Image-Quality Prediction of Synthetic Aperture Sonar Imagery

David P. Williams

williams@nurc.nato.int

NATO Undersea Research Centre • Viale San Bartolomeo 400 • 19126 La Spezia (SP) • Italy

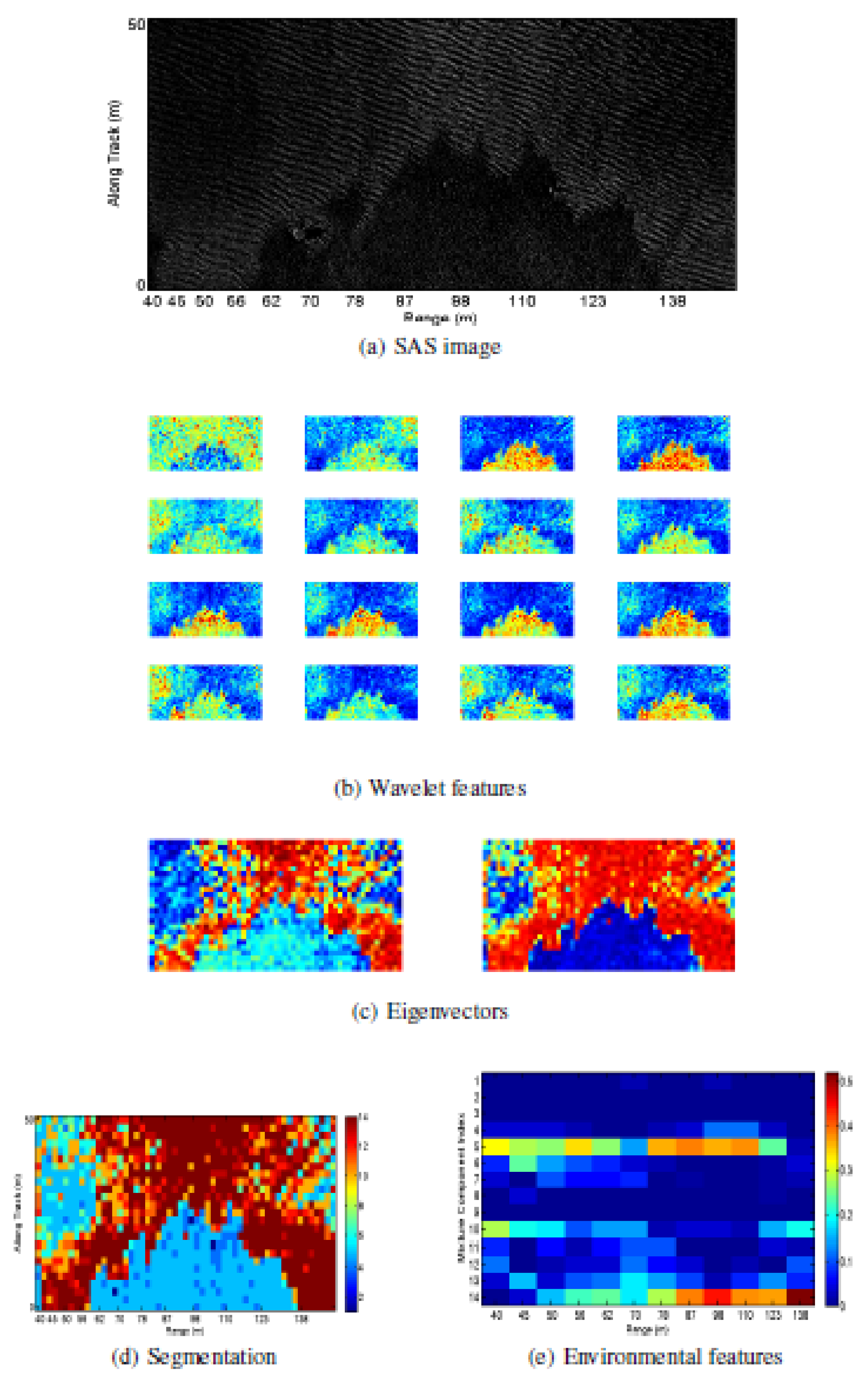
ABSTRACT

This work exploits several machine-learning techniques to address the problem of image-quality prediction of synthetic aperture sonar (SAS) imagery. The objective is to predict the correlation of sonar ping-returns as a function of range from the sonar by using measurements of sonar-platform motion and estimates of environmental characteristics. The environmental characteristics are estimated by effectively performing unsupervised seabed segmentation, which entails extracting wavelet-based features, performing spectral clustering, and learning a variational Bayesian Gaussian mixture model. The motion measurements and environmental features are then used to learn a Gaussian process regression model so that ping correlations can be predicted. To handle issues related to the large size of the data set considered, sparse methods and an out-of-sample extension for spectral clustering are also exploited. The approach is demonstrated on an enormous data set of real SAS images collected in the Baltic Sea.

Motivation:
• Adapt route of a sonar-equipped AUV in-mission to maximize coverage rate and prevent having areas of insufficient image-quality.
• Ping-to-ping correlation is directly proportional to SNR.

Overview:
• Extract motion features
• Extract environmental features
• Build GP regression model to predict ping-to-ping correlation for every range

Data set:
• 8,097 SAS images
• 10,984,025 seabed blocks of 2*m* x 2*m* [spectral clustering]
• 99,120 image-range pairs with a ping-correlation value [GP]
• Used for training: 200 / 271,250 / 2,437



(a) SAS image

(b) Wavelet features

(c) Eigenvectors

(d) Segmentation

(e) Environmental features

Fig. 1. Example of environmental feature extraction process for a test image. From a SAS image (a), 16 wavelet features (b) are extracted for each 2 m × 2 m area of seabed. An out-of-sample extension for spectral clustering is applied, reducing the 16 wavelet features to 2 eigenvector features (c). A previously-learned variational Bayesian GMM is used to assign the eigen-data to mixture components, effecting a segmentation (d) of the seabed. The proportions of data points within each range window of interest that are assigned to each mixture component are subsequently used as environmental features (e) in a GP regression model.

Modifications to spectral clustering for large data sets:
• "Sparsify" distance matrix (zero out if not a *t* nearest neighbor) [7]
• Automatic self-tuning of affinity matrix parameter [10]
• Out-of-sample extension for testing data points [8]

[5] C. Constantinopoulos and A. Likas, "Unsupervised learning of Gaussian mixtures based on variational component splitting," *IEEE Trans. Neural Networks*, vol. 18, no. 3, pp. 745–755, 2007.

[7] Y. Song, W. Chen, H. Bai, C. Lin, and E. Chang, "Parallel spectral clustering," in *Proc. ECML/PKDD*, 2008.

[8] Y. Bengio, J. Paiement, P. Vincent, O. Delalleau, N. Le Roux, and M. Ouimet, "Out-of-sample extensions for LLE, isomap, MDS, eigenmaps, and spectral clustering," in *NIPS*. MIT Press, 2004, pp. 177–184.

[10] L. Zelnik-Manor and P. Perona, "Self-tuning spectral clustering," in *NIPS*. MIT Press, 2004, pp. 1601–1608.

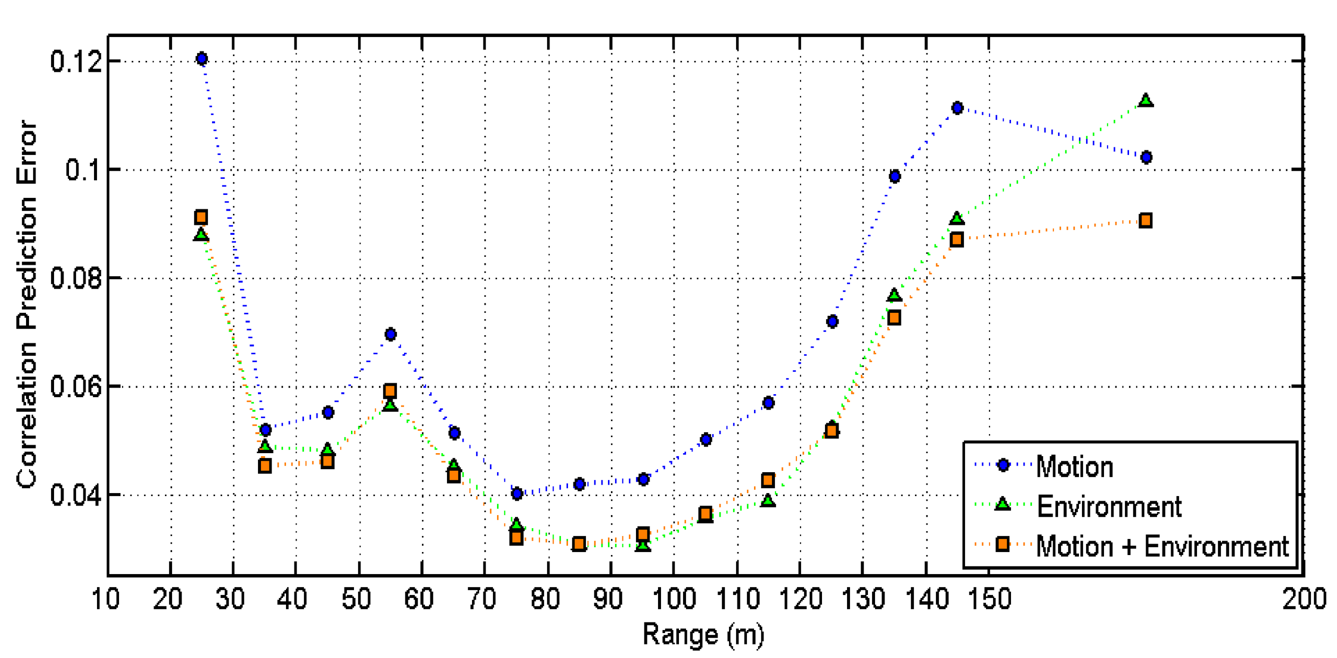


Fig. 1. Mean prediction error as a function of range bin for each GP regression model.

Table 1. Proportion of **image-range pairs** for which each model obtained a lower prediction error than each competing model.

MODEL	COMPETING MODEL M	E	M+E
MOTION (M)	——	0.4268	0.4015
ENVIRONMENT (E)	0.5732	——	0.4860
M+E	0.5985	0.5140	——

Table 2. Proportion of **images** for which each model obtained a lower mean prediction error than each competing model.

MODEL	COMPETING MODEL M	E	M+E
MOTION (M)	——	0.3586	0.3109
ENVIRONMENT (E)	0.6414	——	0.4541
M+E	0.6891	0.5459	——