SURPRISE

SUPER-RESOLVED COMPRESSIVE INSTRUMENT IN THE VISIBLE AND MEDIUM INFRARED FOR EARTH OBSERVATION APPLICATIONS

Deliverable “Preliminary algorythm” [D5.1]

Politecnico di Torino (PoliTo)

Compressed Sensing (CS) is a signal processing technique that allows acquisition of a signal in a very compact fashion, and its reconstruction using suitable solutions to an underdetermined linear system. CS can be used to acquire images (e.g. satellite images) in a conveniently compact way, called “compressive imaging”. An underdetermined system of linear equations has more unknowns than equations and generally has an infinite number of solutions (i.e. possible reconstructed images). In order to choose a solution to the system, one must impose extra constraints or conditions as appropriate. In the CS case, one typically adds the constraint of “sparsity” that allows only solutions with a small number of nonzero coefficients in a suitable signal representation (e.g., a linear transform such as the discrete cosine transform, also employed in the JPEG image compression standard). This condition enables recovery of a signal starting from a number of measurements lower than indicated by the Nyquist-Shannon theorem.

Despite guaranteeing image recovery under some conditions, in practice traditional algorithms are very complex, and performing an exhaustive search of the sparsest solution is not feasible. Several other approaches are possible, such as iterative and greedy algorithms. However, these methods do not achieve excellent results for real images because they are based on rather simple models. Moreover, their complexity is typically large.

In the last decade, there has been an incredible growth of Artificial Intelligence (AI). AI can be defined as a computer system trained to perceive its environment, take decisions and actions. It relies on learning algorithms, such as machine learning and deep learning. In particular, the latter is the branch of machine learning inspired by the neural pathways of the human brain. Based on a suitable training set, e.g. many pairs of compressively sensed images and the corresponding reconstructed images, deep learning can learn a suitable reconstruction method that outperforms traditional techniques. “Deep” refers to the number of cascaded operations between the input (the sensed image data) and the output (the reconstructed image). This kind of algorithms are able to learn nonlinear models very well and are increasingly used in many fields. In particular, deep learning algorithms are widely used in image processing and can be used to address the CS problem.

Deliverable 5.1 has dealt with exactly this problem. After an introduction on CS and an overview of the state-of-the-art reconstruction algorithms for CS, based on traditional and deep learning approaches, an exhaustive comparison of the reconstruction performance has been carried out, comparing a traditional model-based method, and a deep network inspired by the iterative shrinkage-thresholding algorithm. Eexperiments have assessed the sensitivity of reconstruction quality to different factors, such as the amount of compression, the type of sensing matrix and the block size. The experiments have been performed in the framework of a preliminary model of the SURPRISE instrument, in order to generate a suitable amount of super-resolution.

From the experiments we concluded that, in the context of the SURPRISE instrument design, deep learning achieves much better results than traditional methods, when used for compressive imaging reconstruction at a higher resolution than a classic acquisition (super-resolution). The specific innovation brought by this deliverable consists in the tailoring of the reconstruction algorithm, initially developed for a general-purpose compressed sensing instrument, to the specific case of SURPRISE satellite imaging. Indeed, the SURPRISE instrument poses significant requirements on the choice of the sensing matrix; suitable sensing matrices typically lead to poor reconstruction quality using traditional methods, whereas the deep learning method developed during the project achieves much better quality.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 870390.