Jl. watch on Transactions of Signal Processing Feb 2013 (Vol. 3 & 4)

T. Ganesan
SPC Lab
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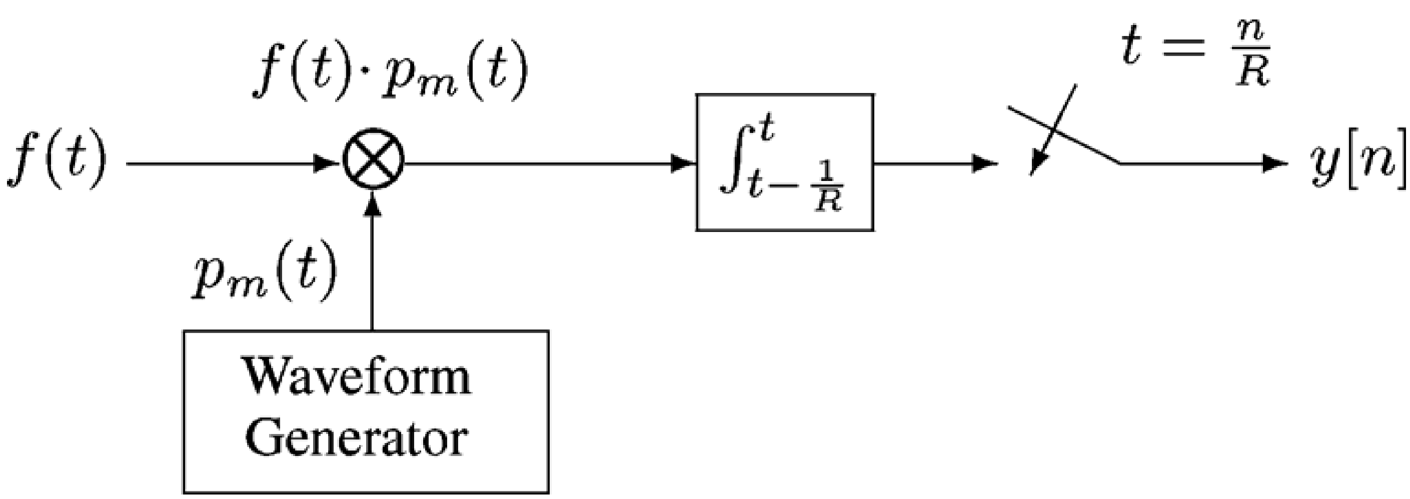
A Constrained Random Demodulator for Sub-Nyquist Sampling

- **Author(s):** A. Harms, *Princeton Univ., W. U. Bajwa, Rutgers Univ. and R. Calderbank, Duke Univ.*

Problem Addressed:

- **Spectrally Sparse signal being recovered by sampling the randomly demodulated signal output**
  - Random demodulator proposed by Tropp is modified with constrained random waveforms which has less stringent raise-time requirements for ease of hardware implementation.
  - It is known that if the sampling rate R scales with no. of tones S as R > C S $\log^6(W)$, where W is the Nyquist rate and C is a constant, then signal can be recovered reliably by random demodulator.



Contributions:

- Lessons learnt from magnetic recording was applied here, i.e., Run-length coding is used in place of random waveform which reduces the no. of transition by a factor L, which is the run-length.

- For certain choice of constrained random demodulation waveforms, theoretical guarantees are given for reconstruction.

- Trade-off between the signal sparsity and acquirable bandwidth of the signal is studied.

- Foundations of “Knowledge-Enhanced compressive sensing” is given. I.e., if we know statistically if some tone has more probability of occurrence than others, how does it affect reconstruction or sampling.

Convolutional Compressed Sensing Using Deterministic Sequences

Author(s) K. Li*, Imperial college, London, L. Gan, Brunel Univ., London, and C. Ling, Imperial college, London*

Problem Addressed:

- Compressive sensing using structured sensing matrices esp, circulant structure.
- The coefficients of the matrix are obtained from the DFT of a deterministic sequence with good auto-correlation properties.

Contributions

- Convolution based CS involves convolving the desired signal with a random filter (filter which has random coefficients) and sub-sampling.
- Here, a deterministic filter is proposed for convolution followed by the random sampling.
- The proposed scheme can recover K-sparse signals in time/frequency/space with number of measurements $M > O(K \log^4 N)$
- When the filter is constructed using FZC sequence, it can also recover K-sparse signal in DCT domain also.

New Bounds for Restricted Isometry Constants With Coherent Tight Frames

- **Author(s):** J. Lin, S. Li, and Y. Shen, Zhejiang University, Hangzhou,

Problem Addressed:

- Given a tight-frame D for **R^**n, such that D.f is s-sparse or nearly s-sparse, for all f in **R^**n, what are the conditions for recovery of the signal from m linear measurements of D.f ?
- The conditions are given in terms of D-RIP and D-ROC

Contributions:

- Standard RIP gives condition on δ for stable recovery.
- Similarly, D-RIP condition is given by

$$(1-\delta)||Dv||_2^2 \leq ||ADv||_2^2 \leq (1+\delta)||Dv||_2^2$$

where v is s-sparse vector.

- The smallest δ which satisfies the D-RIP is known as D-RIP constant δs for s-sparse signal.
- Here it is shown that δs < 0.307, whereas the existing conditions are on δcs for some constant c > 0.

Generalized Eigenvector for Decentralized Transmit Beamforming in the MISO Interference Channel

- **Author(s):** *M. Á. Vázquez, A. Pérez-Neira, and M. Á. Lagunas,* CTTC and the Universitat Politècnica de Catalunya, Barcelona, Spain

Problem Addressed:

- Sum-rate optimal beamforming in a MISO interference channel in a decentralized manner.

Contributions:

- Decentralized transmit beamformer for a K-user interference channel has been proposed earlier which achieves the maximum sum-rate.
- This paper provides analytical proof for the good behaviour.
- Here, the design is decentralized because the Tx do not exchange information.

Generalized eigenvector Beamformer (Contd)

- The rate for k-th user, by treating interference as noise as get

$$R_k = \log\left(1 + \frac{D_k}{\sum_{j \neq k} I_{jk} + \sigma^2}\right)$$

$$D_k = P\left|\mathbf{h}_{kk}^H \mathbf{h} b_k\right|^2 \quad I_{jk} = P\left|\mathbf{h}_{jk}^H \mathbf{h} b_j\right|^2$$

where b_k is the unit-norm beamforming vector

- The optimal beamformer for 2-user case is shown to be

$$\left(P\mathbf{h}_{kk}\mathbf{h}_{kk}^H + \sigma^2\mathbf{I}\right)\mathbf{b}_k^{EIG} = \lambda_{\max}\left(P\mathbf{h}_{kj}\mathbf{h}_{kj}^H + \sigma^2\mathbf{I}\right)\mathbf{b}_k^{EIG}$$

Backup

Other Interesting Papers in Feb Vol. 3&4 Issues

1. Multicell MISO DownlinkWeighted Sum-Rate Maximization: A Distributed Approach
2. Chebyshev Polynomials in Distributed Consensus Applications
3. Estimation of Primary User Parameters in Cognitive Radio Systems via Hidden Markov Model
4. Bayesian Estimation for Continuous-Time Sparse Stochastic Processes
5. A Framework for Inference Using Goodness of Fit Tests Based on Ensemble of Phi-Divergences