ON UNSUPERVISED TRACK CLASSIFICATION BASED ON ENTROPY DISTRIBUTION ESTIMATED ALONG TRACK RELATED DETECTIONS

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Abstract: We address the problem of track classification on board autonomous underwater vehicles (AUVs) in the bistatic sonar framework. Towed array measurements obtained on AUVs result in tracks caused both by echo repeater returns and by bottom clutter. Insufficient knowledge of different environmental clutter characteristics motivates the use of a feature, recently developed, that aggregates the responses of non-target-like clutter for the discrimination of target responses under realistic environmental conditions.

In the recently developed feature (Sildam and Ehlers, UAM 2011), we used the entropy of a statistical similarity test, conducted both along- and across the beams of detections associated with a track, to construct two supervised classes. Here we extend the approach to unsupervised estimation of an unknown number of clusters estimated from field data using an infinite Hidden Markov Model (iHMM). The result of the iHMM clustering, formulated in terms of a finite number of mixture models, is used to classify tracks through differences in the entropy distribution of detections associated with the respective tracks.

Comparing the classified tracks to the ground truth information collected from both the summer training set used for training, and a winter data set subsequently collected in 2012, we show that the feature is robust yielding a single class of tracks corresponded to the echo-repeater target for both data sets.

Keywords: clustering, tracking, infinite HMM
1. INTRODUCTION

The problem of target detection inherently involves the decision making about the presence or the absence of a target of interest (TOI) using data acquired by one or more sensor systems. Therefore target detection assumes data partitioning into two parts, one corresponding to the target and other to the non-target partitions respectively. Such a division requires a definition of at least one out of two statistical models describing respectively either data partitions. In a noisy environment even when the assumptions about the model generating data are valid but when a number of parameters $M$ governing the statistical model is comparable to a number of measurements $N$ collected by sensors, reliable estimation of the model parameters is not possible.

The situation described above explains a high number of false target tracks created by an active multi-static sonar system, which includes an active source, one or more autonomous underwater vehicles towing a linear array of hydrophones, and the data preprocessing and the tracking algorithms.

A possible solution to this problem, using track classification, is presented in [1,2]. In the present work we present this solution in a general context of consecutive data discriminative-aggregative mappings or simply discriminative aggregation (DA), followed by grouping of the obtained multinomial feature. That is, first, data is aggregated via a series of consecutive mappings. Second, the multinomial feature obtained from aggregation is grouped into sets. Third, a statistical model, defining the feature generating model is learned from data in an unsupervised manner.

By constructing a multinomial discriminative-aggregative feature that can be grouped, it is appropriate to use a statistical feature generative model based on Dirichlet processes. In our case, an inference of such a model is readily available and is presented by an infinite hidden Markov Model (iHMM).

The paper is organized as follows. In the second section, a background motivating the track classification is given. Section three introduces a concept of discriminative aggregation used for the feature construction, which is based on estimation of the entropy difference of the similarity test (DEST) distribution. Section four, describes the framework required for the modeling of generative processes of the DEST, followed by the DEST grouping and inference of the DEST posterior distribution. Finally, the section seven presents the results, followed by the discussion and the summary.

2. BACKGROUND

The existing active sonar systems make assumptions about probability distributions of match-filtered envelope of noise and clutter [e.g. 3]. In this case, the pre-processed data can be used to estimate the parameters of the underlying distributions, followed by a declaration of target detection at a pre-defined false-alarm rate. In practice, often a fixed detector threshold is used to declare the target detections.

At this point a set $S_i = \{S^{FD}_{k}, S^{UO}_{l}, S^{TOI}_{im}\}$ of $J = K + M + L$ target detections of a ping $i$ includes the $S^{FD}_{k}$ ($k=1,\ldots,K$) detections due to the reverberation and the uniform scattering of the $K$ cells obtained at a fixed false-alarm rate, the $S^{UO}_{l}$ ($l=1,\ldots,L$) reflections from the $L$ spatially compact unknown objects, and finally the $S^{TOI}_{im}$
(m = 1,...,M) reflections of the M TOIs. Further discrimination of members of the set 
\[ S = \{S_{i=1,...,I}\} \] is possible via grouping of detections respective to the reflecting object using
some grouping (e.g. tracking) mechanism. As long as the \( S^{FD} = \{S_{i=1,...,I}^{FD}\} \) estimated over
the consecutive I pings are spatially uniformly distributed, most of the tracking
algorithms easily reject \( S^{FD} \) detections. As a result, the tracks are mostly associated with
either the \( S^{UO} \) or with the \( S^{TO} \) detections. The discrimination of these two track types
requires comparison of the respective distributions based on data collected along tracks.
The problem here is that even when the \( S^{UO} \) or the \( S^{TO} \) sets are generated from some
known underlying parametric (e.g. K) distribution, the parameters defining the respective
distributions are likely to change from a ping to a ping. The values of these parameters
depend on a target response, on a bi-static target aspect of target response, and on the
errors of parameter estimation.

The problem of target detection involves partitioning all measured data into a discrete
unknown number of classes so that \( S^{Label} \sim i.i.d. \) can be seen as a valid approximation. The
number of classes depends on the granularity of data partitioning into subclasses and
therefore, in principal, can be infinite.

In practice having a finite number of data samples \( N \), the number of classes \( M \) is also
finite since \( M \leq N \). Common knowledge dictates that to improve confidence in the
statistical estimates one should have \( M << N \). A procedure to achieve the
condition \( M << N \), implicitly incorporated into many data processing approaches, lies in
data aggregation via a single or via a set of consecutive mappings, which reduces the
degrees of freedom of data while remaining discriminative with the respect of TOI.

3. DATA DISCRIMINATIVE AGGREGATION

3.1. DATA PREPROCESSING

Data preprocessing, consisting from the base-banding, the filtering, the beam-forming,
the match-filtering, and the normalization implemented in CMRE, can be seen as the
consecutive data discriminative aggregation that results in the reduction of degrees of
freedom of the target detection model.

That is, the beam-forming aggregates recorded data in respect to time-and space
coherence of the signal measured by a set of hydrophones i.e. the coherent signals are
aggregated as opposed to the non-coherent signals and the noise, and discriminated in
terms of the directions of signal arrival.

The matched-filtering performs discriminative aggregation of the reflected signals with
respect to their correlation with a known incident signal. Finally, the normalization tries to
remove the range dependence of amplitude envelope.

3.2 THE DEST FEATURE CONSTRUCTION

Frequent presence of the false tracks in the existing target tracking systems motivated
us to construct a new DA feature, based on the beam-formed, the match-filtered, and the
normalized data [1, 2]. As described in [1-3], the new feature called the entropy difference
of Maximum Mean Discrepancy [3] (MMD or simply similarity) tests DEST was
constructed in three steps (see the Appendix for the details). The first step conducted a series of MMD tests in the beam-number bi-static-travel time space in the vicinity of each of the detections, the second step calculated for each detection two histograms: one, estimated along- and other, estimated across beams, followed by the entropy difference estimation. This way the DEST performed a triple aggregation of relative changes around each of the detections.

More formally, the first step carried out the embedding probability distributions of the couples of time-series snippets in a reproducing kernel Hilbert space, and estimated the MMD distance between them [3]. The MMD distance between the embedded probability distributions of dimension $N$ live in a lower-dimensional manifold of dimension $M<<N$. In this way we aggregated possibly different probability distributions respective to their MMD distance. The second aggregation took place when the probability mass functions of the MMD distance distributions were aggregated with respect to their entropies. The final aggregative mapping was carried out by estimating the difference of entropies, the distribution of which served as a final discriminative feature of detections.

4. MODELING THE DEST GENERATIVE PROCESSES

The field experiments show that the target tracks frequently exhibit an intermittent pattern due to the track breakage. Since the shorter tracks have only a limited set of detections associated with them, we are motivated to infer the latent variables by sharing the sets that have common probability distributions.

Assuming that physical (e.g. scattering) properties of any target do not change over time scales of interest, the extracted features of target response have stationary distribution. Dependence of the target response function on the bi-static angle of arrival can be captured by a mixture of less complex elements of the DEST probability distributions.

We assume that the elements of the stationary mixtures, labeled as virtual reflecting objects (VRO) [2], form the mixture components with the unknown weights. Since a number and the associated distributions of VRO are unknown, the respective variables should be treated as the latent parameters that should be inferred from data.

A statistical framework appropriate for the inference of multinomial variables that shares the multinomial priors is given by the hierarchical Dirichlet Processes (HDP, [4]). Generally, under the exchangeability assumption, the order of detections can be ignored. We model the distribution of DEST as a mixture, where each VRO component specifies a multinomial distribution over the feature, which is shared among different tracks. We wish to find a probabilistic model that places significant probability not only over the observed but also over future unobserved tracks if they are “similar” to the tracks already observed.

5. THE DEST GROUPING

In our application, a statistical aim of the DEST grouping is formation of the DEST sets associated with a target such that $g(S_{label}) \sim i.i.d.$, where $g$ is a feature aggregative operator, is valid. An empirical verification of this assumption is usually complicated. We assume that it can be achieved by a proper discriminative aggregation.

More generally, the required DEST grouping can be carried out by a tracking approach, or by some other processing e.g. a sorting algorithm forming sequences of the detections.
associated with a target. For other sensors it can be spectral processing and extraction of 
the spectral lines associated with a target or some other approaches. While tracking 
applications form explicitly such groups then using the series of contacts, the required 
groups can be discovered from an unsupervised analysis of the respective sequences of 
detections.

When a number of target types is unknown, most of the tracks cannot be labeled in a 
supervised manner. The unsupervised track labeling requires construction of a track 
clustering approach. On the other hand, presence of the statistically homogenous groups 
can be learned from the ordered sequences of detections that include the subsequences 
associated with the targets.

Preliminary analysis of field data have shown that frequently a target can be associated 
with the second or with the third detection sorted by its signal-to-noise ratio (SNR) value 
relative to the first detection with the highest SNR of the direct blast. Such an order 
usually persists over a number of consecutive pings. This observation was used in our 
work where the first twenty highest detections of each ping of all pings of the GLINT11 
experiment were sorted and concatenated into a single sequence so that the first part of 
this sequence was formed from the detections corresponding to the highest SNR of each 
ping, followed by the detections corresponding to the second highest SNR of each ping, 
etc.

6. AN INCLUSION OF THE DEST SEQUENCE POSTERIOR DISTRIBUTION 
VIA INFINITE HIDDEN MARKOV MODEL

In our application, the DEST grouping can be seen as a doubly stochastic process 
where first a probability distribution of probability distributions is sampled, and then given 
a probability distribution, the DEST value is sampled.

A statistical framework appropriate for inference of the DEST multinomial variables 
sharing the multinomial priors is given by a hierarchical Dirichlet Processes (HDP).

A DP mixture can be used to learn a mixture model with a countably infinite number of 
mixture components. To accommodate a countably infinite number of mixture models one 
needs a mechanism to couple the respective DP models [4]. Such a mechanism is the 
hierarchical DP and the resulting HMM model is called HDP-HMM or infinite HMM.

Coupling across transitions can be obtained using hierarchical Bayesian formalism by 
introducing the Dirichlet priors with the shared parameters, and a higher level prior, and a 
base measure [4]).

Inference of the HDP-HMM can be carried out by a Gibbs sampler, which converges to 
the true posterior. The implementation of Gibbs sampler suffers from slow mixing 
“behavior” when applied to strongly correlated time series. An approach, coined by the 
authors the beam sampler [5], overcomes the problem of slow mixing.

The beam sampler introduces an auxiliary variable \( \nu \) such that conditioned on \( \nu \) the 
number of trajectories in the HMM is finite. As a result, such an approach adaptively 
truncates (i.e. only the paths that have large than \( \nu \) transition matrix values are used) the 
ininitely large transition matrix, and makes possible to use dynamic programming in the 
forward calculation. In the backward calculation the whole sequence is re-sampled.

Finally, tracks are classified assuming that all detections associated with any given 
track can be classified using one of the finite mixture models defined by the IHMM. If 
none of the models provide a fit better than 0.95, then the respective track remains 
unclassified.
7. RESULTS

The tracking classification results for the OEX AUVs Groucho and Harpo are shown in the figures 1 and 2 respectively. The tracks not classified (i.e. rejected by the classifier) are not shown. The tracks with a probability of classification exceeding 0.95 are numbered and indicated by thick colored lines. The colors span linearly on red-green-blue light scale, scaled by a number of classes i.e. the IHMM states. Black thick line corresponds to the echo-repeater (ER) track. The starting and the end points of the tracks are shown by the filled circles and filled triangles respectively. The AUV tracks are shown by the thick blue lines, one of the origins of which being close to the beginning of the ER track. The yellow filled diamond corresponds to the position of the static source. In these figures, one can see that obviously the track colored in light brown corresponds to the ER. A number of brown tracks that are far from the ER are the ambiguous tracks.

8. SUMMARY

In this work we presented a general framework of track classification. The main components of this framework consisted from data aggregation via series of consecutive mappings, from construction of the multinomial feature DEST obtained from aggregation, grouping the DEST into the sets, and finally from learning the underlying statistical model in an unsupervised manner.
We demonstrated the track classification results based on an iHMM model learned from GLINT 11 data, which was collected in summer 2011, and applied for testing using data collected in winter 2012 by two AUVs. The overall improvement of tracking over the initial non-classified tracking has been demonstrated in [2].

The general framework presented in this work makes possible to extend this approach to the fusion of acoustic and the other sensors providing the target contextual information.

REFERENCES


A1. DESI FEATURE CONSTRUCTION

We apply the Maximum Mean Discrepancy \([\cdot]\) test on a pair of interleaved bearing-time cells in a time-bearing (TB) window (TBW) with a predefined non-dimensional range \(\hat{N} = f_s R/(2c)\), (where \(f_s\) is the normalised data sampling frequency, \(R\) is the expected length of target, and \(c\) is sound speed) and number of beams \((M=3)\) support. An empirical biased estimate of MMD defined for the pair of TB cells \(\hat{Z}\) and \(\tilde{Z}\) in the TBW can be written as

\[
d[\hat{Z}, \tilde{Z}] = \left| 1/M^2 \sum_{s,o}^M k(\hat{z}_s, \tilde{z}_o) - 2/(MN) \sum_{s,o}^{M,N} k(\hat{z}_s, \tilde{z}_o) + 1/N^2 \sum_{s,o}^N k(\hat{z}_s, \tilde{z}_o) \right|
\]

where \(k(\hat{z}_s, \tilde{z}_o)\) is a kernel function, \(\hat{z}_s\) and \(\tilde{z}_o\) are vectors of the TBW cells, and \(N\) and \(M\) correspond to the numbers of vectors in the respective two adjacent cells of the TB window. We used the Gaussian radial basis function \(k(\hat{z}_s, \tilde{z}_o) = \left(-\|\hat{z}_s - \tilde{z}_o\|^2/\sigma^2\right)\), where \(\sigma^2\) is a scaling parameter. Normalization of \(\hat{z}_s\) data cells is given by \(\hat{z}_s = z_s / \sum_{i,j}^M \sum_{r=1}^N \|z_{i,j}\|\), where \(M\) and \(N\) are the number of data points in the TBW in the range and bearing direction respectively. Note that \(\hat{Z} = \{\hat{z}_1, \hat{z}_2, \hat{z}_3\}\), and \(\tilde{Z} = \{\tilde{z}_1, \tilde{z}_2, \tilde{z}_3\}\) overlap so that \(\tilde{z}_3 = \hat{z}_1\). Thus the difference in signal spread required for the classification is estimated using only three grid points in each bearing and range direction. That is by moving the TB window relatively to \(\hat{z}_{i,j}\) in range space at a constant bearing \(b_j\) and in bearing space at a constant range \(r_j\), we obtain two sets of dissimilarity indexes \(d_\tau = \{d_{i-1,j}, d_{i,j}, d_{i+1,j}\}\) and \(d_b = \{d_{i,j-1}, d_{i,j}, d_{i,j+1}\}\). Each of the sets of the dissimilarity indexes of a single contact can be used to estimate a three-bin histogram \(p(d_r = W_r / M)\) where \(W_r\) is the number of \(d_r\) values (counted either in \(\{d_{i-1,j}, d_{i,j}, d_{i+1,j}\}\) or in \(\{d_{i,j-1}, d_{i,j}, d_{i,j+1}\}\)) falling within the \(r\)-th bin, and \(M=3\) is the overall number of values used in the histogram estimation. A probability mass function in the range and the bearing directions can be estimated from the respective normalised histograms such that \(\sum_{r=1}^M p_r(d_r) = 1\), \(\sum_{r=1}^M p_b(d_r) = 1\). The entropy at constant bearing can be then estimated as \(h_\tau = -\sum_{r=1}^M p_r(d_r) \log(p_r(d_r))\). Similarly the entropy at constant range can be then estimated as \(h_b = -\sum_{r=1}^M p_b(d_r) \log(p_b(d_r))\). Finally, the entropy difference, which is the final feature used below for clustering and classification, is given as \(\Delta h = h_\tau - h_b\).