of the Kalman filter, but this time using a model of rotation.

Using direction cosine matrices, the rotation of the predicted state $\hat{\mathbf{x}}_{k|k-1}$ is obtained by multiplying it by

$$\mathbf{F}_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \otimes \begin{bmatrix} \cos\theta_k & -\sin\theta_k \\ \sin\theta_k & \cos\theta_k \end{bmatrix}. \tag{20}$$

As before, the rotation can not be known perfectly since the rotational velocity ω_k is subject to noise. This is modelled by the inclusion of a zero-mean Gaussian noise variable ϵ_ω with variance σ_ω^2. An estimate of the uncertainty introduced due to this noise is obtained as discussed earlier, by linearising the rotation through Taylor series expansion to provide

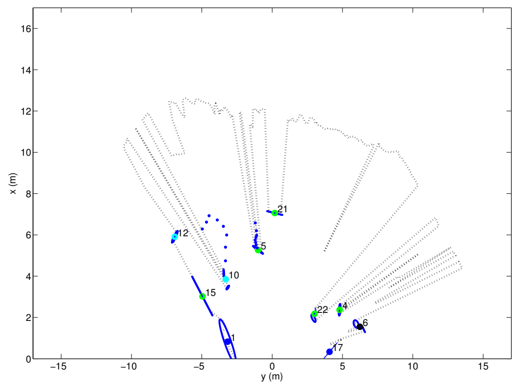
$$\mathbf{T}_u = \begin{bmatrix} -x\sin\theta_k - y\cos\theta_k \\ x\cos\theta_k - y\sin\theta_k \\ -\dot{x}\sin\theta_k - \dot{y}\cos\theta_k \\ \dot{x}\cos\theta_k - \dot{y}\sin\theta_k \end{bmatrix}, \quad \mathbf{C}_u = \sigma_\omega^2. \tag{21}$$

Here, (x, y) and $(\dot{x}, \dot{y})$ represent the position and velocities of the translated segment.

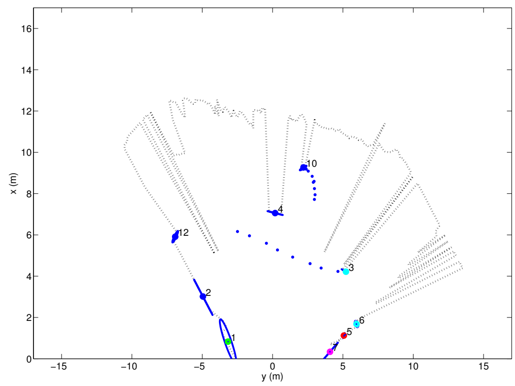
Of course, the uncertainty introduced through rotation can not be directly summed with the uncertainty in estimates after translation, since the rotation is a non-linear operation that affects the existing uncertainty in states. Thus, the uncertainty is included by repeating the prediction phase of the Kalman filter, updating the state and propagating the uncertainty through the rotation $\mathbf{F}_k$, and introducing the new uncertainty as process noise $\mathbf{Q}_k = \mathbf{T}_u \mathbf{C}_u \mathbf{T}_u^{\mathrm{T}}$.

F. Update Models

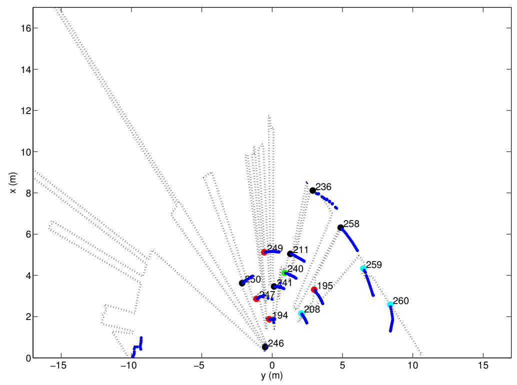
Once a prediction of a target's position is made, first by predicting its own motion and then incorporating the effects of laser scanner motion, the objects in scans should be aligned, allowing for data association and the update stage of the Kalman filter tracker to proceed.



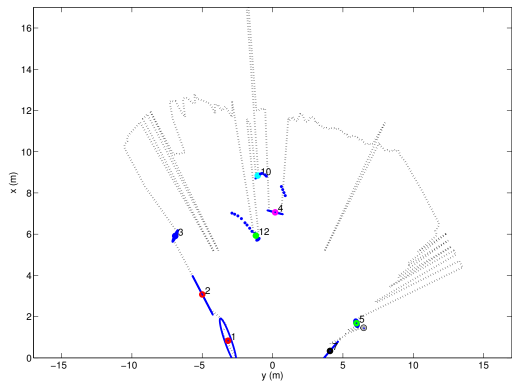
(a) Target 10 is tracked while undergoing a sharp set of turns.



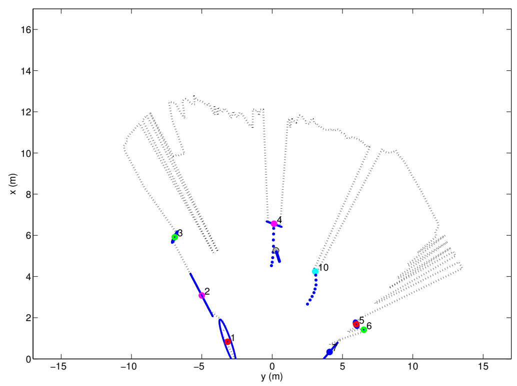
(b) Target 3 is tracked at a speed of over 6 m/s.



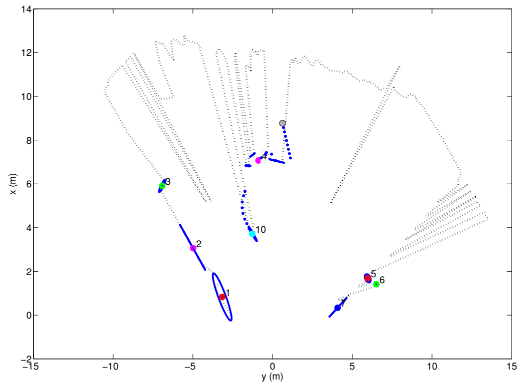
(c) Stationary objects are tracked while the scanner moves. Target 246 is moving with zero velocity relative to the scanner.



(d) Target 10 is tracked through an occlusion.



(e) An object is merged with target 4 as they coalesce.



(f) A target is lost in an occlusion and assigned the incorrect label when emerging.

Fig. 2: Experimental results showing the success and failure modes of the laser tracking. Objects are marked on the raw laser data, with ellipses showing the most recent target detections. Tracked objects are labelled with a unique number and marked as randomly coloured circles to aid discrimination. A grey object represents a target that has not been detected in the current scan, but is yet to be removed from the list of tracked targets. Target trajectories are marked by dotted blue trails and all measurements are in the coordinate frame of the current scan.

Data association takes place through the use of a nearest neighbour search, operating on the 4 tuple descriptor introduced in Section II-B. A match is only accepted if the difference in the Euclidean distance between the first two nearest neighbours is greater than some threshold. Once segments are matched, the update stage of the Kalman filter takes place. As only the position of each target is measured, and not the velocity, the measurement model is

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}. \tag{22}$$

The potential error in measurement is obtained from laser scanner specifications, but requires the inclusion of an additional quantity that accounts for potential error due to a moving target centroid. This is likely to occur as points in a segment move in and out of view. Denoting the standard deviation of these errors as σ_m, the measurement noise is

$$\mathbf{R} = \begin{bmatrix} \sigma_m^2 & 0 \\ 0 & \sigma_m^2 \end{bmatrix}. \tag{23}$$

III. Results and Conclusions

The results of experiments on two sets of data are discussed here. The first, obtained under laboratory conditions, involves scans of rapidly manoeuvring targets captured from a stationary laser scanner. The use of a stationary scanner allows for modes of interest to be tested directly. The second set of data was obtained in a conference venue with uncontrolled targets, using a wheeled platform that navigates autonomously and randomly, pausing for approaching targets.

Unfortunately, it is difficult to quantify the performance of a laser-based tracking system designed to operate in unstructured environments. Tracking performance is typically dependent on the end application, and ground truth data is not readily available for comparison. Due to this difficulty, the experimental work presented here only aims to identify and explain any system failure modes.

Three primary scenarios are of interest when tracking moving targets in laser scans, detecting high speed manoeuvring targets, handling coalescing objects and tracking objects through occlusions. Figure 2 shows the tracker performance in these situations.

The system proved extremely robust to rapidly moving, manoeuvring targets, and was able to follow a human running at over 6 m/s (Figure 2b) with a stationary scanner. While this is extremely fast, it does constrain the allowable platform motion, if objects are to be tracked using a moving scanner. Nevertheless good results are still obtained with a moving scanner. Figure 2c illustrates this using a scan captured in the conference setting, an extremely challenging data set containing numerous targets.

The tracking system is able to cope with temporary occlusions, as indicated by Figure 2d, provided the trajectory of the target does not change significantly when occluded.

Figure 2e shows how the tracking system is able to merge objects that are close together. In this case, a person picked up and moved another object in the scan, before separating. Unfortunately, the ability to coalesce objects decreases the system's ability to discriminate between closely positioned objects.

This is indicated by Figure 2f, which shows a failure in the tracking system. In this situation, a target object entered an occluded region, but changed trajectory in this region causing it to be lost. The lost target then emerged from the occluded region close to a stationary target of similar size and was incorrectly merged with this target. This behaviour is difficult to counter, and a secondary sensor is required for better target discrimination.

Despite this failure mode, the tracking system performs well and is able to overcome a wide variety of scenarios. The use of principal components in the extracted descriptor allows for closely located objects of differing sizes to be discriminated between, while the Kalman filter allows both platform and object motion to be accounted for.

Acknowledgment

This work was supported by funding from the Council for Scientific and Industrial Research (CSIR), South Africa.

References

[1] J.-S. Gutmann and C. Schlegel, "Amos: Comparison of scan matching approaches for self-localization in indoor environments," in *Advanced Mobile Robot, 1996., Proceedings of the First Euromicro Workshop on*, Oct. 1996, pp. 61 – 67.

[2] L. E. Navarro-Serment, C. Mertz, and M. Hebert, "Predictive mover detection and tracking in cluttered environments," in *Proc. of the 25th. Army Science Conference*, November 2006.

[3] J. Xavier, M. Pacheco, D. Castro, and A. Ruano, "Fast line, arc/circle and leg detection from laser scan data in a player driver," in *in Proc. of the IEEE Int. Conference on Robotics and Automation (ICRA 05)*, 2005.

[4] M. Scheutz, J. McRaven, and G. Cserey, "Fast, reliable, adaptive, bimodal people tracking for indoor environments," in *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, vol. 2, 28 2004, pp. 1347 – 1352 vol.2.

[5] K. O. Arras, Ó. Martínez, and M. W. Burgard, "Using boosted features for detection of people in 2d range scans," in *In Proc. of the IEEE Intl. Conf. on Robotics and Automation (ICRA 07)*, 2007.

[6] C. Premebida, O. Ludwig, and U. Nunes, "Exploiting lidar-based features on pedestrian detection in urban scenarios," in *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, October 2009, pp. 1 – 6.

[7] Z. Zivkovic and B. Krose, "Part based people detection using 2d range data and images," in *Intelligent Robots and Systems, 2007. (IROS 2007). Proceedings. 2007 IEEE/RSJ International Conference on*, October 2007, pp. 214 – 219.

[8] G. Gallagher, S. Srinivasa, J. A. D. Bagnell, and D. Ferguson, "Gatmo: a generalized approach to tracking movable objects," in *IEEE International Conference on Robotics and Automation*, May 2009.

[9] C.-C. Wang, C. Thorpe, and S. Thrun, "Online simultaneous localization and mapping with detection and tracking of moving objects: Theory and results from a ground vehicle in crowded urban areas," in *In Proc. of the IEEE Intl. Conf. on Robotics and Automation (ICRA 03)*, 2003.

[10] A. Mendes, L. Bento, and U. Nunes, "Multi-target detection and tracking with a laser scanner," in *Intelligent Vehicles Symposium, 2004 IEEE*, 14-17 2004, pp. 796 – 801.

[11] A. Mendes and U. Nunes, "Situation-based multi-target detection and tracking with laserscanner in outdoor semi-structured environment," in *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, vol. 1, 28 2004, pp. 88 – 93.

[12] R. MacLachlan and C. Mertz, "Tracking of moving objects from a moving vehicle using a scanning laser rangefinder," in *Intelligent Transportation Systems Conference, 2006. ITSC '06. IEEE*, 17-20 2006, pp. 301 – 306.