

Compressive Sensing in Video Reconstruction

Outline

For the MPhil project, a complete Compressive Sensing system was developed that achieves near-perfect reconstruction of video signals from as few as $N = 0.3M$ compressed samples, where M is the original signal length.

Background

In conventional signal processing pipelines, signals are sampled at or above the Nyquist Rate and the acquired samples are then compressed for efficient storage and transmission. For many applications, including digital image and video processing, this is highly inefficient since a lot of data is collected at the acquisition stage only to be - in large part - thrown away during compression.

Formulation

Compressive Sensing (CS) [1, 2] is a novel technique that is able to acquire signals *directly in a compressed format*. Let $\mathbf{v} \in \mathbb{R}^M$ be the underlying signal. In CS, a compressed data set $\mathbf{y} \in \mathbb{R}^N$, with $N \ll M$, is acquired via the linear sensing mechanism $\Theta\mathbf{v} = \mathbf{y}$, where the sensing matrix Θ is independent of \mathbf{v} . To reconstruct \mathbf{v} from the measurements \mathbf{y} , CS uses the fact that many common classes of signals are *sparse* when represented in a certain basis Ψ : $\mathbf{v} = \Psi\mathbf{w}$ and $\mathbf{w} \in \mathbb{R}^M$ has few non-zero entries. (Digital image and video signals are well approximated by sparse signals when expressed in wavelet bases.) The signal \mathbf{v} can be recovered by finding the sparsest solution \mathbf{w} to the under-determined system

$$\mathbf{y} (= \Theta\mathbf{v} = \Theta\Psi\mathbf{w}) = \Phi\mathbf{w}$$

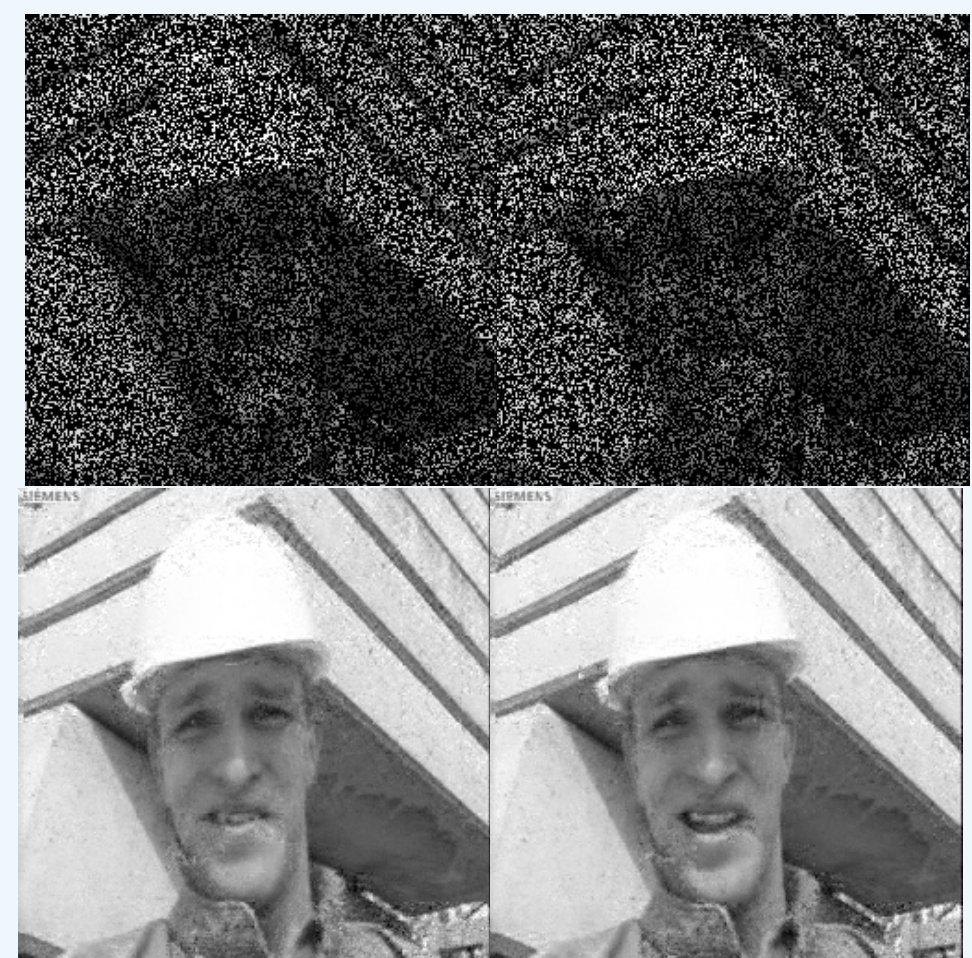
This is an NP-hard problem and alternative approaches are required.

Methods

A machine learning approach is used and the Compressive Sensing problem is formulated as a Bayesian regression: $\mathbf{y} = \Phi\mathbf{w} + \epsilon$, where ϵ is a zero-mean Gaussian error. The *Relevance Vector Machine* (RVM) [3, 4] is used to find a solution \mathbf{w} with a very sparse posterior mean.

For sensing mechanisms that measure a subset of individual pixel values directly, a cascade of RVMs [5] is build to further improve the reconstruction quality.

Results



frame 42

frame 43

Figure 1: Two consecutive frames of a sample video signal. Top row: CS measurements \mathbf{y} . Bottom row: Recovered video $\hat{\mathbf{v}}$

In Figure 1, the sensing mechanism Θ has measured 30% of the data in \mathbf{v} . The video is recovered using a cascade of RVMs, with a reconstruction error of 6.9%.

References and Acknowledgements

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- [3] M. E. Tipping. *The journal of machine learning research* 1 (2001).
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- [5] G. Pilikos. MPhil Thesis. University of Cambridge, 2014.