At my job, I read various research papers to extract new ideas for the projects I participate in. Recently, an article “An Introduction To Compressive Sampling” was analyzed by our team, as we aim to implement the so-called Compressive Sensing method for on the fly image compression during photographing. This paper was partially written and substantially motivated by Emmanuel J. Candès, the inventor of this method of compression, thus the text is very clear despite serious math being present.

Compressive Sensing allows to squeeze sparse data of quite large dimensionality and represent it by new encoding data in a lower-dimensional space. Simply put, sparsity means a situation when there is more than enough data to represent information. Encoding is performed by vector-matrix multiplication, and it was shown that with the elements of the matrix being randomized, the dimensionality of the encoding space can be approximately equal to the sparsity of the initial signal. In other words, a randomized matrix models input data sampling with randomized weights. In fact, this result implies that sparse data can be approximated with high precision by using less samples than required by the Nyquist limit. As an example, consider a sinusoidal signal of frequency *f*, which conventionally requires *2f* sampling rate to decode it without aliasing. However, if we somehow know that the input data never contains low-frequency signals, then such data is sparse in the sense we can unambiguously decode it using a lower sampling rate.

One major drawback of such an approach is reconstruction algorithms, which tend to be slow. The most popular approach is L1-optimization, allowing to derive the most sparse solution. In our project, we are developing a new reconstruction algorithm based on gradient approaches for image reconstruction in a sparse domain. Although an image might not seem sparse in its initial form, it indeed is in a space of local discrete gradients. To preprocess an image and view it in such space, one should calculate differences between local pixels: smooth textures will derive low values close to zero, while the bounds between objects are tracked and interpreted with high differences.

In voice conversion, Compressive Sensing might be used for preliminary data encoding as a part of data augmentation. Pitch and formants of one’s speech are sparse in the frequency domain, thus could possibly be represented by a quite smaller number of values.