Preface

The aim of this book is to give a concrete answer to the following question:

Can compressed sensing effectively yield optimized means for signal acquisition, encoding, and encryption, either in analog or digital circuits and systems, when implementation constraints are considered in its realization?

The reason why this question is important is that compressed-sensing (CS) has been intensely discussed in the engineering community for more than a decade as a hot research topic, gathering a great deal of effort from a large community that unites scientists in applied mathematics and information theory, as well as engineers of analog/digital circuits and optical systems. Yet, several investigations have been dominated by a few misconceptions that somehow hindered the application of this promising technique to real-world systems.

The first concept is that optimization and adaptivity are fundamentally pointless since CS is born as a universal technique that cannot be significantly improved.

The second is that even if one wants to optimize CS, the degrees of freedom to do it are not there, since it is a technique that spreads information so uniformly that no criteria are able to tell important parts to emphasize from less important parts to neglect.

Both concepts are grounded in fundamental mathematical results that are indeed the pillars of CS and are indispensable pieces of the formal construction on which the whole discipline relies. Regrettably, starting from formally true theorems, the folklore has sometimes derived misleading design guidelines.

The idea that adaptivity is useless, often indicated as *universality*, has its roots in the seminal papers originating the very concept of CS and in other later information-theoretic results. In the original setting, such an idea is extremely important to put CS in the right perspective and give it the full dignity of an acquisition method with general applicability. The mathematical derivations produce upper bounds on the ratio between the performance of an adaptive strategy with respect to that of non-adaptive CS. Such bounds being finite, we know that the performance of an agnostic CS is not too far away for the most specialized technique one may devise. Yet, in practical cases, constants are so large that the theoretical bounds say, nothing but that adaptivity cannot outperform non-adaptivity by more than a factor, say 100. Clearly, no engineer would be prevented from trying the optimization of a system by the knowledge that improvements will be less than 10000%!

The other concept that is sometimes invoked to divert people from serious CS optimization is that of *democracy*. CS works by encoding high-dimensional signals into lower-dimensional collections of measurements, and *democracy* has been developed to decide how to deal with measurements that may have been corrupted during acquisition. Under suitably specified conditions, all measurements can be considered as equally important as they all contribute in the same way to the mathematical properties that guarantee that the original signal can be retrieved. This implies that simply discarding the corrupted information leads to a graceful degradation in performance.

The development is based on a worst-case analysis that is intrinsically invariant with respect to symmetries of the system since worst-case configurations can be replicated exploiting the same symmetry. It is not surprising that measurements computed with substantially the same procedure are equally important from such a pessimistic point of view. Nevertheless, this does not prevent some measurement from being more informative than others in non-worst-case conditions.

The truth is that, overall, mathematical *universality* and *democracy* have very little to do with the real performance of CS systems. Measurements can be selected and can be optimized in a variety of quite effective ways, even taking into account typical implementation constraints and the need to make the final embodiment less expensive with respect to common cost functions like area, power, time, etc.

The aim of this book is to show how this can be done and what benefits can be expected as far as acquisition performance and implementation costs are concerned.

Chapter 1 is dedicated to a brief review of the main ideas defining CS and guaranteeing that it is a viable option. Chapters 2 and 3 address rakeness-based design of CS describing how it derives from the highly *non-democratic* nature of non-worst-case CS, showing how it improves reconstruction performance over *universal* and agnostic CS, and finally discussing pros and cons of adapting sensing to the class of signals to acquire.

Chapter 4 addresses the computational complexity of CS from the point of view of hardware implementations. After identifying the key parameters on which the operating cost of CS-based acquisition depends, it adapts rakeness-based design to address the trade-off between such a cost and reconstruction performance.

Chapter 5 takes a brief detour to discuss how random processes can be generated so that they have only a very limited number of values while also reproducing some prescribed second-order statistical feature. This is a general problem with applications going beyond implementation-friendly rakeness-based CS.

Chapter 6 describes the main architectural options in implementing CS systems and shows their implications on signal-level functionality. It also tackles the problem of saturation with an approach aiming at extracting every little piece of information even from corrupted measurements with a truly "everything but the *oink*" philosophy.

Chapter 7 lists and discusses several CS implementations that see it embedded in the analog-to-digital part of the signal chain, giving rise to an analog-to-information stage. A final comparison chart shows how rakeness-based design of CS allows to obtain the most effective implementation.

Chapter 8 takes a different point of view and looks at CS as a purely digital lossy compression stage whose main feature is that of being extremely simple. CS lossy compression is paired with lossless compression, and overall performance is evaluated to show that, when rakeness-based CS is adopted, one obtains an extremely simple but effective bit squeezing mechanism. Such a mechanism is then put to work for the acquisition of biosignals and implementations with various levels of complexity being analyzed.

Finally, Chap. 9 focuses on an extremely useful side effect of CS, i.e., that it may be used simultaneously as an efficient acquisition scheme and as a low-complexity encryption stage. The fact that encryption comes almost for free implies that security is somehow limited, but the overall robustness to classical attacks is good enough to be considered when very low-cost systems are sought.

The book spans a quite wide range of concepts and, though it aims at being self-contained and easy to follow for those interested in application of CS, it requires some taste for mathematical issues, especially in the first few chapters. Though not overly detailed, also system- and circuit-level considerations may require some confidence in the design of mixed-signal circuits or digital architectures.

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Adapted Compressed Sensing for Effective Hardware
Implementations
A Design Flow for Signal-Level Optimization of
Compressed Sensing Stages

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