

RADAR-BASED HUMAN DETECTION VIA ORTHOGONAL MATCHING PURSUIT

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ABSTRACT

Many current radar-based human detection systems employ some type of Doppler or Fourier-based processing, followed by spectrogram and gait analysis to classify detected targets. However, Fourier-based techniques inherently assume a linear variation in target phase over the aperture, whereas human targets have a highly nonlinear phase history. This mismatch leads to significant loss in SNR and integration gain. In this paper, an Enhanced Optimized Non-Linear Phase (EnONLP) detector is proposed that employs a dictionary to store possible target returns generated from the human model for each combination of parameter values. An orthogonal matching pursuit algorithm is used to compute a sparse approximation to the radar return that is optimal in the least squares sense. Performance of the EnONLP algorithm is compared to that of a parameter-estimation based algorithm and conventional, fully-adaptive STAP.

Index Terms— Human detection, radar signal processing, sparse approximation, orthogonal matching pursuit

1. INTRODUCTION

The problem of human detection with radar may be broken down into two key tasks: 1) detecting the presence of a target, and 2) deciding whether or not the target detected is human. Much of the research in human detection with radar has focused on the latter task, resulting in key results in human modeling and gait analysis. The former task, however, has primarily been dealt with in the wider context of slow-moving target detection and clutter cancellation using space-time adaptive processing (STAP).

Human targets present unique challenges because they are slow-moving targets with low radar cross-section (RCS). Furthermore, the highly nonlinear phase history of human targets leads to significant losses in SNR, integration gain, and, hence, detection performance when matched filtered with a linear phase signal, as is done in Fourier-based techniques [1].

Previous work [2,3] has shown that in the noise-limited case the losses due to phase mismatch between the true target phase history and matched filter may be reduced by modeling the unique structure of human motion to derive a more accurate estimate of the human target return. One approach – the Optimized Non-Linear Phase (ONLP) detector [3] – is to model just the torso return, as most of the energy is reflected from the torso, to compute maximum likelihood estimates (MLEs) of the unknown model parameters and, thus, approximate the expected return. However, this approach requires implementing a complex numerical search to find the MLEs that satisfy a set of four non-linearly constrained equations.

This work explores another approach – the Enhanced Optimized Non-Linear Phase (EnONLP) detector – which instead converts the problem of computing real-time MLE estimates into one of storing possible target returns in a dictionary and using orthogonal matching pursuit (OMP) to search for the optimal combination of dictionary entries that matches the received data. Receiver operating characteristic (ROC) curves are used to compare the performance of the EnONLP detector to that of ONLP and conventional, fully-adaptive STAP.

2. SIGNAL MODELING

Consider a radar antenna transmitting a series of chirped pulses at constant intervals in time and space while moving along a straight path. In general, the total received signal is comprised of the received radar return plus clutter and noise.

In this work, noise is modeled as complex white Gaussian distributed, while clutter is modeled by a generic physical model that computes the sum of all the clutter returns from a ring of scatterers located at a fixed range, R_c , from the radar.

2.1. Human Radar Return

A human is a complicated target because of the intricate motion of body parts moving along different trajectories at different speeds. In this work, the human body is divided into twelve basic body parts: the head, upper arms, lower arms, torso, thighs, lower legs and feet - each modeled as a

point target located at the center of the body part.

The time-varying position of each point target may be computed using the kinematic model of a walking human developed by Thalmann [4]. The equations for the motion of the spine and charts of the time-varying joint angles may be combined with data on the dimensions of the human body to compute the time-varying positions of each body part.

Exploiting the work of Geisheimer [5] and Van Dorp [6], who showed that the principle of superposition could be applied to human modeling, the total return at a single channel from a human target may be expressed as

$$s_h(n, t) = \sum_{i=1}^{12} a_{t,i} \text{rect}\left(\frac{\hat{t} - t_{d,i}}{\tau}\right) e^{j[l-2\pi f_c t_{d,i} + \pi\gamma(\hat{t} - t_{d,i})^2]}, \quad (1)$$

where the time t is defined as $t = T(n-1) + \hat{t}$ in terms of the pulse repetition interval (PRI), T , the pulse number, n , and the time relative to the start of each PRI, \hat{t} ; $a_{t,i}$ is the amplitude as given by the radar range equation; τ is the pulse width; c is the speed of light; γ is the chirp slope; f_c is the transmitted center frequency; and $t_{d,i}$ is the round trip time delay between antenna and each body part.

The slow-time, fast-time data matrix is pulse compressed so that the peak occurs at the range bin in which the target is present. Taking a slice across slow-time at the range bin of the peak output,

$$x_p[n] = \sum_{i=1}^{12} a_{t,i} \tau e^{-j\frac{4\pi f_c}{c} R_{d,i}}, \quad (2)$$

where $R_{d,i}$ is the range from the antenna to each body part.

Although of limited value for classifying these targets, one way of visualizing the human return is via spectrograms, computed from the fast Fourier transforms (FFT) of short, overlapping time segments taken from the slow-time slice in (2), as illustrated in Fig. 1. The strongest return is received from the torso, while the feet appear with the largest amplitude oscillation. This signal structure is unique to humans [7] and exploited in our proposed detector design.

The multi-channel formulation of (2) may be obtained by incorporating the time delay Δt in the radar return between adjacent elements of the uniform array $\Delta t = d \sin(\phi) / c$, where d is the inter-element spacing, so that the target's contribution to the array's space-time snapshot is

$$\chi_t = [\mathbf{x}_p \circ \mathbf{b}_t(\varpi_t)] \otimes \mathbf{a}_s(\nu_t), \quad (3)$$

where \mathbf{a}_s is the target's spatial steering vector, \mathbf{b}_t is the target's temporal steering vector, the spatial frequency ν_t is

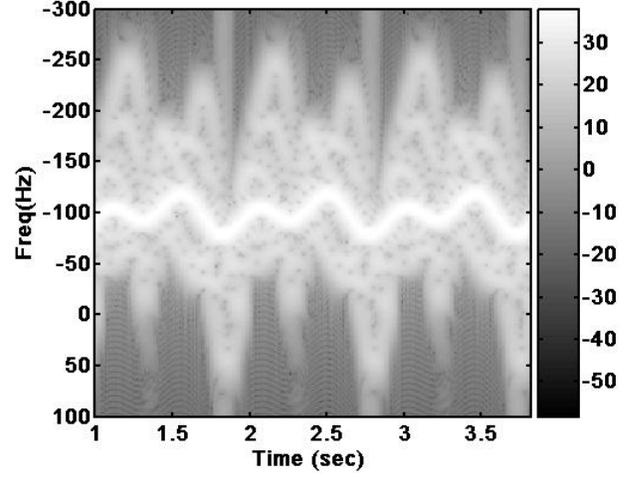


Fig. 1. Example human spectrogram.

$f_c n d \sin(\phi) / c$, ϖ_t is the target Doppler shift normalized by the pulse repetition frequency (PRF), and \circ represents the Hadamard product.

2.2. Inherent SNR Loss

The FFT used in Doppler processing leads to maximum output SNR when the inputs likewise exhibit constant amplitude and linear phase variation over the aperture. However, the phase history of a human target can be highly nonlinear, resulting in an inherent SNR loss when processed by a linear-phase filter, such as the FFT. As shown in Fig 2., collecting data over a longer dwell is not a remedy, as the SNR loss, as shown by the difference between the curves for the ideal, clairvoyant detector and FFT, simply increases with dwell.

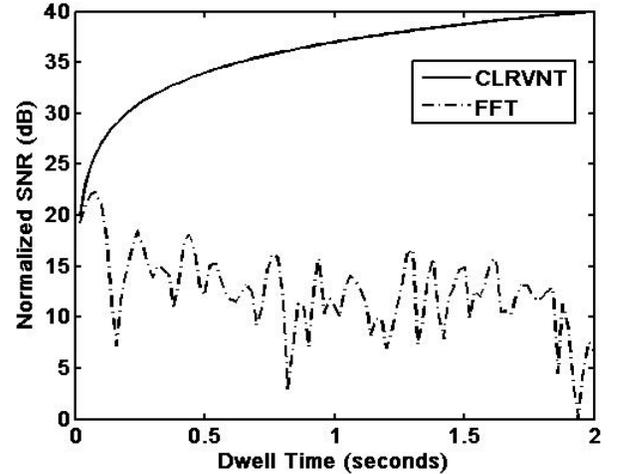


Figure 2. Output SNR variation over dwell time normalized by input SNR for a typical target phase history.

3. ENHANCED ONLP (ENONLP)

The proposed EnONLP method finds the optimal sparse representation of the received signal by using an orthogonal matching pursuit algorithm to search a dictionary of expected target returns.

3.1. Approximating Expected Human Return

The model for the expected human target response used in the EnONLP detector is derived by first approximating the range term, $R_{d,i}$, in (2). Since the overall SNR loss is caused primarily by phase mismatch, the received signal amplitude, $a_{t,i}$, is approximated as being a constant, A/r_b^2 , where r_b is the center of the target range bin. A more accurate approximation to the range term in the phase is obtained by assuming that the human motion is linear along a constant angle, θ , relative to the vector from the antenna to the target's initial position, \mathbf{r} . Assuming that the total distance travelled \mathbf{h} is much less than the observation distance, the expected target snapshot is approximated as

$$\boldsymbol{\chi}_{EnONLP} = [\hat{\mathbf{x}}_p \circ \mathbf{b}_t(\overline{\omega}_t)] \otimes \mathbf{a}_s(v_t), \quad (4)$$

where $\hat{\mathbf{x}}_p \approx \frac{A}{r_b^2} \sum_{k=1}^{12} e^{-j \frac{4\pi f_c}{c} (r_k - \mathbf{h}_k \cos \theta_k)}$, and $r = |\mathbf{r}|$.

The human motion vector \mathbf{h} is given by the time-varying positions derived for each body part in the Thalmann model. The EnONLP approximation thus contains five unknown parameters: target velocity (v) and height of thigh (HT) from the Thalmann model, the motion vector angle (θ), incidence angle (ϕ), and target range (r). These parameters take on values within a finite range. The Thalmann model is defined for values of v/HT between 0 and 2.3, while the target range must lie within the range bin being tested and all angles are limited between 0 and 360°.

3.2. Basic Formulation

The dictionary is created by discretizing the range of possible parameter values into a finite number of samples for each parameter. Define $\boldsymbol{\xi} = [v \ HT \ \phi \ \theta \ r]$ as the vector of unknown parameters. For each possible combination of parameters, $\boldsymbol{\xi}_j$, the corresponding target return model is computed and stored as an entry in a dictionary (\mathbf{D}) of size $MN \times Q$

$$\mathbf{D} = [\hat{\boldsymbol{\chi}}_{EnONLP}(\boldsymbol{\xi}_1) \ \cdots \ \hat{\boldsymbol{\chi}}_{EnONLP}(\boldsymbol{\xi}_j) \ \cdots \ \hat{\boldsymbol{\chi}}_{EnONLP}(\boldsymbol{\xi}_Q)] \quad (5)$$

If multiple targets are present in the data, a linear combination of dictionary entries will best represent the received data. Orthogonal matching pursuit (OMP) [8] is a

robust version of a number of sparse approximation techniques, such as basis pursuit or matching pursuit, which may be applied to solve this problem. First, an optimal, fully-adaptive space-time filter is applied to the data to mitigate the affect of clutter. Thus, the residual of the OMP algorithm is initialized to $\mathbf{r}_0 = \mathbf{R}_1^{-1} \boldsymbol{\chi}$. Then, the dictionary entry for which the projection onto the residual is maximized

$$\hat{\boldsymbol{\chi}}_{optimal} \rightarrow \max \{ \mathbf{r}_0^H \mathbf{D} \} \quad (6)$$

is tested for the presence of a target using the Adaptive Matched Filter detector [9]. If a target is present, then the entry index is stored in a vector $\boldsymbol{\eta}$ and the coefficient vector \mathbf{C} that solves the least squares problem

$$\min \left\| \mathbf{R}_1^{-1} \boldsymbol{\chi} - \sum_{j=1}^t \mathbf{C}(\boldsymbol{\eta}_j) \hat{\boldsymbol{\chi}}_{EnONLP}(\boldsymbol{\eta}_j) \right\|_2 \quad (7)$$

is computed. The residual is then updated by subtracting out the components already found, and the procedure is repeated until no more components yield a detection. Note that this procedure yields additional information about the detected target, as the parameters used to generate the dictionary entries found to comprise the signal are known.

5. PERFORMANCE

Detector performance is evaluated by comparing the receiver operating characteristics (ROC) for the proposed EnONLP detector with that of ONLP and fully adaptive, optimum STAP in simulated data of a 5-channel radar with characteristics shown in Table 1, chosen as being typical of a representative radar system.

Table 1

Parameters	Value	Parameters	Value
Pulses #	500	PRI	0.2 ms
Center Freq.	1 GHz	Pulse Width	40 μ s
Samp Freq.	20 MHz	Trans. Power	1.8 kW
Bandwidth	10 MHz	Nom. Range	8,760 m

The dictionary used by the EnONLP algorithm is generated by discretizing the unknown velocity at 0.1 m/s increments between 1.5 m/s and 2.7 m/s, and the unknown angles at 5 degree intervals over 360°, for a dictionary of 936 entries. Dictionary size is minimized by storing data for only one channel, using convolution instead of multiplication in (6) to avoid storing phase (range) information, and generating all entries for a fixed-size human, in this case, an average male. Thus, an increase in computational load is traded off for savings in memory.

ROC curves for the EnONLP, ONLP, and STAP detectors are shown in Fig. 1 and Fig. 2 for an average-sized male walking at a 45° angle relative to the x-axis with a speed of 2 m/s. The proposed EnONLP detector exhibits the best performance with a P_D of 0.77 at a P_{FA} at 10^{-6} , steadily increasing as the P_{FA} increases, with the other methods matching performance only when the P_{FA} has risen to 0.01. As the clutter-to-noise ratio (CNR) increases to beyond 15 dB, the other methods exhibit a sharp drop in detection rate, whereas EnONLP is able to maintain good performance.

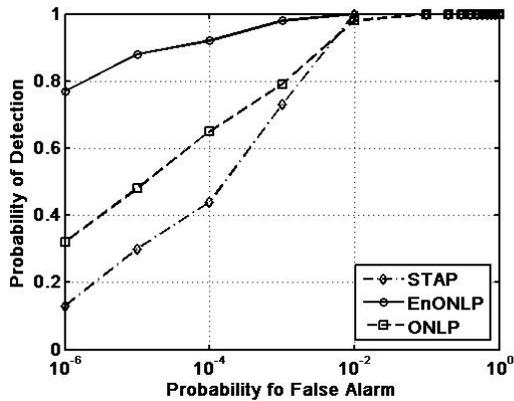


Fig. 1. P_D v P_{FA} for a human target with SNR = 0 dB and CNR = 30 dB.

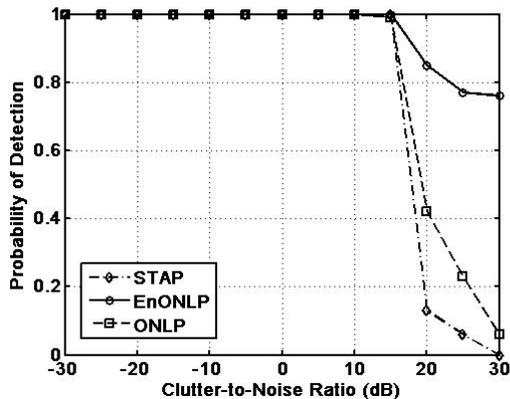


Fig. 2. P_D v CNR for a human target with $P_{FA} = 10^{-6}$.

The EnONLP framework has the additional advantage of being able to detect the number of human targets present in a single range bin, as well as extract an estimate of the modeled parameters for each target. If models for other non-human targets are also included in the dictionary, then EnONLP may also be exploited as a target classifier.

Consider a scenario in which a vehicle, a tall male with thigh height (HT) of 1 meter, and a small female with a thigh height of 0.74 meters are all moving within a single range gate in clutter with an SINR of 20 dB. The vehicle is modeled as a point target with a reflection 10 dB stronger than the male target. Additional scenario parameters are provided in Table 2. Thus, the dictionary is augmented with entries generated from discretized linear spatial and

temporal steering vectors. The EnONLP algorithm was able to successfully detect all targets, with model parameter estimates as shown in Table 2.

Table 2

	TRUE		DETECTED	
	Male	Female	Male	Female
Azimuth	60°	-30°	65°	-30°
Direction	15°	30°	15°	35°
Velocity	2 m/s	2.4 m/s	2 m/s	2.3 m/s
	Vehicle		Vehicle	
Azimuth	37°		37°	
Rad. Vel.	14 m/s		14 m/s	

6. CONCLUSION

The proposed EnONLP algorithm exhibits a significant improvement in performance over conventional linear-phase detectors. EnONLP can be used not only for detecting human targets, but for detecting targets of any type, including animals, just so long as the appropriate model is included in the dictionary. Estimates of the model parameters yielded by the EnONLP algorithm may be also used to extract additional information about detected targets.

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