Title: Bayesian max-product expectation maximization algorithm for structured sparse signals reconstruction

ABSTRACT: We propose a Bayesian expectation-maximization (EM) algorithm for reconstructing structured approximately sparse signals via belief propagation. The measurements follow an underdetermined linear model where the regression-coefficient vector is the sum of an unknown approximately sparse signal and a zero-mean white Gaussian noise with an unknown variance. The signal is composed of large- and small-magnitude components identified by binary state variables whose probabilistic dependence structure is described by a hidden Markov tree. Gaussian priors are assigned to the signal coefficients given their state variables and the Jeffreys’ noninformative prior is assigned to the noise variance. Our signal reconstruction scheme is based on an EM iteration that aims at maximizing the posterior distribution of the signal and its state variables given the noise variance. We employ a max-product algorithm to implement the maximization (M) step of our EM iteration. The proposed EM algorithm estimates the vector of state variables as well as solves iteratively a linear system of equations to obtain the corresponding signal estimate. We select the noise variance so that the corresponding estimated signal and state variables (obtained upon convergence of the EM iteration) have the largest marginal posterior distribution. Our numerical examples show that the proposed algorithm achieves better reconstruction performance compared with the state-of-the-art methods.