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JOINT BEAM FORMING, POWER AND CHANNEL ALLOCATION IN MULTI-USER AND MULTI-CHANNEL UNDERLAY MISO COGNITIVE RADIO NETWORK

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ABSTRACT

In this paper, we consider a joint beamforming , power, and channel allocation in a multi-user and multi-channel underlay multiple input single output (MISO) Cognitive radio network (CRN). In this system, primary users' (PUs') spectrum can be reused by the secondary user transmitters (SUTXs) to maximize the spectrum utilization while the intra-user interference is minimized by implementing beamforming at each SU-TX. After formulating the joint optimization problem a non-convex, mixed integer nonlinear programming (MINLP) problem, we propose a solution which consists of two stages .In the first stage, a feasible solution for power allocation and beamforming vectors is derived under a given channel allocation by converting the original problem into a convex form with an introduced optimal auxiliary variable and semi definite relaxation (SDR) approach.

After that, in the second stage, two explicit searching algorithms, i.e., genetic algorithm (GA) and simulated annealing (SA)-based algorithm, are proposed to determine suboptimal channel allocations. Simulation results show that beamforming, power and channel allocation with SA (BPCA-SA) algorithm can achieve close-to-optimal sum-rate while having a lower computational complexity compared with beamforming,power and channel allocation with GA (BPCA-GA) algorithm. Furthermore, our proposed allocation scheme has significant improvement in achievable sum-rate compared to the existing zero-forcing beamforming (ZFBF).

Index Terms—Cognitive radio network, beamforming, semidefinite relaxation, genetic algorithm, simulated annealing.

INTRODUCTION

Beamforming is a general signal processing technique used to control the directionality of the reception or transmission of a signal on a transducer array. Using beamforming you can direct the majority of signal energy you transmit from a group of transducers in a chosen angular direction. Or you can calibrate your group of transducers when receiving signals such that you predominently receive from a chosen angular direction. The physics and math are essentially the same for both the transmitting and receiving cases, so General Block diagram of analysis of speech signal.

SPEECH RECOGNITION SYSTEM

Fig.2.2 shows a flowchart of a speech recognition system. This flowchart is based on our developed, complete recognition system. In the speech analysis part, speech feature vectors are extracted from a time series of short-duration speech signals. Traditional speech recognition systems directly handed these feature vectors over, from speech analysis to speech recognition. Currently, many systems employ robust processing that removes noise interferences because the raw data is very sensitive to noise. In the robust processing part, the feature vectors are re-generated by shaping, e.g., subtracting the noise components.

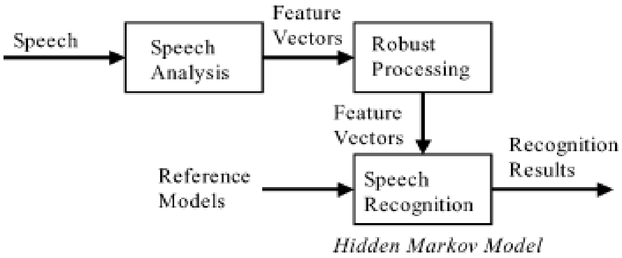


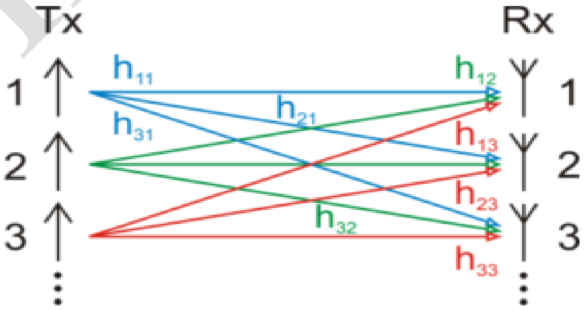
Fig 2.2 Flowchart of speech recognition system.

During the speech recognition part, the recognizer computes the likelihood scores and finds the best match using test utterances. Reference models are generated from HMM training in advance. Because the training is assumed to have been executed by the software, the system does not include a training function. The complete system unifies speech analysis, robust processing, and speech recognition.

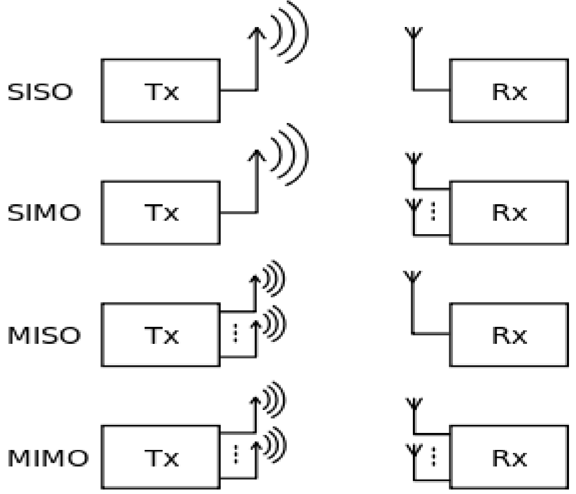
HIDDEN MARKOV MODEL

A **hidden Markov model** (HMM) is a five-tuple (Omega_X,Omega_O,A,B,pi). Let lambda = {A,B,pi} denote the parameters for a given HMM with fixed Omega_X and Omega_O. A discrete-time, discrete-space dynamical system governed by a Markov chain emits a sequence of observable outputs: one output (observation) for each state in a trajectory of such states. From the observable sequence of outputs, infer the most likely dynamical system. The result is a model for the underlying process. Alternatively, given a sequence of outputs, infer the most likely sequence of states. We might also use the model to predict the next observation or more generally a continuation of the sequence of observations.
To solve Problem 3 we need a method of adjusting the lambda parameters to maximize the likelihood of the training set. Suppose that the outputs (observations) are in a 1-1 correspondence with the states so that N = M, varphi(q_i) = v_i and b_i(j) = 1 for j = i and 0 for j != i. Now the Markov process is not hidden at all and the HMM is just a Markov chain.

To estimate the lambda parameters for this Markov chain it is enough just to calculate the appropriate frequencies from the observed sequence of outputs. These frequencies constitute sufficient statistics for the underlying distributions.
In the more general case, we can't observe the states directly so we can't calculate the required frequencies. In the hidden case, we use expectation maximization (EM) as described. Instead of calculating the required frequencies directly from the observed outputs, we iteratively estimated the parameters. We start by choosing arbitrary values for the parameters (just make sure that the values satisfy the requirements for probability distributions).
We then compute the expected frequencies given the model and the observations. The expected frequencies are obtained by weighting the observed transitions by the probabilities specified in the current model. The expected frequencies so obtained are then substituted for the old parameters and we iterate until there is no improvement. On each iteration we improve the probability of O being observed from the model until some limiting probability is reached. This iterative procedure is guaranteed to converge on a local maximum of the cross entropy (Kullback-Leibler)



Beamforming is a general signal processing technique



RESULT AND DISCUSSION

The simulation results has been given in this chapter. 100 channel realizations has been used for simulations

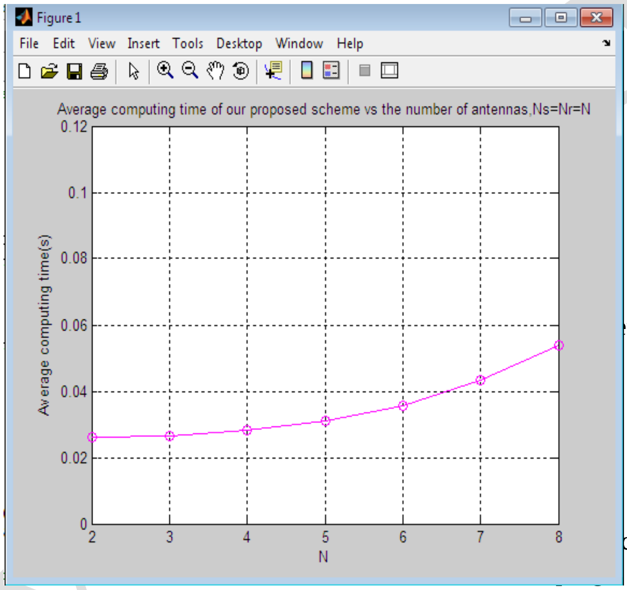
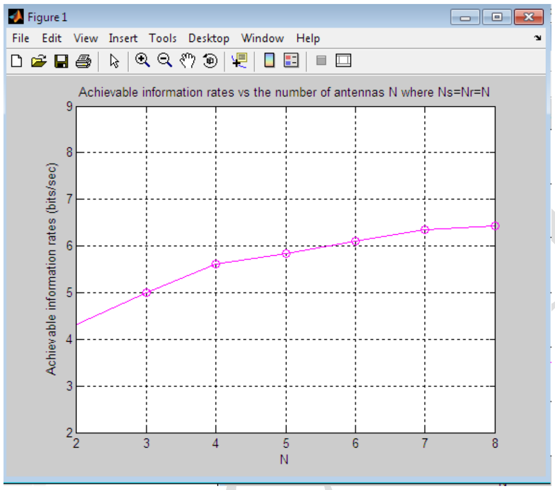


Fig 6.1 Achievable information rate vs the number of antennas N where NS=Nr=N



FUTURE ENHACEMENTS

In this paper, a problem of joint beamforming, power and channel allocation is considered for multi user multi channel underlay cognitive radio networks. The problem is formulated as a non convex MINLP problem, which is NP hard. In order to reduce the computational complexity, we decouple the original problem into two sub-problems. At first, a feasible solution for beamforming vectors and power allocation is obtained for a known channel allocation by an iterative algorithm, which uses the SDR approach with an auxiliary variable. After that,GA and SA based algorithms have been applied to determine suboptimal channel allocations. Simulation results show that BPCA GA can obtain close to optimal solution with a price of high computation complexity. Whereas, BPCA SA can significantly the computational complexity with marginal performance degradation compared to BPCA GA. Moreover,beamforming with interference tolerance capability introduced by our system model can achieve better performance than traditional ZFBF.**MATLAB**

MATLAB is a high-performance language for computing. It integrates computation, visualization, and an easytouse environment where problems and solutions are expressed in familiar mathematical notation. Typical uses includ

- Math and computation
- Algorithm development
- Modeling, simulation, and prototyping
- Data analysis, exploration, and visualization
- Scientific and engineering graphics

- Application development, including graphical user interface building

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