With high dimensional longitudinal and functional data becoming much more common, there is a strong need for methods of estimating large covariance matrices. Estimation is made difficult by the instability of sample covariance matrices in high dimensions and a positive-definite constraint we desire to impose on estimates. 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.

Covariance estimation is achieved via the estimation of a two-dimensional varying coefficient model by way of the Cholesky decomposition. 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 difficult task 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.