

Gaussian Target Detection in Multipath Clutter with Single Antenna Time Reversal by Improving SNR

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ABSTRACT: Derive the time reversal likelihood ratio optimal detector for a target in stationary random multipath clutter. Provide analytical results on the performance of the time reversal detector by approximating it with the Time Reversal Linear Quadratic detector. Show that the Time Reversal Likelihood Ratio Test performs much better than the conventional Weighted Energy Detector. Simulations show that the Linear Quadratic detector is a good approximation to the Time Reversal Likelihood Ratio Test. Improvement of 4 to 7 dB effective signal-to-noise ratio gain over the Weighted Energy Detector. This gain is dependent on the target and clutter power spectral densities. The Time Reversal Linear Quadratic Detector is used instead of the Weighted Energy detector for improving the performance of the system. The hamming window function is used in the proposed system the gain of the generated signal will be improved by this window function and improving the SNR of the multipath clutter. The obtain waveform by using the hamming window function is compared with the analytical waveform of the clutter that performance analysis show that the detection of Gaussian target.

KEYWORDS: Gaussian detection, likelihood ratio test, SNR ratio, hamming window.

I.INTRODUCTION

The problem of detecting a target embedded in clutter or in multipath has been studied extensively and is of great importance in many applications, including Radar and Sonar scenarios. The matched filter has been shown to be optimal for a known signal in the absence of clutter and the presence of both white and colored noise. These results break down when the transmission channel exhibits multipath effects. Multipath results in the interference of several delayed and attenuated versions of the probing signal. These interference patterns obscure the known signal and negatively affect the performance of matched filters. The traditional approach to compensation for multipath is to model the channel and construct a variant of the matched filter, called matched field processing. This approach requires either explicit or implicit modelling of the channel, e.g., by the wave equation, and detailed modeling of the boundary conditions. Matched field processing is computationally very intensive. Thus, traditional consideration of multipath either views it as detrimental to performance or exacts a heavy modeling and computational cost; Time Reversal presents an alternative inexpensive solutions in certain applications so that Multipath can be constructively interfered to improve the received signal-to-noise ratio.

Time Reversal

Time Reversal, which can at least be dated back to a 1965 acoustical experiment by Parvulescu and Clay, has received renewed attention following the more recent work of M. Fink and others. A concise and descriptive review of Time Reversal in the acoustic domain can be found. Time Reversal relies on the reciprocity of the channel and the invariance of the Green's field to a reversal of the time operator [1].

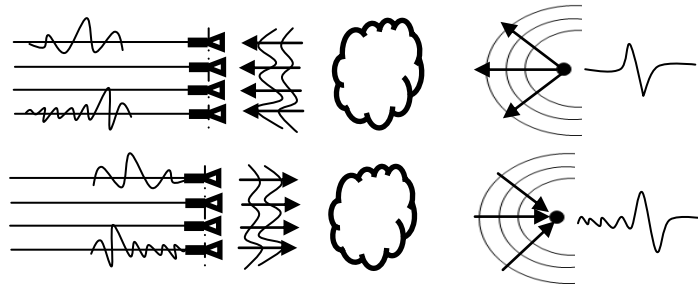


Fig.1: Illustration of the Time Reversal process

Reciprocity implies that a transmission from point source (A) to receiver (B) will result in the same received signal as transmitting that same probing signal from (B) to (A). Invariance of the Green's field to a reversal of the time operator implies that signals propagate the same way whether time is moving forward or backward from the onset of the impulse. These two factors allow for the construction of Time Reversal Mirrors (TRMs) in acoustics and electromagnetics, also called Optical Phase Conjugators in optics. A TRM is an array of sensors (in either one, two, or three-dimensions) that collect a time history of some incident signal and then re-transmit what they have received in a First-In Last-Out manner. This process produces a time-reversed incident signal that has been proven to converge back on the original source of the transmission, we illustrate this phenomenon in Fig. 1.

It has been shown through experiments in a water tank and in the open ocean that this convergence exhibits super-resolution. This means that the focused incident signal generated by a TRM exhibits resolution that outperforms the predicted Rayleigh resolution limit. This convergence of energy intensifies Time Reversal signal processing. Super-resolution focusing is intuitively understood through an effect known as virtual arrays. Applications of Time Reversal include detection, imaging, communications, non-destructive testing, and beam steering, among others.

Multipath Channel Effects

Jin and Moura propose the use of Time Reversal to detect targets embedded in dense multipath channels. They model the channel's frequency response as the summation of two terms, one due solely to the background (clutter) and the other due to the presence of the target. The background component is called the clutter response and is denoted $H_c(f)$, while the remainder is called the target response and is denoted $H_t(f)$.

The combined channel response is given by:

$$H(f) = H_c(f) + H_t(f) \dots \dots \dots (1)$$

They use a priori information to characterize the clutter response and remove it through direct subtraction. This leaves the target channel response $H_t(f)$, which is characterized not just by a response from the target, but also by interaction of the target with the background (multipath) channel, as shown in Fig. 1.2. They perform Time Reversal on this component of the channel response and show that detectors based on this signal outperform conventional detection algorithms.

These results are based on the assumption that the clutter response is deterministic and, thus, can be removed through subtraction.

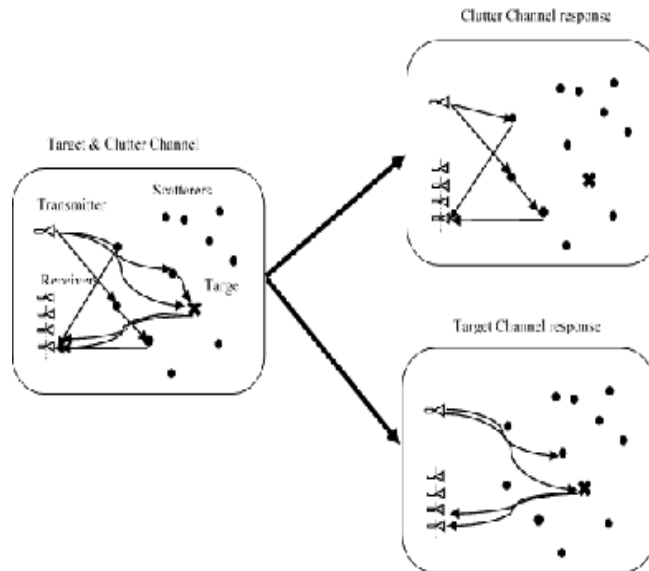


Fig.2: Target and clutter Channel Response

In the regime of ray propagation, the multipath channel response can be written as the discrete sum of the L independent propagation paths present:

$$H(f) = \sum_{l=1}^L \eta_l(f) e^{j\phi_l(f)} \dots\dots (2)$$

The incoherent summation of a large number of independent paths motivates the consideration of this response as a random variable, since relatively minor changes in the propagation environment can affect the amplitude and delay of a large number of these paths in different ways. This contrasts with the work of Jin and Moura, where the aggregate response $H(f)$ is assumed to be deterministic. Consider Rayleigh Fading channels.

The channel response $H(f)$ is represented by:

$$H(f) = r(f) e^{j\phi(f)} \dots\dots (3)$$

Where the random amplitude $r(f)$ is Rayleigh distributed with parameter $\sigma(f)$, and the random phase $\phi(f)$ is uniformly distributed between 0 and 2π . We note that the product of a Rayleigh amplitude and independent uniform phase can be represented as a circular symmetric complex Gaussian random variable:

$$H(f) \sim CN(0, \sigma^2(f)) \dots\dots (4)$$

Thus, I assume that complex Gaussian random variables are suitable to model the random clutter response and the random target response in the presence of multipath. The random variable $H(f)$ has distribution:

$$f_f(h) = \left(2\pi\sigma^2(f)\right)^{-1} e^{-\frac{h^2}{2\sigma^2(f)}} \dots\dots (5)$$

In the general case, the distribution of a complex Gaussian random vector h , with mean m and covariance matrix Σ , is given by:

$$f(h) = (2\pi)^{-N/2} \det\{\Sigma\}^{-1/2} e^{-0.5(h-m)^H \Sigma^{-1}(h-m)} \dots\dots (6)$$

As with the real Gaussian distribution, the complex Gaussian distribution is closed under linear transformations, and the summation of jointly complex Gaussian random variables yields a complex Gaussian random variable.

Multi-Input Multi-Output (MIMO) Radar

The term multiple-input multiple-output (MIMO) refers to the use of multiple-transmit as well as multiple-receive antennas. The vast majority of MIMO radar systems fall into one of two categories: widely separated antennas and colocated antennas. The former leverages the fact that, if the antennas are separated far enough, the target radar cross sections (RCS) for different transmitting paths become independent random variables. The latter utilizes far-field wave front assumptions that are well-known through phased array signal processing, but transmits orthogonal waveforms from each antenna or a set of sub arrays, instead of standard phased array waveforms. The key to both approaches is that MIMO radar leverages increased diversity (either spatial or coded) to improve system performance, by sacrificing main lobe width. We now discuss both of these methodologies for MIMO radar and illustrate the relative strengths and applications of each.

Literature Survey

Address the design of an optimal Transmit signal and its corresponding optimal detector for a radar or active sonar system. The focus is on the temporal aspects of the waveform with the spatial aspects to be described in a future paper. The assumptions involved in modeling the clutter/reverberation return are crucial to the development of the optimal detector and its consequent optimal signal design [2].

An analysis of the detection of radar targets in multipath environments is presented. Radar targets often undergo enhancements or fades due to multipath where the direct-path energy combines with a phase-shifted reflection to enhance or reduce the received energy. This phenomenon is a function of frequency [3].

Conventional spotlight Synthetic Aperture Radar (SAR) assumes a single reflection of transmitted waveforms from targets. Multiple reflections of targets due to surrounding scatterers appear as ghosting artefacts in conventional SAR images, which obscures true target image and leads to poor resolution [4].

Consider two independent complex Gaussian vectors having arbitrary mean vectors and covariance matrices which are scaled versions of the identity matrix. The joint characteristic function (c.f.) of the real and imaginary parts of the inner product of these two vectors is derived in closed form. This joint c.f. is applied to the analysis of the symbol error probability (SEP) of a multibank diversity reception system in flat Rayleigh fading using M-ary phase-shift keying (MPSK) [5].

Detection of a target buried in a rich scattering medium by time reversal. I use a multi-static configuration with receive and transmit arrays of antennas. In time reversal, the backscattered field is recorded, time reversed, and retransmitted (mathematically or physically) into the same scattering medium [6].

Time reversal explores the rich scattering in a multipath environment to achieve high target detectability. Multiple-input multiple-output (MIMO) radar is an emerging active sensing technology that uses diverse waveforms transmitted from widely spaced antennas to achieve increased target sensitivity when compared to standard phased arrays. In this paper, we combine MIMO radar with time reversal to automatically match waveforms to a scattering channel and further improve the performance of radar detection. Establish a radar target model in multipath rich environments and develop likelihood ratio tests for the proposed time-reversal MIMO radar (TR-MIMO). Numerical simulations demonstrate improved target detectability compared with the commonly used statistical MIMO strategy [7].

Detection of targets in complex environments is of importance in both radar and sonar applications. Recent work has shown that the use of Time Reversal (TR) techniques improves the performance of systems operating in deterministic channels with a significant multipath return. This paper extends those results to stationary random channels with significant multipath [8].

II. PROPOSED METHOD

Consider the problem of detecting a target embedded in stationary random multipath clutter. Derive a Time-Reversal (TR) based approach to detect the presence of a target in the ideal case, where the second order statistics are all known (or can be learned). Propose a Time Reversal detection scheme that is based on prior work for deterministic channels. Show how this detection scheme must be modified for treatment of random Gaussian targets and derive several detectors based on Time Reversal. The optimal detector, which term the Time Reversal Likelihood Ratio Test (TR-LRT), is shown to perform very well as compared to a conventional Weighted Energy Detector (WED) through Monte Carlo trials, but lacks an analytical expression for threshold computation and performance analysis. In addition to the TR-LRT, we propose a suboptimal approach, the Time-Reversal Linear-Quadratic (TR-LQ) detector. The TR-LQ detector is derived through approximating the received time reversal signal as a complex Gaussian, instead of the product of two complex Gaussian random variables. Through this approximation, we compute the statistics of the TR-LQ detector, and present analytical detection results, in addition to the Monte Carlo trials, and performance analysis.

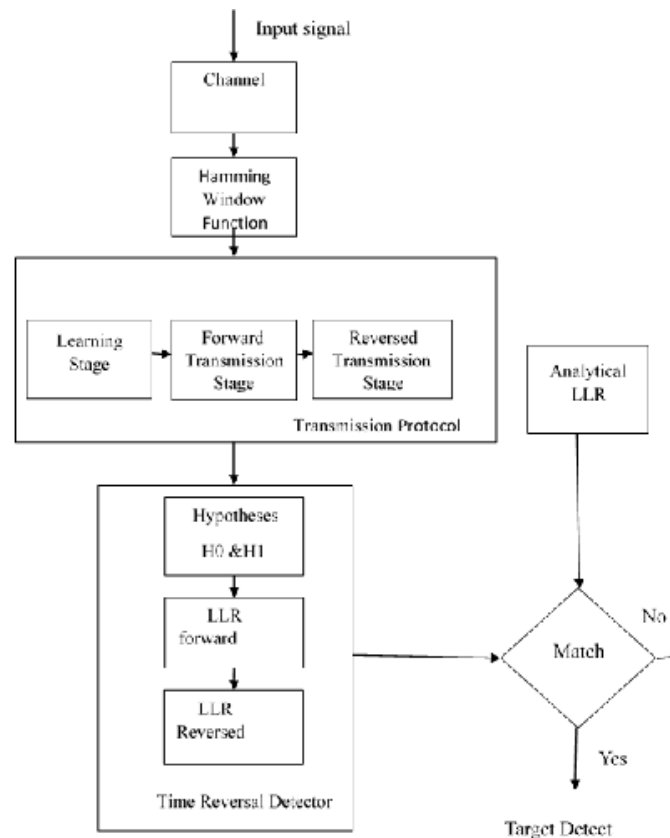


Fig. 3: Flow Diagram of process

For a comparison, we also present the optimal conventional detector, the Weighted Energy Detector (WED) with two different signal design strategies:

Flat PSD: A blind approach that allocates power equally among frequencies. *Water Filling*: An adaptive approach that seeks to minimize the clutter response by assuming that the target’s PSD is flat.

III. PROBLEM FORMULATION

Consider the problem of detecting a target in the presence of clutter (sometimes referred to as reverberation). . To be clear, we are referring to signal-dependent responses when we discuss clutter. Thus, if we transmit the signal $S(f)$, the received signal $Y(f)$ is given by:

$$Y(f) = [H_t(f) + H_c(f)] S(f) + V(f) \dots\dots\dots (7)$$

Where $H_t(f)$ is the target’s frequency response and $H_c(f)$ is the clutter frequency response. $V(f)$ is a combination of additive noise and non-signal-dependent interference (such as jamming). The assumption of a Poisson spatial process to model the physical distribution of clutter leads to a complex Gaussian process model for the impulse response. Thus, I can model the clutter’s frequency response as a complex Gaussian random variable:

$$H_c(f) \sim CN(0, P_c(f)) \dots\dots\dots (8)$$

Where $P_c(f)$ is the clutter’s Power Spectral Density (PSD). Consider a general (non-point) Gaussian target, which conforms to the standard target model considered. Thus, similar to the clutter frequency response, model the target’s frequency response with:

$$H_t(f) \sim CN(0, P_t(f)), \dots\dots\dots (9)$$

Where $P_t(f)$ is the target’s PSD. The target channel model (2.3) implies that the variance (i.e., the power spectrum density) is frequency dependent, which is intensified by the multipath scattering. The aggregate channel response $H(f)$ is taken to be the superposition of the target and clutter channel responses:

Make the simplifying assumption that the target and clutter are independent, thus we can express the aggregate channel’s PSD with $P_h(f) = P_t(f) + P_c(f)$. This model agrees with the formulation in Fig. 1.2. The rays that comprise the target channel response follow different paths than those for the clutter channel response and, thus, are independent

IV. TRANSMISSION PROTOCOL

This protocol will consist of two distinct transmission stages: a forward ($A \rightarrow B$) transmission and a reverse ($B \rightarrow A$) transmission. This is necessary for active Time Reversal methods and will also provide a diversity gain for conventional methods To begin with, we define the probing signal sent from antenna A as $S_A(f)$. I will later define a probing signal $S_B(f)$ to be sent from antenna B. The proposed transmission protocol can be broken into three communication stages:

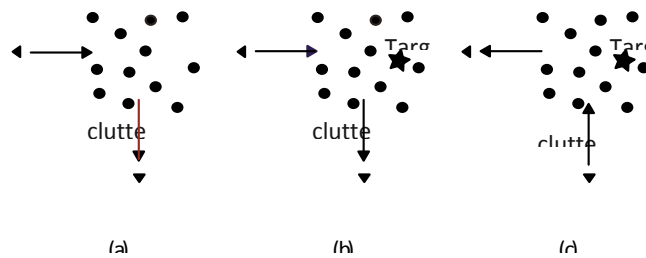


Fig. 4: Transmission Protocol.

Learning Stage: This is the a priori stage during which the clutter channel is probed, prior to the presence of a target.

Forward Transmission Stage: The forward probing signal $S_A(f)$ is transmitted through the channel from antenna A and is received at antenna B.

Reverse Transmission Stage: The reverse probing signal $S_B(f)$ is transmitted through the channel from antenna B and is received at antenna A.

The selection of the probing signals $S_A(f)$ and $S_B(f)$ are a significant part of what makes this a Time Reversal process, since $S_B(f)$ will be constructed from the response at antenna B. benchmark our approach against several conventional signal design strategies for $S_A(f)$ and $S_B(f)$.

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Hamming Window

Windowing of a simple waveform like $\cos \omega t$ causes its Fourier transform to develop non-zero values (commonly called spectral leakage) at frequencies other than ω . The leakage tends to be worst (highest) near ω and least at frequencies farthest from ω . If the waveform under analysis comprises two sinusoids of different frequencies, leakage can interfere with the ability to distinguish them spectrally. If their frequencies are dissimilar and one component is weaker, then leakage from the larger component can obscure the weaker one's presence.

$$\omega(n) = \alpha - \beta \cos\left(\frac{2\pi n}{N-1}\right) \tag{10}$$

And $\alpha = 0.54, \beta = 1 - \alpha = 0.46$

But if the frequencies are similar, leakage can render them unresolvable even when the sinusoids are of equal strength. The rectangular window has excellent resolution characteristics for sinusoids of comparable strength, but it is a poor choice for sinusoids of disparate amplitudes. This characteristic is sometimes described as low-dynamic-range Hamming window 3/22. At the other extreme of dynamic range are the windows with the poorest resolution.

V. TIME REVERSAL DETECTORS

The optimal detector, in a Neyman-Pearson sense, is the log-likelihood ratio test:

$$l(z) = \ln\left(\frac{f(z|H_1)}{f(z|H_0)}\right) \underset{<H_0}{\overset{>H_1}{>}} \eta \tag{11}$$

For some threshold η . We consider M independent trials and use the subscript z_m to refer to each of the trials. Thus, when we consider the ensemble of data, the likelihood ratio test becomes:

$$l(z) = \sum_{m=0}^{M-1} \ln\left(\frac{f(z_m|H_1)}{f(z_m|H_0)}\right) \underset{<H_0}{\overset{>H_1}{>}} \eta \tag{12}$$

Time Reversal Likelihood Ratio Test (TR-LRT)

Under the null hypothesis H_0 and under the alternative hypothesis H_1 ($H(f) = H_c(f)$) the Time Reversal Likelihood Ratio Test (TR-LRT):

$$l_{TR-LRT}(z) \underset{<H_0}{\overset{>H_1}{>}} \mu_{TR-LRT} \tag{13}$$

Time Reversal Linear Quadratic Test (TR-LQ)

To simplify the detector design and allow for more detailed analysis, we replace the conditional distribution of $X_m(f_q)$, with the approximate marginal distribution and repeat the likelihood ratio test carried out. Our approach is the same as for the TR-LRT, with the exception that the power spectral density $P_x(f_q)$ is replaced with the approximate power spectral density. Through this approximation, the log term at the end of becomes a constant and can be absorbed into the threshold. Thus, the TR-LQ detector is given by:

Compute the expected probability of detection P_D with the equation:

$$P_D = 1 - \Phi\left(\frac{\mu_{TR-LQ} - \mu_{TR-LQ|H_1}}{\sigma_{TR-LQ|H_1}^{1/2}}\right) \tag{14}$$

VI. CONCLUSION

Presented a single-antenna Gaussian detection strategy and derived a Time Reversal Likelihood Ratio Test (TR-LRT) and Time Reversal Linear Quadratic Test (TR-LQ). I also presented a Multi-Input Multi-Output (MIMO) radar detection strategy that utilizes multipath to create spatial diversity and derived a Time Reversal MIMO (TR-MIMO)

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detector. I have shown that, in both scenarios, Time Reversal has the potential for improvements upon conventional transmission methods.

Derived a new statistical distribution, the complex Double Gaussian distribution, to describe the product of two independent complex Gaussian random variables. Analyzed the behavior and implementation of this distribution and the output waveform was generated. The generated waveform was compared with the analytical waveform of the multipath clutter. If both the waveforms are matched then the Gaussian target of the multipath clutter was detected. This is the main application for target detection.

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