Sparse Channel Estimation

The ever increasing demand for higher bandwidths in mobile communication systems led to the development of new standards such as *3GPP Long Term Evolution* (LTE). LTE supports comparatively large bandwidths of up to 20 MHz, which makes it possible to resolve the individual propagation paths (by multiple reflections) from transmitters to receivers. This results in a channel impulse response similar to Fig. 1, showing only a few peaks and many (almost) zeros – a sparse signal.

The currently very active research field of *Compressed Sensing* (CS) deals with the exploitation of such sparse signals. CS describes how sparse signals can be reconstructed from very few measurements and offers a large variety of reconstruction algorithms. For LTE systems, the number of channel measurements is fixed by the standard, but CS can still be applied to increase the quality of the channel estimation. LTE uses OFDM modulation in the down-link, where channel measurements are performed in the frequency domain. Sparsity in the time domain can then be exploited for denoising. While most work in CS is of purely theoretical nature, our goal was to apply this theory to a real-world problem, such as LTE channel estimation, and to implement CS algorithms in hardware which processes data in real-time, thus showing the practical feasibility of this approach. There are two main classes of algorithms: convex optimizers and greedy algorithms. The class of greedy algorithms seems particularly well suited for hardware implementation due to their regular structure. Greedy algorithms iteratively add the most significant taps to the estimation (Fig. 2) and perform an update only on these selected taps. We chose three greedy algorithms which differ in their update function: *Matching Pursuit (MP)* has very low complexity, *Orthogonal Matching Pursuit (OMP)* provides the best possible update function but at very high complexity costs, and *Gradient Pursuit (GP)* is an approximation for OMP's performance with reduced complexity. An important aspect of all greedy algorithms is to determine when to stop the iterations. Ideally, a stopping criterion depending on the signal-to-noise ratio (SNR) is applied. But in a real-time system, an algorithm must terminate no later than at its scheduled time. Therefore, the number of iterations is limited to K and the effect of this limitation is shown in Fig. 3, where the mean squared error (MSE) is plotted for the three algorithms and for varying K. As a reference, the performance of a least squares (LS) estimator is shown, which does not assume any sparsity. One can see that, by exploiting sparsity, gains of up to 9 dB can be realized in the low-SNR regime. In the high-SNR regime, gains are limited by the number of iterations and by a reduced effective sparsity. It can also be seen that OMP reaches the highest performance but MP and especially GP are very close. Although CS algorithms are quite complex, they could be implemented on an area which is only a small percentage of a baseband receiver chip. While MP is very area-efficient, GP is three times larger and OMP is more than six times larger. Chips supporting 10 MHz bandwidth were fabricated for all three implementations (Fig. 4). Compressed Sensing is a research area with potential applications in many different fields. Wherever a signal is compressible, i.e. it can be sparsely represented in any given basis, there is a chance that applying CS can reduce complexity.

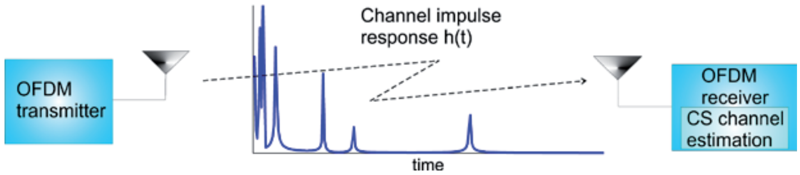

Fig. 1 Model of wireless OFDM transmitter and receiver over channel with sparse impulse response.

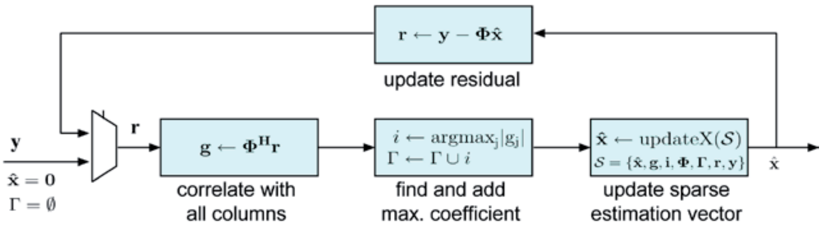

Fig. 2 Diagram of a greedy algorithm processing measurements y and producing sparse channel estimates x. Definition of 'updateX' depends on chosen algorithm.

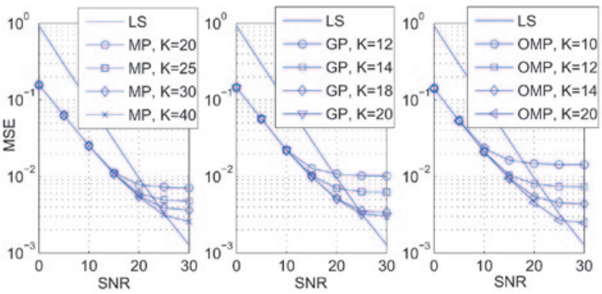

Fig. 3 Fixed-point performance of the three greedy algorithms with number of iterations limited to K.

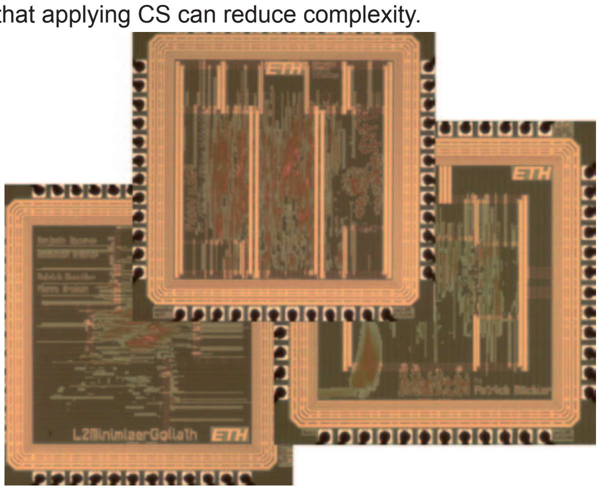

Fig. 4 Chip photographs of OMP (left), GP (middle) and MP (right) fabricated in 180 nm CMOS technology.