Signal Processing 127 (2016) 44–55

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Target tracking using adaptive compressive sensing and processing

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A R T I C L E I N F O

Article history:
Received 8 August 2015
Received in revised form
23 February 2016
Accepted 26 February 2016
Available online 3 March 2016

Keywords:
Compressive sensing
Particle filtering
Target tracking

A B S T R A C T

Compressive sensing and processing (CSP) performs signal acquisition and processing at sub-Nyquist rates. This makes CSP an attractive option in radar target tracking as it reduces computational load in sequential signal acquisition and processing. However, CSP is accompanied by a reduction in signal to noise ratio (SNR) which results to a deterioration of tracking performance. In order to improve tracking performance CSP can be configured using information available on the target state which is provided by the sequential estimation process. In this work, adaptive CSP is applied to a target tracking scenario. A particle filtering implementation using adaptive CSP is developed for tracking a single target. Simulation results are provided to demonstrate the improvement in SNR and in tracking a single target by adaptive CSP over non-adaptive CSP and previously proposed adaptive CSP methods.

1. Introduction

In target tracking applications the sensing and processing of high dimensional signals collected by multiple sensors at the Nyquist rate places a high computational burden on the acquisition and processing system of the tracker. Compressive sensing offers the possibility of signal acquisition at a sub-Nyquist rate while preserving the information contained in the received signal. Sub-Nyquist acquisition is possible when signals are sparse in a certain basis or dictionary [1–6]. In radar target tracking applications received signals are indeed sparse due to the presence of only a few targets in a wide observation field [5]. Therefore, compressive sensing can reduce the size of data needed to be taken at each time step of the tracking scenario. Compressive sensing is most often applied using a universal mechanism that does not need to be adapted to the specific application considered. Therefore, non-adaptive compressive sensing has the potential to operate with simple and inexpensive hardware [4]. After compressive sensing l_1-norm optimization [7–11] can be used to identify the sparse elements and reconstruct the original signal. Adaptive compressive sensing methods also exist [12,13] that are able to improve signal recovery in noise. In this class of adaptive methods the compressive sampling process is configured during signal acquisition.

Instead of using reconstruction, measurements can be processed directly in their compressed form using compressive sensing and processing (CSP) [14]. CSP simplifies receiver design and reduces computational complexity by processing low-dimensional signals. CSP, however, reduces signal to noise ratio (SNR) [14] and increases ambiguity function surface sidelobes compared to Nyquist sensing and processing (NSP) [15], therefore, deteriorating tracking performance [16].

Adaptive compressive sensing and processing (ACSP) methods were proposed in [16,17,15] that are able to improve SNR and enhance tracking performance compared to non-adaptive CSP. Adaptive CSP methods use information on the structure of signals that will be received at the next time step of the tracking scenario. The information on the

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http://dx.doi.org/10.1016/j.sigpro.2016.02.019
0165-1684/

structure of signals to be received is derived from available information on the target state given by the Bayesian sequential tracking process. This information is embedded in the sensing matrix used in compressive sensing in a single step prior to the acquisition of new signals. Therefore, the adaptive methods proposed differ from other work on adaptive compressive sensing where the adaptation process generates rows of the acquisition matrix based on measurements obtained using previously generated rows of the matrix [12,13,18–21]. The benefits of ACSP were demonstrated in [17] where it was shown that the identification of the true sparse elements in the signal when using ACSP was improved compared to non-adaptive CSP. In addition, in [16] it was shown that when using adaptation in CSP the SNR improves compared to the non-adaptive CSP case. In [15] a novel method to adapt the sensing matrix using tracking information in ACSP was shown to improve the mainlobe to maximum sidelobe ratio of the radar ambiguity function surface.

In this work, the ACSP method proposed in [15] is utilized in a single target tracking application and compared to other ACSP methods and the non-adaptive CSP method in terms of SNR and tracking performance in a single target tracking scenario. Moreover, ACSP is combined with a particle filtering method based on likelihood sampling [22] and is capable of data fusion of measurements from multiple independently reconfigurable radar sensors. The benefits of using the ACSP method over non-adaptive CSP is shown in terms of improvement in the SNR and gains in single target tracking performance.

In Section 2 the target motion and signal acquisition models are described along with the measurement processing method the definition of the SNR. In Section 3 Bayesian target tracking is outlined and the structure of the received radar signal in a tracking scenario is estimated one step ahead. Moreover, the expected SNR estimated one step ahead is provided based on the prediction of the structure of the signal to be received. The expected SNR forms the basis for configuring the ACSP mechanism. In Section 4, sensing matrix constructions defining the sensing and processing mechanism are provided. In Section 5 a practical target tracking algorithm is described using a likelihood particle filter. In Section 6 simulations of a single target tracking scenario and a numerical comparison of the expected SNR are used to compare tracking performance when using adaptive methods and non-adaptive CSP. A list of important notation and acronyms is provided in Table 1.

Table 1
Notation and acronyms.

$\mathbf{x}_k$: Target state vector at time step k.
$p(\mathbf{x}_k|\mathbf{x}_{k-1})$: Target kinematic distribution.
C, M: Number of compressive and Nyquist rate measurements respectively.
$\mathbf{s}_l$: Length M elementary signal with energy ξ_s corresponding to target state vector $\mathbf{x}_k$ according to (2) indexed by l.
$\mathcal{L}_u$: Set of signal elements that may appear in the field of view of sensor u with cardinality $L_u = |\mathcal{L}_u|$.
$\mathbf{\Psi}$: Size $M \times L_u$ matrix which contains elements $\frac{1}{\sqrt{\xi_s}}\mathbf{s}_l$ in its columns having indices l that belong to set $\mathcal{L}_u$.
$\mathbf{r}_{l,u,k}$: The length M received radar signal acquired at the Nyquist rate by sensor u at time step k.
$\mathbf{h}_{l,u,k}$: The length C received signal acquired at a sub-Nyquist rate.
$\mathbf{\Phi}_{u,k}$: The $C \times M$ sensing matrix where $C < M$.
$\mathbf{g}_l$: Length C elementary signal templates representing compressive counterparts of elementary signals $\mathbf{s}_l$.
$y_{u,k}(\bar{l}, l)$: Matched filter statistic for sensor u at time step k.
$R_{u,k}$: The output SNR when acquiring measurements with sensing matrix $\mathbf{\Phi}_{u,k}$.
R_{IP}: The SNR of the received signal.
$p(\mathbf{x}_k|\mathbf{y}_{k-1})$: The posterior distribution of the unknown state, using measurements up to time step $k-1$.
$p_{u,k}(l)$: The probability of an element indexed by l appearing in the received waveform at time k can be expressed
$\mathcal{L}_{u,k}$: Set containing signal elements l having probability $p_{u,k}(l) > \epsilon_p$ where ϵ_p is a probability threshold.
$p(\mathbf{x}_k|\mathbf{y}_k)$: The posterior distribution of the target state.
$\hat{\mathbf{x}}_k$: Estimate of the target state.
$\overline{R}_{u,k}$: The expected SNR.
$\mathbf{S}$: Size $M \times L_{u,k}$ matrix which contains elements $\frac{1}{\sqrt{\xi_s}}\mathbf{s}_l$ in its columns having indices l that belong to set $\mathcal{L}_{u,k}$.
$\mathbf{A}$: Size $L_{u,k} \times L_{u,k}$ diagonal matrix with diagonal entries $\alpha_l = \sqrt{L_{u,k} p_{u,k}(l)},\ l = 1, \ldots, L_{u,k}$.
$\mathbf{Q}$: Random $C \times L_{u,k}$ with orthonormal rows.
$\mathbf{x}_k^n$: Realization of the target state vector at time step k where $n=1,\ldots,N$.
w_k^n: Particle weights representing discrete values of the multitarget posterior at time step k where $n=1,\ldots,N$.
$\Lambda_{u,k}^n(l)$: Normalized likelihood ratio from sensor u at time k for $l = 1, \ldots, L_{u,k}$.
CSP: Compressive sensing and processing.
ACSP: Adaptive compressive sensing and processing.
AWCSP: Adaptive weights compressive sensing and processing.
ADCSP: Adaptive dictionary compressive sensing and processing.
ASCSP: Adaptive sampling compressive sensing and processing.
NSP: Nyquist sensing and processing.
RIP: Restricted isometry property.
CAZAC: Constant amplitude zero autocorrelation waveforms.
SNR: Signal to noise ratio.