Part III develops signature spectral statistics-based recursive hyperspectral sample processing (RHSP) algorithms that allow data processing to be executed sample by sample in a progressive manner but that also produce signatures in a recursive manner. The main goal of Part III is to find new target signatures signature by signature recursively while data processing is being carried out sample by sample progressively. This part is completely different from Part II, which implements RHSP algorithms in real time sample by sample in a recursive manner like a Kalman filter but without finding signatures. In particular, these algorithms produce new targets one at a time recursively, and their processing can also be implemented in a progressive manner. More specifically, the algorithms developed in Part III grow signature matrices by augmenting one target signature at a time without reference to the causal sample correlation matrix/causal sample covariance matrix (CSCRM/CSCVM) used in Part II. Since such grown signature matrices only involve newly generated target signatures, while the previously known and available target signatures remain unchanged, these algorithms can also be implemented as recursive algorithms in the sense that only newly generated target signatures are used to update data information for processing. In other words, as mentioned in Part II, a recursive process decomposes data information into three pieces of information: (1) processed information obtained by processing already visited data sample vectors, (2) new information given by data sample vectors currently being processed, and (3) innovation information provided by new information that cannot be obtained by the processed information. Thus, a recursive process makes use of recursive equations to update results only through innovation information. It is this innovation information that significantly reduces computational complexity and processing time. In addition, this innovation information can not only be used to generate new target signatures of interest; it can also be used to determine how many of these generated target signatures are indeed real targets. To resolve the issue of how to automatically terminate a recursive process in real time, a Neyman–Pearson detector (NPD) is developed. The idea is to compute and consider the maximal orthogonal projection (OP) leakage of each newly generated target signature into the complement subspaces linearly spanned by previous target signatures.
as a signal source and then use this signal source to formulate a binary hypothesis testing problem. A desired NPD can be developed in a manner similar to how the Harsanyi–Farrand–Chang (HFC) method was developed by Harsanyi et al. (1994) to estimate the virtual dimensionality (VD), which is extended to target-specified VD in Chap. 4, where target signatures to be specified can be generated by a recursive process. The NPD determines whether or not a signal source specified by the maximal OP leakage of a target signature fails the test, in which case the considered target signature is declared to be a real target. Since the maximal OP leakages calculated from progressively generated targets are monotonically decreasing, the NPD generally fails in the beginning and the test is then continued until it reaches the first time the NPD passes the test, in which case the NPD is terminated. Because Neyman–Pearson detection is performed in conjunction with a recursive process that generates each new target signature, it can be implemented in real time while a new target is being generated at the same time.

Part III is mainly focused on RHSP. Chapter 7, “Recursive Hyperspectral Sample Processing of the Automatic Target Generation Process,” extends a well-known automatic target detection algorithm, the automatic target generation process (ATGP), to RHSP-ATGP, which can implement ATGP recursively. Using an idea similar to that used to derive RHSP-ATGP, Chap. 8, “Recursive Hyperspectral Sample Processing of Orthogonal Subspace Projection,” also extends the well-known orthogonal subspace projection (OSP) to RHSP-OSP. Similar to OP used by both ATGP and OSP to derive recursive equations, a second application is discussed in Chap. 9, “Recursive Hyperspectral Sample Processing of Linear Spectral Mixture Analysis,” and Chap. 10, “Recursive Hyperspectral Sample Processing of Maximum Likelihood Estimation,” use least-squares error (LSE) in RHSP-LSMA and RHSP-MLE, respectively. Finally, growing simplex volume analysis (GSVA) is considered as a third application in finding endmembers. Chapter 11, “Recursive Hyperspectral Sample Processing of Growing Simplex Volume Analysis” makes use of OP to derive a recursive version of SGA developed in Chang et al. (2006) called RHSP OP-Based Simple Growing Algorithm (RHSP-OPSGA), which not only quickly computes simplex volumes but also significantly reduces computer processing time. With another new approach different from RHSP-OPSGA, Chap. 12, “Recursive Hyperspectral Sample Processing of Geometric Simplex Growing Algorithm” makes use of the Gram–Schmidt orthogonalization process (GSOP) to derive an RHSP-geometric SGA (RHSP-GSGA). It turns out that RHSP-OPSGA and RHSP-GSGA are the best algorithms of all the SGA-based variants reported in the literature in terms of computational complexity and computing time.