Distributed Wideband Spectrum Sensing

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Aims: To Compressively Sense and estimate wideband frequency spectra for white spaces using heterogeneous sensor networks.

Introduction

• We present a novel frequency estimation framework for spectral White Spaces.
• Databases are one way to maintain information about White Spaces to devices.
• However, there is an overhead in maintaining databases.
• Spectrum sensing, could be a cognitive complement (and eventual replacement) to databases.
• Sensing requires that the entire frequency band be scanned, which may not be feasible (in terms of time of battery life) for single devices.
• The sensing load can be reduced by distributing it across a network.
• Our approach is a fast, low complexity, decentralised, and compressive method of white space detection.
• The sampling rates at each sensor are below Nyquist rates (25%), making the sensing greener.
• Can be implemented on a range of devices such as COTS components or Raspberry Pi.

Algorithm

During each round of computation the nodes each complete the following set of iterations:

\[ x_j^{k+1} = (A_j^T A_j + \rho (D_p + 1))^{-1} (A_j^T y_j + \rho z_j^k - \nu - \theta) \]

\[ z_j^{k+1} = \text{sign} \left( \frac{x_j^{k+1} + \theta}{\rho} \right) \left( \frac{x_j^{k+1} + \theta - \beta}{\rho} \right)^* \]

\[ \nu^{k+1} = \nu^k + \rho \sum_{N_j}(x_j - x_{N_j}) \]

\[ \theta^{k+1} = \theta^k + \rho (x_j^{k+1} - z_j^{k+1}) \]

Node \( j \) then communicates \( x_j^{k+1} \) to its neighbours.

These can be understood statistically:

• The \( x \) step solves a weighted least squares (minimising a quadratic function) with the previous round's estimation as a prior.
• The \( z \) step then penalises large components of the estimate to promote sparse solutions.
• The \( \nu, \theta \) steps update the Lagrange multipliers: they represent the rate of change of the estimate along the series of iterations.

Application of Modern Maths

• We model the network as a random graph, \( G = (V, E) \) with sensors as nodes and an edge between two sensors if their relative distance is small enough.
• Each sensor takes measurements by convolving the spectrum with a random low frequency signal:
  \[ y_j = A_j x_j + n_j \]
  • The matrix \( A_j \) represents the random convolution, as well as channel effects such as multipath and fading. \( n_j \) is white Gaussian noise.
• From these low frequency samples, we can reconstruct the signal.

Conclusions:

• Reduced computation time from 13 hours (previous benchmark algorithm) to 30 seconds (above algorithm) for 500 rounds.
• A fast, low complexity, cheap, and cognitive method of detecting TVWS.
• Requires sampling rates well below Nyquist theory (25% of Nyquist theory).