Target Classification in SAS Imagery using Orthogonal Basis Selection

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This work proposes an approach that finds efficient representations for training and classification of different mine like objects (MLOs) in underwater imagery, e.g. side scan sonar and synthetic aperture sonar (SAS). The focus is on the design and selection of a compact, optimal and a non-linear subspace, a dictionary, based on the gradient and curvature models in 2D images. Here, the traditional sparse approximation formulation is decoupled and modified by an additional discriminating objective function and a corresponding selection strategy is proposed. During training, using a set of labelled sonar images, a single optimised discriminatory dictionary is learnt which can then be used to represent MLOs. During classification, this dictionary together with optimised coefficient vectors is used to label scene entities. Evaluation of our approach has resulted in classification accuracies of 95% and 94% on realistic synthetic side-scan images and real CMRE SAS imagery, respectively.

Dictionary learning (DL) for signal approximation and discrimination [2, 4] is equal to identifying, given a set of training samples, an appropriate set, a dictionary, such that any K-subset of it spans a K-dimensional subspace. It is know that over-complete DL methods [1, 2] can provide maximum sparsity, but the dictionaries lack structure and can be highly redundant. Our approach shows that an orthogonal dictionary, with significantly smaller cardinality compared to over-complete dictionaries, can provide state-of-the-art classification accuracy on SAS imagery. We also compare our DL approach against other DL methods and hand-crafter dictionaries. A two stage approach to SAS image discrimination is proposed. The dictionaries are adapted to curve singularities and strong gradients, e.g. extracting features from strong contrast caused due to target shadows underwater. Given a measurement vector, $\mathbf{w} \in \mathbb{R}^P \subset \mathbf{W} \in \mathbb{R}^{P \times N}$, the aim is to extract a sparse vector, $\mathbf{q} \in \mathbb{R}^K \subset \mathbf{Q} \in \mathbb{R}^{N \times K}$, and learn a dictionary $\mathbf{Z} = [z_1, ..., z_K] \subset \mathbb{R}^{P \times K}$, simultaneously. The learnt dictionary, $\mathbf{Z}$ is an an orthogonal dictionary when $K = P$. Traditional DL algorithms have two steps:

1. **Sparse Coding**:

$$\min_{\mathbf{q}} ||\mathbf{w} - \mathbf{Zq}||^2 + \beta_1 ||\mathbf{q}||_0, \text{subject to} ||\mathbf{q}|| \leq 1 \tag{1}$$

2. **Dictionary Learning**:

$$\min_{\mathbf{Z}} \left[||\mathbf{W} - \sum_{k=1}^{K} \mathbf{z}_k \mathbf{q}_k^T ||^2 \right] \forall k = 1, 2, ..., K \tag{2}$$

We prove that, assuming $\mathbf{Z^T Z} = I$, the original sparse coding (1) can be re-written as:

$$J(\mathbf{Q}) = \min_{\mathbf{Q}} ||\mathbf{W} - \mathbf{ZQ}||^2 + \beta_1 ||\mathbf{Q}||_0 + \beta_2 ||\mathbf{G}(\mathbf{Q})||, \quad \text{subject to} ||\mathbf{Q}||_1 \leq 1 \tag{3}$$

and has a unique solution $\mathbf{Q}^* = \mathrm{T}_{\beta_1}(\mathbf{ZW})$. We add a discriminatory function $\mathbf{G}(\mathbf{Q})$ that maximises inter-class variance and minimises intra-class variance of dictionary coefficients [3]. We solve (3) using a soft-threshold operator $\mathrm{T}_{\beta_1}(\mathbf{ZW}) = sign(\mathbf{W}) max(|\mathbf{W}| - \beta_1, 0)$.

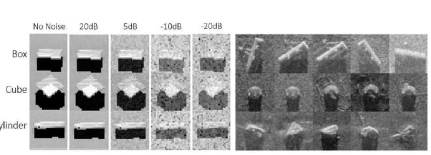

Figure 1: Exemplar Side-scan sonar (Left) and (Right) CMRE SAS imagery.

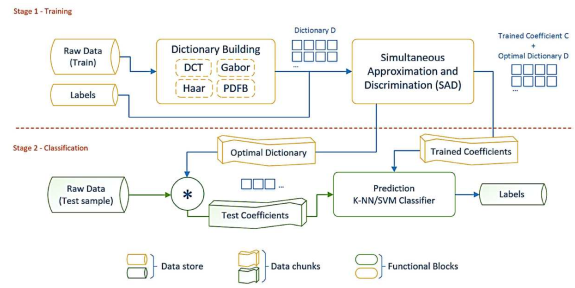

Figure 2: The proposed algorithm.

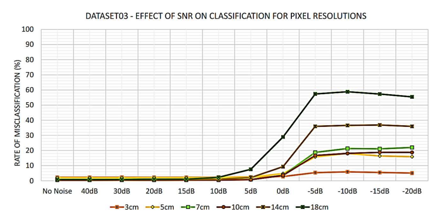

Figure 3: The rate of misclassification stays below 22% for -20dB SNR.

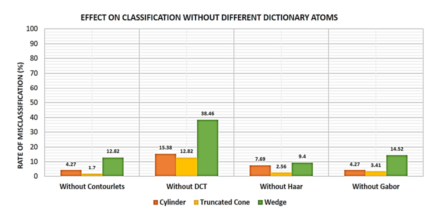

Figure 4: Impact of different dictionary categories on rate of misclassification for different MLOs.

In this work we have also tried to answer the following questions: i) Can a combined dictionary optimised for discriminating different MLO classes be found and learnt? ii) What influence does noise and pixel resolution have on accuracy? Signal to noise ratio (SNR) in SAS images limits the efficiency of detection and classification algorithms. In this work, the effect of noise on the classification process is also tested. Sonar noise is modelled by a coherent Rayleigh noise for the synthetic datasets. Figure 3 illustrates rate of misclassification rate on the SSS dataset for different pixel resolutions.

1 References

[1] Michal Aharon, Michael Elad, and Alfred Bruckstein. K-svd: An algorithm for designing overcomplete dictionaries for sparse representation. *Signal Processing, IEEE Transactions on*, 54(11):4311–4322, 2006.

[2] Mahmood R Azimi-Sadjadi, Justin Kopacz, and Nick Klausner. K-svd dictionary learning using a fast omp with applications. In *2014 IEEE International Conference on Image Processing (ICIP)*, pages 1599–1603. IEEE, 2014.

[3] Puneet S Chhabra, Andrew M Wallace, and James R Hopgood. Anomaly detection in clutter using spectrally enhanced ladar. In *SPIE Defense+ Security*, pages 946508–946508. International Society for Optics and Photonics, 2015.

[4] Justin Kopacz. *Optimal dictionary learning with application to underwater target detection from synthetic aperture sonar imagery*. PhD thesis, Colorado State University. Libraries, 2007.

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