3D MARKOV RANDOM FIELD IN REALISTIC INVERSE SCATTERING

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MOTIVATIONS AND RESULTS

The inverse scattering problems deal with the estimation of physical parameters and features (position, form, size and complex permittivity) of unknown objects [1-5] from a limited set of measurements of scattered field data. Generally, the unknown of these inverse problems is the contrast function (related to the complex equivalent permittivity of the object) which depends on the data of the problem (*i.e.* the scattered field samples) through a non-linear mapping.

The wide range of applications of inverse scattering techniques, spreading from non-invasive medical diagnostics to detection of buried structures, has stimulated the development of a large number of different approaches. Traditionally, the adopted solutions consist of minimizing (or maximizing), with respect to the unknowns, a proper defined cost functional involving the mismatch between the measured and expected scattered fields. Since these problems are ill-posed, the adoption of proper regularization strategies is mandatory. In Tikhonov-like regularization techniques, the cost functional to be minimized involves the choice of the tuning parameter adopted to weight the regularization term through empirical ad-hoc techniques. Its choice affects the accuracy of the global solution of the imaging problem. Bayesian approaches [2,3] have recently been adopted to obtain unsupervised inversion procedures, where the unknowns are modelled by means of random process and the regularization parameters are estimated starting from the (corrupted) scattered fields data without using any *a priori* information on the unknown targets to reconstruct.

In particular, we formulate the solution of the inverse problem in terms of a Maximum a Posteriori (MAP) estimation and we adopt a Gaussian Markov Random Fields (GMRF) as an *a priori* model for the unknown image. Moreover we have introduced in the inversion procedure the knowledge of the real noise disturbing the scattered field measurements, as discussed in [5]. To define the *a priori* function, we have to estimate two hyper-parameter maps (for the real and imaginary part of the overall unknowns of the imaging problem) before actually performing the inversion. Notably, the regularization parameters values are very high in presence of discontinuities in the image to be retrieved, while they are low in homogeneous regions. Accordingly, the estimated parameters maps return an estimation of the edge of the unknown contrast profile, thus allowing for a preliminary estimate of the targets shape and size. Once these parameters have been estimated, they are exploited in the inversion procedure to retrieve the unknown contrast profile, *i.e.* the permittivity and conductivity profiles of the system of obstacles located in the region under test. Note that the joint action of the ML estimation of the hyper-parameters to be included in the MRF *a priori* model, and of the MAP estimation of the permittivity profiles allows reconstructed profiles that follow the actual shape of the permittivity profiles better that the ones that can be obtained without regularization. Numerical results will be presented during the conference to highlight such effects.

Then, since the Bayesian regularization schemes are characterized by a computational complexity which rapidly increases when the inverse scattering problem has to be solved in its full non-linearity, we adopt an extended range linear approximation [2] derived from the CS-EB model [4] to invert the measured data and solve the imaging problem.

We tested the developed algorithm on three-dimensional targets, by considering experimental multiple-frequency data measured in the anechoic chamber of the Institut Fresnel of Marseille [6]. In order to take into account the random noise which is present in the experiment, we also considered an adequate cost functional appropriately weighted by coefficients which change with the frequency, the incident angle and the receiving angle [5]. In particular, each scattered field measurement is balanced with the noise disturbing the data.

The obtained results prove the effectiveness and usefulness of the method. In particular, as it will be discussed during the conference, by processing the three-dimensional experimental data of [6], it is possible to achieve nice results in terms of shapes and permittivity values of the unknown objects.

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