

Dictionary learning is the task of determining a data-dependent transform that yields a sparse representation of some observed data. The dictionary learning problem is nonconvex, and usually solved via computationally complex iterative algorithms. Furthermore, the resulting transforms obtained generally lack structure that permits their fast application to data. To address this issue, this paper develops a framework for learning orthonormal dictionaries, which are built from products of a few Householder reflectors. Two algorithms are proposed to learn the reflector coefficients: one that considers a sequential update of the reflectors and one with a simultaneous update of all reflectors that imposes an additional internal orthogonal constraint. The proposed methods have low computational complexity and are shown to converge to local minimum points, which can be described in terms of the spectral properties of the matrices involved. The resulting dictionaries balance between the computational complexity and the quality of the sparse representations by controlling the number of householder reflectors in their product. Simulations of the proposed algorithms are shown in the image processing setting, where well-known fast transforms are available for comparisons. The proposed algorithms have favorable reconstruction error and the advantage of a fast implementation relative to the classical, unstructured dictionaries.