With high dimensional longitudinal and functional data becoming much more common, there is a strong need for methods of estimating large covariance matrices. This task difficult due to the instability of sample covariance matrices in high dimensions in addition to the desire for constraining estimates to be positive-definite. A modified Cholesky decomposition of the covariance matrix allows for parameter estimation via unconstrained optimization as well as a statistically meaningful interpretation of the parameter estimates. Regularization improves stability of covariance estimates in high dimensions, as well as in the case where functional data are sparse and individual curves are sampled at different and possibly unequally spaced time points.

The reparameterization of the precision matrix through the Cholesky decomposition permits covariance estimation to be accomplished by fitting a two-dimensional varying coefficient model. We propose a general approach to the potentially ill-posed problem using penalized tensor product B-splines; by using a large number of equidistant knots, simple difference penalties allow us to sidestep the difficulty of selecting the number and position of the knots. We impose regularization in the directions orthogonal to the natural axes of the measurements, leading to null models presented in the literature which rely only on the time difference between measurements. We present numerical results and data analysis to illustrate the utility of the proposed method.