Near Sea Surface Target Tracking by Extended Kalman Filtering of the GPS Reflected Signals

Sarab Tay and Frédéric Maussang
Institut Telecom/Telecom Bretagne
CNRS LabSTICC UMR 3192
29238 Brest Cedex 3, France
sarab.tay@telecom-bretagne.eu
frederic.maussang@telecom-bretagne.eu

Arnaud Coatanhay
ENSTA Bretagne
Laboratoire E3I2 CNRS EA 3872
29806 Brest Cedex 9, France
arnaud.coatanhay@ensta-bretagne.fr

Thierry Chonavel and René Garello
Institut Telecom/Telecom Bretagne
CNRS LabSTICC UMR 3192
29238 Brest Cedex 3, France
thierry.chonavel@telecom-bretagne.eu
rene.garello@telecom-bretagne.eu

***Abstract*—This paper addresses the use of Global Navigation Satellite Systems (GNSS) as a remote sensing tool for oceanographic applications. In this paper we use the Global Positioning System (GPS) signals reflected off the sea surface along with a coastal receiver to perform detection and tracking of a near sea surface mobile target. Because these signals have a very low Signal to Noise Ratio (SNR) in a non stationary medium, a matched filter is required. A filter based on the Extended Kalman process is presented here.**

I. Introduction

Monitoring the sea surface by using electromagnetic source of opportunity owes its success to the progress of Global Navigation Satellite Systems (GNSS). Typically, GPS signals are the most exploited. Thanks to the GPS signal properties, it is possible to find some parameters such as the ocean surface roughness, wind direction and speed, currents and surface altimetry [1], [2], [3] and [4], by studying the waveform shape of the reflected GPS signal correlated with a replica of its code. Therefore the GPS constitutes a relevant and inexpensive bistatic passive remote sensing tool. Space and airborne platforms, and radars often served as the receiver in this kind of observations. In the present, we use near sea surface observation systems for an accurate analysis of the diffusion and the scattering of GPS signals.

II. Coastal monitoring

A. Project MOPS

For an airborne receiver, the scattered GPS signal is extended to an area around a nominal specular point on the mean sea surface (glistening zone), which does not allow for observation of the elementary sea wave movement [3]. Therefore, to allow fine detection of the sea movement during very small time intervals, we consider a coastal receiver located dozens of meters above the sea surface that can record the scattered GPS signal (*MOPS*) [5].

Project MOPS studies the feasibility of passive systems in the vicinity of the sea surface for applications in oceanography. Due to the complexity of this objective, this project manages different scientific academic domains (electromagnetism, signal processing, oceanography, etc.), to develop an experimental testbed at a Brest coastal spot.

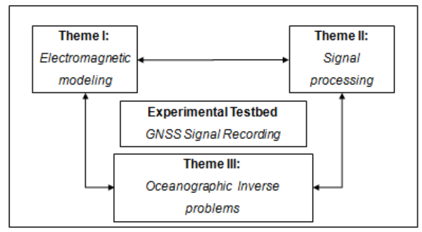

Fig. 1. Project MOPS

This project (Fig. 1) is composed of four main themes :

- Physical modeling: Numerical modeling of the electromagnetic field in the vicinity of scattered waves[6].
- Signal and raw data processing: Extraction of information from the Doppler Delay Map *DDM*[7].
- Inverse problem: inversion of the physical problem and identification of oceanographic information.
- Experimental platform: validation of the work with real measurements[8].

B. Initilazing and modeling

For the very near sea surface configuration, we showed in [7] how the integration of the GPS signals scattered by some targets on sea surface can provide elementary information in order to detect them by extracting the reflected signal from the noise and sea clutter, where we presented the sea surface particles as mobile targets.

In this paper, the detection issue is extended to track the evolution of the target trajectory in an analogy with the problem of radar moving target tracking, in order to perform a close monitoring of the specular point itself.

- The target is a wave peak moving along the mean sea surface. The target has a uniform linear movement. The target speed depends on its position with respect to the receiver x_0, its wavelength and water depth h_w.
- The target is a buoy floating on the surface which oscillates in place, or a small boat located at a distance x_0 from the receiver. The movement is then vertical and sinusoidal (Fig. 2).

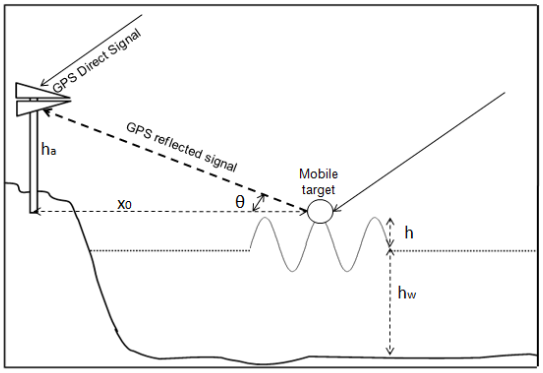

Fig. 2. GPS and Reflected signals on sea surface

The main objective is to estimate (δ_k, τ_k) at every instant t_k to be able to locate the target on the DDM.

Before proceeding to the EKF issue, let us recall some information about the GPS signal structure and the ambiguity function in order to explain the different hypothesis defined later to simulate and implement our filtering system.

C. GPS Signal Structure

The GPS satellites emit their code on two carriers, with frequencies L_1 and L_2, defined by the fundamental frequency $F_0 = 10.23$MHz:

$$\left\{ \begin{array}{lcl} L_1 & = & 154 * F_0 \\ L_2 & = & 120 * F_0 \end{array} \right. \tag{1}$$

L_1 wave is modulated by two codes: a civil code C/A and a military one, $P(Y)$, whereas L_2 wave is modulated only by the code $P(Y)$. The signal spectrum is spread using a BPSK modulation. The C/A code is composed of the Pseudo-Random Noise sequence (PRN) which is a sequence of $+1$ and -1 known and unique for each satellite. It has a length of 1023 chips, corresponding to a period of 1 ms [9]. By measuring the cross correlation product of the reflected GPS signal and the receiver generated replica PRN code, for a particular satellite, we show the peak corresponding to the direct signal emitted by the satellite and the secondary peaks corresponding to the reflection phenomena.

D. Ambiguity function

The ambiguity function of a signal $x(t)$ is defined by:

$$A_x(\tau, f) = \int_{-\infty}^{+\infty} x(t)\bar{x}(t-\tau)e^{-j2\pi ft}dt \tag{2}$$

where $\bar{x}$ represents the conjugate of x.

for a PRN sequence, the ambiguity function is approximately [10]:

$$A_x(\tau, f) \approx e^{-j\pi T_{seq} f} sinc(T_{seq} f) R(\tau) \tag{3}$$

where T_{seq} is the PRN sequence duration and $R(\tau)$ is the autocorrelation function ACF of this sequence.

1) Cut at zero Doppler : the ACF has a perfect triangular shape (Fig. 3)

$$R(\tau)_{/\{\delta=0\}} = \left\{ \begin{array}{ll} 1 - \left|\frac{\tau}{T_c}\right|, & \left|\frac{\tau}{T_c}\right| \leq 1 \\ 0, & elsewhere \end{array} \right. \tag{4}$$

where $T_c = \frac{1ms}{1023}$ is the duration of a chip. The triangular ACF width is $2T_c$.

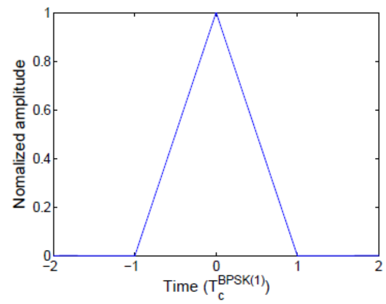

Fig. 3. The ambiguity function projection on τ direction

2) Cut at zero delay:

$$R(\delta)_{/\{\tau=0\}} = \alpha sinc(\pi f T_c) \tag{5}$$

In the Fig. 4, the main lobe is included in $[-\frac{1}{T}, \frac{1}{T}]$, where T is the integration time.

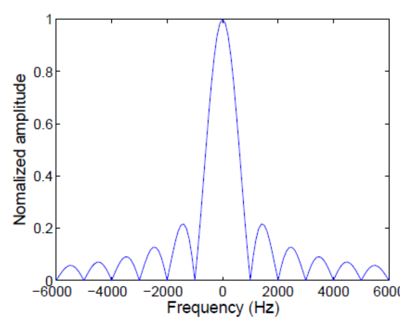

Fig. 4. The ambiguity function projection on δ direction

The standard deviation of the Doppler and the time delay, respectively σ_δ and σ_τ, are found by computing the half of the width, respectively at the mid height of the triangular shape and the main lobe of the $sinc$ function.

III. Matched filter: Extended Kalman Filter

A. EKF: state model

The Kalman filter carries out recursive target state estimation given the target dynamic equation, sensor measurements, and the target originated measurements [11].

Let us define the state vector s_k at time t_k;

$$s_k = [\ \delta_k \quad \tau_k\ ]^T. \tag{6}$$

and the state equations

$$s_{k+1} = f(s_k) + v_k \tag{7}$$

$$z_k = g(s_k, w_k) \tag{8}$$

Eq. 7 represents the dynamic evolution of the system where f is a linear function and $v_k \sim \mathcal{N}(0, \sigma_v^2)$. While the sensor measurements z_k are related to the target state via the function g in the observation equation (8).

$w_k \sim \mathcal{N}(0, \sigma_w^2)$ theoretically.

The efficiency of the linear Kalman filtering used in [12] to track this target was limited, since the model used was relatively simplified and doesn't reveal exact information about the target. To have an optimal observation, we must choose measurements of the energy distribution of the signal which could be more representative of the model and more realistic.

B. EKF: Measurements Model and Simulator

Actually the z_k represents a series of *DDM* measured at time $t_k = k * 0.45s$. Therefore, as we can see in the Fig. 4, the ambiguity function representation at zero delay cut has important secondary lobes. To simplify and obtain a robust model, we choose to simulate this function with a gaussian form g_k.

As we do not have real measures for the moment, we will generate simulated observations using the target's motion equations Then, for every (δ_k, τ_k) estimated at time t_k, we generate a noise-corrupted Power Spectral Density PSD g_k.

We suppose that our target has a sinusoidal motion as in the following

$$\begin{cases} x &= x_0 \\ z &= h \cdot \sin(2\pi f_m t) \end{cases} \tag{9}$$

Theoretically the originated measurements of the Doppler and the time delay can be obtained by the equations

$$\delta_k = -\frac{f_0}{c}\cos(\theta) \tag{10}$$

$$\tau_k = \frac{\sqrt{(x - x_0)^2 + (z - h_a)^2}}{c} \tag{11}$$

where $x_0 = 10m$, $h = 1m$, $f_m = 2Hz$ and $h_a = 22m$.

$$g_k = \left[w_k + \frac{1}{2\pi\sigma_\delta\sigma_\tau} \cdot e^{\left(-\frac{(\delta_i - \delta_k)^2}{2\sigma_\delta^2} - \frac{(\tau_j - \tau_k)^2}{2\sigma_\tau^2}\right)} \right]^2 \tag{12}$$

$\delta_i = i\Delta_\delta + \delta_0$ and $\tau_j = j\Delta_\tau + \tau_0$ define the transitions of the DD cell in the DDM. Δ_δ and Δ_τ are the transition steps, and δ_0 and τ_0 the originated measurements.

1) Statistical Properties:

$$\begin{cases} \sigma_\tau &\approx \frac{2T_c}{4} \\ &\approx 0.5\mu s \end{cases} \tag{13}$$

If we suppose that the Doppler does not change during $T = 20ms$, then:

$$\begin{cases} lobe_{width} &= \frac{2}{T} \\ \sigma_\delta &\approx 22.8Hz \end{cases} \tag{14}$$

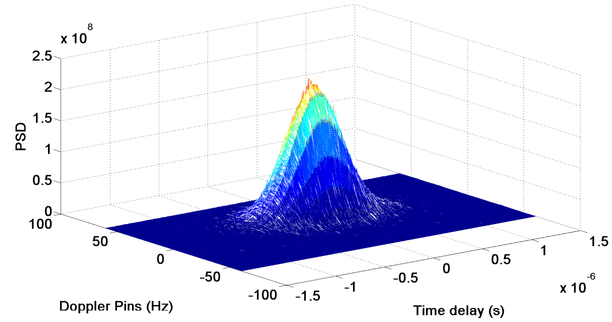

Fig. 5. Noise corrupted observation function

2) Observation noise distribution w_k: The noise in this distribution here has 2 dimensions.

At the receiver input, $w_0(t)$ represents a possibly correlated zero-mean Gaussian noise with estimated autocorrelation function $\Omega_0(t)$ [10].

- Fixed $f = f_\delta$:
  $A_x(\tau, f)$ in (2) will represent the output of a matched filter when the input signal has been Doppler-shifted by f. The output signal is then:

  $$y_f(t) = e^{-2j\pi f\tau} A_x(t - \tau, f - f_\delta) + w_f(t) \tag{15}$$

  $w_f(t)$ is a centered Gaussian noise, with : $\Omega_f(t) = \Omega_0(t) * ACF(x(t))$.
- Fixed $\tau = t_\tau$:
  The output noise is $\mathcal{E}(w_f) = \sigma_\delta^2 sinc(\pi f T)$ mean.

To simulate w_f and use it in the observation equation, these parameters should be considered.

IV. Results & Conclusion

In this paper, we have performed several simulations parameterized by wave height, distance from the target relative to the origin, distribution and level of observation noise. Then we have compared the theoretical target paths and those obtained at the output of the filter to analyze the performance and robustness of the extended Kalman filter for marine target tracking.

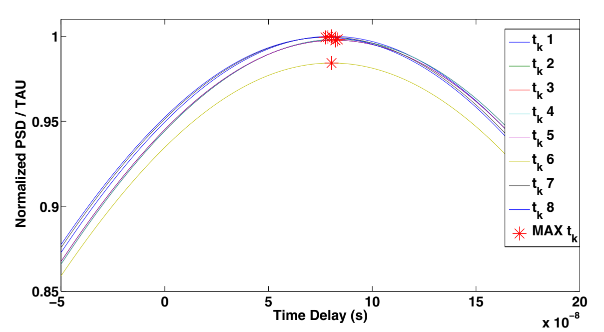

Fig. 6. The PSD projection on τ direction for $k = 8$ observations

In the Fig. 6, we can find the PSD projection on the τ direction for every observation of the $k = 8$ observations separated by $0.45s$ set. We have estimated the time delay difference is so small $(\Delta_{\tau,max} - \Delta_{\tau,min} = 6.06ns)$. In the same way and for these same observations, we have estimated the Doppler difference $(\Delta_{\delta,max} - \Delta_{\delta,min} = 120Hz)$ (Fig. 7).

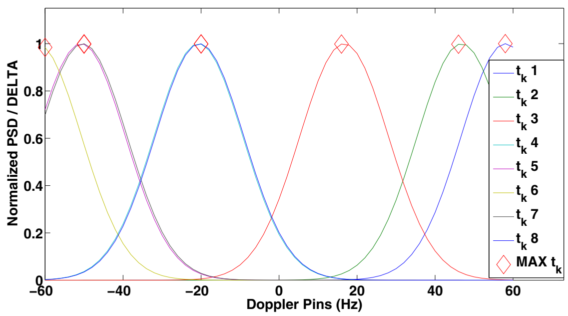

Fig. 7. The PSD projection on δ direction for $k = 8$ observations

We can see that the time delay difference is so small that it makes it hard to detect this tiny even with the sampling frequency $f_s = 8GHz$ used here. Anyway, we still have to work on this assumption else we may use only the Doppler shift for our tracking filter.

At the filter output, the target position in the DDM looks like in the Fig. 8.

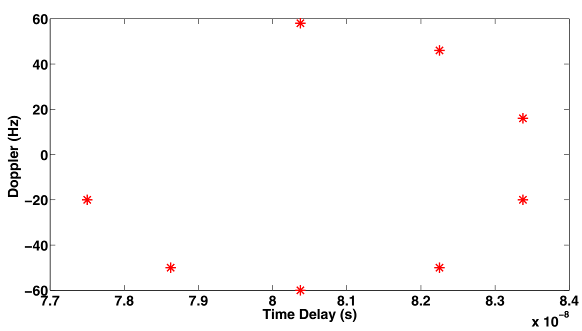

Fig. 8. Estimated target position through $k = 8$ observations

The encouraging results of this study allow us to predict multiple scientific extensions on several axes. We consider measures of the function of ambiguity, from a GPS signal simulator.

Depending on results and performance of our filtering system in the case of a single target, other hypotheses, such as the presence of another target or significant noise level, will also be discussed. Anlso, assuming a rather disturbed marine environment, we may need to develop a particle filter (or other) in the context of *Track - Before - Detect* .

Validation of our method with real measures is planned in the future, with a final objective of developing an experimental testbed for measurement and processing of scattered GPS signals.

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