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Editorial

Algorithms for Multispectral and Hyperspectral Image Analysis

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Recent advances in multispectral and hyperspectral sensing technologies coupled with rapid growth in computing power have led to new opportunities in remote sensing—higher spatial and/or spectral resolution over larger areas leads to more detailed and comprehensive land cover mapping and more sensitive target detection. However, these massive hyperspectral datasets provide new challenges as well. Accurate and timely processing of hyperspectral data in large volumes must be treated in a nonconventional way in order to drastically enhance data modeling and representation, learning and inference, physics-based analysis, computational complexity, and so forth. Current practical issues in processing multispectral and hyperspectral data include robust characterization of target and background signatures and scene characterization [1–3], joint exploitation of spatial and spectral features [4], background modeling for anomaly detection [5, 6], robust target detection techniques [7], low-dimensional representation, fusion of learning algorithms, the balance of statistical and physical modeling, and real-time computation [8, 9].

The aim of this special issue is to advance the capabilities of algorithms and analysis technologies for multispectral and hyperspectral imagery by addressing some of the above-mentioned critical issues. We have received many submissions and selected six papers after careful and rigorous peer review. The accepted papers cover a wide range of topics, such as anomaly detection, target detection and classification, dimensionality reduction and reconstruction, fusion of hyperspectral detection algorithms, and non-Gaussian mixture modeling for hyperspectral imagery. The brief summaries of the accepted papers are as follows.

The paper "*Hyperspectral anomaly detection: comparative evaluation in scenes with diverse complexity*," by D. Borghys et al., provides a comprehensive review of popular hyperspectral anomaly detection methods, an important problem in hyperspectral signal processing, including the global Reed-Xiaoli (RX) method, subspace methods, local methods, and segmentation based methods. The extensive performance analysis of these methods is presented in scenes with various backgrounds and different representative targets. The comparative results reveal the superiority of some detectors in certain scenes over other detectors.

The paper "*Non-Gaussian linear mixing models for hyperspectral images*," by P. Bajorski, addresses the problem of modeling hyperspectral data using non-Gaussian distribution. It is done by assuming a linear mixing model consisting of nonrandom-structured background and random noise terms. The nonvariable part of a hyperspectral image (structured background) can be assumed to be deterministic because of the strong presence of certain known materials. The variable noise term is modeled as two different multivariate distributions in the paper. The model is tested on two sets of hyperspectral data, one AVIRIS and one HyMap image, to determine which model best fits the data. Comprehensive results are provided along with a complete analysis of how researchers can verify how well a particular model fits a particular dataset. The significance of this paper lies in the fact that, often, in applications such as detection, classification, and synthetic data generation, a Gaussian distribution cannot be used to model hyperspectral data distributions, and other multivariate distributions are required instead.

The paper "*Randomized SVD methods in hyperspectral imaging*," by J. Zhang et al., addresses the problem of dimensionality reduction, compression, classification, and reconstruction of massive hyperspectral datasets by using a recently developed novel probabilistic approach called a randomized singular value decomposition (rSVD) technique. In rSVD, a large data matrix is iteratively approximated by random projection and factorized into low-dimensional matrices. In this paper, it was also demonstrated that fast computation in compression and reconstruction of large HSI datasets can be effectively achieved using the rSVDs approach.

The paper "*Evaluating subpixel target detection algorithms in hyperspectral imagery*," by Y. Cohen et al., considers algorithms for subpixel target detection and emphasizes the importance of good evaluation protocols for assessing those algorithms. The choice of algorithms (and, just as importantly, of parameters within a given algorithm) depends on image statistics, the target's spectral signature, and spatial size. By artificially emplacing simulated targets in a scene of interest, they are able to evaluate the effectiveness of different algorithms at detecting those targets and do so in a way that avoids the anecdotal statistics and inherent uncertainties that arise with real targets and real (which is to say, imperfect) ground truth. This work, in particular, extends the authors' previous work in the field by making the emplacement more realistic by incorporating "pixel phasing" effects (which occur when the target straddles two or more pixels) and image blurring. The authors use this approach to identify good detection algorithms for subpixel targets in the RIT Blind Test dataset [10] and demonstrate their efficacy by obtaining excellent scores on the blind test challenge. Although they do not claim to have found a universally optimal detector, their experiments consistently preferred a local ACE detector with a 3×3 moving window.

The paper "*Target detection using nonsingular approximations for a singular covariance matrix*," by N. Gorelik et al., introduces nonsingular matrix approximation techniques to improve the performance of the Reed-Xiaoli (RX) hyperspectral anomaly target detection approach, which normally involves singular covariance matrices. In this paper, the performance evaluation of the RX techniques based on these two nonsingular matrix approximations instead of a singular covariance matrix is presented. The experimental results characterize the pros and cons of the two methods in different scenes.

The last paper "*A semiparametric model for hyperspectral anomaly detection*," by D. Rosario, addresses the problem of anomaly detection in hyperspectral imagery. Because anomalies are by definition undefined, this is a problem that is fraught with pitfalls. Nonetheless, a scheme is developed that incorporates both physical intuition and mathematical sophistication and is applied to both the ubiquitous Forest Radiance dataset and some forward-looking imagery in the visible and near infrared. One of the innovations in the algorithm is a conversion of high-dimensional pixel descriptors to scalar values, based on angular distances to an appropriate centroid.

This special issue provides the reader with an overview of many (though certainly not all) of the current critical issues in multispectral and hyperspectral image analysis. We thank all the authors who responded to the call for papers, and we are especially grateful to the anonymous reviewers for their considerable time and tremendous effort in evaluating the manuscripts and providing invaluable comments to improve the quality of the papers in this special issue.

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