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Online glint noise identification for tracking manoeuvring targets

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The glint noise arising from a radar tracking system exhibits non-Gaussian statistics. Pure noise data, usually not available in on-line applications, are required in conventional glint identification methods. A new algorithm is presented for online glint identification using radar measurement data. Simulations show that the identified results of the proposed algorithm using measurement data are close to those using pure noise data.

Introduction: In radar tracking systems, due to target glint, measurement noise may exhibit a 'spiky' behaviour, which manifests itself in a non-Gaussian heavy-tailed distribution [1]. This form of noise can severely affect the performance of conventional Kalman tracking algorithms. Nonlinear algorithms have been developed to cope with the problem [2, 3]. To use these nonlinear algorithms, a glint noise distribution model is required and the model parameters need to be identified online.

The empirical work in [4] showed that glint noise can be decomposed into a Gaussian process plus outliers. Considering this decomposition, a Gaussian mixture model has been proposed to approximate the glint noise distribution [2, 3]. Assuming that pure glint noise data are available, Wu [5] has employed the maximum likelihood (ML) method to identify the mixture model parameters. However, in online tracking applications, noise data are not directly observable; they are embedded in radar measurements. To solve this problem, we propose a new algorithm for glint identification using radar measurements.

The proposed algorithm consists of two parts: noise extraction and ML identification. The noise-extraction process uses a first-order differentiator and a trimmed mean filter to extract glint data from target measurements. The ML method is then applied to the extracted data to identify the model parameters. Simulation results show that the proposed algorithm is effective in that the identified parameters are close to those obtained with exact knowledge of the noise data.

Algorithm derivation: Here we consider the one-dimensional tracking problem. The state-space representation of the target dynamic and measurement can be described by the following equations:

$$\mathbf{X}_{k+1} = \Phi \mathbf{X}_k + \mathbf{G}w_k \quad (1)$$

$$y_k = \mathbf{H}\mathbf{X}_k + v_k \quad (2)$$

where \mathbf{X}_k is the state vector $[x_k \ v_k \ a_k]^T$ consisting of the position, velocity and acceleration of the target at the k th sampling instant, w_k is the state noise, and v_k is the glint measurement noise. If y_k corresponds to the target position measurement, eqn. 2 becomes

$$y_k = x_k + v_k \quad (3)$$

A mixture of two Gaussian components has been proposed to model the glint noise distribution [2, 3]:

$$f_v(v_k) = c_1 \cdot \phi(v_k; 0, \sigma_1) + c_2 \cdot \phi(v_k; 0, \sigma_2) \quad (4)$$

where $\phi(v_k; \mu, \sigma)$ denotes the Gaussian density function with mean μ and variance σ , $0 < c_1 < 1$, $c_2 = 1 - c_1 \ll 1$, and $\sigma_2 > \sigma_1$. Wu [5] has employed the ML method to identify the model parameters c_1 , σ_1 and σ_2 in eqn. 4 from pure glint noise data v_k . However, in online applications, those samples are usually not available. In the following, we present an algorithm for overcoming this problem. Our method identifies the glint model directly from the target position measurement y_k .

Consider a first-order differentiation using two successive measurements

$$\bar{y}_k = y_k - y_{k-1} = (x_k - x_{k-1}) + (v_k - v_{k-1}) = \bar{x}_k + \bar{v}_k \quad (5)$$

It is clear that $\bar{x}_k = v_{k-1}T + a_{k-1}T^2/2$ where T denotes the sampling period. When the target is nonmanoeuvring, \bar{x}_k equals VT where V is the target speed. When the target is manoeuvring, \bar{x}_k becomes a linear function of the acceleration. If the glint noise is white, we can find the distribution of \bar{v}_k by convolving $f_v(v_k)$ and $f_v(v_{k-1})$. From eqns. 4 and 5 we have

$$f_{\bar{v}}(\bar{v}_k) = c_1^2 \cdot \phi(\bar{v}_k; 0, \sqrt{2}\sigma_1) + 2c_1c_2 \cdot \phi(\bar{v}_k; 0, \sqrt{\sigma_1^2 + \sigma_2^2}) + c_2^2 \cdot \phi(\bar{v}_k; 0, \sqrt{2}\sigma_2) \quad (6)$$

Since only \bar{y}_k is available, we must remove \bar{x}_k from \bar{y}_k to obtain \bar{v}_k . Using \bar{v}_k and $f_{\bar{v}}(\bar{v}_k)$, the ML identification can then be applied.

As \bar{x}_k is either a constant or a linear function, we can estimate it using an order-statistic filter. Taking the non-Gaussian distribution of \bar{v}_k and the manoeuvring effect into consideration, we propose use of the trimmed mean filter [6]. Let a window of size $2N+1$ centred at \bar{y}_k cover data $\bar{y}_{k-N}, \dots, \bar{y}_{k+N}$. The output of the trimmed mean filter is

$$\hat{\bar{x}}_k = \frac{1}{(2M+1)} \sum_{i=N-M+1}^{N+M+1} \bar{Y}_i \quad (7)$$

where $M < N$ and $\bar{Y}_1 \leq \bar{Y}_2 \leq \dots \leq \bar{Y}_{2N+1}$ is the sorted sequence of $\bar{y}_{k-N}, \dots, \bar{y}_{k+N}$. Let $\bar{v}_k = \bar{y}_k - \hat{\bar{x}}_k$. We can then perform ML identification

$$\hat{c}_1, \hat{\sigma}_1, \hat{\sigma}_2 = \arg \max_{c_1, \sigma_1, \sigma_2} \prod_{k=1}^L f_{\bar{v}}(\hat{\bar{v}}_k; c_1, \sigma_1, \sigma_2) \quad (8)$$

where L is the length of the data record. Fig. 1 summarises the proposed online identification algorithm.

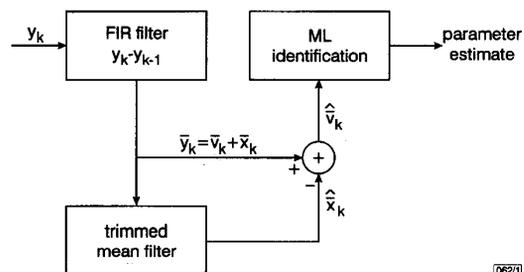


Fig. 1 Proposed glint identification algorithm

Table 1: Performance comparison of glint identification using noise samples (A) and glint identification using measurements (B)

	A		B	
	Mean	MSE	Mean	MSE
$c_1 = 0.9$	0.8920	0.0010	0.8834	0.0018
$\sigma_1 = 1$	1.0011	0.0028	1.0043	0.0092
$\sigma_2 = 5$	4.8397	0.5708	4.7828	0.8352

Glint noise has Gaussian mixture distribution

Table 2: Performance comparison of glint identification using noise samples

	A	B
c_1	0.9387	0.9505
σ_1	3.2482	3.3436
σ_2	22.6284	24.7782

(A): glint identification using measurements; (B): synthetic glint noise shown in Fig. 2

Results and discussion: In this Section, we present some simulation results to demonstrate the performance of the proposed algorithm. The simulation environment is summarised as follows. The position measurement y_k was generated according to eqn. 3 with $x_{k+1} = x_k + v_k T + a_k T^2/2$. The initial target position was $x_0 = 10\ 000$ m and the initial velocity was $v_0 = 150$ m/s. The sampling period T was 0.1 s and the sample size L was 300. The target manoeuvre was set to occur from $k = 151$ to $k = 200$ with $a_k = 40$ m/s². The size of the trimmed mean filter was 25 ($N = 12$) and the M in eqn. 7 was 1. Two sets of measurement noise v_k were generated: the first was from a true mixture of two Gaussian distributions and the other was from the synthetic glint model in [1].

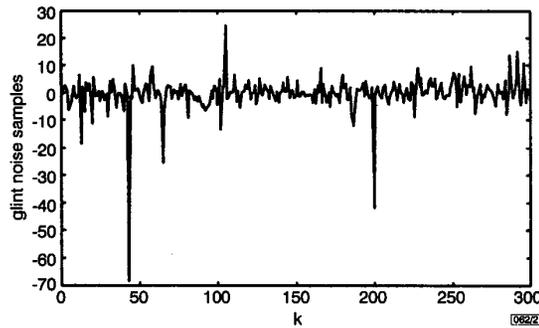


Fig. 2 Synthetic glint noise record

We first examined the results when the measurement noise was generated from a Gaussian mixture of parameters $c_1 = 0.9$, $\sigma_1 = 1$ and $\sigma_2 = 5$. A Monte Carlo simulation of 50 runs was conducted, and the initial parameter estimates were set as $\hat{c}_1 = 0.75$, $\hat{\sigma}_1 = 2$ and $\hat{\sigma}_2 = 10$. The mean values and the mean squared errors (MSEs) of the identified parameter are listed in Table 1. As we can see, the mean estimates for the proposed algorithm are very close to the true parameter values. Compared with the identification using the pure noise data, our method yields somewhat larger MSEs.

Next we examine the results for identifying the synthetic glint noise record in Fig. 2. The same initial estimates were used and the results are listed in Table 2. From this Table, we see that the identified parameters using the measurements are similar to those using the pure glint data. Thus, we can conclude that the proposed algorithm is effective for online glint identification.

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Transmission of UHF radiowaves through buildings in urban microcell environments

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Results are presented of high-resolution time delay and angle-of-arrival measurements behind a large building in an urban microcell. It is demonstrated that in this particular case the electromagnetic field is dominated by contributions resulting from transmission through the building. The associated loss over free-space loss is < 30dB. This makes clear the importance of modelling propagation through buildings surrounding the base station in the planning stage of urban microcells.

Introduction: The current growth of the personal wireless communications market is pushing operators of mobile radio networks to explore capacity-increasing techniques such as the use of microcells. Whereas the base station (BS) antennas used in conventional macrocells are usually situated at high elevations, the idea of microcells is to place the BS antenna below the average height of the surrounding buildings to confine the radiated power within a small coverage area, such that the same frequency channels can be re-used at short distances without introducing an unacceptable degree of inter-user interference.

The efficient planning of microcells requires an accurate prediction of the electromagnetic field strength distribution. Various groups have been active in the development of so-called deterministic propagation models based on an accurate description of the buildings around the BS, and ray-tracing algorithms incorporating multiple reflection and diffraction [1–3]. Although considerably better than their statistical counterparts, these models have been found to provide an unsatisfactory prediction accuracy in some situations [3]. In particular, it was shown in [3] that deterministic models treating the buildings as being opaque at UHF frequencies can seriously underestimate the field strength behind the first buildings surrounding the BS. Since the shielding of the BS antenna from its nearby environment is essential in the microcellular concept, it is of special interest to obtain a better understanding of the propagation phenomena responsible for this discrepancy.

In the framework of a collaboration between EUT, KPN Research and Swisscom, an extensive measurement campaign was carried out in several urban microcell environments in Switzerland. In this Letter, we present the results of a high-resolution angle-of-arrival (AOA) measurement conducted behind a large building obstructing the line-of-sight to the BS antenna.

Experimental arrangement: The measurements reported in this Letter were conducted using a wideband radio channel sounding system previously described in [4]. In summary, a 50Mchip/s pseudonoise (PN) sequence is used as the sounding signal which modulates a 2000MHz carrier, and estimation of the complex impulse response (CIR) of the radio channel is performed at the mobile receiver through correlation of the demodulated received signal with a replica PN sequence. The resulting time delay resolution is equal to the chip period T_c of the applied PN sequence, which is 20ns.

Transmission was from a 3dBi BS antenna (5m above ground level, which was well below the average roof top level of the surrounding buildings) to a mobile station (MS) equipped with a rotatable 2dBi omnidirectional antenna (2.2m above ground level). Impulse responses were measured along a horizontal circle with radius $r = 30$ cm, thus effecting a synthetic uniform circular array (UCA) consisting of $M = 106$ elements.