MODELLING TEMPORAL VARIATIONS BY POLYNOMIAL REGRESSION FOR CLASSIFICATION OF RADAR TRACKS

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ABSTRACT

The sampling rate of a radar is often too low to reliably capture the acceleration of moving targets such as birds. Moreover, the sampling rate depends upon the target's acceleration and heading and will therefore generally be time varying. When classifying radar tracks using temporal features, too low or highly varying sampling rates deteriorates the classifier's performance. In this work, we propose to model the temporal variations of the target's speed by low-order polynomial regression. Using the polynomial we obtain the conditional statistics of the targets speed at some future time given its speed at the current time. When used in a classifier based on Gaussian mixture models and with real radar data, it is shown that the inclusions of conditional statistics describing the targets temporal variations, leads to a substantial improvement in the overall classification performance.

Index Terms— Automatic target classification, Machine learning, Radar, Surveillance

1. INTRODUCTION

The aim of this work is to provide a better overview for a radar operator and thereby enhanced situation awareness in mission critical environments. This is done by real–time classification of radar tracks. A commercial state of the art surveillance radar provides a huge amount of information and it can therefore be difficult for a radar operator to keep up with the information, see Fig. 1. Integrated tracking in radars are becoming standard and in coastal surveillance small targets are of great importance. Consequently the radar and tracker must be sensitive enough to track these small targets. It will therefore be likely that unwanted tracks, like birds, will be tracked as well. Suppression of such tracks requires real–time classification. Compared to synthetic aperture radar (SAR) a 2D surveillance radar does not have height, Doppler or radar imagery available in the classification process. Therefore a method must be developed which uses other attributes like for example kinematic and geographic attributes. By exploiting the temporal development of the kinematic data more information can be extracted from the data. Two of the main problems with using the temporal feature is the low sampling rate for a radar compared with the typically acceleration of targets like birds etc. The second problem is that the sampling rate is inconsistent because of the targets movements and scan period is different for short and long range profiles in the radar.

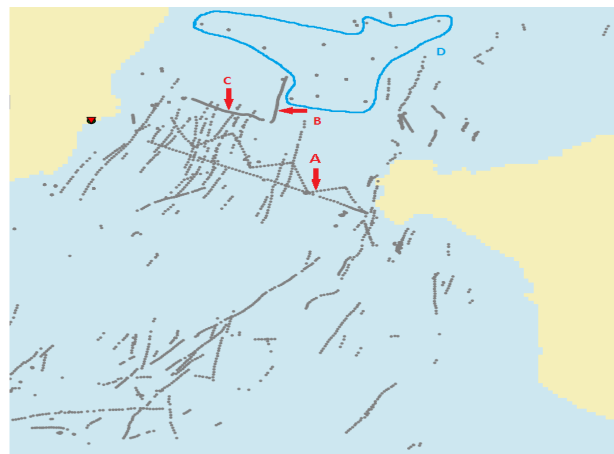


Fig. 1. Radar scenario from Egaa Marina in Denmark showing a rigid inflatable boat (RIB) sailing out and zigzagging back. A large quantity of bird tracks is observed. A is the RIB, B and C are unknown vessels, D is an area with a number of sea buoys, and the rest of the tracks are birds.

There are two main reasons for target classification. The first is improving situation awareness for a radar operator by filtering or color coding tracks according to their classes. The second reason is with the knowledge of the target class the tracker parameters can be optimized and thereby lead to a joint classification and tracking approach [1].

An advanced knowledge–based radar tracker [2] converts the measured backscatter from the radar sweeps into a number of observation called plots. These plots are then used for the actual tracking algorithm and the classification algorithms gets the kinematic information from the tracker.

In the following the term classification is used to describe the broad identification of a track belonging to a given class of targets such as "large ship", "bird" etc.

A lot of work has been carried out for classification in SAR systems ([3] and [4]) but only very little has been done for 2D surveillance radars [5]. In [6] the authors are using a tree–based approach with kinematic features from a 3D radar. In [1], the authors are using joint tracking and classification where they have multiple tracking algorithms, one for each target classes and in [7] kinematic and radar cross section (RCS) are used for joint classification and tracking. In [8] the authors are using high range resolution (HRR) profiles to classify ground moving targets.

In this work, we consider the situation where a radar and its tracker provide information about the target's speed as well as the back scatter intensity. We then propose to model changes in the target's speed over time by polynomial regression. In particular, a low order polynomial is fitted in a least squares sense to training data acquired by commercial radars in realistic scenarios. Based on this model, we provide a closed-form expression to an approximation of the conditional probability density function (PDF) of the target's speed at time $t+\Delta t$ given its speed at time t. This PDF consists of a weighted sum between the target's native PDF and a Gaussian kernel whose standard deviation characterizes the uncertainty of the target's speed. The optimal weight depends upon the target class and is numerically obtained by solving a maximum likelihood estimation problem. We then use the naive Bayesian classifier proposed in [5] for online classification of real radar data. It is shown that a substantial improvement is possible when including the statistics of the speed's temporal variations. For comparison, we also propose to simply model these variations by a Gaussian mixture model (GMM) using the framework of [5]. In this case, the proposed polynomial modelling of velocity GMM (PMVGMM) based on polynomial regression shows a slight improvement over the purely GMM based scheme.

2. METHOD

In this section, we first briefly introduce the naive Bayesian framework proposed in [5], which we will base our classifier upon. For more details about this framework, we refer the reader to [5]. Then, we present our main contributions, i.e., a model of the conditional probability of a target's speed (6). This is given as a weighted sum of the target's native PDF i.e. the PDF of the speed and a Gaussian kernel. The Gaussian kernel introduces uncertainty into the model and whose standard deviation depends upon the time lag and target class.

2.1. Recursive naive Bayesian

The framework is based on [5] where a recursive update algorithm is used. From [5] (1) is the update and smoothing equation which will prevent the probability for a given class to reach zero.

$$P_s(c_p|X_n, X_{n-1}) = \frac{P(c_p|X_n, X_{n-1}) + \epsilon}{\sum_{y=1}^{N_c}(P(c_y|X_n, X_{n-1}) + \epsilon)}, \quad (1)$$

where $X_n = [V_n, I_{nr,n}, I_{mti,n}, \Delta t]^T$, further Δt is the time since last update to the newest update from the radar for a given track. The radar information is: normal radar intensity I_{nr} and moving target indication (MTI) intensity I_{mti}. The information used for kinematic update are: Speed over ground V_n and temporal dynamic e.g. how the target speed evolve. N_c is the number of classes. c_p is the given class and ϵ is some constant Further $P(c_p|X_n, X_{n-1})$ is define as (2).

The recursive Bayesian update rule can be extended with more features, using a naive approach by making the assumption that the features are mutually independent.

The probability for a given class will then be provided by

$$p(c_p|X_n, X_{n-1}) = \frac{P(X_n|c_p, X_{n-1})P(c_p|X_{n-1}, X_{n-2})}{\sum_{i=1}^{N_c} P(X_n|c_i, X_{n-1}))P(c_i|X_{n-1}, X_{n-2})}, \quad (2)$$

and,

$$P(X_n|c_p, X_{n-1}) = P(V_n|V_{n-1}, \Delta t, c_p)P(I_{nr}, I_{mti}|c_p), \quad (3)$$

where $P(V_n|V_{n-1}, \Delta t, c_p)$ denotes the kinematic PDF i.e. (6) and $P(I_{nr}, I_{mti}|c_p) = P(I_{nr}|c_p)P(I_{mti}|c_p)$ is the intensity PDF and they are both modelled as a GMMs. It is assumed that the radar intensity features are mutually independent.

2.2. The proposed PMVGMM method

The main problem with classifying with a temporal feature is that the sampling rate is low as compared to moving targets e.g. between 10 to 40 scans per minute. Secondary is the radar does not have a constant sampling rate. Therefore a method must be developed which can handle the slow and varying sampling rate.

Let us assume that the measurements are noise free. A measurement of a target's speed is obtained at time t, which will give a probability of one for that particular speed (Fig. 2, blue). After some time, say Δt, the target may have accelerated or de-accelerated and we are therefore less certain about its speed. Thus, the PDF of the target's speed, which was initially a delta function at time t should reflect the uncertainty in the speed at time $t + \Delta t$ (red and green). Indeed, as more time passes the less is known about the speed, and the PDF should tend to the targets native PDF (black). We model this uncertainty by convolving the probability of V_n (that is a delta function) with a Gaussian kernel (4). We let the mean of the kernel be the previous measurement V_{n-1}, and let the standard deviation depend upon $V_n, V_{n-1}, \Delta t$. By using the Gaussian kernel, it is assumed that the acceleration and deceleration is equally distributed and therefore no skewness is present. For example, in the case of the speed feature we propose the following PDF P_u for modelling the uncertainty:

$$P_u(V_n|V_{n-1}, \Delta t) = \frac{1}{\sqrt{2\pi}\sigma(V_n, V_{n-1}, \Delta t)} \exp\left(\frac{-(V_n - V_{n-1})^2}{2\sigma(V_n, V_{n-1}, \Delta t)^2}\right). \quad (4)$$

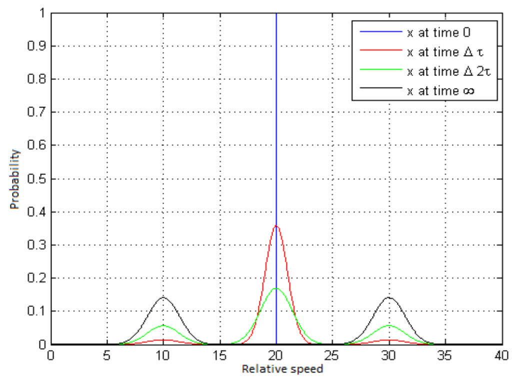


Fig. 2. A simple example, with synthetic data, $K(X_n|C_p)$ is the conditional PDF that will be model in the following.

We require that $\Delta t \gg 1$ implies $\sigma \gg 1$. With this, we therefore propose the following formula for the standard deviation:

$$\sigma(V_n, V_{n-1}, \Delta t) = \left| \frac{\Delta t}{V_{n-1} - V_n} \int_{V_{n-1}}^{V_n} T_{acc}(v')dv' \right|, \quad (5)$$

where $T_{acc}(v')$ is a fit of the acceleration given the speed described in section 2.2.1.

The standard deviation $\sigma(V_n, V_{n-1}, \Delta t)$ of the Gaussian kernel is then the average acceleration from the last measurement to the new measurement given the speed multiplied with the time since the last measurement. As time increases from the last measurement the variance will also increase because less is known about the speed. For $\Delta t \to \infty$ one cannot expect to have much knowledge about the speed except for the native information given by the speed without temporal dynamics $P_{native}(V_n)$. The transition from P_u to P_{native} depends upon the class. We describe this dependency by an exponential weighting function with time constant C. The resulting PDF is the weighted sum of P_u and P_{native}:

$$\begin{aligned} P(V_n|V_{n-1}, \Delta t) = &\exp(-C\Delta t)P_u(V_n|V_{n-1}, \Delta t) \\ &+ (1 - \exp(-C\Delta t))P_{native}(V_n), \end{aligned} \quad (6)$$

where

$$P_{native} = \sum_{i=1}^{N} \pi_i \mathcal{N}(V_n; \phi_i) \quad (7)$$

and π_i is the weighing factor of the i^{th} Gaussian distribution. The kinematic model (6) must be modelled for each target class and hence it depends on the given class, that is $P(V_n|V_{n-1}, \Delta t, c_p)$.

2.2.1. *Finding the* $T_{acc}(v')$

The function T_{acc} from (5) is found from training data based on real radar measurements, GPS logs, automatic identification system (AIS) and automatic dependent surveillance-broadcast ADS-B data. Since the data are noisy we have

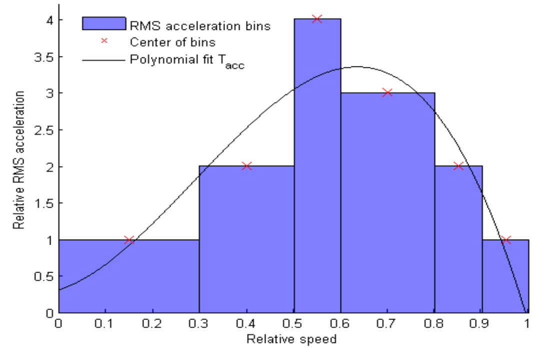


Fig. 3. An example of the polynomial fit using synthetic data

applied fixed interval smoothing [9] in order to reduce the noise.[1] A dataset $\{(V_n, \Delta V_n)\}$ which consist of pairs of speeds and associated accelerations $\Delta V_n = V_n - V_{n-1}$ are divided into bins based on the first coordinate, i.e. V_n. Each bin contains an equal amount of pairs see Fig. 3 for an example. From this it is now possible to calculate the acceleration RMS value for each speed bin.

$$Acc_{RMS}(i) = \sqrt{\frac{1}{N} \sum_{n=1}^{N} \Delta V_n^2(i)}, \quad (8)$$

where i is the speed bin number, N is the number of data points in each bin and $\Delta V_n(i)$ is the n^{th}acceleration in the i^{th} speed bin. We fit a k^{th} order polynomial $T_{acc}(v')$ to the bins using the center of each bin. The polynomial thus provides the average acceleration given any speed V_n. See Fig. 3. By applying the histogram and the RMS the estimate of the fit will be more immune of outliers. Further we want a continues function as jumps between the bins can have a negative impact on the performance of the classification.

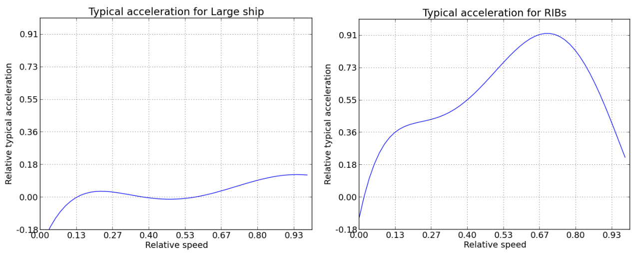
In Fig. 4 a subset of the class's acceleration fit is shown. It is clearly visible that the large ships do not accelerate much and the RIBs are a lot more agile than the large ships. A sixth order fit has been use in the shown fit. In the following the order are chosen empirically. The order used is a fourth order fit except the birds class here a eight order fit is used.

2.2.2. *Finding the time constant* C

The time constant C that is used in the weighting which combines P_u and P_{native} can be obtained off-line for each class by maximizing the following likelihood function:

$$\begin{aligned} L(C) = \prod_{n=1}^{N} \prod_{\Delta t} &\exp(-C\Delta t)P_u(V_n|V_{n-1}, \Delta t) \\ &+ (1 - \exp(-C\Delta t))\, P_{native}(V_n), \end{aligned} \quad (9)$$

[1]Due to the filtering the training are less noisy than the test data and we are therefore able to deduce the target's acceleration based on the filtered speed training data. Due to the on-line classification we cannot apply fixed interval smoothing on the test data in a similar manner

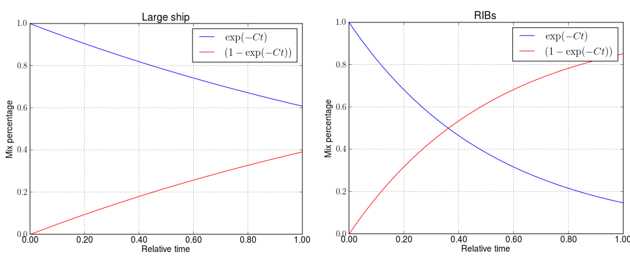


(a) Large ship (b) RIBs

Fig. 4. A sixth order acceleration fit for (a) Large ship (b) RIB

where σ is described in (5).

Fig. 5 shows the amount of information the algorithm uses from the uncertainty and the native PDF given the time since last measurement. It is cleat that is more difficult to predict the RIB as the native information is used quickly compared to the large ship. This is as expected because a large ship will normally not change speed as often as RIBs will.



(a) Large ship (b) RIBs

Fig. 5. A plot over the relative weight of the the uncertainty and the native PDF. The weight is given by $exp(-C\Delta t)$. (a) large ship, (b) RIB

3. RESULTS OF EXPERIMENTS

In this section we present the performance of the algorithm. For comparison the results for RGMM, which do not use temporal information and DeltaGMM which does use temporal information [5] are also shown. The database is the same as described in [5] however in the Egaa marina scenario unwanted tracks originating from returns associated with static land features are removed. In table 1 the matrix is shown for the PMVGMM. In table 2 the confusion matrix from the RGMM method is shown. This algorithm does not use the temporal information. In table 3 the DeltaGMM algorihm is shown. This algorithm exploit the temporal feature by making a GMM of the entire feature space. The bold font is the best performing algorithm for that class. The matrices are shown in percentage. In Fig. 7, 6 and 8 a scenario is shown where a RIB is sailing out from Egaa marina in Aarhus, Denmark and zigzagging back. It is clear from both the confusion matrices and the radar scenario that the PMVGMM algorithm is the best performing. There is an improvement in the RIB track and the PMVGMM is keeping the performance for the birds.

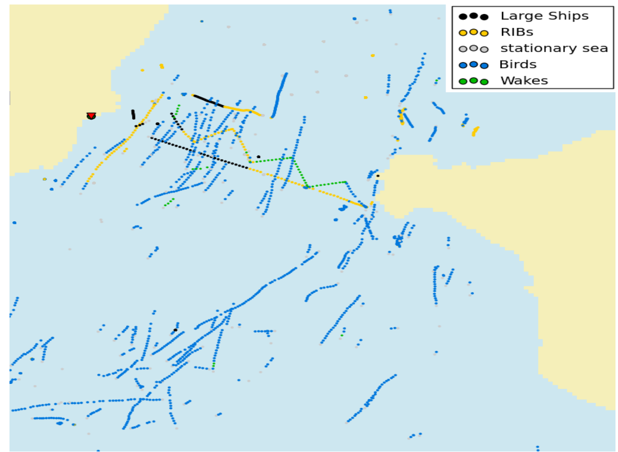


Fig. 6. Egaa Marina scenario with colored tracks from the classification using the PMVGMM method.

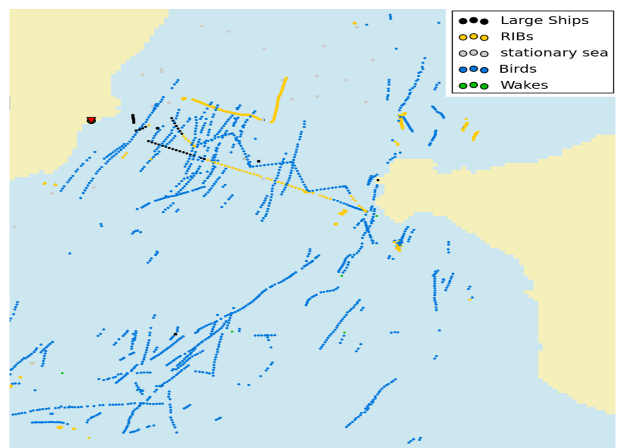


Fig. 7. Egaa Marina scenario with colored tracks from the classification using the RGMM method.

4. DISCUSSION

From Table 2 and 1 the PMVGMM is classifying with an overall accuracy of 12.9% better than the RGMM method and 1.3% better then DeltaGMM. The large ships and wakes are classified better with the PMVGMM algorithm. We believe this is because that the PMVGMM is requiring less training data then the DeltaGMM and RGMM as large ships are sailing with a constant speed. Therefore a large amount of different large ships must then be added to the database to get the right PDF. Because PMVGMM does not depend as much on the speed feature and more on the typical acceleration fewer types of large ships can be used to train the class. For more agile targets like birds and RIBs it is more difficult to predict the

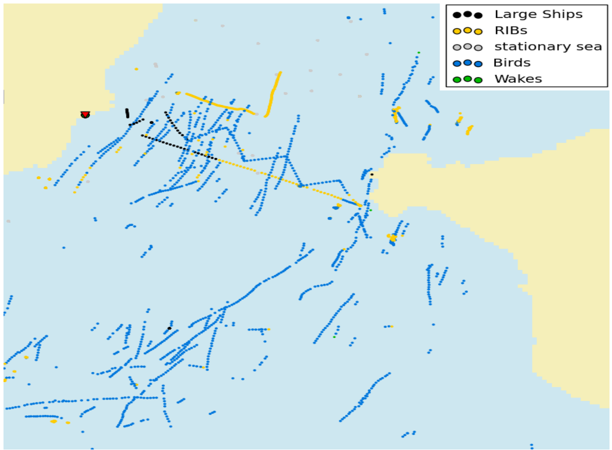


Fig. 8. Egaa Marina scenario with colored tracks from the classification using the DeltaGMM method.

Predicted:					
Actual:	Large ships	Birds	Wakes	RIBs	Stationary sea targets
Large ships	**85.4**	3.9	0.8	9.6	0.2
Birds	16.8	79.0	0.8	0.8	2.7
Wakes	0.0	1.7	**97.5**	0.0	0.8
RIBs	51.4	2.6	0.4	36.7	8.9
Stationary sea targets	0.0	4.6	0.0	0.0	95.4
Overall performance	78.8				

Table 1. PMVGMM confusion matrix

targets movements and therefore RGMM and DeltaGMM are better at these targets. The radar scenario is shown in Fig. 6, Fig. 7 and 8. All of the classifiers has difficulty with classifying the RIB. The RGMM and DeltaGMM is classifying a large part of the RIB track as birds, however the PMVGMM is only classifying a small part as birds. False negative classification of e.g. RIBs as birds is not desirable, as this may cause targets to be removed from the situations display when applying class filters such as birds. All of the algorithms is classifying most of the birds correctly.

5. CONCLUSION

In this paper we present an algorithm which uses a polynomial to predict the acceleration given the speed for a target class. This is combined with a native GMM as time passes and less is known of the targets speed and position. The results shows clearly that by exploiting the temporal information it is possible to give a better estimate of which target class a track belongs to i.e. DeltaGMM and PMVGMM is better then RGMM. Further is shows that by using a polynomial to predict the targets acceleration a slight improvement of classification can be achieve in comparing with the DeltaGMM method. In the Egaa scenario the improvement for real world use is significant.

Predicted:					
Actual:	Large ships	Birds	Wakes	RIBs	Stationary sea targets
Large ships	67.5	5.5	0.0	27.1	0.0
Birds	12.6	**87.4**	0.0	0.0	0.0
Wakes	0.0	72.3	27.7	0.0	0.0
RIBs	52.2	0.3	0.0	47.5	0.0
Stationary sea targets	0.0	0.0	0.0	0.6	**99.4**
Overall performance	65.9				

Table 2. RGMM confusion matrix

Predicted:					
Actual:	Large ships	Birds	Wakes	RIBs	Stationary sea targets
Large ships	58.9	7.3	0.3	33.5	0.0
Birds	0.0	85.5	14.5	0.0	0.0
Wakes	0.0	3.4	96.6	0.0	0.0
RIBs	51.5	1.2	0.0	47.2	0.0
Stationary sea targets	0.0	0.0	0.0	0.9	99.1
Overall performance	77.5				

Table 3. DeltaGMM confusion matrix

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