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• **LETTER** •

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Multi-target positioning for passive sensor network via bistatic range space projection

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Dear editor,

Positioning target is a classical topic in radar and sonar research. In a passive (radar) sensor system, target can be located using either the time of arrival (TOA) [1], the time difference of arrival (TDOA) [2], the angle of arrival (AOA) information [3], or a combination of the three. Compared with the TOA approach, the TDOA approach has no need for the sensor clocks to be synchronized with that of the target and only assumed clock synchronization across sensors. Compared with the AOA approach, the TDOA approach is low-cost due to no need for installing an antenna array for each receiver. In this paper, therefore, we consider the TDOA approach for target positioning.

For the localization of multi-target, data association is required and extremely complex [4]. Multiple hypothesis tracking (MHT) [5] and joint probabilistic data association (JPDA) [4] are the classical data association algorithms for multi-target multi-sensor positioning.

In this letter, the multi-target positioning problem is modeled as an imaging problem by considering the sensor network as a 2D sparse array, which can solve the data association problem easily. In the face of the surveillance mission, the bistatic range space (BR space) projection is used to overcome the space-variant feature of the system resolution. Based on the sparsity of the BR space projection, the sparse recovery technique is used to improve the positioning performance. The performances of the BR space projection are analyzed via some numerical experiments.

Methodology. The passive sensor network is typically realized with multiple sensors and a single transmitter. There is a transmitter emitting a group of broadband (or narrow pulse) signals with a specific pulse repetition frequency (PRF) to the surveillance region, and there are $N (N > 3)$ sensors deployed in a vast area receiving the echoes of the region. Assuming that the time of the transmitter and sensors is synchronized accurately and the transmitter and sensors' positions are given, the positioning problem can be expressed as a group of hyperbolic equations,

$$\begin{cases} \|\boldsymbol{x}-\boldsymbol{r}_2\|_2 - \|\boldsymbol{x}\|_2 = r_2 - r_1, \\ \|\boldsymbol{x}-\boldsymbol{r}_3\|_2 - \|\boldsymbol{x}\|_2 = r_3 - r_1, \\ \qquad \cdots \\ \|\boldsymbol{x}-\boldsymbol{r}_N\|_2 - \|\boldsymbol{x}\|_2 = r_N - r_1, \end{cases} \tag{1}$$

where, $\boldsymbol{x}$ denotes the target's position in the geographic space, $\boldsymbol{r}_n$ denotes the positions of the n^{th} sensor, r_n denotes the bistatic range of the n^{th} sensor that can be obtained according to the propagation delay.

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Algorithm 1 Positioning via Greedy and Cleaning (PGC) algorithm

Task: Extract the probabilities and positions of the targets.
Parameter: Given the BR image $\boldsymbol{I}$, the positions of the sensors $\boldsymbol{r}_n$, the range resolution ρ, the delay-probability pair set of Ξ , the termination threshold ε_0.
Main iteration: increment m by 1 and perform the following steps:
Detection: find out the maximum value of $\boldsymbol{I}$, record the value and calculate its position $\boldsymbol{x}_{\max}^{[m]}$ in the geographic space.
Elimination: select one pixel $\boldsymbol{y}_{i,j,k}$ in the BR space and perform the following steps:
(1) select a sensor $\boldsymbol{r}_n$, and calculate the bistatic range associated to $\boldsymbol{x}_{\max}^{[m]}$, denoted as $R_{\max}^{[m]}$;
(2) select the same sensor $\boldsymbol{r}_n$, and calculate the bistatic range associated to the pixel, denoted as $R^{[m]}$;
(3) if $|R_{\max}^{[m]} - R^{[m]}| > \rho/2$, continue;
(4) if $R_{\max}^{[m]}$ belongs the delay-probability pair set $\Xi^{[n]}$, $\boldsymbol{I}(\boldsymbol{y}_{i,j,k}) = \boldsymbol{I}(\boldsymbol{y}_{i,j,k}) - I\left[P_{R_{\max}^m}^{[n]}\right]$;
(5) repeat steps (1)–(4), until all sensors are processed;
(6) repeat steps (1)–(5), until all pixels are processed;
Stopping rule: if the maximum value is less than ε_0, stop. Otherwise, apply another iteration.
Output:
The proposed results are the maximum values and their positions in the geographic space obtained in every iterations.

For multi-target positioning, one need to construct the correct equation by allocating the bistatic ranges to the corresponding targets before solving the targets' positions. In the consideration with the decoherence of different sensors, the space-variant feature of the system resolution and the reservation of sparse characteristic, the BR space projection is a reasonable choice, which can be expressed as

$$\boldsymbol{I}(\boldsymbol{y}_{i,j,k}/\Xi) \triangleq \sum_{n=1}^{N} I(\boldsymbol{y}_{i,j,k}/\Xi^{[n]}), \tag{2}$$

$$I(\boldsymbol{y}_{i,j,k}/\Xi^{[n]}) \triangleq \boldsymbol{L} \sum_{m=1}^{M^{[n]}} P_m^{[n]},$$
$$\phi(\|\boldsymbol{x}_{i,j,k} - \boldsymbol{r}_n\|_2 + \|\boldsymbol{x}_{i,j,k}\|_2 - r_n), \tag{3}$$

where Ξ denotes the data collection of all sensors, $\Xi = \{\Xi^{[n]}, n = 1, \ldots, N\}$, $\boldsymbol{y}_{i,j,k}$ denotes the representative in the BR space, $\boldsymbol{y}_{i,j,k} \triangleq [\rho i, \rho j, \rho k]^{\mathrm{T}}$, $i, j, k \in \mathbb{Z}$, whose counterpart in the geographic space is denoted as $\boldsymbol{x}_{i,j,k}$ (see literature [6] for detail), ρ denotes the system's resolution, $P_m^{[n]}$ denotes the m^{th} target's existence probability in the n^{th} sensor, $\boldsymbol{L}(x) \triangleq (\ln(x + 0^+) - \ln(0^+))/\ln((1 + 0^+)/0^+)$, $\phi(\cdot)$ is a kernel function related to the system's ambiguity function.

Since the accumulation of the BR space projection is operated on a group of nonnegative values, the side-lobes of different targets might crosstalk to each other and lead to some false targets. To overcome this, a multi-target positioning method based on the greed strategy (called as Positioning via Greedy and Cleaning algorithm (PGC)) is presented herein aiming to eliminate the sidelobes, which includes two steps: **Detection:** find out the maximum value in the BR image as one of the targets and record the position associated to the maximum value; **Elimination:** traverse the whole BR image and remove the value corresponding to the position. The pseudo-codes of the PGC algorithm are listed Algorithm 1:

Results and discussion. Some numerical experiments are carried out to validate the performance of the BR space projection and PGC algorithm. The transmitter is placed at the origin, and there are 20 sensors, three of them are located at [−25, 0, 0] km, [25, 0, 0] km and [0, 43, 0] km, and the others distribute uniformly in the triangle determined by the three sensors. In Figure S1, the vectorized BR images at different iterations and the positioning result of the PGC algorithm are given. From them, we find that the five targets are picked out one by one with the iterations and the positioning result matches the actual positions soundly.

A group of experiments are conducted with the standard deviations of noise 0.0, 0.2, 0.4, 0.6, the number of sensors 5, 10, 30, 50, and the experimental region located at [50, 100, 10] km. The root-mean-square errors (RMSE) are listed in Table S1. When there is no noise, almost all of the sensor networks with 5, 10, 30 and 50 sensors can position the 5 targets correctly. When the standard deviation is 0.2, the deviations of RMSEs with 5 sensors change dramatically, which reflects the uncertainty of system; on the contrary, the other sensor networks can still position the 5 targets correctly. When the standard deviation is 0.4, the positioning results with 5, 10 and 30 sensors go worse significantly, 50 sensors are necessary to obtain a sound result. When the standard deviation is 0.6, all of the results fluctuate violently. In a word, though the increase of sensors cannot improve the positioning precision provided that the size of the sensor network is fixed, it is beneficial to promoting the systems anti-noise performance.

A group of experiments are conducted with the standard deviations of noise 0.0 and the number of sensors 20 to demonstrate the relationship between the positioning precision and targets locations. The experimental regions are located at [0, 0, 10] km, [60, 80, 10] km, and [−60, 80, 10] km and [300, 200, 10] km respectively. Table S2 lists the RMSEs in the geographic and BR spaces. From them, we find that no matter where the targets are located, the RMSEs in the BR space are approximately invariant. On the contrary, the RMSEs in the geographic space vary significantly. This phenomenon is similar to the geometric dilution of precision(GDOP) in the GPS theory. Thus, the layout of the sensors should be considered for actual system for the sake of positioning precision.

Conclusion. In the face of a vast surveillance region, the BR space projection is a reasonable choice for passive sensor network multi-target positioning. Based on the sparsity, the greedy and cleaning strategy can be used to improve the positioning performances. One can promote the anti-noise performance by increasing the number of sensors, but not the positioning precision when the size of the sensor work is fixed. The positioning precision of the BR space projection is similar to the GDOP in the GPS theory, which can be improved by increasing the ranging accuracy or the size of the sensor network.

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Conflict of interest The authors declare that they have no conflict of interest.

Supporting information Figure S1. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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