

Inverting OBS compliance signals for oceanic crust and sediment velocity structure using mixture density neural networks

*Stephen Glenn Mosher¹, Zach Eilon², Pascal Audet¹

1. University of Ottawa, 2. University of California Santa Barbara

Extremely long wavelength infra-gravity waves propagating along the ocean surface induce a loading of the seafloor, which elastically deforms in response to associated pressure changes in the overlying water column. This phenomenon is known as seafloor compliance and is often considered to be a source of noise contaminating ocean-bottom seismometer (OBS) data. However, OBSs equipped with pressure gauges are able to exploit compliance signals for structural imaging. In particular, seafloor compliance signals are most sensitive to the shear modulus, and therefore, are sensitive to the shear wave velocity (V_s) structure of the sediment column and uppermost crust.

The non-linear inverse problem of predicting shallow 1D V_s profiles from compliance signals has been addressed in several previous studies, often through the use of linearizing techniques. In this study we explore the possibility of instead solving for V_s structure through the use of a neural network, specifically a mixture density network. Mixture density networks are extensions of standard neural networks that are able to approximate arbitrary probability density functions, including ones that are highly multi-modal (i.e., strongly non-linear). In detail, trained mixture density networks are able to map M -dimensional variables to (posterior) probability functions of N -dimensional observations by expressing these arbitrarily complex functions as a mixture of multiple $M+N$ dimensional Gaussians. Using this framework, the posterior probability distribution of the network output can be computed for any input. In our context this means that once a network has been trained, probabilistic 1D V_s profiles can be computed given any observed compliance data. In this study we restrict our focus to synthetic signals generated for sensors at deep water sites (depths > 1 km) and we parametrize V_s structures using cubic splines down to 3 km, below which a half-space is assumed. We test the feasibility of this method by training a mixture density network on 100,000 synthetically generated compliance signals, and report its effectiveness in recovering shallow elastic structure. This work holds promise for widespread application across the hundreds of recent and planned OBS deployments across the world's oceans as it is a fast and effective means to image oceanic structures.

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