# A NEW BEARINGS-ONLY TRACKING ALGORITHM FOR GROUND MOVING TARGETS CONSTRAINED TO ROADS

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**ABSTRACT**

We propose a new recursive algorithm for tracking ground moving targets from multiple bearings-only measurements in clutter, collected by a ground moving observer. The scenario represents a target moving along a realistic road network with junctions, roads branching or crossing, where the probability of having measured the line-of-sight bearing, among the multiple observed ones, is less than the unity. This constrained motion estimation is performed using particle filters. Realistic simulations are presented to support our findings.

## 1. INTRODUCTION

Tracking the kinematical parameters (i.e. position, velocity, etc.) of a transmitting target from passive measurements of the line-of-sight (LOS) bearings collected by a moving observer, is a classical problem in the field of nonlinear estimation [1, 2]. Such a problem, commonly known as bearings-only tracking (BOT), has been the object of several contributions over the last two decades [3–6] as it can be applied in passive sonar tracking and aircraft surveillance by using radar in a passive mode.

BOT is a challenging problem because of the nonlinearity of the measurements, which even in the absence of noise, may conduce to a non-observability of the state vector (it is not possible to estimate the parameters of the target motion) if the observer does not maneuver [7]. In addition, such non-observability may produce unstable behavior in some Cartesian coordinates based-algorithms [3]. BOT is further complicated by presence of multiple spurious measurements due to clutter [6], which may be originated from multipath propagation from valid targets due to ground reflection, atmospheric ducting or ionospheric reflection/refraction.

More stable algorithms have been reported in the literature by representing the BOT problem in alternative coordinate systems [3, 8]. Aidala and Hammel proposed the utilization of the modified polar (MP) coordinates in order to stabilize extended Kalman filters [3]. They noted that the MP coordinates representation of the state vector automatically decouples observable and unobservable components of the estimated state vector. In a more recent contribution [8], Bréhard proposed the use of logarithmic polar (LP) coordinates in order to render particle filter-based algorithms more stable. However, the accuracy of the proposed algorithms is not only strongly dependent on the observer's maneuver, but also on its initialization [9]. Besides, these algorithms have not been examined in situations where the probability of target detection is less than the unity (i.e. when LOS bearings are not always present).

The treatment of multiple simultaneous bearing measurements at each sensor scan has been treated in [10] and [9]. Contribution [10] proposes an algorithm based on the probabilistic data association (PDA) technique, in conjunction with the maximum likelihood (ML) approach, resulting in a batch procedure to estimate the state vector of a constant velocity target. On the other hand, [9] presents a batch-recursive algorithm for tracking maneuvering targets, which first uses the batch procedure of [10] to better track initialization and then, a recursive approach to provide track maintenance. In order to improve observability, a common strand of these approaches is the incorporation of signal's amplitude information (AI) in the BOT algorithm.

Due to the increasing development of digital maps containing terrain information, such as roads, open fields, hills, tunnels, etc. [11, 12], recent contributions to the target tracking problem consider this valuable source of information to improve accuracy (see [13–16] as examples). In this paper, we adopt such an approach and adapt it to the classical problem of bearings-only tracking. The scenario represents two platforms (target and observer) moving in a surveillance region constrained by known road networks. Moreover, we also consider the presence of multiple spurious bearing measurements at each sensor scan where, due to obstacles between platforms, the probability of having measured the LOS bearing is less than the unity. We use the modified polar coordinates system to represent the state vector and we perform its estimation via particle filters. The proposed algorithm results in a new recursive procedure that exploits road network information by incorporating it into the target state and measurement equations. This not only leads to a significant improvement on the observability and accuracy in the estimation of the target state vector, but also permits the use of a low complexity target dynamic model to deal with target maneuvers. The analysis of the proposed approach trough simulated data is an original contribution of this paper.

The remainder of this paper is organized as follows. In section 2, we present the state and measurement equations to road constrained motion. In section 3, we describe the particle filter implementation. In section 4, simulation results are given. Finally, in section 5, we give the conclusions.

## 2. ROAD CONSTRAINED TARGET DYNAMICS AND MEASUREMENT MODELS

The basis of the BOT problem relies on estimating the trajectory of a target, i.e. position and velocity from noise-corrupted bearing measurements, performed by a single-maneuvering observer. Since, in this paper, the target and the observer are supposed to evolve in a surveillance region constrained by known road networks, we consider such an information as *a prior* to be integrated in the tracker system.

Commonly, road network information is modeled as a large collection of roads, each of which consists of a number of interconnected segments. Each segment is assumed to be a straight line between two georeferenced nodes [17], [18].

Our approach incorporates such information at three different stages: 1) constraining the direction of the velocity components of the target state vector to be parallel to the direction of the road segment in which the target is supposed to travel [19], 2) using the concept of *directional process noise* [16], that assumes for on-road targets more uncertainty along a road segment than orthogonal to it, and 3) considering the road network information as a pseudo-measurement [14, 15, 17].

In the following, the stochastic target dynamic and the measurement models are presented.

### 2.1. Constrained Dynamic Model Formulation

Knowing the event that the target is evolving on a specific road segment $s$ and considering that its relative velocity vector is parallel to the direction of $s$ (eq. A.3), it can be proved, by combining the noiseless approximate[1] dynamic equations (eqs. A.1) and the Cartesian to MP coordinates (and vice versa) transformation equations (eqs. A.2), that the constrained relative dynamics of a constant velocity target w.r.t. a maneuvering observer can be expressed as

$$\boldsymbol{\chi}_{k+1} = \boldsymbol{f}_s(\boldsymbol{\chi}_k) - \boldsymbol{\varrho}_k + \boldsymbol{\upsilon}_k \tag{1}$$

where

• $\boldsymbol{\chi}_k$ is the relative discrete target state vector at time $k$ in modified polar coordinates defined as

$$\boldsymbol{\chi}_k = \begin{bmatrix} \theta_k & \dot{\theta}_k & \xi_k & r_k \end{bmatrix}' \tag{2}$$

where $\theta_k$ and $r_k$ stand, respectively, for the relative bearing angle and range, with first order derivatives $\dot{\theta}_k$ and $\dot{r}_k$, and where $\xi_k = \dot{r}_k/r_k$ is the normalized range rate,

• $\boldsymbol{f}_s(\boldsymbol{\chi}_k)$ is a vector function describing the noiseless relative dynamics of a target, w.r.t a non-maneuvering observer, whose velocity vector is parallel to the road segment $s$ and which is given by

$$\boldsymbol{f}_s(\boldsymbol{\chi}_k) = \begin{bmatrix} \arctan(A_k/B_k) \\ E_k(m_s B_k - A_k) \\ E_k(B_k + m_s A_k) \\ r_k C_k \end{bmatrix} \tag{3}$$

with

$$\begin{aligned} A_k &= \sin\theta_k + m_s T D_k \\ B_k &= \cos\theta_k + T D_k \\ C_k^2 &= A_k^2 + B_k^2 \\ D_k &= \xi_k \cos\theta_k - \dot{\theta}_k \sin\theta_k \\ E_k &= D_k / C_k^2 \end{aligned}$$

where $m_s$ stands for the slope of the road segment $s$ and $T$ represents the sampling time,

• $\boldsymbol{\varrho}_k$ is a vector function accounting for a constant observer acceleration and given by

$$\boldsymbol{\varrho}_k = \frac{T}{r_k C_k^2} \begin{bmatrix} 0 \\ \gamma_y B_k - \gamma_x A_k \\ \gamma_y A_k + \gamma_x B_k \\ 0 \end{bmatrix} \tag{4}$$

[1] In order to make it exact we must consider the appropriate displacement terms for the position resulting from an observer acceleration. However, because the time between samples is small relative to the time constants of the dynamics, these terms have been neglected as in [20].

where $(\gamma_x, \gamma_y)$ stand, respectively, for the known observer acceleration components in $x$ and $y$ directions, and

• $\boldsymbol{\upsilon}_k$ is the process noise used to model unpredictable target accelerations, assumed to be zero-mean, white and Gaussian whose covariance matrix is given by

$$\mathbf{Q}_{k,s} = \mathbf{J}_k \begin{bmatrix} \mathbf{Q}_{k,s}^p & \mathbf{0} \\ \mathbf{0} & \mathbf{Q}_{k,s}^v \end{bmatrix} \mathbf{J}_k^T \tag{5}$$

where $\mathbf{J}_k$ stands for the Jacobian matrix containing the partial derivatives of $\boldsymbol{\chi}_k$ w.r.t. the position and velocity components and where $\mathbf{Q}_{s,k}^p$ and $\mathbf{Q}_{s,k}^v$ stand, respectively, for the noise covariance matrices for the position and velocity components built using the *directional process noise* [16]. Therefore, considering $\sigma_a^2$ and $\sigma_o^2$ as the (generic) variances along and orthogonal to the road segment $s$ (for the position or the velocity components), subject to the constraint $\sigma_a^2 >> \sigma_o^2$, the expression of $\mathbf{Q}_{s,k}^p$ or $\mathbf{Q}_{s,k}^v$ in Cartesian coordinates is given by

$$\mathbf{Q}_{k,s}^{p \text{ or } v} = \begin{bmatrix} -\cos\alpha_s & \sin\alpha_s \\ \sin\alpha_s & \cos\alpha_s \end{bmatrix} \begin{bmatrix} \sigma_o^2 & 0 \\ 0 & \sigma_a^2 \end{bmatrix} \begin{bmatrix} -\cos\alpha_s & \sin\alpha_s \\ \sin\alpha_s & \cos\alpha_s \end{bmatrix}$$

where $\alpha_s$ is the angle between the geographic north and the road segment $s$ [16].

### 2.2. Measurement Equations

Traditional BOT scheme considers a single bearing measurement at each sensor scan. However, in practical situations signals coming from the target may propagate via multiple paths due to reflection/refraction before reaching the observer. Furthermore, it may happen that in presence of obstacles between target and observer all measured bearings belong to non-line-of-sight paths only. Hence, measurement models which take into account such impairments are necessary to track the target properly.

#### *2.2.1. Bearing Measurements*

The $M_k$ bearing measurements available at time $k$ are disposed in vector $\mathbf{z}_{1,k}$, whose elements are given by

$$z_{k,j} = \begin{cases} \theta_k + w_{1,k} & \text{if } \psi_k = j, \\ u_k & \text{if } \psi_k \neq j \text{ or } \psi_k = 0 \end{cases} \tag{6}$$

where the following assumptions take place:

• $j \in \{1, \ldots, M_k\}$ denotes the index element in vector $\mathbf{z}_{1,k}$,

• $w_{1,k}$ is a zero-mean independent Gaussian noise with variance $\sigma_\theta^2$,

• $u_k$ is a random variable accounting for the bearings due to clutter. For simplicity, we assume that for a bearing due to clutter all values in the interval $\mathcal{I} = [0, 2\pi]$ are equally likely. Meaning that $u_k$ is distributed as an uniform random variable in $\mathcal{I}$ [10],

• $\psi_k$ is a $\{0, 1, \ldots, M_k\}$-valued random variable with probability

$$p(\psi_k = i) = \begin{cases} 1 - P_D & \text{if} \quad i = 0 \\ P_D/M_k & \text{if} \quad i \neq 0 \end{cases} \tag{7}$$

where $P_D$ is the prior probability of target detection. It should be noticed that for $\psi_k \neq 0$, $\psi_k$ denotes the index of the LOS bearing in vector $\mathbf{z}_{1,k}$, and for $\psi_k = 0$, it represents the absence of LOS bearing in $\mathbf{z}_{1,k}$.

### 2.2.2. *Pseudo-Measurement*

An alternative approach to incorporate road network information is through the use of pseudo-measurements [14] or fictitious measurements [15, 17], which represent "synthetic" measurements usually created to constrain the target dynamics to the road network. In this paper we use such an approach for three purposes; *i)* to define the road segment in which the target is evolving, *ii)* to handle target transitions between road segments (e.i. when the target approaches a node) and *iii)* to penalize the target evolution far away from the road network. Thus, let define

$$z_{2,k} = h(p_{\mathbf{x}_k}, s) + w_{2,k} \tag{8}$$

as an independent pseudo-measurement of the minimum Euclidian distance between the target's position $p_{\mathbf{x}_k}$ at time $k$ and the nearest road segment $s$ [15,17], $h(\cdot)$ denotes the non linear function providing the distance, and $\omega_{2,k}$ is the measurement noise, assumed to be zero-mean white Gaussian process with variance $\sigma_d^2$.

In order to satisfy purpose *i)* we consider that the dynamics of the target state is constrained to the road segment $s$, if $s$ is the nearest road segment to the current position of the target. To avoid computation burden in the search of the nearest road, we compute such a distance for a reduced number of road segments laying within a bounding box which guaranties that no road laying outside of it is closest to the target [17]. It should be noticed that such a search also satisfies *ii)*. Purpose *iii)* is satisfied by assuming the pseudo-measurements as normally distributed with zero-mean (on-road condition).

## 3. PARTICLE FILTER IMPLEMENTATION

Consider the system described by equations (1), (6) and (8) and let denote the set of available observations at time $k$ by $\mathbf{Z}_k = \{\mathbf{z}_0, \ldots, \mathbf{z}_k\}$, with $\mathbf{z}_k = [\ \mathbf{z}_{1,k}^T \quad z_{2,k}\ ]^T$. From a Bayesian perspective, the tracking problem is to recursively calculate some degree of belief in the state $\boldsymbol{\chi}_k$ at time $k$, taking different values, given the data $\mathbf{Z}_k$ up to time $k$. Hence, it is required to construct the posterior density $p(\boldsymbol{\chi}_k|\mathbf{Z}_k)$. In this procedure, it is assumed that the initial density $p(\boldsymbol{\chi}_0)$ is available.

One simple method to approximate the posterior density is by means of particle filters [21]. Thus, starting with a weighted set of samples (particles) $\{\boldsymbol{\chi}_{k-1}^i, \omega_{k-1}^i\}_{i=1}^N$ approximately distributed according to $p(\boldsymbol{\chi}_{k-1}|\mathbf{Z}_{k-1})$, new samples are generated from a suitable proposal distribution, which may depend on the previous state and the new measurements, however, for simplicity it is often chosen to be the prior, i.e. $\boldsymbol{\chi}_k^i \sim p(\boldsymbol{\chi}_k|\boldsymbol{\chi}_{k-1})$. In order to maintain a consistent sample, the new importance weights are set to

$$\omega_k^i \propto \omega_{k-1}^i p(\mathbf{Z}_k|\boldsymbol{\chi}_k^i) \tag{9}$$

where $\sum_{i=1}^N \omega_k^i = 1$. Thus, the new particle set $\{\boldsymbol{\chi}_k^i, \omega_k^i\}_{i=1}^N$ is then approximately distributed according to $p(\boldsymbol{\chi}_k|\mathbf{Z}_k)$ and, therefore, an estimate of the state can be obtained using, for instance, the minimum mean square (MMS) [15]. It should be noticed that in order to consider multiple bearing measurements and pseudo-measurements, the likelihood of the observations $p(\mathbf{Z}_k|\boldsymbol{\chi}_k^i)$ may be written as

$$p(\mathbf{Z}_k|\boldsymbol{\chi}_k^i) \quad = p(z_{2,k}^i|\boldsymbol{\chi}_k^i) \sum_{\psi_k=0}^{M_k} p(\mathbf{z}_{1,k}|\boldsymbol{\chi}_k^i, \psi_k)p(\psi_k) \tag{10}$$

where $z_{2,k}^i$ is the minimum Euclidian distance from particle $i$ to the nearest road segment, eq. (8).

It is well known that particle filters suffer from *degeneracy problem*, where after a few iterations all but one particle will have negligible weight [21]. To overcome this problem the concept of *resampling* is used. Therefore, we take $N$ samples with replacement from the set $\{\boldsymbol{\chi}_k^i\}_{i=1}^N$ if

$$N_{\text{eff}} = \frac{1}{\sum_i (\omega_k^i)^2} < N_{\text{thr}} \tag{11}$$

where the probability to take sample $i$ is $\omega_k^i$ and where $N_{\text{eff}}$ is the effective number of samples and $N_{\text{thr}} = 2/3N$ is a threshold [15].

## 4. SIMULATION RESULTS

The scenario used to demonstrate the performance of the proposed algorithm is depicted in figure 1. The road network consists in twenty six roads (dashed lines) crossing at different nodes (solid triangles labeled by its node number). The target initially situated at node 11 maintains a constant velocity course, $v_T = 19$ m/s, changing its direction at nodes $\{16, 15, 2, 3, 4, 18\}$ and describing the solid line trajectory at the bottom of figure 1. The observer departs from node 12 with a constant velocity of $v_o = 15$ m/s and undergoes a constant acceleration of $a_o = 0.5$ m/s$^2$ in the interval 0.5-1.0 minutes. Afterwards, it maintains the initial constant velocity changing its course at nodes $\{13, 9, 10, 5\}$ and describing the doted line trajectory at the top of figure 1. Three bearing measurements are received at each sensor scan $T = 0.5\ s$, for an approximated observation period of 6 minutes. When present, the LOS bearings are measured with an accuracy of $\sigma_\theta = 0.5$ deg.

The following nominal filter parameters were used in the simulations: the directional process noise standard deviations (STDs) for the position and velocity components orthogonal to the road were respectively set to $\sigma_{o,p} = 14$ m and $\sigma_{o,v} = 3$ m/s. The corresponding STDs for the components along the direction of the road were $\sigma_{a,p} = \sqrt{10}\sigma_{o,p}$ and $\sigma_{a,v} = \sqrt{3}\sigma_{o,v}$. The pseudo-measurement STD was $\sigma_d = 4.5$ m and the particle filter used $N = 1000$ particles, carrying out resampling if $N_{\text{eff}} < N_{\text{thr}}$, with $N_{\text{thr}} = 2/3N$. Initial particles were uniformly spread over the whole road network and its velocity components were set to zero.

The estimation performance of the proposed algorithm is provided in terms of the root-mean-square (RMS) position errors using 100MC trials. The RMS position error at time $k$ is computed according to

$$\text{RMS}_k = \sqrt{\frac{1}{n}\sum_{i=1}^n (\hat{x}_k^i - x_k^i)^2 + (\hat{y}_k^i - y_k^i)^2} \tag{12}$$

where $(x_k^i, y_k^i)$ and $(\hat{x}_k^i, \hat{y}_k^i)$ denote the true and estimated target positions at time $k$ at the $i$th MC trial.

Figure 2 shows the RMS error curves corresponding to three different target detection probabilities $P_D = \{1.0, 0.9, 0.8\}$. As expected, low target detection probabilities lead to a degradation of the accuracy of the target tracking. However, in spite of multiple simultaneous bearing measurements and a target detection probability of less than the unity, the proposed algorithm exhibits a comparable performance to the algorithms studied in [22] for maneuvering targets in a typical BOT problem (RMS errors between 0.20-1.04kms). Moreover, our approach may not require observer maneuver because the road network provides enough information to improve range observability.

It should be noticed that, for a fixed target detection probability, the highest RMS position errors are observed at the beginning of the target tracking process (0-0.2 minutes) and when the target travels through road segments $\overline{N2N3}$, $\overline{N3N4}$ and $\overline{N4N18}$ (3.59-5.97 minutes). The former case is due to the initialization process, where particles, initially spread uniformly over the whole road network, do not approximate well the posterior density. The latter case, is related to: 1) the number of connected roads at nodes N2, N3 and N4, which produce particles to spread over the connected ones increasing uncertainty about the road in which the target is actually evolving, and 2) the sudden turns performed by the target at nodes N2, N3 and N4, which are not described by the constant velocity model.

Figure 3 depicts the average over the trajectories followed by the target for 100MC trials. As we can see, even for a target detection probability of 0.8, in most of the cases the estimated trajectory is the right one. This can be deduced by noticing that the average trajectory resembles rather the true one than any other composed trajectory in the road network. Major differences can be observed at the first segment and in the last three segments, where the target is sometimes detected in a neighboring road of the road on which the target is actually evolving.

## 5. CONCLUSIONS

We proposed a new recursive bearings-only tracking algorithm for ground moving targets constrained to roads, able to handle multiple bearing measurements in clutter. Observer maneuver may not be a requirement because the information provided by the road network improves observability of the state vector. Simulation results showed an improvement on the accuracy of target tracking using low complexity target evolution models, even for a probability of target detection less than the unity.

## 6. ACKNOWLEDGMENT

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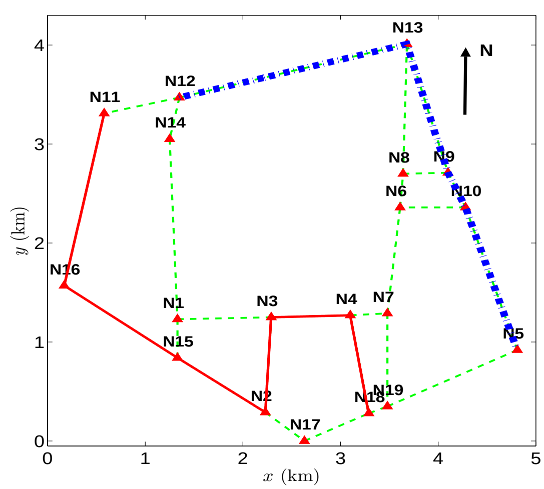


**Fig. 1**. Simulation scenario: dashed lines and solid triangles represent respectively the road segments and nodes of the road network. The bottom solid trajectory represents the target path. The top doted trajectory is the observer's path.

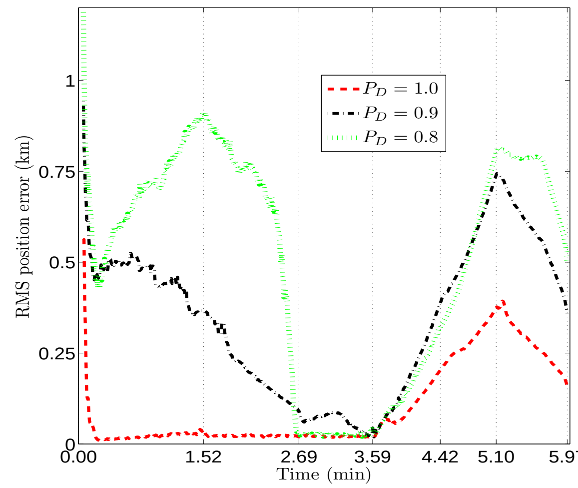


**Fig. 2**. RMS position error versus time. Vertical dashed lines represent transition instants between road segments in the target trajectory.

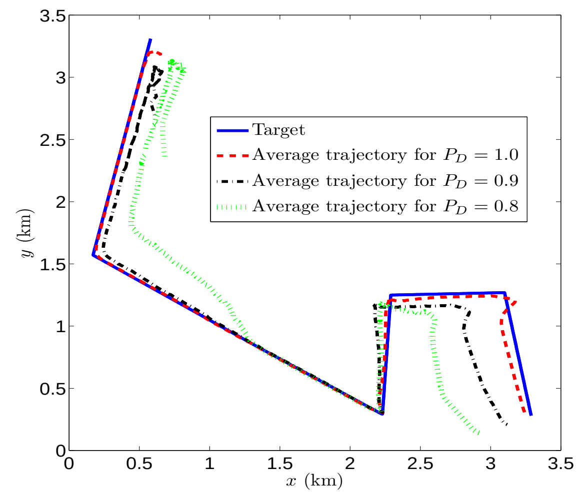


**Fig. 3**. Actual and average trajectories obtained from 100MC trials.

## A. APPENDIX

### A.1. Relative Noiseless Target Dynamics

The relative noiseless target dynamics at time $k+1$ w.r.t. a maneuvering observer is given by

$$X_{k+1} = X_k^t - X_k^o = \mathbf{F}X_k - \mathbf{u}_k$$

where $X_k = \begin{bmatrix} x_k & y_k & \dot{x}_k & \dot{y}_k \end{bmatrix}'$ stands for the relative target state vector at time $k$, with relative position and velocity components given by $(x_k, y_k)$ and $(\dot{x}_k, \dot{y}_k)$, respectively. The target and observer state vectors defined similarly to $X_k$, are denoted here as $X_k^t$ and $X_k^o$ respectively, $\mathbf{u}_k$ accounts for the effects of observer accelerations, and the transition matrix $\mathbf{F}$ is defined as

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

### A.2. MP ⇔ Cartesian Transformation Equations

| MP to Cartesian | Cartesian to MP |
|---|---|
| $x_k = r_k \cos\theta_k$ | $\theta_k = \arctan\left(\dfrac{y_k}{x_k}\right)$ |
| $y_k = r_k \sin\theta_k$ | $\dot{\theta}_k = \dfrac{\dot{y}_k x_k - \dot{x}_k y_k}{x_k^2 + y_k^2}$ |
| $\dot{x}_k = \xi_k r_k \cos\theta_k - \dot{\theta}_k r_k \sin\theta_k$ | $\xi_k = \dfrac{\dot{x}_k x_k + \dot{y}_k y_k}{x_k^2 + y_k^2}$ |
| $\dot{y}_k = \xi_k r_k \sin\theta_k + \dot{\theta}_k r_k \cos\theta_k$ | $r_k = \sqrt{x_k^2 + y_k^2}$ |

### A.3. Constraint on the Direction of the Velocity Vector

The velocity vector of the target evolving on a road segment $s$ is parallel to the direction of that specific road, thus

$$\langle (\dot{x}_k, \dot{y}_k)' \mid \vec{n}_s \rangle = 0$$

where, $\vec{n}_s$ is the orthogonal vector to the segment $s$.

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