Correction to 'Robust Doppler classification technique based on hidden Markov models'

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Mohammed Jahangir
Aveillant Ltd

Robust Doppler classification technique based on hidden Markov models

M. Jahangir, K.M. Ponting and J.W. O'Loghlen

Abstract: A classification algorithm is presented that uses hidden Markov models (HMMs) to carry out recognition between three classes of targets: personnel, tracked vehicles and wheeled vehicles. It exploits the time-varying nature of radar Doppler data in a manner similar to techniques used in speech recognition, albeit with a modified topology, to distinguish targets with different Doppler characteristics. The algorithm was trained and tested on real radar signatures of multiple examples of moving targets from each class, and the performance was shown to be invariant to target speed and orientation and was able to be generalised with respect to variants within a class.

1 Introduction

MTI (moving target indication) radars can provide all-weather, day/night, surveillance capability. Such radar systems provide very efficient location information on moving targets but traditionally have limited recognition capability. Automatic recognition algorithms developed for imaging radars, which exploit target spatial information, are not applicable for MTI systems because they operate in a low resolution mode. However, there is potential for classification based on target Doppler signatures. The main difficulty with such an approach is that Doppler signatures have a tendency to evolve over time according to certain deterministic motion patterns of the targets. Conventional classification techniques that assume the Doppler signature to be stationary, and therefore use the information only in the instantaneous Doppler, are likely to be sub-optimal. Such techniques fail to utilise the pattern in the time-evolving nature of the signature. This may be compared with the human ear, which is adopt at recognising frequency components in time-varying signatures. It is a recognised fact that skilled operators can distinguish between target types when the radar signal is played as an audio output. Jahangir and Ponting [1] used this parallel between the time-varying nature of Doppler and speech signals to devise an HMM algorithm for classifying targets on the basis of their radar Doppler signature.

Jahangir and Ponting [1] showed that by adapting the topology of basic speech recognition HMM models, a Doppler classification algorithm can be defined to distinguish between classes of targets defined by the categories of personnel, wheeled and tracked vehicles. Later in this paper we shall need to refer to sub-categories within these 'broad classes' which we term 'fine classes'. The original paper presented results of a pilot study that had a limited target set and restricted the problem to targets moving only in the radial direction with respect to the radar. However, there are many factors that can give rise to within-class signature variability. For practical, robust classifiers it is necessary that the classification performance is invariant to such factors. In this paper, we assess the robustness of the HMM classifier by training and testing against a larger data set. The data set was constructed to represent the following within class signature variations: variation with target type; variation with target aspect angle and variation with target speed. Following the approach in Jahangir and Ponting [1], the HMM classifier is defined through a method of trial and error to establish the optimum model topology.

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M. Jahangir and J.W. O'Loghlen are with QinetiQ Ltd., St. Andrew's Road, Malvern, Worcs. WR14 3PS, UK

K.M. Ponting is with 20/20 Speech Ltd, Malvern Hills Science Park, Geraldine Road, Malvern, Worcs. WR14 3SZ, UK

2 HMM algorithm

The task of developing an HMM classification algorithm requires the identification of suitable feature vectors, the selection of appropriate HMM models, the definition of the class structure and the estimation of the model parameters using labelled training data. The classification performance is then evaluated using independent test data.

The feature vectors are obtained by pre-processing target signature files, with the range resolution set to be larger than the maximum dimension of the target. The signature files are generated by firstly identifying the range gate in which the target is present within any single radar pulse. Radar signals are then extracted at the specified range gate from a number of consecutive pulses. This produces a 1-D target signature file of temporal complex data samples all taken from the same range bin. The temporal duration of each of the signature files is chosen such that the target is allowed to transit through the chosen range gate. Fig. 1 is the plot of the real part of an example signature file with the instances where a target appears and leaves the range gate clearly marked.

The 1-D target signature files are then pre-processed to obtain the feature vectors using the following steps:

Step 1: Apply a constant Doppler shift to the entire file to centre the target bulk Doppler at zero frequency, thereby

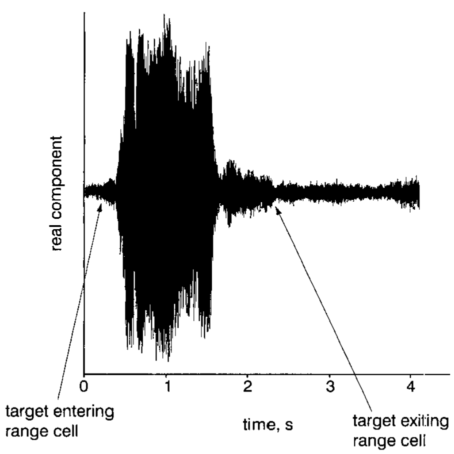

Fig. 1 *Example of a single-target signature file*

ensuring that the signals are invariant with respect to the target bulk velocity.

Step 2: Convert the 1-D temporal data into a set of Doppler frames using a 128 point Hamming weighted FFT and an FFT window overlap such that for a 4 kHz pulse repetition system it produces 100 frames per second of data.

Step 3: Convert the FFT complex samples to log amplitude samples.

Step 4: Transform each Doppler frame comprising 128 log amplitude samples into a reduced dimensionality vector using linear discriminant analysis (LDA), Hunt and Richardson [2]. The LDA process is designed to sharpen the partition of the training data into fine class categories and can loosely be thought of as linearly transforming the feature space to a new one in which the ratio of between category to within category variance is maximised.

Each of these LDA-transformed Doppler frames is taken to be an HMM feature vector and the set of frames extracted from a signature file defines an observation sequence.

In designing an HMM, it is necessary to identify an appropriate topology, the complexity in terms of the number of states and the model for the state-observation probability. Since target Doppler signatures may exhibit a periodic behaviour in time, Jahangir and Ponting [1] suggested that a good choice of HMM type is the one based on a cyclic topology. Fig. 2 illustrates this topology for a three-state model. Any state may be the initial state and any state the final state; additionally, a loop-back is

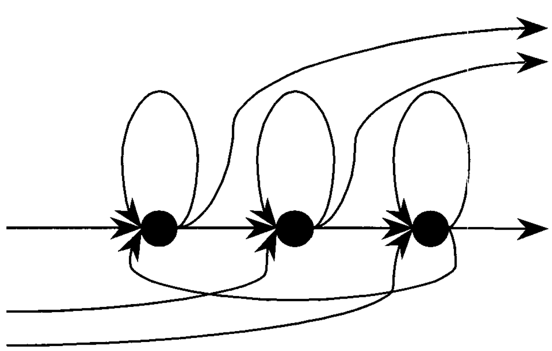

Fig. 2 *HMM topology used for Doppler recognition*

inserted to allow multiple cycles through the model. The appropriate number of HMM states is chosen through trial and error. Finally, the state probability density functions (PDFs) are specified as four-component multivariate elliptical Gaussian mixture distributions, as in Jahangir and Ponting [1] (where the dimensionality of the Gaussian PDFs is determined by the number of elements in the HMM feature vector).

The classification algorithm employs a system of broad and fine class labels. Three broad target classes are defined: personnel 'P', tracked vehicles 'T' and wheeled vehicles 'W'. An additional broad class labelled '_' representing background is also defined. Data from each target broad class is used to train separate HMM target models. The individual target signature files are, however, labelled using a fine labelling system based on target type and its orientation. Thus, for example, a file would be labelled as 'veh_1_045' denoting target type 'veh_1' at an orientation of 45°. A look-up dictionary is used to specify the grouping of the fine classes into a broad class. The LDA process uses the fine-class labels to determine the optimum transformation for feature length reduction. On the other hand, the HMM algorithm uses the broad class labels for determining the number of models, the estimation of the model parameters and the scoring of the recognition performance.

For each broad class, the HMM model building starts from 'blank' models created with the desired topology. The optimum parameters are estimated using a set of pre-processed target signature files belonging to a chosen broad class. The Baum–Welch algorithm (Holmes and Holmes [3]) iteratively aligns the appropriate sequence of models with the feature vectors in each training file and uses that (soft) alignment to re-estimate the parameters of the models.

Models with multiple mixture components per state are generated from models with smaller numbers of components by splitting the mean of each component into two and perturbing the values slightly (as otherwise the re-estimation process would never separate the means). First, single component models were generated; the means were then split and models generated with two components per state; finally another split resulted in the generation of four-component models. Each stage of this process used 20 iterations of the re-estimation algorithm.

The manner in which a target transits through a range cell means that not all the frames in a target signature file correspond to the target, there being a number of frames at the beginning or end of the file (or both) that are background only. The training process allows for this by including optional background class models before and after the appropriate target model for each training file. Thus the (soft) alignment is allowed to allocate leading and trailing feature vectors to the background class instead of the target model.

Recognition is performed on each target signature file submitted. An HMM feature vector sequence is derived from the signature file using the same pre-processing steps as in the training stage. The Viterbi dynamic programming algorithm (Holmes and Holmes [3]) is used to obtain the most likely sequence of models and time alignment of those models to the unknown input. The allowed sequences were constrained by the use of a finite state syntax to prohibit the recognition of more than one target in any one file. The recognition system was used in two modes: 'forced choice' between any of the target classes which recognises exactly one target per file and, 'unforced' recognition which recognises at most one target class per

Table 1: Radar operating parameters

Centre frequency	15.75 GHz
Pulse repetition frequency	4 kHz
Polarisation	Horizontal
Grazing angle	0°
Slant range to beam centre	~500 m

Table 2: Range of target configurations for each broad class for which data were collected

Class	Target type	Aspect angle	Speed	Total runs
Personnel	2	2	2	8
Tracked	3	9	1	27
Wheeled	2	9	1	18

file or the background class. Classifier performance was evaluated through an error count of misclassified files together with a confusion matrix.

3 Data set

The data used for training and testing the HMM classifier was obtained from real radar measurements of moving targets from a static ground-based system. Table 1 summarises the system parameters.

The radar measurements were taken with the antenna pointing in a fixed direction and a control target moving through the radar swath at a specified aspect angle and speed. This constituted a single imaging run and the process was repeated for a number of different target types belonging to the three broad classes. The personnel data were obtained from a trial where two subjects were imaged walking and jogging either towards the radar or moving directly away from it. The vehicle data were obtained from a separate trial where three tracked and two wheeled vehicle types were imaged along nine different aspect angles travelling at a nominal constant speed. This provided 53 different imaging runs (see Table 2) for which data were extracted.

For each imaging run, a number of independent target signature files of four seconds dwell were generated by processing data from different locations along the range swath. Target signature files were selected at random from each of the imaging runs to form a training set and two test sets. Each data set contained 53 target signature files with the data sets being disjoint. The data set was chosen to include every target type and aspect angle so that the algorithm would generalise.

4 Results

The topology of the HMM Doppler classification algorithm was based on the suggested topology in [1] as shown in Fig. 2. The appropriate complexity of the model in terms of number of states, LDA features and number of mixture components per states was established through assessing the performance of models built using a wide range of conditions as listed in Table 3. The classification stage also assessed the performance using a varying number of frames taken from the centre of the target signature files to assess the effect of target dwell time on performance.

Table 3: HMM model conditions used for Doppler classification experiments

Number of HMM states	3, 5, 7, 9, 11, 13, 15
Number of Gaussian components per state	1, 2, 4
Number of LDA features	4, 8, 12, 16, 20, 24, 32, 120
Number of frames	400, 100, 50, 25, 12, 6

Fig. 3 shows the error count for forced recognition for a HMM model using nine states, 120 LDA features and mixtures with four Gaussian components. The error count is reasonably low and remains fairly constant as the number of frames (and therefore dwell time) is reduced. The results are consistent for the two independent test sets with performance marginally better for test set 2.

The performance drops for 6 frames (60 ms dwell) and part of the reason for this is that in some of the files there is no target signature present for this short window. For such cases unforced recognition is a better measure, because the algorithm will classify these files as background. Fig. 4 is a comparison of the forced and unforced recognition, where the difference is only significant for the very narrow dwell time where there is an increased possibility of no target present.

There was no clear trend in performance versus model complexity, but generally models with a higher number of states and feature vectors performed better. Furthermore, models with four Gaussian mixtures always performed better than those with fewer mixture components and these are the results quoted here.

Table 4 shows the confusion matrix for the results in Fig. 3 for test set 2 using 100 frames. The classifier

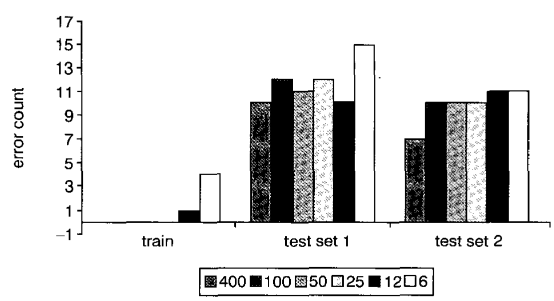

Fig. 3 *Error count out of 53 files for forced recognition*

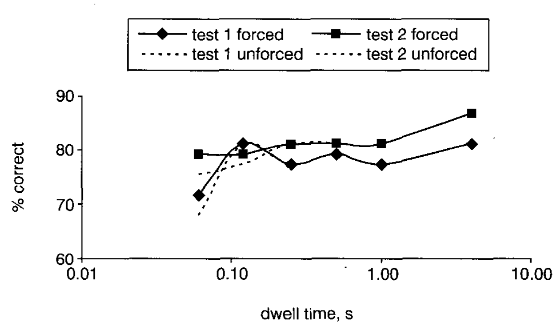

Fig. 4 *Comparison between forced and unforced recognition for the three-class problem*

Table 4: Confusion matrix for 3-class problem for test set 2 and 100 frames

True class	Output class Personnel	Tracked	Wheeled
Personnel	100%	0	0
Tracked	0	78%	22%
Wheeled	0	17%	83%

obtained a 100% success rate in recognising personnel with the main confusion being between the tracked and wheeled vehicles. The overall performance was 87% correct classification. The corresponding figure on test set 1 is 86%, giving an overall average of 86.5%.

5 Conclusions

Results for personnel, tracked and wheeled vehicle classification show that almost 100% discrimination between personnel and vehicles can be achieved with the HMM algorithm. Overall about 87% correct classification was obtained for the three-class problem.

The problem was adequately modelled with an HMM algorithm using a cyclic topology with 9 states and 120 LDA features. The classifier required only a modest amount of data for training. The recognition performance was not degraded significantly even when the dwell time was reduced to 120 ms. This makes the algorithm feasible to operate with scanning systems that have a short dwell time on target and are designed for rapid wide-area coverage.

The classifier was shown to be invariant to target aspect angle and speed, and was able to model multiple target types. Models for additional classes that have distinct Doppler characteristics, such as helicopters, can be easily incorporated into the algorithm. The HMM algorithm, therefore, offers a very powerful tool for the automatic classification of moving targets in the absence of high range resolution. However, to understand the connection between the physical properties of the target motion and the stochastic process that the HMM algorithm is modelling, greater insight is required into how the state sequence maps onto the Doppler frame sequence.

This study was based on 0° grazing angle data which are only directly relevant to ground-based radar. However, it can be easily extended to airborne systems with a suitable choice of training data set.

6 Acknowledgment

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7 References

1 JAHANGIR, M., and PONTING, K.: 'Application of hidden Markov models to the classification of ground moving targets'. Presented at IGARSS 2000, Honolulu, USA, 2000

2 HUNT, M.J., and RICHARDSON, S.M.: 'An investigation of PLP and IMELDA acoustic representations and of their potential combination'. Proceeding of IEEE ICASSP 1991, Toronto, Vol. 2, pp. 881–884

3 HOLMES, J.N., and HOLMES, W.J.: 'Speech synthesis and recognition' (Taylor and Francis, UK, 2001, 2nd edn.)