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Jointly Optimized Target Detection and Tracking Using Compressive Samples

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ABSTRACT In this paper, we consider the problem of joint target detection and tracking in compressive sampling and processing (CSP-JDT). CSP can process the compressive samples of sparse signals directly without signal reconstruction, which is suitable for handling high-resolution radar signals. However, in CSP, the radar target detection and tracking problems are usually solved separately or by a two-stage strategy, which cannot obtain a globally optimal solution. To jointly optimize the target detection and tracking performance and inspired by the optimal Bayes joint decision and estimation (JDE) framework, a jointly optimized target detection and tracking algorithm in CSP is proposed. Since detection and tracking are highly correlated, we first develop a measurement matrix construction method to acquire the compressive samples, and then a joint CSP Bayesian approach is developed for target detection and tracking. The experimental results demonstrate that the proposed method outperforms the two-stage algorithms in terms of the joint performance metric.

INDEX TERMS Compressive samples, joint decision and estimation, joint detection and tracking, joint performance metric.

I. INTRODUCTION

Compressive sensing/sampling (CS) is a new theory of signal acquisition that can acquire sparse signals at sub-Nyquist rates and reconstruct the original signals through compressive samples and recovery algorithms [1], [2]. Recently, applying CS to radar systems has become a popular research topic, especially in signal recovery, signal detection and parameter estimation [3]–[5]. Since modern radar systems often work on wide bandwidths, which require a high sampling rate and processing speed to meet the real-time requirements in transmission, calculation and storage, CS can alleviate these pressures.

Most prevailing CS radars require complete or partial recovery of the original signal. However, the recovery algorithms often lead to problems of high computational complexity and large time consumption due to their nonlinear and iterative processes [6]. For many cases, such as target detection, estimation and classification, reconstructing the compressively measured radar signal is unnecessary. Thus, a new framework called compressive sensing and processing (CSP) [6] is proposed. This approach can avoid the above difficulties by processing the compressive samples directly without signal recovery. Compared to Nyquist sampling and processing (NSP), CSP possesses the ability to reduce the computational pressure and the transmission burden for wide bandwidth signals, but the low signal-to-noise-ratio (SNR) of the compressive samples gives rise to the main difficulty of CSP.

In recent years, CSP has been studied to solve many signal processing problems in radar systems, such as detection, classification, estimation, and filtering. The existing compressive radar detectors in CSP can be mainly divided into three categories. The first category consists of detectors that are designed by directly using the compressive samples to achieve signal detection. In [7] and [8], the compressive detectors based on matched filters are designed without reconstruction. In [9], the compressive detection problem with a low SNR is studied by considering the accumulation of the compressive samples and the distribution of the sparse signal nonzero element amplitudes. The detectors in the second category are designed by constructing a

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measurement matrix with prior information. In [10] and [11], compressive Bayesian detectors are proposed under the condition that the prior probabilities of two hypotheses are available. In addition, a random subspace detector is studied for unknown-parameter sparse signal detection [12], but the fixed subspace must be acknowledged before detection, which may limit the application of this detector. The third category consists of detectors designed by optimizing the transmitted waveform. In [13] and [14], waveform optimization methods without signal recovery are proposed to increase the detection performance by increasing the SNR of the transmitted waveform before detection.

The existing CS tracking algorithms mainly focus on how to track time-varying sparse signals whose sparse nonzero elements change slowly. Different types of filters based on CS are exploited to reduce the workload when sensing dynamic sparse signals, such as the CS-Kalman, CS-MUSIC, CS-Bayesian, and CS-Particle filters [15]–[18]. However, these filters are not suitable for radar target tracking when the target signals are changing rapidly. To solve this problem, two compressive tracking approaches have been studied in CSP. The first approach, as shown in Fig. 1(a), uses detection before tracking in CSP (CSP-DBT), where a CS detector [7]–[14] performs the target detection first, and then a traditional tracking filter accomplishes the target tracking. The second approach, as shown in Fig. 1(b), uses tracking before detection in CSP (CSP-TBD), where novel methods are proposed by feeding the tracking results to a compressive sampling procedure to improve the detection performance at next time step [19], [20]. In [19], an adaptive particle filter-based tracking algorithm is developed for radar target tracking, where the filtered target result is adopted to construct the measurement matrix for the next moment, and the signal detection is performed in a compressive matched filter. In [20], a variational Bayesian adaptive Kalman filter (VBAKF) method based on a pretracking compressive subspace detector is developed for

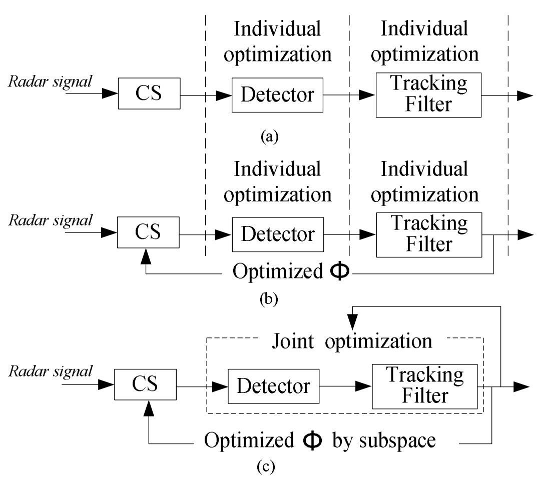

FIGURE 1. Approaches for target detection and tracking in CSP: (a) detection before tracking; (b) tracking before detection; (c) joint detection and tracking.

target tracking, where the pretracking detector utilizes the tracking result from the previous moment to improve the detection performance at the current moment.

The above studies in CSP focus either on CS-detection or CS-tracking only. The same problem also exists in the NSP framework, i.e., target detection and tracking in radar systems are optimized individually. In NSP, detection before tracking (DBT) is the most widely used strategy, where the detection is performed with different kinds of constant false alarm rate (CFAR) detectors or generalized likelihood ratio test (GLRT) detectors. Different tracking algorithms are exploited for different tracking problems. Typically, the Markovian jump system (MJS) and the interacting multiple model (IMM) algorithm can solve the maneuvering target tracking problems [21]. The unscented Kalman filter (UKF) [22], extended Kalman filter (EKF) [23], and particle filter (PF) [24] are exploited for nonlinear uncertainty problems. The expectation-maximization (EM) [25] method and variational Bayes (VB) [26] method are popular for unknown parameter problems. The joint probabilistic data association (JPDA) [27] and multiple hypothesis tracker (MHT) [28] can handle multiple target tracking problems by using data association. Moreover, to avoid data association, the probability hypothesis density (PHD) filter [29], cardinality probability hypothesis density (CPHD) [30], and Bernoulli filter (BF) [31] can calculate the intensity of the targets directly based on the finite set statistics (FISST). However, the DBT may fail to handle weak targets with a low SNR. Thus, the tracking before detection (TBD) strategy is considered to improve the detection ability of weak targets. The prevailing TBD methods include three-dimensional matched filtering (3DMF-TBD) [32], Hough transform (HT-TBD) [33], dynamic programming (DP-TBD) [34], and PF-TBD [35]. The specific progress of the DBT and TBD strategies can be found in comprehensive surveys [36]–[40], but the DBT and TBD strategies still follow the individual optimization approach, which does not take joint optimization into account. Since target detection and tracking are highly coupled, the separate solutions are likely to propagate the cumulative errors, which means that poor detection may deteriorate the tracking result and that the error yielded in the tracking filter can lead to incorrect target detection. Intuitively, the joint optimization of detection and tracking is more promising than separate solutions. Thus, Li proposed a joint Bayesian approach to make the most of the correlation between the decision and estimation (JDE) [41]–[44]. In the JDE approach, the decision is to choose a discrete value, which includes the detection, classification, association and other problems over discrete data. Estimation is a parameter inference problem, such as that of prediction, filtering, smoothing and tracking. From the optimization theoretic view, this joint approach can achieve a globally optimal solution. Following the Bayes JDE framework, a conditional JDE (CJDE) algorithm is developed in [42] to simplify the calculation of JDE, and a recursive JDE (RJDE) [43] is derived for the dynamic JDE problems. In [44], a joint tracking and identification (JTI) problem is handled by using a compact CJDE (CCJDE) scheme to improve the joint performance. However, to the best of our knowledge, the joint optimization for target detection and tracking in CSP has not yet been studied. Since compressive samples are different from Nyquist samples, the optimal Bayes JDE in NSP cannot directly deal with CSP problems.

Inspired by the optimal Bayes JDE, this paper proposes a jointly optimized target detection and tracking (CSP-JDT) method within the CSP framework, which can directly detect and track a target with the compressive samples of radar echo. As shown in Fig. 1(c), to optimize the CS-detection and CS-tracking performance jointly, the tracking result is fed back to the compressive sampling and tracking procedures. This double closed-loop feedback structure can make the most of the target tracking results and perform system adjustment automatically. Specifically, the filtered target position from the previous moment is utilized as a priori information for the compressive sampling at the current moment. In CSP-JDT, an adaptive compressive subspace detector is first developed to detect whether there is a target in the compressive samples, although this detector cannot obtain the target position. Then, a JDT algorithm is adopted to locate and track the target. Since the detection and tracking are highly coupled, the proposed CSP-JDT defines a new CSP-JDT risk that unifies the detection risk and tracking risk and presents the optimal CSP-JDT solution by minimizing the risk. The effectiveness of the proposed CSP-JDT is verified by handling two illustrative JDT problems. The experimental results show that the proposed detector in CSP-JDT can achieve a high detection probability with a low SNR, and the proposed CSP-JDT method outperforms the two-stage categories in the joint performance metric (JPM).

The main contributions are given as follows:

1) A novel joint optimization method for target detection and tracking in CSP (CSP-JDT) is developed in this paper. Compared with the local optimization obtained by separate CS-detection or individual CS-tracking, the proposed CSP-JDT integrates the CS-detection and CS-tracking risks in an effective way, which can guarantee the joint global optimality of the detection probability and position estimation.

2) In this paper, a new CSP-JDT risk is derived, and the optimal CSP-JDT solution is given. The CSP-JDT method is proposed for processing compressive samples, which is different from the optimal Bayes JDE for processing Nyquist samples. Due to the direct processing of compressive samples, CSP-JDT can avoid the high computational complexity caused by recovery algorithms.

3) CSP-JDT adopts a double closed-loop feedback structure, which can fully exploit the filtered target kinematic state. First, CSP-JDT utilizes this prior information to construct the measurement matrix and determines the subspace where the target may exist. Different from the fixed subspace in [12], the proposed subspace is adaptively changed with the prior information, and it can further reduce the calculation amount by reducing the detection range. Then, CSP-JDT uses the prior information to jointly locate and track the target in the subspace range, which can achieve a global optimization. Thus, CSP-JDT can handle the coupled detection and tracking problem effectively.

4) By applying CSP-JDT to two dynamic JDT problems, the superiority of CSP-JDT is demonstrated in the joint detection and tracking performance.

This paper is organized into five sections. Section II presents important preliminary knowledge of sparse radar signals and compressive measurements and briefly introduces the Bayes JDE. Section III proposes the CSP-JDT method and its solution. Section IV presents the experimental results and the performance comparison with the two-stage methods. Section V concludes the paper.

II. SYSTEM MODEL

A. SPARSE RADAR WAVEFORM MODEL

A radar echo is the reflection signal after the transmitted signal $s(t)$ encounters the targets, where $t \in [0, T]$, and T is the pulse repetition interval. Suppose there are I targets, and each target falls into one distance cell. Then, the received waveform of the lth target is given by

$$g_l(\tau_l, t) = a_l s(t - \tau_l) e^{j2\pi v_l t} \tag{1}$$

where τ_l, a_l and v_l denote the delay, amplitude, and Doppler shift, respectively, $l = 1, \cdots, I$. Each a_l is assumed independent of each other and obeys a Gaussian distribution $N(0, \sigma_x^2)$. The range and velocity are defined as $d_l = c\tau_l/2$ and $\dot{d}_l = cv_l/2f_c$, where c denotes the speed of light, and f_c is the carrier frequency. Thus, the received radar echo is formulated as

$$\tilde{r}(t) = r(t) + w(t) = \sum_{l=1}^{I} g_l(\tau_l, t) + w(t) \tag{2}$$

where $w(t)$ obeys the additive white Gaussian noise distribution $N(0, \sigma_0^2)$.

Because a target only falls into one distance cell in a radar observation range, $r(t)$ is indeed sparse. With the sampling frequency f_s, the received waveform length is $N = Tf_s$. Suppose the radar observation interval is $[D_0, D_1]$ and the bandwidth is B, then the range resolution is $\Delta d = c/2B$ and the total number of distance cells is $L = (D_1 - D_0)/\Delta d$. $r(t)$ is sparse in the received waveform space $\mathbf{\Psi} = span\{s_1(t), s_2(t), \cdots, s_L(t)\}$, where $s_l(t) = s(t - \tau_l)e^{j2\pi v_l t}$, and τ_l is the delay.

B. COMPRESSIVE MEASUREMENT MODEL

In CS, the received radar echo $r(t)$ can be compressively sampled by a measurement matrix $\mathbf{\Phi} = span\{\phi_1(t), \phi_2(t), \cdots, \phi_M(t)\}$, then the compressive samples $\mathbf{y} = [y_1, y_2, \cdots, y_M]^T$ are given by

$$y_m = \int_{-\infty}^{\infty} r(t)\phi_m(t)dt = \sum_{i=1}^{I} a_{l_i} \int_{-\infty}^{\infty} s_{l_i}(t)\phi_m(t)dt \tag{3}$$

where $m = 1, \cdots, M$. Since the SNR of $r(t)$ is decreased in $\mathbf{y}$, most existing CS detectors need to reconstruct the signal $r(t)$ from $\mathbf{y}$ for target detection, which is time-consuming [6]. However, the CSP detectors [7]–[14] can perform target detection without signal recovery, which can meet the real-time requirements for target tracking.

C. REVIEW OF THE BAYES JDE

Many practical applications often involve discrete and continuous uncertainties, such as target recognition and tracking and target detection and tracking. These problems can be considered as joint decision and estimation (JDE) problems, where the decision and estimation affect each other. Two prevailing methods for solving the JDE problems can be summarized as follows: a) decision before estimation (DBE): an optimal decision is determined by its own information, and then a corresponding estimation is made by the estimator based on this decision. Here, the estimation result fails to help the decision, and the decision error may make the estimation result worse. b) Estimation before decision (EBD): the estimation is conducted first to assist the decision-making, where the estimation error may lead to the reduction of the decision performance.

To overcome the above drawbacks, Li proposed a new generalized Bayes risk by jointly solving the decision problem and estimation problem [41]:

$$\bar{R} = \sum_i \sum_j (\alpha_{ij} c_{ij} + \beta_{ij} E[C(x,\hat{x})|D_i, H_j]) P\{D_i, H_j\} \tag{4}$$

where $\hat{x}$ is the estimate of the true x. H_j denotes the jth hypothesis, D_i denotes the ith decision, and $C(x,\hat{x})$ stands for the estimating cost. c_{ij} is the decision cost, and $E[C(x,\hat{x})|D_i, H_j]$ is the expectation of the conditioned estimation cost when D_i is decided but H_j is true. According to practical JDE problems, the nonnegative decision cost weight α_{ij} and estimation cost weight β_{ij} are chosen differently.

This risk possesses the following advantages: (a) It is a joint risk that considers the decision cost, the estimation cost and their coupling together. (b) The hypothesis set and the decision set need not have one-to-one correspondence. (c) The weight factors (α_{ij}, β_{ij}) provide additional flexibility. Thus, it theoretically outperforms the two-stage methods.

Following the concept of the JDE, a CJDE risk [42] is proposed to simplify the calculation of the JDE by utilizing the measurement z:

$$R_C(z) = \sum_i \sum_j (\alpha_{ij} c_{ij} + \beta_{ij} E[C(x,\hat{x})|D_i, H_j, z]) P\{D_i, H_j|z\} \tag{5}$$

Moreover, the recursive JDE risk [43] and recursive CJDE risk [42] are studied for dynamic JDE problems.

III. JOINT DETECTION AND TRACKING IN CSP

Traditional JDE algorithms [41]–[44] have been proposed for processing the Nyquist sampling measurements, which do not fit the CSP problems. In this paper, our goal is to jointly detect and track a single target by directly using the compressive radar data without signal reconstruction. More specifically, detection is used to locate the target position in the compressive samples, and tracking is used to estimate the true target state. To make full use of the target spatial correlation in the radar echoes, the filtered target position is fed back to the sampling procedure at the next moment, which means we adopt the filtered target position at the last moment to construct the measurement matrix to guide the signal acquisition at the current moment. Thus, in CSP-JDT, we first construct the subspace by utilizing the tracking result at the last time step. Then, we develop an adaptive compressive subspace detector to judge whether there is a target in the compressive samples. Finally, we perform a JDT algorithm to determine the target location and accomplish target tracking in CSP.

A. SUBSPACE CONSTRUCTION

In [12], a random signal with a known sparsity can be detected by a compressive detector with a fixed subspace. However, this detector is not suitable for time-varying sparse signals. To solve this problem, the fixed subspace is replaced by an adaptive subspace $\mathbf{\Lambda}_k$. The subspace $\mathbf{\Lambda}_k$ is obtained by the predicted $\hat{x}_{k|k-1}$, which can be calculated from the filtered $\hat{x}_{k-1}$ by a target motion model. Since the target true position is near the predicted position, we suppose that the error between them will not exceed $K/2$ distance cells, then the target is likely to fall within K distance cells.

Consider a noiseless return waveform

$$r(t) = \sum_{i=1}^{K} a_{l_i} s_{l_i}(t) \tag{6}$$

where $a_{l_1}, a_{l_2}, \cdots a_{l_K}$ are the nonzero sparse coefficients. Thus, $\mathbf{\Lambda}_k = span\{s_{l_1}(t), s_{l_2}(t), \cdots, s_{l_K}(t)\}$ can be considered as a subspace of $\mathbf{\Psi}$.

For simplicity, $s_{l_i}(t)$ can be rewritten in its discrete form as

$$s_{l_i}(t) = s(t-\tau_{l_i})e^{j2\pi vt} = \sum_{n=0}^{N-1} s(n-n_{l_i}) \sin \mathrm{c}(tf_s - n) \tag{7}$$

where $i = 1, 2, \cdots, K$. The predicted subspace $\mathbf{\Lambda}_k$ can be represented in its discrete form as

$$\mathbf{\Lambda}_k = \begin{bmatrix} s(-n_{l_1}) & \cdots & s(-n_{l_K}) \\ s(1-n_{l_1}) & \cdots & s(1-n_{l_K}) \\ \vdots & \vdots & \vdots \\ s(N-1-n_{l_1}) & \cdots & s(N-1-n_{l_K}) \end{bmatrix} \tag{8}$$

B. ADAPTIVE COMPRESSIVE SUBSPACE DETECTOR

The hypothesis testing problem can be formulated as

$$\begin{cases} \tilde{H}_0 : \mathbf{y}_k = \mathbf{w}_k \\ \tilde{H}_1 : \mathbf{y}_k = \mathbf{\Phi}_k \mathbf{r}_k + \mathbf{w}_k \end{cases} \tag{9}$$

Here, the same detector design method in [12] is adopted to design the adaptive compressive subspace detector. The measurement matrix $\mathbf{\Phi}_k$ is constructed by $\mathbf{\Lambda}_k$. The SVD of the discrete $\mathbf{\Lambda}_k$ is given by

$$\mathbf{\Lambda}_k = \mathbf{U}_k \mathbf{D}_k \mathbf{V}_k \tag{10}$$

Then, we can obtain two orthogonal matrices $\mathbf{U}_k \in N \times N$ and $\mathbf{V}_k \in K \times K$, and a diagonal matrix $\mathbf{D}_k \in N \times K$. $\rho_1^2 \geq \rho_2^2 \geq \cdots \geq \rho_N^2 \geq 0$ are the nonnegative eigenvalues of $\mathbf{\Lambda}_k \mathbf{\Lambda}_k{}^T$ and $\rho_1^2 > \rho_N^2$. The first M_1 columns of $\mathbf{U}_k$ are denoted as $\mathbf{U}_{s,k}$ and the last M_2 columns as $\mathbf{U}_{o,k}$, where $M = M_1 + M_2$. Then, $\mathbf{\Phi}_k$ is designed as

$$\mathbf{\Phi}_{s,k} = \frac{1}{\sqrt{M}} \mathbf{T}_{s,k} \mathbf{U}_{s,k}^T, \quad \mathbf{\Phi}_{s,k} \in M_1 \times N$$
$$\mathbf{\Phi}_{o,k} = \frac{1}{\sqrt{M}} \mathbf{T}_{o,k} \mathbf{U}_{o,k}^T, \quad \mathbf{\Phi}_{o,k} \in M_2 \times N \tag{11}$$

where $\mathbf{T}_{s,k} \in M_1 \times M_1$ and $\mathbf{T}_{o,k} \in M_2 \times M_2$ are orthogonal matrices. Specifically, $\mathbf{\Phi}_{s,k}$ can be rewritten as

$$\mathbf{\Phi}_{s,k} = \begin{bmatrix} \phi_{s,k}(1,1) & \cdots & \phi_{s,k}(1,N) \\ \phi_{s,k}(2,1) & \cdots & \phi_{s,k}(2,N) \\ \vdots & \vdots & \vdots \\ \phi_{s,k}(M_1,1) & \cdots & \phi_{s,k}(M_1,N) \end{bmatrix} \tag{12}$$

and $\mathbf{\Phi}_{o,k}$ is in the similar form. The base of $\mathbf{\Phi}_k$ is represented as

$$\phi_{s,m_s}(t) = \sum_{n=0}^{N-1} \phi_s(m_s, n) \sin c(tf_s - n)$$
$$\phi_{o,m_o}(t) = \sum_{n=0}^{N-1} \phi_o(m_o, n) \sin c(tf_s - n) \tag{13}$$

where ϕ_{s,m_s} denotes the m_sth row of $\mathbf{\Phi}_{s,k}$, and $m_s = 1, \cdots, M_1$(likewise for ϕ_{o,m_o}). Thus,

$$\mathbf{\Phi}_k = span\{\phi_{s,1}(t), \cdots, \phi_{s,M_1}(t), \phi_{o,1}(t), \cdots, \phi_{o,M_2}(t)\} \tag{14}$$

Through CS $r(t)$ by $\mathbf{\Phi}_k$

$$y_{s,m} = \int_{-\infty}^{\infty} r(t)\phi_{s,m} dt = \sum_{i=1}^{K} a_{l_i} \int_{-\infty}^{\infty} s_{l_i}(t)\phi_{s,m}(t) dt$$
$$y_{o,m} = \int_{-\infty}^{\infty} r(t)\phi_{o,m} dt = \sum_{i=1}^{K} a_{l_i} \int_{-\infty}^{\infty} s_{l_i}(t)\phi_{o,m}(t) dt \tag{15}$$

The compressive samples can be obtained as $\mathbf{y}_k = [y_{s,1}, y_{s,2}, \cdots, y_{s,M_1}, y_{o,1}, y_{o,2}, \cdots, y_{o,M_2}]^T$. As proven in [12, Theorem 1], the designed $\mathbf{\Phi}_{s,k}$ and $\mathbf{\Phi}_{o,k}$ in (11) can solve the following optimization problems:

$$\arg\max_{\mathbf{\Phi}_{s,k}} \mathbf{E}_{\mathbf{r},\mathbf{w}}(||\mathbf{y}_{s,k}||_2^2), \ s.t. \ M\mathbf{\Phi}_{s,k}\mathbf{\Phi}_{s,k}{}^T = \mathbf{I}_{M_1}$$
$$\arg\min_{\mathbf{\Phi}_{o,k}} \mathbf{E}_{\mathbf{r},\mathbf{w}}(||\mathbf{y}_{o,k}||_2^2), \ s.t. \ M\mathbf{\Phi}_{o,k}\mathbf{\Phi}_{o,k}{}^T = \mathbf{I}_{M2} \tag{16}$$

Thus, $r(t)$ can be separated into its largest energy part and its smallest energy part by $\mathbf{\Phi}_{s,k}$ and $\mathbf{\Phi}_{o,k}$, respectively. As shown in [12, Theorem 2], we can obtain the test statistic

$$\mathcal{T} = \frac{\mathbf{y}_{s,k}{}^T \mathbf{y}_{s,k}}{\mathbf{y}_{o,k}{}^T \mathbf{y}_{o,k}} \mathop{\gtrless}_{\tilde{H}_0}^{\tilde{H}_1} \gamma \tag{17}$$

where γ is the threshold. Define the probability of false alarm as $P_{FA} = Q_{F(M_1,M_2)}(\gamma)$. The probability of detection is bounded within $P_{D,low} \leq P_D \leq P_{D,up}$

$$P_{D,low} = Q_{F(M_1,M_2)}(\eta_{low}\gamma)$$
$$P_{D,up} = Q_{F(M_1,M_2)}(\eta_{up}\gamma) \tag{18}$$

where $\eta_{low} = \frac{\sigma_0^2 + \sigma_x^2 \rho_{N-M_2+1}^2}{\sigma_0^2 + \sigma_x^2 \rho_{M_1}^2}$, $\eta_{up} = \frac{\sigma_0^2 + \sigma_x^2 \rho_N^2}{\sigma_0^2 + \sigma_x^2 \rho_1^2}$, and $Q_{F(M_1,M_2)}(\eta_{low}\gamma)$ obeys an F-distribution with M_1 and M_2 degrees of freedom at point $\eta_{low}\gamma$.

If no target is detected by the proposed detector in $\mathbf{y}_k$, the following target location and target tracking can be skipped for this $\mathbf{y}_k$, which can accelerate the processing speed. If a target is detected by the proposed detector in $\mathbf{y}_k$, which means the target exists in the subspace $\mathbf{\Lambda}_k$, then a JDT method in CSP is adopted to locate and track the target in $\mathbf{\Lambda}_k$.

C. CSP-JOINT DETECTION AND TRACKING RISK

Applying the JDT algorithm to target detection and tracking for compressive samples requires first determining the detection and tracking problems. Since the tracking result of the previous time step is utilized, the target exists in the distance cells corresponding to the subspace $\mathbf{\Lambda}_k$, so the detection problem at the current time step is to determine the specific position of the target in the subspace $\mathbf{\Lambda}_k$, and the tracking problem is to estimate the true target position. Therefore, in the CSP-JDT problem, the conditions are set as

$$\mathrm{H}(\mathbf{\Lambda}_k) = \left\{H_0^k, H_1^k, \cdots, H_K^k\right\} \tag{19}$$
$$\mathrm{D}(\mathbf{\Lambda}_k) = \left\{D_0^k, D_1^k, \cdots, D_K^k\right\} \tag{20}$$

The hypothesis set $\mathrm{H}(\mathbf{\Lambda}_k)$ contains $K+1$ hypotheses at time k, where H_0^k indicates that the target appears outside the subspace $\mathbf{\Lambda}_k$, and the last K hypotheses indicate that the target appears in the K distance units corresponding to their respective subspace $\mathbf{\Lambda}_k$. The detection set $\mathrm{D}(\mathbf{\Lambda}_k)$ contains $K+1$ detection decisions at time k, where D_0^k indicates that the decision target appears outside the subspace $\mathbf{\Lambda}_k$, and the last K detections indicate that the decision target falls in the K distance units corresponding to their respective subspace $\mathbf{\Lambda}_k$.

In CSP-JDT, the core idea is to minimize the Bayesian risk function at time k.

$$\bar{R}(\mathbf{\Lambda}_k) = \sum_i \sum_j (\alpha_{ij} c_{ij}(\mathbf{\Lambda}_k) + \beta_{ij} E[C(x_k, \hat{x}_k)|D_i^k, H_j^k]) P\{D_i^k, H_j^k\} \tag{21}$$

where D_i^k represents the ith decision at time k, i.e., the compressive samples $\mathbf{y}^k \in \mathcal{D}_i^k$ ($\mathcal{D}_i^k$ represents the region for D_i^k). Here, as shown in (22),we design a method to judge whether $\mathbf{y}^k$ falls into $\mathcal{D}_i^k$. Supposing the decision D_i^k is made, which means the target falls in the distance cell corresponding to D_i^k, we can use the corresponding signal $s(t - \tau_{l_i})$, denoted by s_{l_i}, to construct the compressive samples $\mathbf{y}_i^k = \mathbf{\Phi} s_{l_i}$. If the inner product of $\mathbf{y}^k$ and $\mathbf{y}_i^k$ exceeds a certain threshold Th, then $\mathbf{y}^k$

falls into $\mathcal{D}_i^k$, otherwise $\mathbf{y}^k \notin \mathcal{D}_i^k$.

$$\mathcal{D}_i^k = \{\mathbf{y}^k | \left|\left\langle \mathbf{y}^k, \mathbf{y}_i^k \right\rangle\right| \geq Th\} \quad (22)$$

D. OPTIMAL CSP-JDT SOLUTION

We can obtain the optimal CSP-JDT solution by minimizing the above CSP-JDT risk $\bar{R}(\mathbf{\Lambda}_k)$.

1) OPTIMAL DECISION

For any given $\varepsilon_{ij}^k = E[C(x_k, \hat{x}_k)|D_i^k, H_j^k]$, the optimal decision $D(\mathbf{\Lambda}_k)$ is given by

$$D(\mathbf{\Lambda}_k) = D_i^k, \text{if } C_i^k(\mathbf{y}^k) \leq C_h^k(\mathbf{y}^k), \quad h = 1, 2, \cdots, K \quad (23)$$

where the posterior decision cost is given by

$$C_i^k(\mathbf{y}^k) = \sum_j (\alpha_{ij} c_{ij}(\mathbf{\Lambda}_k) + \beta_{ij}\varepsilon_{ij}^k) P\{H_j^k|\mathbf{y}^k\}, \quad \forall i \quad (24)$$

2) OPTIMAL ESTIMATION

For any decision D_i^k, the optimal estimator with estimation cost $C(x_k, \hat{x}_k)$ for calculating $\bar{R}_i(\mathbf{\Lambda}_k)$ is formulated as

$$\hat{x}_k = {x_k}^{(i)} = \sum_j \hat{x}_k^{(j)} \bar{P}_k^{(i)}\{H_j^k|\mathbf{y}^k\} \quad (25)$$

where $\hat{x}_k^{(j)} = E[x_k|\mathbf{y}^k, D_i^k, H_j^k]$ is the conditioned state when the hypothesis is H_j^k. The generalized posterior probability $\bar{P}_k^{(i)}\{H_j^k|\mathbf{y}^k\}$ can be calculated by

$$\bar{P}_k^{(i)}\{H_j^k|\mathbf{y}^k\} = \frac{\beta_{ij}^k P\{H_j^k|\mathbf{y}^k\}}{\sum_h \beta_{ih}^k P\{H_h^k|\mathbf{y}^k\}} \quad (26)$$

Note that in the above (23) and (24), the key is to obtain the posterior probability $P\{H_j^k|\mathbf{y}^k\}$, the conditioned state estimate $\hat{x}_k^{(j)}$ and the expected estimation cost ε_{ij}^k.

Specifically, $P\{H_j^k|\mathbf{y}^k\}$ can be formulated as

$$P\{H_j^k|\mathbf{y}^k\} = \frac{f\{\mathbf{y}^k|H_j^k\}P\{H_j^k\}}{\sum_{j=1}^{K} f\{\mathbf{y}^k|H_j^k\}P\{H_j^k\}} \quad (27)$$

At different time steps, the hypothesis set $\mathrm{H}(\mathbf{\Lambda}_k)$ and its priori probability $P\{H_j^k\}$ are different. Assume that $\mathrm{H}(\mathbf{\Lambda}_k)$ at time k obeys a Gaussian distribution $N(\hat{x}_{k|k-1}, {\sigma_H}^2 I_4)$, where ${\sigma_H}^2 = \hat{P}_{k|k-1} = F_k \hat{P}_{k-1} {F_k}^T$ is the covariance of the one-step prediction at time $k-1$. Then, $P\{H_j^k\}$ is

$$P\{H_j^k\} = \int_{H_j^k} f(x)dx = \int_{H_j^k} \frac{1}{\sqrt{2\pi}\sigma_H} \exp(-\frac{(x - \hat{x}_{k|k-1})^2}{2{\sigma_H}^2})dx \quad (28)$$

and $P\{H_0^k\} = 1 - \sum_{j=1}^{K} P\{H_j^k\}$. $f\{\mathbf{y}^k|H_j^k\}$ is the probability distribution of $\mathbf{y}^k$ when the hypothesis is H_j. The corresponding signal of H_j is $s(t - \tau_{l_j})$, denoted by s_{l_j}. Then, we can obtain the expectation and covariance of $\mathbf{y}^k$

$$\begin{aligned} E[\mathbf{y}^k] &= E[\mathbf{\Phi} s_{l_j} + \mathbf{\Phi} w] = E[\mathbf{\Phi} s_{l_j}] + E[\mathbf{\Phi} w] \\ &= \mathbf{\Phi} s_{l_j} + \mathbf{\Phi} E[w] = \mathbf{\Phi} s_{l_j} \end{aligned} \quad (29)$$

$$\begin{aligned} cov[\mathbf{y}^k] &= E[(\mathbf{y} - \mathbf{\Phi} s_{l_j})(\mathbf{y} - \mathbf{\Phi} s_{l_j})^H] = E[(\mathbf{\Phi} w)(\mathbf{\Phi} w)^H] \\ &= E[\mathbf{\Phi} w w^H \mathbf{\Phi}^H] = \mathbf{\Phi} E[w w^H] \mathbf{\Phi}^H = \sigma_w^2 \mathbf{\Phi}\mathbf{\Phi}^H \end{aligned} \quad (30)$$

Thus, we consider that $f\{\mathbf{y}^k|H_j^k\}$ obeys a Gaussian distribution $N(\mathbf{\Phi} s_{l_j}, \sigma_w^2 \mathbf{\Phi}\mathbf{\Phi}^H)$, and (27) can be calculated by $P\{H_j^k\}$ and $f\{\mathbf{y}^k|H_j^k\}$.

$\hat{x}_k^{(j)} = E[x_k|\mathbf{y}^k, D_i^k, H_j^k]$ stands for the target state estimate conditioned on hypothesis H_j^k when the decision D_i^k is made, i.e., $\mathbf{y}^k \in \mathcal{D}_i^k$. It equals the estimate of the target state when the target real position is at d_j^k corresponding to H_j^k, and the target measurement position is at d_i^k corresponding to D_i^k. The target measurement equation is given by

$$\mathbf{z}_k = \mathbf{G}\mathbf{x}_k + \mathbf{v}_k \quad (31)$$

where $\mathbf{G}$ denotes the measurement transfer matrix, and $\mathbf{v}_k$ denotes the white Gaussian noise $N(0, \Gamma_k)$.

It can be seen from equation (31) that different D_i^k and H_j^k change the value of Γ_k, that is,

$$\Gamma_k = (d_j^k - d_i^k)^2 \quad (32)$$

Then, the filtered value of the target $\hat{x}_k^{(j)}$ can be obtained by a traditional tracking algorithm, and we can obtain $\varepsilon_{ij}^k = E[(\hat{x}_k - x_k)^2|D_i^k, H_j^k]$ as

$$\varepsilon_{ij}^k = ({x_k}^{(i)} - \hat{x}_{H_j^k})^2 = ({x_k}^{(i)} - d_j^k)^2 \quad (33)$$

In summary, in a single target tracking scenario, one cycle of CSP-JDT at time k consists of the following:

1) Initialization

Obtain the one-step prediction $\hat{x}_{k|k-1}$ of $\hat{x}_{k-1}$ based on the target motion model, construct the $\mathbf{\Phi}_k$ and then get $\mathbf{y}^k$.

2) Update step

Through the adaptive compressive subspace detector, if no target can be detected in $\mathbf{y}^k$, skip this $\mathbf{y}^k$. Otherwise, with $\mathbf{y}^k$ available, update $P\{H_j^k|\mathbf{y}^k\}$ and the initial decision partition $\mathcal{D}(\mathbf{\Lambda}_k) = \left\{\mathcal{D}_0^k, \mathcal{D}_1^k, \cdots, \mathcal{D}_K^k\right\}$.

3) Estimation and decision step

For any decision candidate $D_i^k (i = 1, 2, \cdots, K)$, first make the following judgment: if $\mathbf{y}^k \notin \mathcal{D}_i^k$, skip this iteration; if $\mathbf{y}^k \in \mathcal{D}_i^k$, calculate the optimal state estimate $\hat{x}_k$ corresponding to this iteration. Then, obtain the expected cost ε_{ij}^k and posterior cost $C_i^k(\mathbf{y}^k)$. Finally, obtain the decision D_i^k and the cost $\bar{R}_i(\mathbf{\Lambda}_k)$ of the current iteration.

4) Iteration step

Repeat step 3) K times, and obtain the optimal decision $D(\mathbf{\Lambda}_k)$ through (23) and the smallest $\bar{R}(\mathbf{\Lambda}_k)$.

5) Output

Output the final detection and tracking result $\{D(\mathbf{\Lambda}_k), \hat{x}_k\}$.

E. JOINT PERFORMANCE EVALUATION

Intuitively, to evaluate the target detection and tracking performance, the detection probability (P_d) and root mean square error (RMSE) are often adopted separately. However, without considering the correlation between the detection and tracking in JDE problems, the P_d and RMSE may fail to compare different JDE solutions. Thus, instead of separate evaluations, the detection and tracking performance should be evaluated jointly for JDE problems. For this, a joint performance metric (JPM) was proposed in [41], which is the distance between the real and the one-step measurement. This JPM was extended for the dynamic JDE problems in [42]. In CSP-JDT, we define the JPM as the distance between the true measurement and mock measurement generated by the CSP-JDT method, which is

$$\xi_k = E[(z_k - \hat{z}_{k|k-1})^2 | D^k, D^{k-1}] \tag{34}$$

where z_k represents the target measurement position detected by $\mathbf{y}^k$ and D^k, and $\hat{z}_{k|k-1}$ represents the predicted target measurement position predicted by $\hat{x}_{k-1}$ and D^{k-1}. More details can be seen in [41] and [42].

F. COMPLEXITY ANALYSIS

The leading computational complexity of CSP-JDT is the measurement matrix construction by the adaptive subspace $\mathbf{\Lambda}_k \in N \times K$ (where $K \ll N$), which is $O(N^2K)$ in (10) [45]. Traditionally, after compressively sensing an I-sparse signal $r \in N \times 1$ by the measurement matrix $\mathbf{\Phi} \in M \times N$, the CS methods need to reconstruct the original signal, which is time-consuming. For example, the computational complexity of the orthogonal matching pursuit (OMP) algorithm is $O(IMN)$, and the basis pursuit (BP) algorithm is $O(M^2N^{3/2})$ [46]. However, the CSP-JDT processes the compressive samples directly without signal recovery, which can avoid the above computational complexity caused by the reconstruction algorithms [6]. Then, the computational complexity of CS is $O(MN)$ in (15). Since the subspace reduces the detection range from N distance cells to K, the computational burden of target detection is also reduced. Finally, the joint target detection and tracking can be rapidly achieved through K iterations in (23-25), which is $O(K)$. Therefore, the total computational complexity of CSP-DT to process one frame of a radar signal is $O(N^2K + MN + K)$.

IV. SIMULATION RESULTS

In this section, the simulations are performed to demonstrate the performance of the CSP-JDT for joint target detection and tracking.

A. PERFORMANCE ANALYSIS OF THE PROPOSED DETECTOR

In these experiments, the widely used linear frequency modulation (LFM) radar signals are adopted to verify the adaptive subspace detector when judging whether there is a target in the compression samples, where $T = 1\mu s$, $B = 200$MHz, $N = 2000$.

The first experiment is to examine the detection probability of the detector at different SNRs with different compressive ratios, where SNR $= 10\log_{10}\frac{\sigma_x^2}{\sigma_0^2}$ (in dB). With the prior information of the predicted target position, we construct an adaptive subspace $\mathbf{\Lambda}_k \in N \times K$ for detection, where $K = 15$. The measurement matrix $\mathbf{\Phi}_k = [\mathbf{\Phi}_{s,k}, \mathbf{\Phi}_{o,k}]$ is formed by choosing $M_1 = M_2$, and $M = [100, 200, 300, 400]$. A steady result is obtained by conducting 1000 random computer simulation trials in this experiment. Fig. 2 shows the detection performance with a 10^{-5} false alarm probability (P_{FA}). The detection probability (P_d) increases with the SNR, and a high P_d of 0.95 can be obtained when $M/N = 0.2$ and SNR $= -9$dB. The signal can also be detected with a P_d of 0.86 when $M/N = 0.05$ and SNR $= -5$dB. The algorithm processes the compressive samples and detects the signal without signal reconstruction.

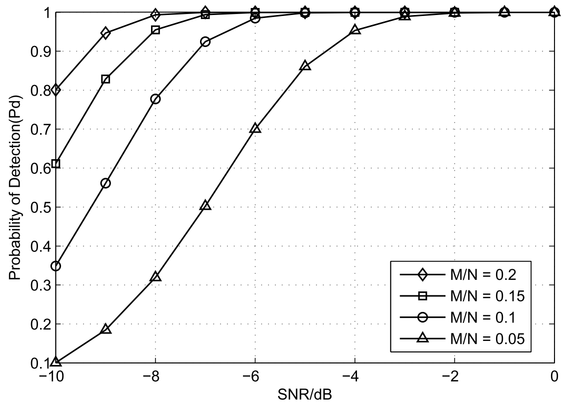

FIGURE 2. The detection probability of the proposed detector at different SNRs with different compression ratios.

The second experiment is devoted to comparing different detectors with the proposed detector. We employ the same LFM signals used in the previous experiment. Fig. 3 shows that the proposed detector outperforms the compressive matched filter (CMF) in [7]. When SNR $= -9$dB, the P_d of the proposed detector and the traditional matched filter (MF) are similar, but eighty percent of the computational data are reduced.

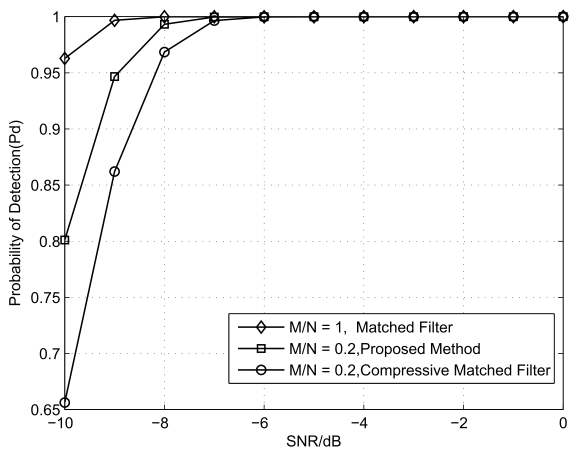

FIGURE 3. Detection performance comparison with different detection methods.

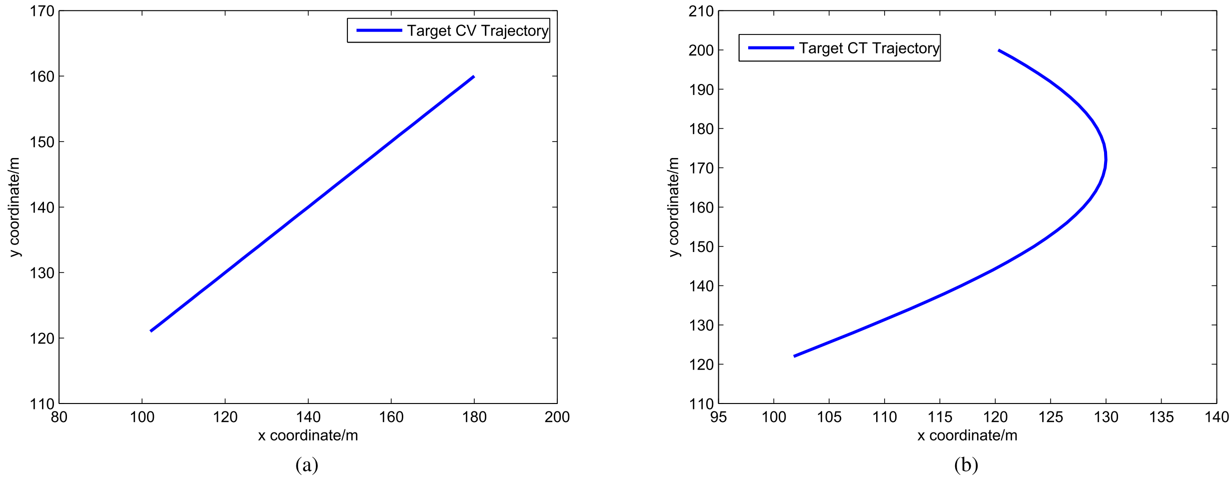

FIGURE 4. Target trajectory in different motion models: (a) CV, (b) CT.

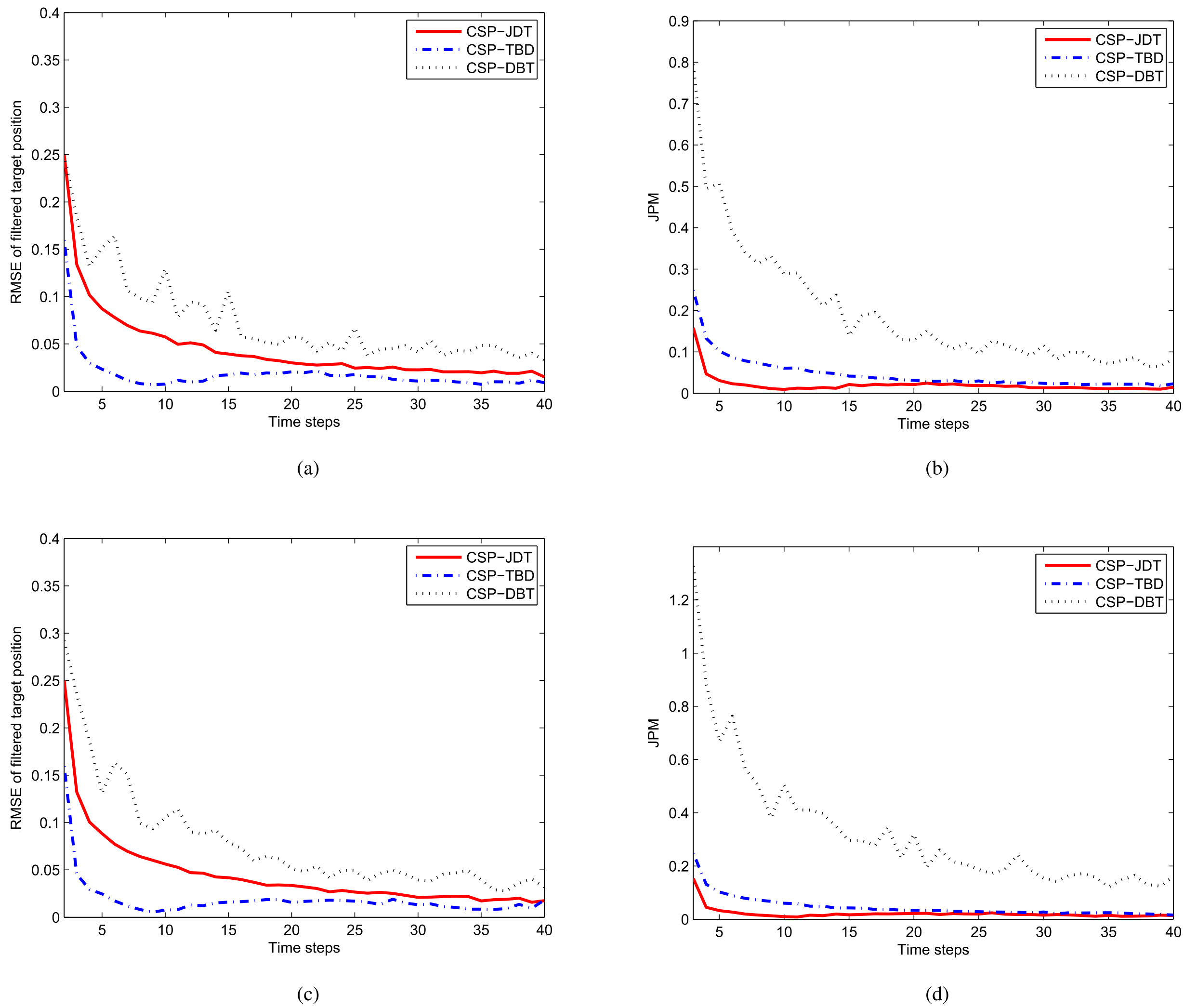

FIGURE 5. Tracking performance comparison in different motion models. (a) RMSE in the CV model, (b) JMP in the CV model, (c) RMSE in the CT model, and (d) JMP in the CT model.

To summarize, the proposed detector can achieve good detection performance for low SNR signals at low compression ratios.

B. PERFORMANCE ANALYSIS OF CSP-JDT METHOD

In these experiments, the performance of the CSP-JDT method is verified by two typical JDT examples. We compare the CSP-JDT with the CSP-DBT and CSP-TBD methods in terms of the root mean square error (RMSE) and joint performance metric (JPM).

The compared methods are as follows:

1) CSP-DBT: a CMF [7] performs the target detection first, then a traditional tracking Kalman filter (KF) accomplishes the target tracking.

2) CSP-TBD: a CSP-VBAKF [20] method is employed by feeding the tracking results into a compressive sampling procedure to improve the detection performance in the next time step.

Suppose there is only one target moving on the Cartesian plane within the radar searching area. The parameters of the LFM radar signals are the same as those of previous experiments. The target state can be described as $\mathbf{x}_k = [x_k, \dot{x}_k, y_k, \dot{y}_k]^T$, where x_k and $\dot{x}_k$ denote the position and velocity in the x-direction (likewise for the y-direction). The initial target position is at (100 m, 120 m), and the sampling time is 1 s. In the first simulation, the target state evolves for 40 time steps according to the constant velocity (CV) model. The target has a speed of 2 m/s in the x-direction and 1 m/s in the y-direction. In the second simulation, the target state evolves for 40 time steps according to the constant turn (CT) model. The target has a speed of $0.6^o/s$ in the x-direction and 1 m/s in the y-direction. At each moment, $\mathbf{\Lambda}_k$ is constructed over time, and $K = 15$. Since the proposed detector can guarantee a high detection rate from the previous experiments, we choose $M_1 = M_2$, $M/N = 0.2$, and SNR $= -5$dB. Fig. 4 shows the target trajectory in different motion models.

The simulation consists of 100 Monte Carlo runs, and simulation results are presented in Fig. 5. The parameters for CSP-JDT are set as follows: $\alpha_{ij} = 1$, $\sum_i \beta_{ij} = 3$, $\beta_{ii} = 1$, $\beta_{ij} = 1/3$, $c_{ij}(\mathbf{\Lambda}_k) = 1$ and $c_{ij}(\mathbf{\Lambda}_k) = 0$. As shown in Fig. 5. (a) and (c), the CV and CT models achieve a consistent tracking performance when estimating the RMSE of the target position in both tracking accuracy and convergence speed: CSP-TBD is the best, CSP-JDT is in the middle, and CSP-DBT is the worst. Here, CSP-TBD performs the best because the tracking is performed first and then detection is made based on the tracking results; thus, the weight of the tracking risk is larger than the weight of the detection risk. In CSP-DBT, the best detection is conducted first without considering the tracking results, and then the tracking is performed based on this detection. Thus, the detection risk plays a more important role than the tracking risk. In the CSP-JDT, we give equal importance to both the detection risk and the tracking risk. However, for the joint performance, as shown in Fig. 5. (b) and (d), CSP-JDT beats CSP-DBT and CSP-TBD. This demonstrates that CSP-JDT can improve the joint detection and tracking performance, which is most important in a JDT problem.

V. CONCLUSION

In this paper, a joint optimization method for target detection and tracking in compressive sensing and processing (CSP-JDT) is proposed. Without signal reconstruction, our method first judges whether there is a target in the compressive samples with the proposed subspace detector, and then determines the target location and accomplishes target tracking in a new JDT manner. To optimize the detection and tracking performance jointly, we propose a new JDT risk in the CSP framework and derive the optimal CSP-JDT solution. CSP-JDT takes advantage of the target spatial correlation in the continuous radar echoes, which can effectively solve the coupled detection and tracking problem with a low SNR. The simulation results showed that the CSP-JDT method outperforms the two-stage strategy in CSP. Applying CSP-JDT to multi-target and extended target problems will be studied in the follow-up work.

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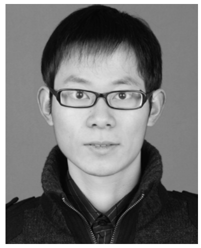

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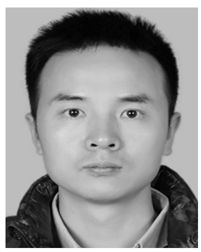

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