Abstract — Signal strength information is a standard output of a modern radar system. Provided the amplitude of the target returns exceeds the false alarm background, the consideration of signal strength may lead to improved target estimates, depending on the scenario. In this paper a Bayesian tracking algorithm is presented which incorporates the signal strength information. In contrast to previous approaches, the knowledge on the target’s signal strength is not only used for an improved calculation of the association probabilities, but it enters into the algorithm as a random variable which is sequentially estimated. By this approach it is not only possible to discriminate closely-spaced targets and improve the track continuity, but also to support possible classification and identification tasks. The signal strength fluctuations of the target returns are modeled by the Swerling-I and Swerling-III cases. As a first performance evaluation, numerical results are presented based on a multi-target simulation scenario.

Keywords: Ground moving target indication (GMTI), target tracking, signal strength, Swerling fluctuation models.

1 Introduction

In ground surveillance with airborne Ground Moving Target Indication (GMTI) radar, the main task of establishing and maintaining tracks of relevant moving objects is challenged not only by imprecise, uncertain and ambiguous measurements. To a large degree, the main difficulty arises from complex target dynamics, e.g. stop & go behavior or strong maneuvers, masking due to the sensors Doppler blind zone, nontrivial topography causing terrain obscuration, situations with closely-spaced targets, a strong false alarm background, etc. In general, these factors quickly lead to a strong performance degradation or even track loss. To counterbalance these factors, it is beneficial to incorporate additional sources of information into the tracking process. In this work, we focus on the impact of the received signal strength of a target on the tracking performance.

Being a standard output of a modern radar system, the target amplitude or the corresponding target signal strength has already been used in the past to facilitate the problem of associating a track with its correct measurement. But in contrast to previous approaches, e.g. [1, 2, 3], in this work the knowledge on the target’s signal strength is not only used for an improved calculation of the association probabilities, but it enters into the algorithm as a random variable which is sequentially estimated. By this approach it is not only possible to discriminate closely-spaced targets and improve the track continuity, but also to support possible subsequent classification and identification tasks. In addition, for phased array antennas the signal strength estimates could also be used to contribute to the radar resource management: Depending on the estimated target SNR, the detection threshold could be adapted to allow better target detections.

The paper is organized as follows: The next part briefly describes the target fluctuation models and the detection process assumed in this work. In part 3 the tracking algorithm is presented which incorporates the signal strength information, followed by the discussion of the simulation scenario and Monte Carlo results. Throughout the paper, a linear scale is used for signal strength values.

2 Signal strength model

2.1 Target fluctuations

Due to its complexity, a realistic modelling of a real target's back-scattering characteristics is in general impossible. Therefore statistical models are used instead which can be handled analytically. In this work it is assumed that the fluctuations of the input signal at the detector, resulting from fluctuations of the target cross section, can be described by the Swerling models [4]. The statistical properties of chi-square target fluctuations are determined by the following general proba-
bility density which depends on the average signal-to-noise ratio, \( \text{SNR}_0 \), and the parameter \( m \), which indicates the degrees of freedom (2 \( m \)) of the associated chi-square distribution:

\[
G_{\text{SNR}_0}^m(\text{SNR}) = \left( \frac{m/\text{SNR}_0}{\Gamma(m)} \right)^m \text{SNR}^{m-1} e^{-m \text{SNR}/\text{SNR}_0} \tag{1}
\]

Assuming independent fluctuations from scan to scan, the relevant Swerling cases are given by \( m = 1 \) (Swerling-I) and \( m = 2 \) (Swerling-III):

\[
G_{\text{SNR}_0}^1(\text{SNR}) = \frac{1}{\text{SNR}_0} e^{-\text{SNR}/\text{SNR}_0} \tag{2}
\]

\[
G_{\text{SNR}_0}^2(\text{SNR}) = \frac{4\text{SNR}}{\text{SNR}_0^2} e^{-2\text{SNR}/\text{SNR}_0} \tag{3}
\]

### 2.2 Detection process

The complex target signal \( \mathbf{v} = (v_1, v_2) \) with orthogonal and statistically independent components is added by white Gaussian noise within the receiver unit. The detector uses the total signal \( \mathbf{u} = (u_1, u_2) \) to form the signal strength \( |\mathbf{u}|^2 = (u_1)^2 + (u_2)^2 \) with the probability density given by the Rice distribution

\[
p(|\mathbf{u}|^2|\mathbf{v}) = \frac{1}{2\sigma_n^2} e^{-|\mathbf{u}|^2/2\sigma_n^2} I_0 \left( \frac{|\mathbf{u}| \cdot |\mathbf{v}|}{\sigma_n} \right) \tag{4}
\]

where \( I_0 \) denotes the modified Bessel function of the first kind. Normalized to the mean noise level, \( E[p(|\mathbf{u}|^2|0)] = 2\sigma_n^2 \), i.e. with \( s = |\mathbf{u}|^2/2\sigma_n^2 \) and \( \text{SNR} = |\mathbf{v}|^2/2\sigma_n^2 \), this can be rewritten as

\[
p(s|\text{SNR}) = e^{-s-\text{SNR}} I_0 \left( 2\sqrt{s \cdot \sqrt{\text{SNR}}} \right) \tag{5}
\]

with expectation value \( E[s] = 1 + \text{SNR} \) and thus unit power for noise (\( \text{SNR}=0 \)). Following the assumption from the last section, the signal-to-noise ratio \( \text{SNR} \) itself fluctuates with mean \( \text{SNR}_0 \). Thus the overall received signal strength is derived by

\[
p(s|\text{SNR}) = \int_0^\infty d\text{SNR} \ p(s|\text{SNR}) \ p(\text{SNR}|\text{SNR}_0) \tag{6}
\]

with \( p(\text{SNR}|\text{SNR}_0) \) given by \( G_{\text{SNR}_0}^m(\text{SNR}) \). Finally one ends up with the well-known distributions for the two Swerling cases:

\[
p(s|\text{SNR}_0, m = 1) = \frac{1}{1 + \text{SNR}_0} e^{-s/(1+\text{SNR}_0)} \tag{7}
\]

\[
p(s|\text{SNR}_0, m = 2) = \frac{1}{(1 + \text{SNR}_0/2)^2} e^{-s/(1+\text{SNR}_0/2)} \cdot \left[ 1 + \frac{s}{1 + 2/\text{SNR}_0} \right] \tag{8}
\]

As soon as signal strength is considered, the detection probability is no longer a parameter but becomes a function of the target’s mean signal-to-noise ratio \( \text{SNR}_0 \) and the detection threshold \( \lambda \):

\[
P(s > \lambda|D) = \text{P}_D(\text{SNR}_0, \lambda, m) = \int_{\lambda}^\infty ds \ p(s|\text{SNR}_0, m) \tag{9}
\]

where \( D \) denotes detection. For the two Swerling models, the integration yields the corresponding detection probabilities, see Fig. (1):

\[
P_D^I = e^{-\lambda/(1+\text{SNR}_0)} \tag{10}
\]

\[
P_D^{III} = e^{-\lambda/(1+\text{SNR}_0/2)} \left[ 1 + \frac{\lambda \cdot \text{SNR}_0/2}{(1 + \text{SNR}_0/2)^2} \right] \tag{11}
\]

Detections are only available, if the signal strength of the input signal exceeds the detection threshold. Thus the probability densities (7) and (8) need to be normalized properly, yielding for \( s \geq \lambda \)

\[
p(s|\text{SNR}_0, \lambda, I) = \frac{1}{\text{P}_D^I} p(s|\text{SNR}_0, m = 1) \tag{12}
\]

\[
p(s|\text{SNR}_0, \lambda, III) = \frac{1}{\text{P}_D^{III}} p(s|\text{SNR}_0, m = 2) \tag{13}
\]

These distributions are plotted in Fig. (1) for different values of \( \text{SNR}_0 \). Measurements which originate from false alarms are modelled by the Swerling-I case, i.e.

\[
p(s|\text{CNR}_0) = \frac{1}{\text{P}_D(\text{CNR}_0)} e^{-s/(1+\text{CNR}_0)} \tag{14}
\]
if \( s \geq \lambda \) with \( \text{CNR}_0 \) being the mean clutter strength-to-noise ratio. It is assumed that the detection threshold \( \lambda \) on the input signal power is high enough to suppress measurements resulting from receiver noise.

3 Incorporation of signal strength information

In Bayesian target tracking, e.g. [5, 6], the probability density \( p(x_k|z^k) \), which describes the target state \( x_k \) at time step \( t_k \), conditioned on the measurement sequence \( z^k = \{z_1, z_2, ..., z_k\} \) with \( z_k = \{s_k^i\}_{i=1}^{n_k} \), is sequentially updated by

\[
p(x_k|z^k) = \frac{p(z_k|x_k) p(x_k|z^{k-1})}{\int dx_k p(z_k|x_k) p(x_k|z^{k-1})} \quad (15)
\]

To incorporate signal strength, the random variable \( s_k \) is introduced, thus the target state becomes \( X_k = (x_k, s_k) \) and \( Z_k = \{s_k^i\}_{i=1}^{n_k} \) with signal strength measurements \( s_k^i \). It follows

\[
p(X_k|z^k) = \frac{p(Z_k|X_k) p(X_k|z^{k-1})}{\int dx_k dz_k p(Z_k|X_k) p(X_k|z^{k-1})} \quad (16)
\]

In the following, expressions for the prior density \( p(X_k|z^{k-1}) \) and the likelihood function \( p(Z_k|X_k) \) will be derived.

3.1 Prediction step

First of all, the density \( p(X_k|z^{k-1}) \) can be split up into the kinematic and the signal strength part:

\[
p(X_k|z^{k-1}) = p(s_k|x_k, z^{k-1}) p(x_k|z^{k-1}) \quad (17)
\]

The kinematic prior is treated in a traditional way: A Gaussian shaped posterior density \( p(X_{k-1}|z^{k-1}) \) is assumed which is propagated to the actual time step \( t_k \) by utilizing a linear dynamics model with additive white Gaussian noise. This yields

\[
p(x_k|z^{k-1}) = N(x_k; x_{k-1}, P_{k|k-1}) \quad (18)
\]

where the estimate \( x_{k|k-1} \) and covariance \( P_{k|k-1} \) are given by the known Kalman prediction equations.

On the other hand, the prior density of the signal strength has to account for the fact that the target’s mean signal-to-noise ratio \( \text{SNR}_0 \) is an a-priori unknown but assumed constant value. Thus for \( p(s_k|x_k, z^{k-1}) \) a class of densities should be chosen which, up to a normalization constant, is invariant under the successive application of Bayes equation (16). Following [7], the class of inverse Gamma densities \( I(s; \hat{s}, \mu) \) is chosen which guarantees the aforementioned behavior:

\[
p(s_k|x_k, z^{k-1}) = I(s_k; \hat{s}_k-1, \mu_k-1) \quad (19)
\]

with normalization constant

\[
N_{\mu_k-1} = \frac{[\mu_k-1]^{\mu_k-1} \hat{s}_k^{-\mu_k-1}}{\Gamma(\mu_k-1)}
\]

The distribution of the inverse Gamma density is shown in Fig. 2. The probability density \( I(s; \hat{s}, \mu) \) has the expectation value \( E[s] = \hat{s} \). If the parameter \( \mu > 2 \), then the variance exists with \( \text{Var}[s] = \hat{s}^2/\mu - 2 \). Because of \( \frac{\partial}{\partial s} \text{SNR}_0 = 0 \), no “dynamics” is needed for the signal strength, thus the prior density at \( t_k \) is identical to the posterior density at \( t_{k-1} \):

\[
I(s_k; \hat{s}_{k-1}, \mu_{k-1}) = I(s_k; s_{k-1}|t_{k-1}, \mu_{k-1}|t_{k-1}) \quad (22)
\]

Figure 2: Distribution of the inverse Gamma density \( I(s_k; s_{k|k-1}, \mu_{k|k-1}) \).

3.2 Combined likelihood

The combined likelihood function \( p(Z_k|X_k) = p(Z_k|x_k, s_k) \) is the probability density of the measurements and comprises all possibilities how the given sensor output \( Z_k \) can be interpreted, given the true target state \( X_k \). Assuming independent, identically distributed false alarm measurements with the number of false alarms determined by the Poisson distribution, the likelihood function, up to a factor which does not depend on \( X_k \), can be written as

\[
p(Z_k|X_k) \propto (1 - P_D(s_k)) \rho_F + P_D(s_k) \sum_{i=1}^{n_k} N(z_k^i; H_k x_k, R_k) \quad (23)
\]

where \( P_D(s_k) \) is the false alarm density and \( N(z_k^i; H_k x_k, R_k) \) is the normally distributed single measurement likelihood, which results from a linear measurement model with additive white Gaussian noise: \( z_k^i = H_k x_k + v_k \), \( v_k \propto N(0, R_k) \) with measurement matrix \( H_k \) and measurement covariance

\[
\rho_F = \frac{[\mu_k-1]^{\mu_k-1} \hat{s}_k^{-\mu_k-1}}{\Gamma(\mu_k-1)}
\]
where \((D, \neg D)\) describe detection and missed detection, respectively. \(p(z_i^k | \neg D, \mathbf{X}_k)\) is given by (14) and \(p(z_i^k | D, \mathbf{X}_k)\) is distributed according to either (12) or (13). In the latter case, the detection probability is approximated by the Swerling-I case, i.e. \(P_H^0 \approx P_D^0\). Finally, the combined likelihood can be calculated, yielding

Swerling-I:

\[
p(Z_k | \mathbf{X}_k) \propto (1 - e^{-\frac{\lambda}{\sigma_k^2}}) \rho_F + \sum_{i=1}^{n_k} \alpha_{e_i} e^{-\frac{\lambda}{s_k}} \mathcal{N}(z_i^k; \mathbf{H}_k \mathbf{x}_k, \mathbf{R}_k)
\]

Swerling-III:

\[
p(Z_k | \mathbf{X}_k) \propto (1 - e^{-\frac{\lambda}{\sigma_k^2}}) \rho_F + \sum_{i=1}^{n_k} \left[ 4 \alpha_{e_i} e^{-\frac{\lambda}{s_k}/(2+s_k)} \right.
\]

\[
\left. \left(1 + \frac{\mu_{i,k} - 1}{2 + s_k} \right) \mathcal{N}(z_i^k; \mathbf{H}_k \mathbf{x}_k, \mathbf{R}_k) \right]
\]

with

\[
\alpha_{e_i} = (1 + c_k) e^{-\frac{s_k^i}{s_k}}
\]

3.3 Filter update step

The posterior density \(p(\mathbf{X}_k | Z^k) = p(\mathbf{x}_k, s_k | Z^k)\) is derived by inserting the prediction and likelihood functions into (16), assuming strong targets, i.e. \(1 + s_k \approx 2 + s_k \approx s_k\), and making use of the product formula for normal distributions [8]. The result is a weighted sum of the product of a Gaussian with an inverse Gamma density, describing the target’s kinematic state and signal strength, respectively:

\[
p(\mathbf{X}_k | Z^k) = \sum_{i=0}^{n_k} w_i^k \mathcal{N}(\mathbf{x}_k; \mathbf{x}_i^{k|k}, \mathbf{P}_i^{k|k}) \mathcal{I}(s_k; s_i^{k|k}, \mu_{i,k}^{k|k})
\]

where the estimates \(\mathbf{x}_i^{k|k}\) and covariances \(\mathbf{P}_i^{k|k}\) are calculated by the known Kalman filter update equations, and weights \(w_i^k\), signal strength estimates \(s_i^{k|k}\) and \(\mu_{i,k}^{k|k}\) are given by (for \(i > 0\))

Swerling-I:

\[
\hat{w}_k^i = \frac{\alpha_{e_i}}{\rho_F} \mathcal{N}(z_i^k; \mathbf{H}_k \mathbf{x}_k^{k|k-1}, \mathbf{S}_i^k) \frac{\mu_{k-1}}{(\mu_{k-1} - 1) \mathbf{s}_{k-1}} \left[ \frac{(\mu_{k-1} - 1) \mathbf{s}_{k-1}}{(\mu_{k-1} - 1) \mathbf{s}_{k-1} + \mu_{k-1}} \right]^{\mu_{k-1} - 1} \left(\mathbf{s}_{k-1} + \frac{\mu_{k-1}}{2}\right)^{\mu_{k-1}/2} \mathbf{s}_{k-1} \cdot \left(\mathbf{s}_{k-1} + \frac{\mu_{k-1}}{2}\right)^{\mu_{k-1}/2} \left(\mathbf{s}_{k-1} + \frac{\mu_{k-1}}{2}\right)^{\mu_{k-1}/2}
\]

\[
\hat{s}_{i,k}^k = \frac{\mu_{k-1}}{\mu_{k-1} + 1} \mathbf{s}_{k-1} + \frac{\mu_{k-1}}{2}
\]

\[
\mu_{i,k}^{k|k} = \frac{\mu_{k-1}}{\mu_{k-1} + 1}
\]

Swerling-III:

\[
\hat{w}_k^i = \frac{\alpha_{e_i}}{\rho_F} \mathcal{N}(z_i^k; \mathbf{H}_k \mathbf{x}_k^{k|k-1}, \mathbf{S}_i^k) / \left(1 + \frac{\sum_{j=0}^{n_k} w_i^j}{\sum_{j=0}^{n_k} w_i^j} \right) \mathcal{N}(z_i^k; \mathbf{H}_k \mathbf{x}_k^{k|k-1}, \mathbf{S}_i^k) \cdot \left[ \frac{\sum_{j=0}^{n_k} w_i^j}{\sum_{j=0}^{n_k} w_i^j} \right] \mathcal{N}(z_i^k; \mathbf{H}_k \mathbf{x}_k^{k|k-1}, \mathbf{S}_i^k)
\]

\[
\hat{s}_{i,k}^k = \frac{\mu_{k-1}}{\mu_{k-1} + 1} \mathbf{s}_{k-1} + \frac{\mu_{k-1}}{2}
\]

\[
\mu_{i,k}^{k|k} = \frac{\mu_{k-1}}{\mu_{k-1} + 1}
\]

3.4 Algorithmic implementation

The presented update scheme is implemented into the single-target PDAF [5] and the multi-target JPDAF [6] tracking algorithms. In the PDAF algorithm, \(n_k\) measurements lead to \(n_k + 1\) hypotheses which are merged to a single main hypothesis by second-order moment
matching at the end of the filter update step. In this case, the implementation is straightforward, because the derived update equations from the last section can be used directly without any further adjustments.

In the JPDAF algorithm, the complete set of possible global hypotheses is processed, i.e. all possible combinations to associate measurements to tracks including missed detections and false alarms are considered. Thus it avoids the association of a certain measurement to more than one track, which is a shortcoming of the simple single-target PDAF. In this case, adjustments need to be made because the individual association probabilities for each target with its relevant measurements are calculated based on the probabilities of the global hypotheses, and are not given by (29), (32) and (35). Therefore, the calculation of the probability of the global hypotheses needs to be adapted to account for the weight factors due to the signal strength incorporation. This is done in the following way:

In the original formulation of the JPDAF, the probability of the global hypothesis $\Theta_i$ is given by

$$P(\Theta_i | \mathbf{Z}^k) = \prod_{i=1}^{n_k} \left\{ \frac{1}{\rho_F} \mathcal{N}(z_{k|1}^i ; H_0 x_{k|k-1}^i, S_{k|k}^i) \right\} \cdot \prod_{t=1}^{T} P_D^d (1 - P_D)^{1-\delta_t} \tag{42}$$

where $\tau_i \in \{0, 1\}$ indicates if measurement $i$ is associated with target $t$, and $\delta_t \in \{0, 1\}$ indicates if target $t$ is associated with a measurement. First of all, $P_D^d$ can be shifted into the first product (dropping the index $\delta_t$). Now the factor

$$\frac{P_D}{\rho_F} \mathcal{N}(z_{k|1}^i ; H_0 x_{k|k-1}^i, S_{k|k}^i) \tag{43}$$

is replaced by (29) for Swerling-I and (32) for Swerling-III. In addition, the probability factor for the missed detection hypothesis, $1 - P_D$, is replaced by (35). With these adjustments, $P(\Theta_i | \mathbf{Z}^k)$ can be written as

**Swerling-I:**

$$P(\Theta_i | \mathbf{Z}^k) = \prod_{i=1}^{n_k} \left\{ \frac{1}{\rho_F} \frac{\mu_k-1}{(\mu_k-1-1)S_k} \cdot \frac{1}{(\mu_k-1-1)S_k + \kappa_k} \right\} \cdot \mathcal{N}(z_{k|1}^i ; H_0 x_{k|k-1}^i, S_{k|k}^i) \cdot \prod_{t=1}^{T} \left( 1 - \left[ \frac{\hat{s}_k - 1}{\hat{s}_k + \frac{1}{\mu_k-1-1}} \right]^{\mu_k-1} \right)^{1-\delta_t} \tag{44}$$

and

**Swerling-III:**

$$P(\Theta_i | \mathbf{Z}^k) = \prod_{i=1}^{n_k} \left\{ \frac{4\alpha_{k+1}^i}{\rho_F} \frac{(\mu_k-1)(\mu_k-1+1)}{[\mu_k-1-1]S_k} \cdot \left( \frac{(\mu_k-1-1)S_k}{(\mu_k-1-1)S_k + 2\kappa_k} \right)^{\mu_k-1+2} \mathcal{N}(z_{k|1}^i; H_0 x_{k|k-1}^i, S_{k|k}^i) \right\} \cdot \prod_{t=1}^{T} \left( 1 - \left[ \frac{\hat{s}_k - 1}{\hat{s}_k + \frac{1}{\mu_k-1-1}} \right]^{\mu_k-1} \right)^{1-\delta_t} \tag{45}$$

From that, the individual association probabilities for each target are calculated in the same way as in the original JPDAF.

![Simulation scenario & results](image)

Figure 3: Single-target (above) and two-target (bottom) simulation scenarios. Shown is the snapshot at the final revisit time.

4 Simulation scenario & results

As a first performance evaluation, the algorithm presented in the last section is applied to a single-target and a two-target scenario with the trajectories shown...
Figure 4: Monte Carlo results for initialization with $\text{SNR}_{\text{ini}} \in [\text{SNR}_0 - 20, \text{SNR}_0 + 20]$ where $\text{SNR}_0 = 30$. The results correspond to Swerling-I (left column) and Swerling-III (right column).

Figure 5: Monte Carlo results for initialization with the first signal strength measurement, $\text{SNR}_{\text{ini}} = \kappa_0$. The results correspond to Swerling-I (left column) and Swerling-III (right column).

In the first scenario, the objective is to analyze the important question of track initialization of the signal strength component, i.e. the parameter sensitivity and convergence. In order to quantify the results, the following errors are calculated: The signal strength root mean square error (RMSE), the target signal strength error ($\text{TsigE}$), given by

$$\text{TsigE}(k) = \frac{1}{N_{MC}} \sum_{n=1}^{N_{MC}} \left( s_{n|k} - \text{SNR}_0 \right)$$ (46)

and the error from the estimated variance. The signal strength component is initialized either with a randomly chosen value from an interval around the true signal strength $\text{SNR}_0$, $\text{SNR}_{\text{ini}} \in [\text{SNR}_0 - \Delta \text{SNR}_{\text{ini}}, \text{SNR}_0 + \Delta \text{SNR}_{\text{ini}}]$ (case 1). This corresponds to the case if the true value is not known, but at least some approximate knowledge from, e.g. a preceding signal processing step is already available. Or the signal strength is initialized simply with the first available measurement in close analogy to the initialization of the kinematic component (case 2). The evolution of the above mentioned signal strength errors for these two possibilities are shown in Fig. 4 with $\text{SNR}_0 = 30$, $\Delta \text{SNR}_{\text{ini}} = 20$ and Fig. 5, respectively, based on the PDAF algorithm and the simulation parameters given in Tab. 1. Different rows correspond to different initial values of the signal strength variance $\text{Var}_{\text{ini}}$, and the columns correspond to Swerling-I and Swerling-III, respectively. As expected, in all cases the RMSE is larger than the TSigE, because the RMSE penalizes larger deviations from the true value more severely due to the mean square. If the initialization is carried out based on case 1, all possible values of the initial variance lead to stable signal strength estimates with good convergence behav-
ior. But for case 2, strong deviations are clearly visible: If the initial variance is too small, no convergence and thus no stable estimation is possible. As expected, larger values of $\text{Var}_{\text{ini}}$ lead to better results. In both cases, obviously the signal strength estimation leads to slightly better results, if the target fluctuation model is Swerling-III. The reason for this might be the fact that the detection probability for Swerling-III is higher compared to Swerling-I for any given $\text{SNR}_d$, see Fig. 1, thus more detections are available to be processed.

In the second simulation scenario, the two targets move along the same trajectory for a considerable period of time, leading to a loss of identity in case of a traditional tracking algorithm. Here, the objective is to determine the capability of target discrimination with signal strength information in the final stage of the scenario. Based on the JPDAF algorithm and the simulation parameters given in Tab. 2, the results are plotted in Fig. 6 for Swerling-I and Fig. 7 for Swerling-III fluctuations, respectively, of the two targets. Shown is the probability for correct (solid lines) and incorrect (dashed lines) association of tracks with true targets at final revisit for different signal strength combinations, based on the fluctuation models. The signal strength of one target is fixed, corresponding to the minimum value of each line. The upper plots correspond to target tracking without signal strength information. In this case, the signal strength only affects the true detection probability and thus the occurrence of target detections. As expected, for all combinations of the two targets’
signal strength the probability for correct association amounts to 50%. The lower plots illustrate the advantage of taking signal strength information into account: A clear performance gain in target discrimination is visible for both fluctuation models, with a stronger separation capability for larger differences in signal strength. Comparing the results in Figs. 6 and 7 (lower plots), apparently the discrimination performance of the algorithm is slightly higher in case of Swerling-III. This is probably due to the distinct peak in the probability density of Swerling-III fluctuations, see Fig. 1, leading to a more obvious discrimination of the two signal strength distributions.

Table 1: Simulation parameters for scenario 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
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<tbody>
<tr>
<td>Monte Carlo runs</td>
<td>$N_{MC} = 1000$</td>
</tr>
<tr>
<td>Target velocity</td>
<td>$v_{target} = 15\text{ m/s}$</td>
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<tr>
<td>Process noise</td>
<td>$\sigma_p = 0.5\text{ m/s}^2$</td>
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<td>Range error</td>
<td>$\sigma_r = 15\text{ m}$</td>
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<tr>
<td>Azimuth error</td>
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<td>Mean false alarms</td>
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<td>Field of view</td>
<td>$</td>
</tr>
<tr>
<td>Sensor position</td>
<td>$\bar{r}_{sensor} = [-5, -5, 10]^{\top}\text{ km}$</td>
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<tr>
<td>Revisit rate</td>
<td>$\Delta_r = 2\text{ s}$</td>
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<tr>
<td>Detector threshold</td>
<td>$\lambda = 4$</td>
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<tr>
<td>Mean target SNR</td>
<td>$\text{SNR}_0 = 30$</td>
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<tr>
<td>Mean clutter SNR</td>
<td>$\text{CNR}_0 = 10$</td>
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<td>Scenario duration</td>
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Table 2: Simulation parameters for scenario 2.

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<tr>
<td>Monte Carlo runs</td>
<td>$N_{MC} = 1000$</td>
</tr>
<tr>
<td>Target velocity</td>
<td>$v_{target} = 15\text{ m/s}$</td>
</tr>
<tr>
<td>Process noise</td>
<td>$\sigma_p = 0.5\text{ m/s}^2$</td>
</tr>
<tr>
<td>Range error</td>
<td>$\sigma_r = 10\text{ m}$</td>
</tr>
<tr>
<td>Azimuth error</td>
<td>$\sigma_{\phi} = 0.25$</td>
</tr>
<tr>
<td>Mean false alarms</td>
<td>$\bar{n}_{FA} = 1$</td>
</tr>
<tr>
<td>Field of view</td>
<td>$</td>
</tr>
<tr>
<td>Sensor position</td>
<td>$\bar{r}_{sensor} = [-1, 5, 10]^{\top}\text{ km}$</td>
</tr>
<tr>
<td>Revisit rate</td>
<td>$\Delta_r = 2\text{ s}$</td>
</tr>
<tr>
<td>Detector threshold</td>
<td>$\lambda = 4$</td>
</tr>
<tr>
<td>Mean clutter SNR</td>
<td>$\text{CNR}_0 = 10$</td>
</tr>
</tbody>
</table>

5 Conclusions
In this paper we developed a tracking algorithm which incorporates signal strength information. In contrast to previous approaches, the knowledge on the target’s signal strength is not only used for an improved calculation of the association probabilities, but it enters into the algorithm as a random variable which is sequentially estimated. Based on simulation scenarios, the performance of the presented algorithm is evaluated. As expected, the exploitation of signal strength leads to a performance gain in target discrimination in a multi-target scenario.

Further work will focus on the incorporation of signal strength information into the CPHD algorithm [10] and on a multiple model approach for different target fluctuation models.

References
[8] $N(z; H x, R) N(x; y, P) = N(z; H y, S) N(x; y + W(z - H y), P - W S W^{\top})$ with $S = H P H^{\top} + R$, $W = P H S^{-1}$