A MULTIMODAL MATCHING PURSUITS DISSIMILARITY MEASURE APPLIED TO LANDMINE/CLUTTER DISCRIMINATION

Taylor C. Glenn[1], Joseph N. Wilson[1], K.C. Ho[2]

Computer and Information Science and Engineering Dept., University of Florida, Gainesville, FL 32611
Dept. of Electrical and Computer Engineering, University of Missouri-Columbia, Columbia, MO 65211

1. INTRODUCTION

We have applied the method of matching pursuits (MP) to the problem of landmine/clutter discrimination using multichannel data from a single sensor in several earlier works leading to the competitive agglomeration matching pursuits (CAMP) algorithm [1,2,3]. In this work, we build on our previous results to adapt the matching pursuits dissimilarity measure (MPDM) to use with multimodal sensors. We demonstrate the concept with a multimodal mine-detection sensor employing both electromagnetic induction and ground-penetrating radar sensors. We discuss the multimodal sensing system, review the MPDM and the CAMP algorithm. We then discuss our approach to generating a multimodal, application-specific dictionary for our CAMP algorithm and our modification to the MDPM and CAMP to support multiple sensing modalities. Finally, we analyze the level of performance improvement yielded by employing the multimodal CAMP as opposed to exploiting either of the sensing modes of our platform alone.

2. THE MPDM AND THE CAMP ALGORITHM

Typical application of matching pursuits approximates a signal *x* in a Hilbert space H using an overcomplete *dictionary* of signals $D = \{g_d\}_{d=1}^{m}$ drawn from the same space [4]. Such an approximation is a linear combination of *p* elements from *D*, namely

$$\hat{x} = w_0{}^{(x)} g_{d_0}{}^{(x)} + w_1{}^{(x)} g_{d_1}{}^{(x)} + \ \dots + \ w_{p-1}{}^{(x)} g_{d_{p-1}}{}^{(x)}$$

where $w_j{}^{(x)}$ is the coefficient of dictionary element $g_{d_j}{}^{(x)}$. The algorithm starts by finding the dictionary element g_{d_0} yielding the largest coefficient when *x* is projected onto it. That is,

$$g_{d_0}{}^{(x)} = g_{d_0} \ where \ d_0 = \arg\max_m |\langle x, g_m \rangle|$$

The MPDM provides a method of using matching pursuits to compare two signals x_1 and x_2 by projecting vector x_1 onto the dictionary elements from the matching pursuits projection sequence $G(x_2)$ of x_2 onto a suitable dictionary and noting the coefficient vector $W\big(x_1, G(x_2)\big)$ and residue $R\big(x_1, G(x_2)\big)$. The MPDM is then defined as

$$\delta(x_1, x_2) = \sqrt{\alpha D_R(x_1, x_2) + (1-\alpha) D_W(x_1, x_2)}$$

where $D_R(x_1, x_2)$ is the difference between the residues of signals x_1 and x_2 when they are both projected onto the projection sequence $G(x_2)$ of x_2, and $D_W(x_1, x_2)$ is the difference of their corresponding MP coefficients. Each are defined as follows:

$$D_R(x_1, x_2) = \left\| R\big(x_1, G(x_2)\big) - R(x_2, G(x_2)) \right\|^2$$

$$D_W(x_1, x_2) = \left\| W\big(x_1, G(x_2)\big) - W(x_2, G(x_2)) \right\|^2$$

Competitive agglomeration can be used to find an optimal collection of cluster centers $C = \{c_1, c_2, \dots, c_M\}$ given data $X = \{x_1, x_2, \dots, x_N\}$. When using the matching pursuits dissimilarity measure, our objective function becomes

$$J(C, U, X) = \sum_{j=1}^{M} \sum_{i=1}^{N} u_{i,j}^2 \left[\alpha D_R\big(x_i, c_j\big) + (1-\alpha) D_W\big(x_i, c_j\big)\right] - \eta \sum_{j=1}^{M} \left[\sum_{i=1}^{N} u_{i,j}\right]^2.$$

subject to $\sum_{i=1}^{M} u_{i,j} = 1 \quad \forall i \in \{1, \dots, N\}$.

In moving to a multimodal framework, each sample point now reflects a collection of signals from each sensor. Referring to these different signals as channels 1 through *K*, a multimodal signal can be expressed as $x = (x_1, \dots, x_k)$, that is, the *k*-tuple of the signals from each of the multiple sensors.

Application of matching pursuits to approximate the set of signals, each in a Hilbert space H_k, uses k overcomplete dictionaries of signals D_k. The *k*-tuple of dictionaries is represented by $D = (D_1, \dots, D_k)$

The matching pursuits approximation of a single channel x_k of x is a linear combination of *p* elements from D_k, namely

$$\hat{x}_k = w_{k,0}{}^{(x)} g_{k,d_0}{}^{(x)} + w_{k,1}{}^{(x)} g_{k,d_1}{}^{(x)} + \dots + w_{k,p-1}{}^{(x)} g_{k,d_{p-1}}{}^{(x)}$$

where $w_{k,j}{}^{(x)}$ is the coefficient of dictionary element $g_{k,d_j}{}^{(x)}$. The algorithm starts by finding the dictionary element g_{k,d_0} in D_k yielding the largest coefficient when x_k is projected onto it. That is,

$$g_{k,d_0}{}^{(x)} = g_{k,d_0} \ \ where\ d_0 = \arg\max_m \left|\langle x_k, g_{k,m}\rangle\right|$$

To effectively handle differences in the matching pursuits characteristics of the multiple sensors, we must introduce normalization constants for each sensor considered. The normalization term γ_k captures the relevance, or importance, or channel k, where $\sum_{k=1}^{K} \gamma_K = 1$.

We define the total residue to be the sum of the gamma-weighted residues across each sensor, and the weight dissimilarity to be the sum of the gamma-weighted weight distances from each sensor as follows:

$$D_R(x_1, x_2, \gamma) = \sum_{k=1}^{K} {\gamma_k}^2 \left\| R\left(x_{1k}, G_k(x_2)\right) - R\left(x_{2k}, G_k(x_2)\right) \right\|^2$$

$$D_W(x_1, x_2, \gamma) = \sum_{k=1}^{K} {\gamma_k}^2 \left\| W\left(x_{1k}, G_k(x_2)\right) - W(x_{2k}, G_k(x_2)) \right\|^2$$

Where $G_k(x) = \left\{ g_{dk_0}^{(x)}, g_{dk_1}^{(x)}, \dots, g_{dk_{p-1}}^{(x)} \right\}$ is the set of signals from channel k of the projection sequence of sample x, and the channel specific residue and weight distance are defined as:

$$D_{Rk}(x_1, x_2) = \left\| R\left(x_{1k}, G_k(x_2)\right) - R\left(x_{2k}, G_k(x_2)\right) \right\|^2$$

$$D_{Wk}(x_1, x_2) = \left\| W\left(x_{1k}, G_k(x_2)\right) - W\left(x_{2k}, G_k(x_2)\right) \right\|^2$$

Then our channel normalized MPDM is expressed as:

$$\hat{\delta}(x_1, x_2, \gamma) = \sqrt{\sum_{k=1}^{K} {\gamma_k}^2 \left(\alpha D_{Rk}(x_1, x_2) + (1 - \alpha) D_{Wk}(x_1, x_2) \right)}$$

The gamma term in the multimodal MPDM is defined as a quantity external to either of the two sample points being compared. We use this fact to our advantage to allow for a unique gamma term for each cluster prototype. Optimal settings of the gamma weights can then be learned in an alternating optimization (along with cluster centers and cluster memberships) of the clustering objective function.

Our objective function for Competitive Agglomeration, with the multimodal MPDM and per center channel weights is as follows:

$$J(C,\Gamma,U,X)=\sum_{j=1}^{M}\sum_{i=1}^{N}u_{i,j}^{2}\sum_{k=1}^{K}\gamma_{jk}{}^{2}\left(\alpha D_{Rk}(x_i,c_j)+(1-\alpha)D_{Wk}(x_i,c_j)\right)-\eta\sum_{j=1}^{M}\left[\sum_{i=1}^{N}u_{i,j}\right]^{2}$$

$$\text{subject to}\sum_{k=1}^{K}\gamma_{jk}=1\quad\forall j\in\{1,..,M\}$$

3. APPLICATION TO LANDMINE/CLUTTER DISCRIMINATION

CAMP has been applied to the landmine/clutter discrimination problem in a single electromagnetic induction sensor setting in the past [1-3]. The same time-domain signals employed in that work are used in current experiments. In this work we incorporate signal channels comprised of features captured from a frequency-swept, continuous-wave radar system [5-7].

We report on evaluation of the multimodal MPDM approach using data collected at three test sites with buried landmines and clutter objects, two temperate sites in the eastern United States and one arid site in the western United States.

4. REFERENCES

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