DISTRIBUTED TARGET DETECTION IN THROUGH-THE-WALL RADAR IMAGING USING THE BOOTSTRAP

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ABSTRACT

The problem of distributed detection and decision fusion in Through-the-Wall Radar Imaging (TWRI) is considered. We deal with the multi-viewing case in which images corresponding to different radar locations can be collected. We present a method to adapt conventional distributed detection schemes to the scenario when no a priori knowledge about image statistics from any view is available. Further, a new scheme for estimating quality information of local detectors in a distributed detection scenario is proposed. We apply bootstrap techniques to draw inference from the radar measurements of the behind the wall scene. Simulation results as well as experimental data are used to demonstrate the performance of the proposed approach.

Index Terms— Distributed detection, decision fusion, bootstrap, Through-the-wall, radar imaging

1. INTRODUCTION

In Through-the-wall radar imaging (TWRI) applications ([1],[2],[3],[4]), the use of multiple vantage points proves advantageous in reducing multipath and noise effects, allowing clearer reading, less cluttered, and more detailed descriptions of indoor target images [5, 6, 7]. The distinct changes of the multipath and clutter signatures with the positions of the radar imaging system, accompanied with invariance or small changes of the target signature, render multi-viewing approach effective and attractive in the underlying TWRI applications. Different views can be achieved by placing the system at different sides of the building, different standoff distances, or/and different positions along the same wall.

We consider K TWRI systems placed along one or multiple walls to illuminate the scene of interest in an enclosed structure. Thus, a set of K radar images, which are independently recorded and generated, are available to perform target detection and parameter estimation. The question arises on how to fuse the K images into to a single common reference image. In [5], this detection problem was tackled using a centralized detection scheme, where the individual sensors transmit the recorded images to a central detector, which then applies a detection scheme based on the Neyman-Pearson test. In [7], an alternative decentralized detection scheme was proposed, where the individual sensors perform local detection and transmit compressed information to a fusion center. This approach simplifies the problem and reduces the transmission complexity. However, although the results in [7] were promising, two difficulties are encountered: In order to perform the optimal decision fusion at the fusion center, a priori knowledge of the image statistics are needed, which generally are not available. Further, the performance of the simple decentralized detector in [7] shows a significant loss in performance compared to the centralized detector.

In this paper, we address the above two issues so as to improve both the robustness and the performance of the decentralized scheme. In Section 2, a simple optimum decision fusion framework is presented. The problem of decision fusion without a priori statistical knowledge is considered in Section 3, where we use an iterative detection approach to extract image statistics from the data. In order to increase the performance of distributed detection schemes it is common to allow local detectors to send quality information along with their decision [8], i.e. information about how confident a detector is with its decision. In Section 4, we demonstrate how quality information can be extracted from the measurement at hand using the bootstrap [9]. Simulation results in Section 5 compare the performance of the proposed methods with a classical centralized detection scheme. Section 6 shows experimental results and demonstrates performance for real data measurements obtained from a two-dimensional scanning system. Conclusions are given in Section 7.

2. DISTRIBUTED DETECTION

We consider a setup with K sensors distributed in space which observe the same scene. The aim is to decide between two hypotheses H_0 (no target present) and H_1 (target present). One way to obtain a global detection is to use a centralized detection scheme [5], where the individual sensors

The work by Moeness Amin is in part supported by ONR, grant no N00014-07-C-0413

send raw or image data to a global detector, which applies the Neyman-Pearson test as

$$\text{LR} = \prod_{k=1}^{K} \frac{p_k(x_k|H_1)}{p_k(x_k|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \tag{1}$$

where x_k is the observation obtained from the k-th sensor and $p_k(x_k|H_0)$ and $p_k(x_k|H_1)$ denote the probability density function under the null and alternative hypothesis, respectively. The threshold γ is obtained for a preset false-alarm rate $\alpha = \int_{\gamma}^{\infty} p(L|H_0)dL$ where $p(L|H_0)$ is the likelihood density under H_0. A centralized scheme that yields the best detection is obtained by using raw data from all sensors. One key advantage of alternatively using a distributed detection scheme [7] is the significant reduction in data rate. Here, each sensor is followed by a local detector which only transmits its (binary) decision to a fusion center. Obviously, this decrease in data rate and complexity comes at the cost of a lower probability of detection compared to a centralized scheme.

A simple fusion rule for a distributed detection scheme has been presented by Chair and Varshney in [10]. Given a set of K detectors, which provide local decisions $B_k \in \{-1; 1\}$, $k = 1, ..., K$, where $B_k = 1$ represents the presence of a target and $B_k = -1$ indicates its absence, local decisions are transmitted to a fusion center which computes the global decision $B = f(B_1, ..., B_K)$. Further, as the observations for $k = 1, ..., K$ are seen as independent, but not identically distributed, each detector may work at a different probability of detection $p_{D,k}$, $k = 1, ..., K$. Assuming equal a priori probabilities for target presence and absence, the optimal fusion rule according to [10] can then be expressed as,

$$B = f(B_1, ..., B_K) = \begin{cases} 1 & \text{if } \sum_{k=1}^{K} a_k B_k \quad > \ 0 \\ -1 & \text{otherwise} \end{cases} \tag{2}$$

where

$$a_k \ = \ \log\left(\frac{p_{D,k}}{\alpha}\right), \qquad \text{if } \ B_k > 0 \tag{3}$$

$$a_k \ = \ \log\left(\frac{1-\alpha}{1-p_{D,k}}\right), \quad \text{if } \ B_k < 0 \tag{4}$$

3. DISTRIBUTED DETECTION USING AN ITERATIVE DETECTION APPROACH

One problem using the simple decision fusion rule (2), is the need to know the probability of detection of every local detector. This information is generally not available, as in many practical situations, additional data is not available or the target statistics may change with time and space.

In [5, 11], an iterative detection approach is presented, which adapts itself to varying image statistics. Its main purpose is to provide an automatic detection scheme in which no a priori knowledge is needed. The iterative detector aims at separating target and noise data, estimating the underlying statistics then proceeding with performing a Neyman-Pearson test. In essence, the byproduct of the approach in [5, 11] are the estimates of the conditional density functions under both hypotheses $p(x|H_0; \hat{\underline{\theta}}_0)$ and $p(x|H_1; \hat{\underline{\theta}}_1)$, where $\hat{\underline{\theta}}_0$ and $\hat{\underline{\theta}}_1$ denote the estimated parameter vectors under the null and alternative hypothesis, respectively. Given $\hat{\underline{\theta}}_0$ and $\hat{\underline{\theta}}_1$, it is straightforward to estimate the probability of detection as,

$$\hat{p}_D = \int_{\gamma_k}^{\infty} p(L|H_1; \hat{\underline{\theta}}_0, ; \hat{\underline{\theta}}_1)dL \tag{5}$$

with γ_k being the likelihood ratio threshold at the k-th detector. For a practical distributed detection TWRI system, our proposed approach is to apply the iterative detection approach at each sensor and transmit B_k and $\hat{p}_{D,k}$, $k = 1, ..., K$ to the fusion center and evaluate the global decision using Equations (2) and (3) with the estimated probabilities of detection.

4. BOOTSTRAP-BASED DISTRIBUTED DETECTION

In Section 2, we reviewed two schemes for multiple sensor data fusion; one uses a high data rate and complexity, yielding the best detection result, whereas the other is of very low data rate and complexity, but leads to a much less favorable detection result.

In order to tradeoff between the above two extremes, one could use quality information in distributed detection [8]. A new method to extract quality information is proposed, stating how confident the respective detector is about its decision. The idea is to draw inference about γ_k and therefore the level of confidence of the detector k. The distribution of the likelihood ratio threshold γ_k is used to draw inference about the detector's level of confidence. In order to obtain the distribution of γ in practice, one would typically make use of repeating the experiment and using Monte Carlo simulations. However, in applications such as TWRI, data acquisition and beamforming are a very time demanding procedure, which would be a critical factor in many applications such as rescue missions or urban operations. Further, it is unlikely that one is able to rerun the experiment under the same conditions.
The bootstrap is an attractive tool for this type of problems, where experiments cannot be repeated and inference must be drawn from small data segments. In Table 1, the bootstrap procedure for estimating the threshold distribution is detailed, whereby we only consider the independent-data bootstrap.

Given a confidence interval for γ_k as $[u_1, u_2]$, one can extract quality information conditional on data x_k by checking whether the realization of the likelihood ratio $\frac{p_k(x_k|H_1)}{p_k(x_k|H_0)}$ is inside $[u_1, u_2]$ (low confidence decision) or outside (high confidence decision). Returning to the distributed detection scenario described in Section 2, we will modify Chair and Varshney's method [10] using the bootstrap-based quality measure as,

Table 1. Bootstrap procedure

Step 0.	*Data Collection*. Conduct the experiment and apply the iterative detector [5] to obtain noise and target vectors $\underline{n}$ and $\underline{t}$
Step 1.	*Resampling*. Apply the bootstrap and resample $\underline{n}$ and $\underline{t}$ R times with replacement to obtain $\underline{n}^{*r}$ and $\underline{t}^{*r}$, $r = 1, ..., R$.
Step 2.	*Parameter estimation*. Estimate the noise and target statistics $\hat{\underline{\theta}}_0^{*r}$ and $\hat{\underline{\theta}}_1^{*r}$, $r = 1, ..., R$ using maximum likelihood estimation.
Step 3.	*Threshold distribution*. From $\hat{\underline{\theta}}_0^{*r}$ and $\hat{\underline{\theta}}_1^{*r}$, obtain γ_k^{*r} via $\alpha = \int_{\gamma_k^{*r}}^{\infty} p(L\|H_0; \hat{\underline{\theta}}_0^{*r}, \hat{\underline{\theta}}_1^{r*}) dL$, $r = 1, ..., R$
Step 4.	*Confidence intervals:* Sort the thresholds in increasing order, i.e. $\gamma_k^{*1} < ... < \gamma_k^{*R}$ and apply $u_1 = \lfloor R\, \frac{c}{2} \rfloor$ and $u_2 = R - u_1 + 1$ which represent the $(1-c)100\%$ confidence interval bounds.

$$B = f(B_1, ..., B_K) = \begin{cases} 1 & \text{if } \sum_{k=1}^{K} q_k a_k B_k \quad > 0 \\ -1 & \text{otherwise} \end{cases} \qquad (6)$$

with q_k being the quality information for the k-th sensor as

$$q_k = \begin{cases} 1, & u_1 < \frac{p_k(x_k|H_1)}{p_k(x_k|H_0)} < u_2 \\ 0, & \text{otherwise} \end{cases} \qquad (7)$$

5. SIMULATION RESULTS

In this Section, the performance of the three detection techniques considered in this paper is assessed, namely centralized detection (Equation (1)), decentralized detection using no quality information (Equation (2)) and decentralized detection using the bootstrap-based quality information (Equation (6)). $K = 3$ simulated images $x_k(i, j)$, $k = 1, ..., K$, $i = 0, ..., I - 1$, $j = 0, ..., J - 1$ are synthesized as

$$x_k(i,j) = \begin{cases} t(i,j) + e(i,j), & \text{target present} \\ e(i,j), & \text{target absent} \end{cases} \qquad (8)$$

where, as in [5], $t(i, j)$ and $e(i, j)$ follow a Gaussian (with fixed mean and standard deviation: $\mu = 0.6$, $\sigma_1 = 0.2$) and Rayleigh distribution (varying scale parameter $\sigma_0 \in \{0.18, 0.12, 0.08\}$), respectively. A typical image resulting from the simulation is depicted in Figure 1 as well as the threshold distribution, including the 90% confidence interval, when using the boostrap-based quality metric. For target detection, the iterative detector described in [5] was used with a square morphological structuring element of size 5×5 [11]. This detector was applied to extract the image statistics for all three methods and, as such, no prior statistical knowledge was assumed. For the bootstrap-based quality information extraction, 200 resamples were used. Simulation results, measuring the probability of detection, and obtained by averaging over 1000 Monte Carlo runs are as shown in Table 2.

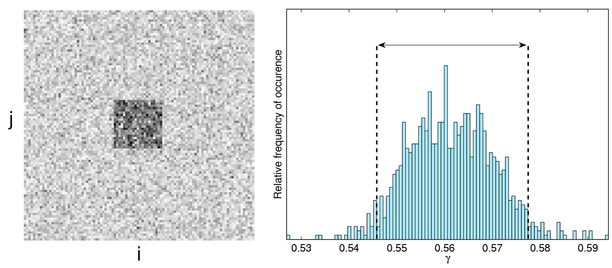


Fig. 1. Synthesized image and threshold distribution

It is evident that, the bootstrap-based quality information

Table 2. Probability of detection, Simulation results

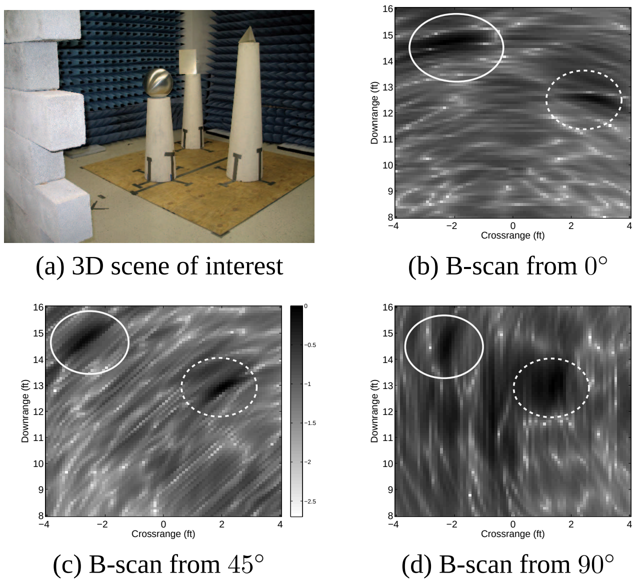
	Centralized	No Quality	Bootstrap
$\alpha = 0.01$	0.92	0.76	0.84
$\alpha = 0.05$	0.98	0.84	0.89
$\alpha = 0.1$	0.99	0.93	0.95
$\alpha = 0.2$	0.99	0.97	0.99
Data rate reduction	0%	$\approx 87.5\%$	$\approx 75\%$

is able to improve the performance of the distributed detector with no quality information added. For small false-alarm rates, the bootstrap-based approach yields a considerably higher probability of detection. The reduction in data rate when using the two decentralized schemes is shown in the last line of Table 2, whereby we assumed the original image pixel values to be represented by 8bit.

The estimation of the quality information requires an additional complexity which amounts to the number of resamples.

6. EXPERIMENTAL RESULTS

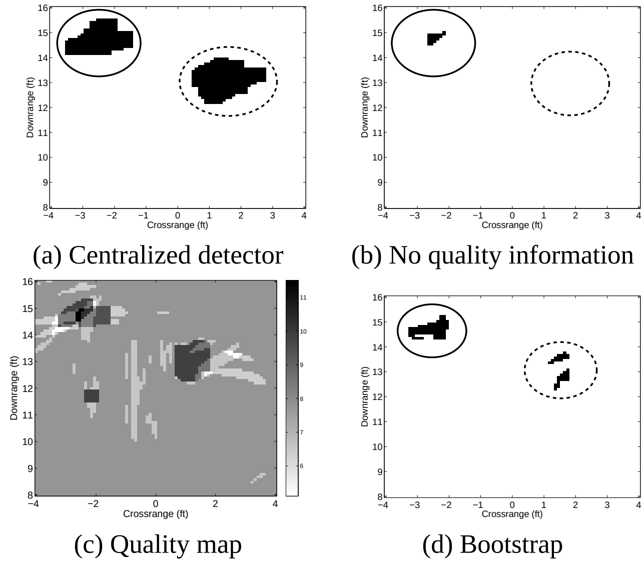
In order to test the proposed methods using real data measurements, TWRI experiments were conducted at the Radar Imaging Lab at Villanova University, Philadelphia, USA. The experimental setup is depicted in Figure 2(a), consisting of a metal sphere, a metal dihedral and a metal trihedral, mounted on high foam columns placed behind a concrete wall. The radar images are reconstructed using a synthetic aperture radar (SAR) and the wideband sum-and-delay beamformer from [6]. Background-subtraction, as in [6, 5], was performed. The scene was illuminated from three vantage points, $0, 45$ and 90 degrees. Considering a height of 6 ft above ground, three B-Scans as shown in Figure 2(b)-(d) can be obtained. At this height, the reflection of the sphere is very weak, thus only the dihedral (solid circle) and the trihedral (dashed circle) can be seen. We further observe a strong amount of clutter present, due to multipath propagation and wall effects. The detection results using the considered detection schemes with a false-alarm rate of 1% are depicted in Figure 3. As in Section 5, the iterative detection approach with a structuring element of size 5×5 is used in all cases so that no a priori knowledge of the image statistics is needed. By fusing the three images using the centralized scheme (Fig-



(a) 3D scene of interest (b) B-scan from $0°$

(c) B-scan from $45°$ (d) B-scan from $90°$

Fig. 2. Experimental setup and acquired B-Scans



(a) Centralized detector (b) No quality information

(c) Quality map (d) Bootstrap

Fig. 3. Detection results

ure 3(a)), clutter can be removed and the two targets of interest are clearly visible. Using the decentralized detector with no additional quality information, a rather poor detection result is obtained, as shown in Figure 3(b). Although clutter is strongly reduced, the probability of detection is far too low to detect the two targets. When the bootstrap-based quality information using a 90% confidence interval is added, a quality map, representing $\sum_{k=1}^{K} q_k a_k$ for each pixel can be obtained and is depicted in Figure 3(c). This quality map represents the joint confidence of all local detectors (dark regions represent pixels with a high joint confidence, bright regions represent pixels with a low joint confidence), which is then processed as in Equation (6) to obtain the final detection result per Figure 3(d). Both targets can be clearly detected. One can observe a slight decrease in performance compared to the centralized detection scheme.

7. CONCLUSION

A new scheme for improving distributed target detection, when no a priori knowledge on target or image statistics are available, was presented. We proposed a new method for quality information extraction based on the bootstrap. Distributed detection with and without additional quality information were tested and compared to the centralized detection scheme. Improved target detection performance was achieved as shown using computer simulations as well as real data collected from Through-the-Wall radar imaging experiments.

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