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Implementation methods of target motion analysis for sonar

CHEN Jing-jun[1,2]，FENG Hai-hong[1]，WU Pei-rong[2]

（1. Institute of Acoustic，Chinese Academy of Science Shanghai 200032，China;
2. Shanghai Marine Electronic Equipment Research Institute，Shanghai 200025，China）

Abstract：Target motion analysis（TMA）is an important problem for sonar. In order to extract target states more effectively，choosing appropriately measurement set is the first thing. The development of powerful estimation algorithms is another crucial step in solving the TMA problem. This paper provides a concise and a up-to-date survey about the implementation methods of TMA problem for sonar. The TMA methods are loosely grouped into two categories. One is a part of the classical target tracking methods，which takes the data association as the inseparable part of the whole estimation process. The other estimates target state without explicit use of a data association algorithm.

Key words：TMA；target tracking；sonar signal processing；track before detect；data association；survey

1　INTRODUCTION

Target motion analysis（TMA）is an important problem to sonar application. The TMA problem for sonar is characterized by measurements extracted from the signal，moreover，in some scensituation；the target may not be observable from the used set. In order to extract target states more effectively，choosing appropriately measurement set and optimal platform maneuver are crucial points. The TMA problem about measurement，observability and optimal observer maneuver have been surveyed in part I[1].

The development of powerful estimation algorithms is another necessary step in solving the TMA problem. Since 1960s，lots of approaches to TMA have been developed[2,3]. These methods are based largely on probability，stochastic processes and estimation theory，which，when combined with systems theory and combinatorial optimization，lead to a plethora of approaches that can seem somewhat daunting to be uninitiated. In order to provide a concise survey of techniques for TMA，some of the current summary in the papers of G.W. Pulford et al.[2,3] are used directly.

In this paper，the TMA methods are loosely grouped into two categories. One is a part of the classical target tracking methods，which takes the data association as the inseparable part of the whole estimation process and is surveyed in section 2. The other estimates target state without data association，which is surveyed in section 3.

2　TMA METHODS WITH DATA ASSOCIATION

The classical TMA method is an inseparable part of the whole target tracking processes. The

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作者簡介：陈敬军(1971-)，男，山东费县人，中科院声学所博士后流动站和天津经济开发区博士后流动站联合培养的博士后，主要从事水声信号处理方面的研究。
通信作者：陈敬军，E-mail:cjj_81@sina.com

target tracking processes can be summarized as follows: data containing one or more potential targets of interest are collected by sensors, and then the sensor data are partitioned into sets of observations or tracks that are produced by the same target. Assume that tracks have been formed from previous data and a new set of input observations becomes available. Then, the input observations are considered for inclusion in existing tracks and for initiation of new tracks. First, a gate, based upon the maximum acceptable measurement plus tracking prediction error magnitudes, is placed around the predicted track. Only those observations that are within the track gate are considered for update of the track. Once observations are assigned to tracks, these tracks are updated during the filtering process. The number of targets of interest can be estimated, and quantities, such as target velocity, future predicted position, and target classification, characteristics, can be computed for each track[2-4].

2.1 Data association

The gating, observation-to-track association and track maintenance functions are part of the overall data association function. First, gating uses a screening mechanism to determine which observations are the valid candidates to update existing tracks. Gating is performed primarily to reduce unnecessary computations by the association and maintenance functions. The rectangular, ellipsoidal, maneuver gates are three widely used gates.

The next function (association) takes the observation-to-track pairing that satisfies gating and determines which observation-to-track assignment will be made. In a single target tracking algorithm, the state of only one target is modeled; detections from other targets are assumed to be false alarms and problems result when tracking closely spaced or crossing targets. Two simpler data association methods are the strongest-neighbor filter (SNF) and the nearest-neighbor filter (NNF). In the SNF, the signal with the highest intensity among the validated measurements (in a gate) is used to track updating and the others are discarded. In the NNF, the measurement closest to the predicted measurement is used. While these simple techniques work well with benign targets in sparse scenarios, they begin to fail as the FA rate increases or with low observable (low probability of target detection) maneuvering targets. A common suboptimal Bayesian approach is known as probabilistic data association (PDA)[5]. The PDA algorithm, instead of using only one measurement among the received ones and discarding the others, uses all of the validated measurements with different weights (probabilities).

SNF, NNF and PDA are all suited for single target tracking. Using SNF and NNF approach, a single observation may be used to update more than one track. They can also regard as the solution approaches for the multiple target tracking (MTT) problem, yet they work well only in the case of widely spaced targets, accurate measurements, and few false alarms in the track gates. Data association becomes more difficult with multiple targets where the tracks are competing for measurements. Here, in addition to a track validating multiple measurements as in the single-target case, a measurement itself can be validated by multiple tracks. Many algorithms exist to handle this contention. The simplest ‘ true MTT ’ algorithm is the global nearest neighbor algorithm, also known as the 2-D assignment algorithm[6]. As the name suggests, an assignment problem is set up that accounts for the distances between all measurements and all tracks. The single best solution to this assignment problem allows each track to be updated with at most one measurement via Kalman filtering. The joint PDA (JPDA) algorithm is used to track multiple targets by evaluating the measurement-to-track association probabilities and combining them to find the state estimate[7-9]. The multiple hypotheses tracking (MHT) is a more powerful (but much more complex) algorithm that handles the MTT problem by evaluating the likelihood that there is a target given a sequence of measurements[4,10-12]. MHT, which is essentially a maximum a posteriori probability（MAP）estimator and allow limited branching in the hypothesis tree，can be formulated in two principal ways referred to as measurement-oriented[10] and track-oriented[13]，depending on the mechanism used to generate the association hypotheses. Implementations of MHT also differ in respect of the strategies used to compute hypothesis probabilities，cluster tracks，merge track histories and prune low probability branches from the hypothesis tree. The N-best assignment algorithm retaining not only the optimal solution， but the N best solutions is also used in target tracking[14-16]. The article by Pattipati et al.[17] provides an in-depth survey of assignment techniques for the MTT problem.

Track maintenance refers to the functions of track initiation，confirmation and deletion. A simple approach to track initiation，used by GNN method，is to start new tracks on those observations that are not to existing tracks. Yet more preferable method，used by MHT method，will start tentative tracks on all observations and use subsequent data to determine which of these newly initiated tracks are valid. A simple approach to track confirmation and deletion is to check whether M correlating observations is received within N scans. However，a much better approach is to define a track score function， and compare the score with the chosen track confirmation or deletion threshold.

2.2　Filtering and prediction

The filtering step incorporates the assigned observations into the updated track parameter estimates. Prediction quantities are of great importance because they define the centre of the gated region. The size of the gate is also directly affected by the prediction uncertainty. Early approaches made use of the state-space representation of the estimation problem and used the extended Kalman filter（EKF）[18]. The EKF estimator was later shown to exhibit divergence problems when the tracking problem is formulated in Cartesian coordinates[18]. The stability of the EKF was improved by implementing it in a new coordinate system known as modified polar coordinates[19]. Being recursive，both versions of the EKF estimator require good initialization to avoid divergence[20]. The maximum likelihood（ML）estimator for target tracking was developed in[21]. T.Kirubarjan and Y.Bar-Shalom[8] make use of the PDA technique for tracking low observable targets with passive sonar measurements. This TMA is an application of the PDA technique，in conjunction with the ML approach，for target motion parameter estimation via a batch procedure. For white Gaussian bearing noise，the ML estimator reduces to a nonlinear least squares estimator. While the ML estimator enjoys certain desirable properties such as asymptotic unbiasedness and efficiency， it does not have a closed-form solution and is often implemented as an iterative numerical search algorithm. The iterative ML solution is computationally expensive because of high-complexity arithmetic operations that must be performed in each iteration. It is also vulnerable to convergence problems. In[22]，a track-before-detect “empirical” maximum a posteriori approach was developed which avoids the gradient computation associated with the iterative ML solution，resulting in lower computational complexity. In[23] the pseudo-linear estimator（PLE）was proposed to alleviate computational complexity and convergence problems. PLE is one of the well known explicit methods which provide solutions in explicit form as a function of the measurements. The PLE method avoids the instability problems of the Cartesian EKF. Despite its simplicity and low computational requirements，the PLE[23,24] suffers from severe bias problems[38, 34]. To overcome the pseudo-linear estimation bias，several approaches have been proposed in the literature[21,26-32]. The most recently developed bias compensated PLE by K. Doǧancay[32] has produced asymptotically unbiased target motion parameter estimates.

In the passive sonar context a long-time source-observer encounter is realistic， so the source maneuver possibilities may be important in regard to the source and array baseline. This advocates for the consideration and modeling of the whole source trajectory including source maneuver uncertainty[33]. A large class of algorithms has been developed for this problem including multiple model filters and filter banks[34], particle filters (PFs)[35-37], interacting multiple model (IMM)[38,39], and generalized pseudo- Bayesian (GPB) algorithms[40]. Li, X. R., and Jilkov, V. P. provide a comprehensive and up-to-date survey of the techniques for tracking maneuvering targets without addressing the so-called measurement-origin uncertainty[41-46]. Part I[41] and Part II[42] deal with general target motion models and ballistic target motion models, respectively. Part III[43] covers measurement models, including measurement model-based techniques. Part IV[44] surveys various decision-based methods. Part V[45] provides a comprehensive survey of techniques for tracking maneuvering targets without addressing the so-called measurement-origin uncertainty. Part VI surveys various nonlinear filtering methods for target tracking, a part of which is [46].

3 TMA WITHOUT DATA ASSOCIATION

In the above mentioned method, some form of observation-to-track data association must be performed before the track state estimation is updated. Recently, some interesting approaches have been proposed whereby the track states are updated directly without the explicit use of a data association algorithm. These methods are outlined next.

3.1 The simple STT systems

The simplest TMA method without data association, still used by some sonar systems, is a single target tracking approach that are designed to perform close-loop tracking on a single target and MTT systems. The STT tracking loop typically measures the offset between the current sensor pointing angle (bearing), and then null the offset. Because the sensor is assumed to point a single target, there is no need to perform a complex data association. The measured bearings are then used directly to estimate the state of the target.

3.2 Event-averaged maximum likelihood estimation (EAMLE)

Kastella have developed a new approach to multi-target tracking based on event-averaged maximum likelihood estimation (EAMLE)[47]. Kastella's method is a sequential approach that performs MLE processing on one scan of data at a time. This method involves the propagation of the PDF associated with the presence of target in target state space, and the target states are assumed to be described by multiple dimensional Gaussian distribution. Unlike the conventional view that data association is central to MTT, EAMLE does not require computing the measurement to track association (MTA) likelihood to form track estimates. the average over all MTA events is computed, weighted by the a priori event likelihoods. In order to simplify the summation over all MTA events in the EAMLE filter, a method using mean-field theory (MFT) is developed, which has been noted the mean-field EAMLE(MFEAMLE)[48].

3.3 Batch processing maximum likelihood estimation methods

Several approaches have been developed for MLE using multiple scans of data[49,50]. These techniques all hypothesis some number of targets to be present and thus attempt to obtain state estimation over the entire batch time interval. In[50], a PDA/ML estimator is derived. In contrast with the standard PDA/JPDA methods, batch processing of prior scans is used and the weights are computed as a part of the MLE state estimation process. In[51], a Newton-type method is used to solve the TMA problem with respect to bearing and frequency measurements from a passive sonar system.

3.4 Bayesian state space estimation

Rather than using a Gaussian assumption to propagate the PDF as in the EAMPLE approach, another convenient implementation approach defines bins in target state space. Then the probability that a target can be computed for all bins[2]. It's well known that DPA seeks the most likely target path in state space. An efficient method is proposed in[52] based on DP. In this method, rather than performing the sum over all previous locations, the most likely transition is found.

3.5 Track-before-detect（TBD）

An alternative approach for data association that has been developed for tracking dim targets consider the detection of a target and estimation of its states are inseparable parts of the same decision process. This approach is frequently denoted track-before-detect （TBD），although the tracking and detection processes occur simultaneously.

In practice，two general approaches are used to implement TBD[2]. The first method relies on a mapping from the measurement space to the target state space，its position in a suitably chosen state space may remain relatively constant. Thus，the signal power in the target state space can be summed over time to determine target presence. A TBD strategy based on matched velocity filtering in[53] is adopted using spatial images constructed from a sequence of power bearing map （PBM） estimates accumulated during a track. To lower the threshold SNR for detection，a discrete bank of matched velocity filters integrates the PBM images over a range of hypothesized trajectories. Such an approach eliminates the need to estimate the number of targets since signal detection is determined by comparing the output of each matched filter（MF） to a decision threshold. The approach is applicable to a single point target or weak point targets that are well separated from each other. Under these conditions a substantial improvement in performance is gained over detect-before-track approaches at low SNR. The TMA method developed by Maranda et al.[54-57] works directly with beam spectra to estimate the target track，rather than using sequence of bearing and/ or frequency estimates as the inputs of conventional TMA techniques. Grid method，a quadratically convergent Newton's method and simulated annealing method are used to find the target track parameters that maximize the sum of the spectral values over the entire observation window. The Maranda's methods can handle fading or weak signals that give rise to large outliers or cause automatic signal-followers to fail，and can enhance detection characteristics.

The second approach for implementing TBD also partitions target space into bins. For this approach，the target is assumed to move through the bins，and the intensity，or likelihood is carried along the various trajectories that are being tested[2].

4 CONCLUSION AND REMARKS

It should be noted that the performance assessment is not involved. It is clear that the current range of TMA algorithms is indeed large. So it is necessary to devise measures of estimation performance so that different algorithms may be compared. The Cramér-Rao lower bound of parameter estimation for some techniques is evaluated[58,59]，a method called tracker operating characteristic（TOC）[60-62] is also developed. Although lots of works have been done，tracker performance analysis is still an open research area: very few analytical performance results are available for even basic algorithms like the nearest neighbor Kalman filter. In practice algorithm performance against an agreed set of criteria for a given application can usually only be assessed after extensive testing on both simulated and real data. It is also apparent that more needs to be done to establish practically meaningful performance benchmarks，using freely available measurement and truth data，so that the relative merits of the individual algorithms can be better understood.

The interest in TMA applications and the sophistication of the methods applied to TMA problem continue to increase concurrently with expansions in computer capabilities. However，despite this increasing interest，no standard approaches are accepted for all applications. The designer must choose the techniques which are best suited to the applications based on his or her knowledge and prior experience. The intent of this paper is to aid in this decision process by presenting a broad survey of available techniques，providing lots of references. We hope that our works presented here can advance the development of the modern sonar systems in some sense.

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声纳目标运动分析的实现方法

陈敬军[1,2]，**冯海泓**[1]，**吴培荣**[2]

（1. 中国科学院声学研究所，Beijing 100081；2. 上海船舶电子设备研究所，上海 200025）

摘要：目标运动分析是声纳的一个重要问题。为了能够有效地估计目标运动状态,选择适当测度集合是第一步。开发出有力的估计算法是解决目标运动分析的另一个关键步骤。本文简练地回顾了声纳目标运动分析的实现方法。在本文中,目标运动分析被松散地分成两大类。一类是经典的目标跟踪方法的一部分,它把数据融合作为整个估计过程的不可分割的一部分;另一类在估计目标状态时并没有利用数据融合。

关键词：目标运动分析;目标跟踪;声纳信号处理;跟踪置前检测;数据融合;回顾

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