remote sensing

Editorial

Editorial for Special Issue "Remote Sensing for Target Object Detection and Identification"

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Abstract: This special issue gathers fourteen papers focused on the application of a variety of target object detection and identification techniques for remotely-sensed data. These data are acquired by different types of sensors (both passive and active) and are located on various platforms, ranging from satellites to unmanned aerial vehicles. This editorial provides an overview of the contributed papers, briefly presenting the technologies and algorithms employed as well as the related applications.

Keywords: target detection; target identification; SAR; visible; infrared; hyperspectral

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Target object detection and identification is among the primary uses for a remote sensing system. It is of paramount importance in several fields, including environmental and urban monitoring, hazard and disaster management, and defense and military applications. In recent years, these analyses have made use of the tremendous amount of data acquired by sensors mounted on satellite, airborne, and unmanned aerial vehicle (UAV) platforms.

The papers included in this special issue exploit different remote sensing phenomenologies for target object detection and identification; this includes synthetic aperture radar (SAR) imaging, which uses active sensors operating in the microwave domain, and multispectral and hyperspectral imaging, which uses passive sensors that typically capture visible and/or infrared radiation. The selection of one particular technology depends on both the specific application and the desired signal detection technique. As such, these aspects will be highlighted when summarizing the aforementioned papers.

Data acquired by SAR sensors are used in two papers [1,2], both focusing on environmental and hazard monitoring. In particular, Biondi et al. [1] present a robust procedure to evaluate water flow elevation by using SAR data (e.g., using COSMO-SkyMed images). By tracking the double-bounce reflections from a bridge crossing a river over time, it is possible to estimate the distance between the river surface and the bridge and, consequently, the water flow level. The paper by Liu et al. [2] is focused on the assessment of flood hazard for power grids using SAR data, where the aim is to assess the safety of the transmission line towers. This is performed by identifying indicators such as the shortest distance from a tower to a flood, the proportion of flood in a search area, and the difference in elevation between the tower base and the flood level.

Another group of papers [3–9] proposes object detection and recognition approaches that use images (or videos) acquired in the visible and near-infrared (VNIR) wavelength range, making use of the high (or very high) spatial resolution and high spectral content. Indeed, the latter are key features in order to identify shapes, thus enabling more reliable object detection and recognition. The use of convolutional neural networks (CNNs) in particular is becoming more widespread, as demonstrated in the work of Zhang et al. [3]. In this paper, a region-based object detection is performed, relying on the so-called feature pyramid network (FPN) which combines high and low resolution features without any additional memory consumption. Alternatively, Ma et al. [4] employ CNNs to perform a stable and robust multi-model decision fusion, which jointly uses contextual features and object spatial structure information. Another interesting application of CNNs is described in Zhang et al. [5], in which vehicle detection for traffic monitoring systems is performed using satellite video data. In contrast, Li et al. [6] focus their work on the design of a parallel hardware architecture, based on multiple neural processing units (NPUs), for performing a power-efficient object detection by using CNNs. Liu et al. [7] explore alternative frameworks to CNNs with the aim of avoiding time-consuming training phases. Specifically, in [7], the authors exploit an unsupervised saliency detection method aimed at the identification of oil tanks when the images are affected by various disturbance factors, such as different colors and shadows (caused by changes in view angles and illumination conditions). The problem of vehicle detection is also addressed by Cao et al. in [8], where the authors present a new object matching framework based on affine-function transformations by using images acquired by UAVs (i.e., the DJI Phantom 4 Pro). Finally, Yang et al. [9] perform anomaly detection by using high spectral resolution hyperspectral data from visible to infrared wavelengths. The anomalies are caused by rare and sparse small objects whose spectra are significantly different from the background. In order to deal with the high dimensionality of the problem and to reduce the computational burden, an approach based on low-rank representations is presented.

The third group of papers [10–14] focuses on object detection using infrared sensors. Zhang et al. [10] propose a method based on a low rank sparse decomposition that uses a non-convex optimization with an *Lp*-norm constraint in order to identify small targets in sequences of infrared images. In this paper, an efficient solver based on the alternating direction method of multipliers (ADMM) is presented. The detection of small targets by using infrared radiation is also the main topic of the contribution by Zhang et al. [11], in which a low-rank-based method with a regularization term based on the nuclear norm is proposed. This approach is able to properly solve the tensor robust principal component analysis (TRPCA) problem which models the separation of targets from the background. Again, ADMM is employed to provide a computationally efficient solver. Sun et al. [12] address the infrared small target detection problem using a noise model based on a non-independent identically distributed mixture of Gaussians, which is able to deal with real and complex scenarios in which the noise can change in different frames of a sequence of infrared images. The final target identification paper is focused on a flux density-based algorithm, which is able to identify the different infrared gradient vector fields between target and noise. Li et al. [13] present a thermal infrared (TIR) target tracking algorithm based on semantic features. Specifically, a mask sparse representation is used to distinguish the reliable pixels (for target tracking) from the unreliable ones in each TIR frame. The last step uses this model to improve a particle filter-based approach for TIR target tracking. The final paper is authored by Niu et al. [14], and in this paper, the authors present a study about the observability of an Earth entry orbital test vehicle (OTV) via ground-based infrared sensors. The physical foundation of this work relies on the high-temperature flow field that originates during the entry phase of an OTV. A suitable physical model is developed in order to simulate the infrared signature of the Earth entry OTV, which is useful in computing the so-called maximum detecting range, and is more broadly useful in designing remote ground-based detection systems.

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