CONTEXT-DEPENDENT LANDMINE DETECTION WITH GROUND-PENETRATING RADAR USING A HIDDEN MARKOV CONTEXT MODEL

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1. INTRODUCTION

It has been well-documented in the literature that Ground-Penetrating Radar (GPR) technology is well-suited for use in landmine detection applications [1,2]. However, a potential drawback of GPR is that its performance is sensitive to varying environmental conditions. These include, but are not limited to, surface roughness [3,4], soil moisture [5,6], and soil heterogeneity [7]. Fig. 1 illustrates the compounded effect of these factors by comparing GPR images of a low-metal antitank landmine buried at the same depth in four different road conditions. Several recently-developed detection algorithms utilize features extracted from GPR images such as these [8,9], and the effects of environmental factors can therefore drastically alter algorithm performance. A recent comparison of several of these algorithms' performance on a large data set illustrated that certain feature-based techniques may be better-suited than others for landmine detection under specific environmental conditions [10].

In recent years, context-dependent learning algorithms have emerged as a potential solution to this problem. The objective of context-dependet learning is to determine how a classification problem varies with respect to some secondary (but measurable) aspect of the data being classified, and learn an ensemble of classifiers with respect to the contexts of the training data. One approach to context-dependent landmine detection has been to learn a clustering of features extracted from data under varying environmental conditions [11], while another approach is to infer environmental conditions from the raw data itself [12]. Experimental results from both types of context-dependent learning showed improved performance over conventional classification techniques for discriminating landmine targets from clutter in GPR data collected across varying environmental conditions.

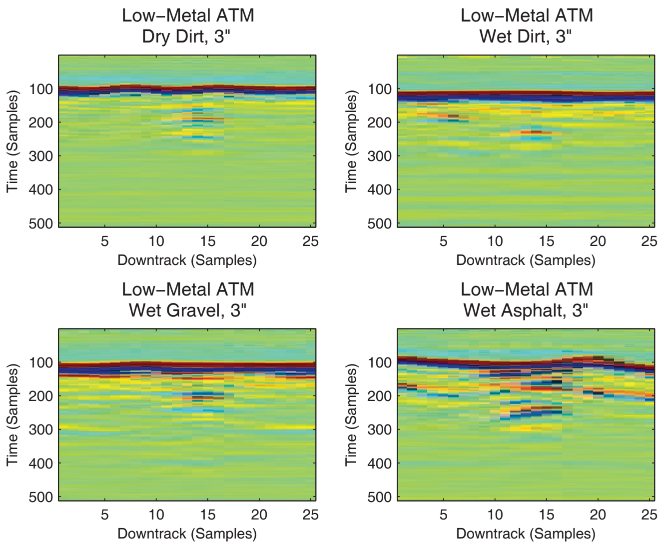

Fig. 1. GPR images of the same type of low-metal AT landmine under four different soil moisture conditions: dry dirt (top-left), wet dirt (top-right), wet gravel (bottom-left), and wet asphalt (bottom-right).

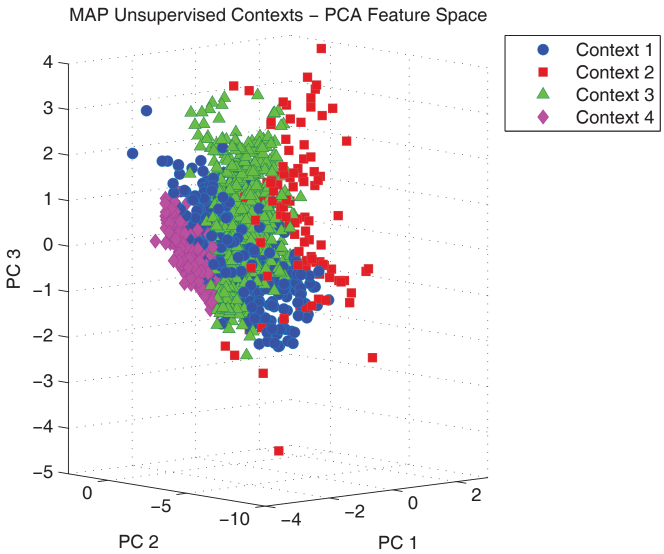

Fig. 2. Scatterplot of 3-D PC space of context identification features. Points are colored according to their MAP context labels determined by VB Gaussian clustering.

2. MOTIVATION AND NEW WORK

While past explorations in context-dependent landmine detection illustrate that use of contextual information can improve classification performance, they do not incorporate any information regarding the spatial correlation between observations. However, it is a plausible assumption that observations of GPR data collected sequentially are more likely to share the same environmental context than observations collected at different locations, or at the same location on different days. Incorporation of this information into a context-dependent framework could aid target discrimination performance. The work presented in this paper models the time-series of GPR observations as an N-state Hidden Markov Model (HMM) [13], in which the underlying state is considered to be the context of the associated observations. In this work, contexts were inferred from physics-based features extracted from the raw GPR data to characterize surface texture and subsurface electromagnetic properties. Because the HMM is an unsupervised learning algorithm, this approach to context identification is particularly useful when discrete environmental labels for the training data are unknown or not available.

HMM posterior state probabilities were used to train an ensemble of N component classifiers for discriminating landmines from clutter. In this paper, the component classifiers are linear Relevant Vector Machines (RVMs) [14], and were trained on a large number of features specially designed for classifying landmines from clutter [8, 15, 16]. The sparseness achieved by the linear RVM is a form of *de facto* feature selection, in which contexts with a more difficult mine/clutter discrimination problem may require more features than contexts with an easier discrimination problem. The context-dependent algorithm presented in this paper is therefore referred to as HMM-Based Context-Dependent Feature Selection (HMM-CDFS).

3. PRELIMINARY RESULTS

To initialize the HMM state model, unsupervised clustering was performed on the three-dimensional principal components (PC) space of the context identification features. Clustering was performed by using Variational Bayes (VB) inference to train a Gaussian mixture model [17]. Fig. 2 illustrates the PC space, with observations colored according to their maximum *a posteriori* (MAP) context. To illustrate the spatial correlation between sequential observations, the data is plotted according to its Northing-Easting coordinates, with color corresponding to MAP context labels, in Fig. 3. Note that observations collected in sequence tend to have similar MAP context labels, despite the fact that the labels were learned via unsupervised clustering. This is the spatial correlation that the HMM exploits when identifying the context of a sequence of GPR data.

The HMM-CDFS algorithm was evaluated on a large set of GPR data collected at three geographically distinct test sites in the Eastern, Central, and Western United States over a span of three years. Data was collected over dirt, gravel, and asphalt test lanes in widely-ranging weather conditions. HMM-CDFS was evaluated using a lane-based cross-validation technique,

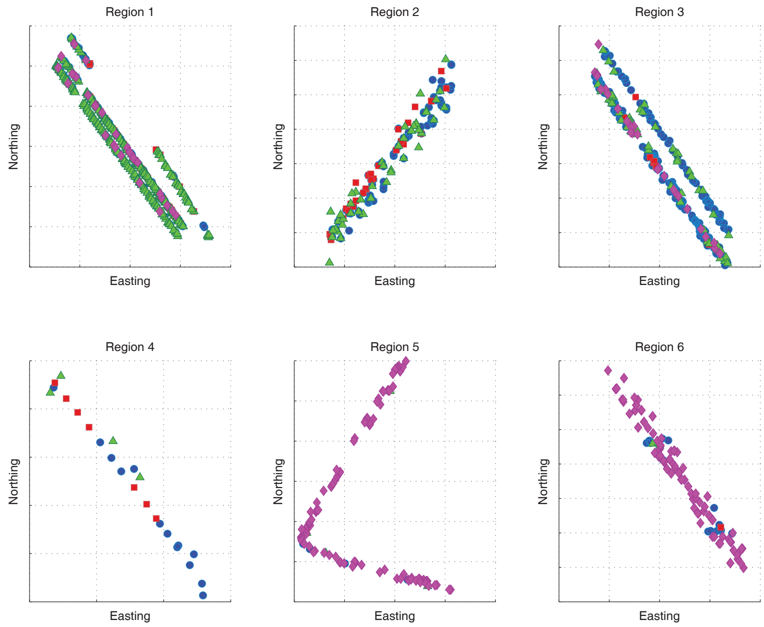

Fig. 3. GPR observations plotted according to geographic coordinates. Points are colored according to their MAP context labels determined by VB Gaussian clustering.

in which each excursion down each lane were considered to be a distinct observation sequence. For each cross-validation fold, HMM-CDFS was trained on the observation sequences for all lanes with one lane's sequences held out for testing. The discrimination performance of HMM-CDFS was compared to the prescreener, a single RVM (which does not use contextual information), and an unsupervised version of the original CDFS (which uses contextual information, but not spatial correlation information). Pseudo-ROC curves illustrating probability of detection (PD) as a function of false alarm rate (FAR) are plotted in Fig. 4. Preliminary experimental results suggest that the incorporation of spatial information into the context model by HMM-CDFS has the potential to improve target discrimination over that of conventional classifiers and previously-developed context-dependent learning algorithms.

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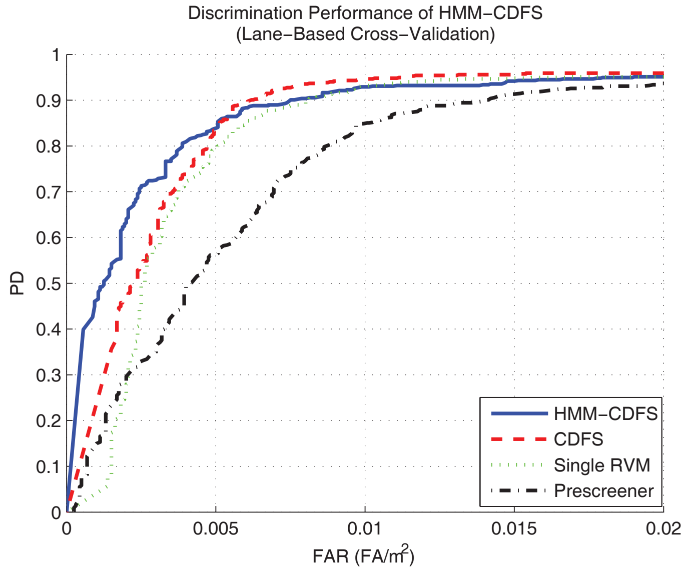

Fig. 4. Pseudo-ROC curve comparing discrimination performance of HMM-CDFS (blue) with CDFS (red), a single RVM (green), and the prescreener (black).

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