Applications for the EM-based Classifier in Radar Sensor Network

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Abstract—This letter focuses on the application and analysis of the new model-based clustering architectures developed in our recent paper, where the analysis is limited to synthetic simulation results, to data collected by a real radar sensor. Specifically, a more comprehensive analysis of the proposed schemes is carried out in challenging real operating scenarios where the real measurements of multiple moving targets are not perfectly matched with the design assumptions due to real-world effects. Moreover, a new initialization procedure is introduced that accounts for multiple target velocities and the radar sampling time interval required by the specific application. Such a procedure is capable of providing the expectation-maximization (EM) procedure with reliable initial parameter values. The performance assessment confirms the effectiveness of these EM-based clustering algorithms not only on synthetic data, as observed in our companion paper, but also over real-recorded data and in comparison with suitable competitors.

Index Terms—Expectation-maximization, measurement clustering, model order selection rules, multiple moving targets, real-recorded data, sensor network.

I. INTRODUCTION

Radar sensor networks are very attractive for high-performance localization, detection and tracking of multiple moving targets [1]–[5]. Due to the advances in electronics and digitalization, these tools are becoming ubiquitous and have a strategical impact in defense as well as civilian applications [6]. In the last decades, with the advent of unmanned/autonomous vehicle systems (airborne, marine, and terrestrial), radar surveillance scenarios are getting increasingly dense [7]–[9]. This imposes higher requirements on data processing performance for sensor networks, especially those comprising a large number of low-cost sensors endowed with signal filtering and detection capabilities only.

In this context, the monostatic nodes of the network share the position estimates corresponding to each detection to a data fusion center, which clusters the received measurements to form multiple target tracks [10], [11]. Nevertheless, in realistic scenarios, measurement clustering process is becoming more and more challenging due to the high computational requirements of the fusion center as well as the presence of outliers caused by environmental noise, positioning errors, and etc. In order to address this issue, two model-based clustering algorithms, resorting to the Expectation Maximization (EM) algorithm [12] and the Model Order Selection (MOS) rules [13], [14], have been proposed in [1]. The preliminary performance assessment conducted in [1] over synthetic data observes that these algorithms exhibit the capability of classifying asynchronous measurements from a monostatic radar sensor network and estimating the targets number along with the related trajectories. It is important to stress here that the analysis in [1] assesses the nominal behavior of the proposed classifiers, namely under their design assumptions including the Gaussian noise distribution, the uniform distribution for the measurement occurrences, and the approximately linear trajectories. These conditions might not be met in real-world environments.

With the above remarks in mind, we frame this letter in the research line started by [1] and complete the performance analysis by using real-recorded data and considering two challenging operating scenarios for known and unknown number of targets. Unlike [1], data processed here are affected by real-world imperfections and comprise unidentified objects. In this context, a different initialization procedure (with respect to [1]) is introduced, that accounts for multiple targets' velocities and radar sampling time interval given by the specific application and provides the EM procedure with reliable initial parameter values. The illustrative examples highlight that the developed EM-based classifiers are capable of providing satisfactory classification and estimation capabilities in contexts of practical interest related to real data used in the next sections.

II. ALGORITHM DESCRIPTION

In this section, for the readers ease we summarize the architectures devised in [1]. Let us denote by $L \in \mathbb{N}$ the number of moving targets whose trajectories can be approximated as a straight line within a sufficiently short time interval. Consider a sensor network of $K \in \mathbb{N}$ monostatic radars deployed to illuminate the same region of interest, and the measurements obtained by each sensor are transmitted to a fusion center that converts the received polar coordinates into Cartesian coordinates. Based on this, we assume that N measurements for L point-like targets are available at a given time instant with Cartesian coordinates $(x_n, y_n) \in \mathbb{R} \times \mathbb{R}$, $n = 1, \ldots, N$. Thus, the model of motion trajectory can be written as [1]:

$$y_n | c_n = l \sim \mathcal{N}(a_l x_n + b_l, \sigma_l^2), \quad n = 1, \ldots, N, \tag{1}$$

where the c_n are independent and identically distributed hidden discrete random variables defined in the latent variable model, a_l and b_l denote the unknown coefficients of lth target motion, and $\mathcal{N}(a_l x_n + b_l, \sigma_l^2)$ means a Gaussian distribution of the measurement

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[1]Notice that since the measurements are asynchronous, we neglect the time index.

noise with mean $a_l x_n + b_l$ and unknown variance σ_l^2. Moreover, the event $c_n = l$ accounts for the classes to which each measurement belongs with unknown probability mass function $\pi_l = P\{c_n = l\}$, $l \in \mathcal{A} = \{1, \dots, L\}$.

At the design stage, two main clustering approaches have been proposed: the first one addresses the case of known number of targets whereas the second approach deals with an unknown number of targets. In the first scenario, the EM algorithm coupled with the latent variable is exploited to develop a model-based estimation procedure. More precisely, there are two main steps derived from heuristic modification of the EM algorithm. The initial step, called E-step, consists in computing the conditional (a posteriori) probability of the event $c_n = l$ given the nth measurement

$$p_n^{(h-1)}(l) = P\left\{c_n = l | y_n; \widehat{\boldsymbol{\theta}}^{(h-1)}, \widehat{\pi}_l^{(h-1)}\right\}, \quad (2)$$

with $\widehat{\boldsymbol{\theta}}^{(h-1)} = [\widehat{a}_1^{(h-1)}, \dots, \widehat{a}_L^{(h-1)}, \widehat{b}_1^{(h-1)}, \dots, \widehat{b}_L^{(h-1)}, (\widehat{\sigma}_1^2)^{(h-1)}, \dots, (\widehat{\sigma}_L^2)^{(h-1)}]^T \in \mathbb{R}^{3L\times 1}$ and $\widehat{\pi}_l^{(h-1)}$ the estimates of unknown parameters vector $\boldsymbol{\theta}$ and π_l at the $(h-1)$th iteration. The second step returns closed-form updates for estimates of $\boldsymbol{\theta}$ and π_l by maximizing the log-likelihood function at the (h)th iteration. The above optimization procedure terminates when the following stopping criterion is satisfied

$$\begin{aligned}\Delta\mathcal{L}(h) = \Big| \Big[&\mathcal{L}\left(y_1, \dots, y_N; \widehat{\boldsymbol{\theta}}^{(h)}, \widehat{\pi}_1^{(h)}, \dots, \widehat{\pi}_L^{(h)}\right) \\ &- \mathcal{L}\left(y_1, \dots, y_N; \widehat{\boldsymbol{\theta}}^{(h-1)}, \widehat{\pi}_l^{(h-1)}, \dots, \widehat{\pi}_L^{(h-1)}\right) \Big] \Big| \\ &/ \left| \mathcal{L}\left(y_1, \dots, y_N; \widehat{\boldsymbol{\theta}}^{(h)}, \widehat{\pi}_1^{(h)}, \dots, \widehat{\pi}_L^{(h)}\right) \right| < \epsilon, \end{aligned} \quad (3)$$

where $\epsilon > 0$ and $\Delta\mathcal{L}(h)$ is the relative variation of the log-likelihood function, $\mathcal{L}(\cdot)$ say. Thus, the final estimates denoted by $p_n^{(\overline{h})}(l)$, $\widehat{\boldsymbol{\theta}}^{(\overline{h})}, \widehat{\pi}_1^{(\overline{h})}, \dots, \widehat{\pi}_L^{(\overline{h})}, n = 1, \dots, N, l \in \mathcal{A}$, are obtained after $\overline{h}$ iterations. The large amount of measurements can be clustered by applying the following maximum a posteriori rule

$$\widehat{l} = \arg\max_{l \in \mathcal{A}} \; p_n^{(\overline{h})}(l). \quad (4)$$

As for the case where the number of targets is unknown, the second estimation procedure is developed by resorting to the EM-algorithm and MOS rules, namely the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Generalized Information Criterion (GIC) [15]. The main idea of this approach consists in reducing the overestimation of L by adding penalty terms to the compressed log-likelihood function, which is computed through EM.[2] Once the estimation of L is accomplished, clustering is performed by selecting the label that returns the highest posterior probability.

III. NUMERICAL EXAMPLES

In this section, we present some illustrative examples to investigate the behavior of the considered architectures in realistic environments. Two operating scenarios, both involving a known number of targets and an unknown number of targets, are considered. To be more precise, the radar systems utilized to record the real data is Thales L-Band Gamekeeper 16U staring radar [16]. The sensor has an instrumental range of 5 km and the field of view (FOV) of 90 degrees in azimuth and 60 degrees in elevation. The radar has 'staring' capability, achieved via a constant broad beam illuminator that covers the entire FOV and the 64 elements receive array which provides full element by element digitized data recordings for beamforming after receive. The University of Birmingham facility [17], [18] consists of 2 of these radar systems, and data from one of these radars have been used in this paper. In this work, we consider as "truth" the output of the tracker implemented in the prototype radar. This output is selected for two sets of targets: birds ans unidentified objects. Furthermore, since data are recorded through a single-node monostatic radar in different epochs, we emulate a sensor network by removing the time information from the measurements and combining them. It is important to stress here that the clustering algorithms are radar-agnostic and can also be fed by data coming from a network of low-cost systems deployed in the region of interest. This situation exhibits a great practical value since the considered algorithms can somehow compensate the low performance associated with low-cost hardware by means of measurement fusion.

TABLE 1. Measurements number for real-recorded data.

	N_1	N_2	N_3	N_4	N_5	N_6	N_7
Unidentified Objects	43	34	33	49	45	33	42

In all the illustrative examples, we set the number of unidentified objects trajectories is $L = 7$, $\pi_l = 1/L$, $l = 1, \dots, L$, and the cyclic estimation procedure of EM terminates when $h_{max} = 30$ or $\epsilon = 10^{-4}$. Furthermore, the challenging situations where trajectories are in close proximity to one another are included in these scenarios, and the number of measurements, namely N_l, $l = 1, \dots, L$, [3] is shown in Table 1. It is important to stress that the considered measurements do not match the design assumptions due to environmental noise, positioning errors, and false or missed detections. Thus, a new initialization strategy is introduced as follows,

1) let $N' = \lfloor N/L \rfloor$, $\widetilde{y}_{n_l} = y_n$, $\widetilde{x}_{n_l} = x_n$, $n_l = n = 1, \dots, N$ for $l = 1$;
2) start from a point with minimum or maximum x or y coordinate in $\{(\widetilde{x}_{n_l}, \widetilde{y}_{n_l}) : n_l = 1, \dots, N\}$, select N' measurements $(x_{n'}, y_{n'})$, $n' = 1, \dots, N'$, within a circle with radius given by the velocities and time interval considered for the specific application;
3) estimate a_l, b_l, and σ_l^2 by

$$a_l = \left(\sum_{n'=1}^{N'} (x_{n'} - \bar{x})(y_{n'} - \bar{y})\right) / \sum_{n'=1}^{N'} (x_{n'} - \bar{x})^2, \;\; b_l = \bar{y} - a_l \bar{x},$$

$$\sigma_l^2 = \sum_{n'=1}^{N'} (y_{n'} - a_l x_{n'} - b_l)^2 / N',$$

with $\bar{x}$ and $\bar{y}$ the mean value of $x_{n'}$ and $y_{n'}$;
4) discard the N' measurements selected in step 2) from $\{(\widetilde{x}_{n_l}, \widetilde{y}_{n_l}) : n_l = 1, \dots, N\}$, then set $l = l + 1$ and go to step 2) using the remaining measurements until $l = L$.

A. Performance for Known Number of Targets

In the first scenario, we assess the classification performance of the proposed approach with known number of targets, namely $L = 7$.

[2]Further details regarding the derivations can be found in [1].

[3]Notice that the constraint $\sum_{l=1}^{L} N_l = N$ holds.

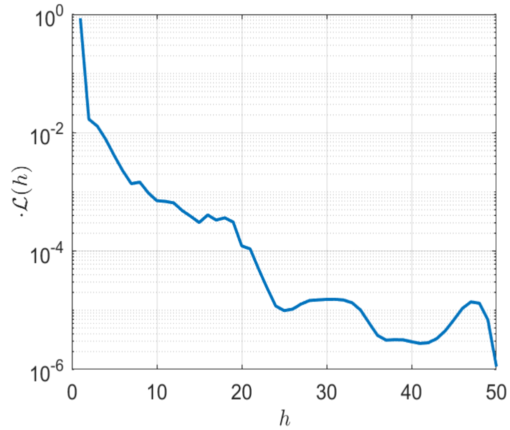
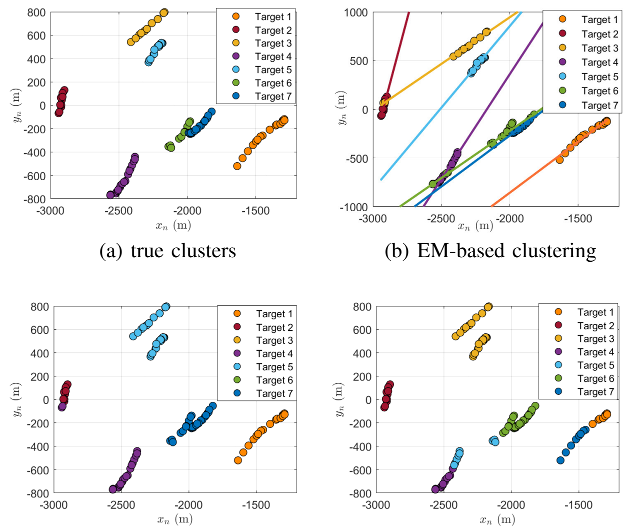


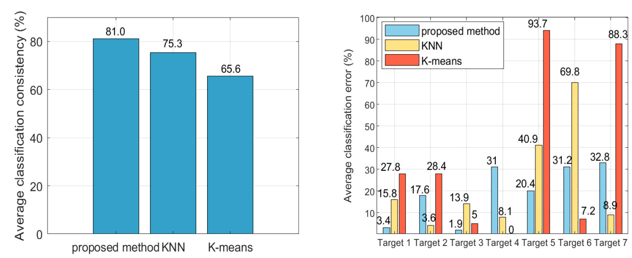
Fig. 1. Average convergence of iterations over 1000 MC trials.



(a) true clusters (b) EM-based clustering

(c) KNN clustering (d) K-means clustering

Fig. 2. Classification results in cartesian coordinates over one trial.



(a) (b)

Fig. 3. Classification accuracy for unidentified object data over 1000 MC trials: (a) average classification consistency (%); (b) average classification error (%) of each target.

For comparison purposes, two data-driven clustering algorithms K-Nearest- Neighbor (KNN) [19] and K-means [20] are considered as natural competitors, which represent the typical supervised and unsupervised clustering techniques. In the ensuing illustrations, the training examples for KNN are selected at random and account for 60% of the total measurements in Table 1, while the remaining 40% is validation data also used by the proposed method and K-means. The considered performance metrics are

- average convergence of iterations defined by $\Delta\mathcal{L}$ versus h for the EM-based estimation procedure over 1000 Monte Carlo (MC) trials;
- the true clusters and the measurement classification in Cartesian coordinates over one trial;
- average classification consistency (%) defined as the ratio between the number of correct classifications and the real categories over 1000 MC trials;
- average classification error (%) defined as the ratio between the number of misclassified measurements for a given target and the true quantity for that category over 1000 MC trials.

First of all, the mean convergence curve is plotted in Fig. 1, which returns a relative variation of $\Delta\mathcal{L}$ less than 10^{-4} when $h > 21$. This inspection clearly clarifies the rationality of the parameter settings in stopping criterion. To assess the classification capabilities, Fig. 2 shows the cartesian coordinates diagrams of the true measurements as well as the clustering results returned by the three considered algorithms in one MC trial. It is evident that the proposed method can provide better clustering results, in addition, notice that the estimated trajectory for each target (straight lines) perfectly fits with the measurements. By contrast, the other two competitors experience significant performance degradation in the presence of target trajectory is in close proximity to another (i.e. Target 6 and Target 7). Besides, the last two clusters are unable to estimate the fitted lines corresponding to these targets. Moreover, the histograms in Fig. 3 highlight that the proposed classifier experiences a gain of about 5.7 % and 15.4 % in terms of classification consistency against KNN and K-means respectively. In addition, the classification errors of each target show the performance decrease of KNN and K-means due to line adjacency (Target 6 and Target 7).

B. Performance for Unknown Number of Targets

In this subsection, we assume that the number of targets is no longer known and set the maximum number of targets $L_{max} = 10$, which is greater than the actual target number. For the sake of Monte Carlo configuration, we use 80% random data in Table 1 for each independent trial. We point out that KNN and K-mean are not included since they cannot be implemented for unknown L. To evaluate the efficiency of the proposed procedure using the MOS rules, we focus on the metrics associated with the estimation precision of L, namely,

1) average convergence of the EM-based classifier using AIC, BIC, and GIC over 1000 independent trials;
2) Root Mean Square Error (RMSE) values for L of the EM-based classifier using AIC, BIC, and GIC over 1000 independent trials;
3) RMSE values for L versus ρ under GIC criterion over 1000 independent trials.

Before presenting the estimation results for L, we provide the convergence curves under AIC, BIC, and GIC criterion in Fig. 4, where the mean curves are roughly lower than 10^{-4} when $h > 30$ and $h > 38$ for GIC, AIC, and BIC, respectively. In Fig. 5 (a), the RMSE values show that the procedure under GIC attains the best

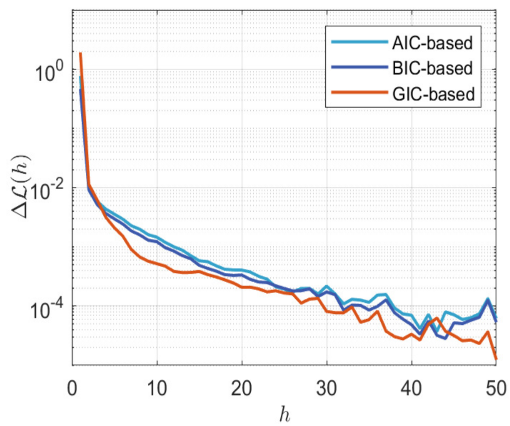
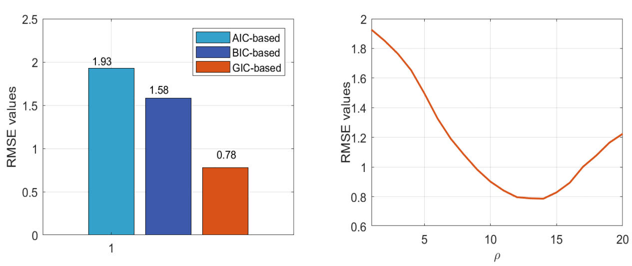


Fig. 4. Average convergence of the EM-based classifier using AIC, BIC, and GIC (ρ = 14) over 1000 MC trials.



(a) (b)

Fig. 5. RMSE values over 1000 MC trials: (a) RMSE values under AIC, BIC and GIC (ρ = 14); (b) RMSE values versus ρ for GIC.

performance and returns an error lower than 0.8. In fact, penalty parameter ρ in GIC can be suitably tuned to attain satisfactory estimation performance. In Fig. 5 (b), it indicates that the RMSE takes the minimum value when $\rho \geq 14$ (at least for the considered parameters).

IV. CONCLUDING REMARKS

In this paper, we have considered the problems of trajectory classification and estimation in the presence of multiple moving targets for a surveillance radar sensor network. Specifically, we assess the performance of the classification architectures proposed in our companion paper [1] by resorting to real-recorded data. Furthermore, a new initialization procedure is introduced that accounts for multiple target velocities and the radar sampling time interval required by the specific application, to ensure reliable parameter initialization for the EM procedure. The analysis has been developed in two operating conditions for known and unknown number of targets. In each scenario, the real dataset containing echoes from unidentified objects is used to evaluate the capabilities of measurement classification, trajectory estimation, or target number estimation. Numerical examples confirm that the architectures in [1] exhibit reliable performances over real-recorded data and overcome the considered competitors that are data-driven classifiers.

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