Literature Review

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1. Training support vector machine without offset

One of the biggest challenges the researchers and industry practitioners are facing in wireless communication area is how to bridge the sharp gap between increasing demand of high speed communication of rich multimedia information with high level Quality of Service (QoS) and the limited radio frequency spectrum over a complex space-time varying environment. As the most promising technology for solving this problem, Multiple Input Multiple Output (MIMO) technology has been of immense research interest over the last several tens of years and become mature, which is incorporated into the emerging wireless broadband standard like 802.11ac [1] long-term evolution (LTE) [2]. The core idea of MIMO system is to use multiple antennas at both transmitting and receiving end, so that multiplexing gain (multiple parallel spatial data pipelines that can improve bandwidth efficiency) and diversity gain (better reliability of communication link) is obtained by employing spatial domain. Large MIMO (also called Massive MIMO) is an upgrade version of conventional MIMO system, it equips unprecedentedly hundreds of low power low price antennas at base station (BS), serving several tens of terminals simultaneously, It can achieve full potential of conventional MIMO system while providing additional power efficiency as well as system robustness [3][4].

The price paid for large MIMO system is the increasing complexities for signal processing at both transmitting and receiving end. Uplink Detector is one of the key components in large MIMO system. With orders magnitude more antennas equipped at BS, benefit and challenge coexist in designing of detection algorithms for large MIMO uplink, on the one hand, large number of receive antennas provide potential of large diversity gain, on the other hand, complexity of the algorithm becomes extremely crucial to make system practical.

The optimal maximum likelihood detector (MLD) for MIMO system requires the complexity increase exponentially with number of transmitted antennas with a factor of the size of size of constellation, which is prohibitive in practical implementations.

Sphere Decoder (SD)[5] is the most prominent algorithm that utilizes lattice structure of MIMO system.

Its variant fixed complexity sphere decoder (FCSD)[6] make it possible to achieve near optimal performance with a fixed complexity under different signal to noise ratio (SNR). However, all the algorithms that based on lattice structure have the same shortage - their complexities increases exponentially with a factor of the size of symbol constellation. Therefore, they are prohibitive when it comes to a high order modulation scheme, for example in IEEE 802.11ac standard [1], the modulation scheme is 256QAM.

Suboptimal linear detectors (LD) like minimum mean square error (MMSE) and zero forcing (ZF) along with their sequential interference cancellation with optimized ordering (OSIC) counterparts [7][8][9] which have good performance for low loading factor in massive MIMO system (that is the number of receive antennas is much larger than the number of transmit antennas) [10]. In the last several years, a set of detection algorithms are proposed with complexities that is comparable with LD-OSIC and suboptimal performance can be achieved. The local search algorithm, such as likelihood ascend searching (LAS) [11][12], an theoretical analysis of upper bound of bit error rate (BER) and lower bound of on asymptotic multiuser efficiency for the LAS detector was presented [13]. Layered Tabu search algorithm presented in [14] is superior to the LAS algorithms because it can move away to new searching area to avoid local minimal. Message passing detectors based on belief propagation (BF) and Gaussian Approximation (GA) [15][16][17][18]. Markov Chain Monte Carlo algorithm [19] and Lattice Reduction aided detectors [20].

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11. A low-complexity detector for large MIMO systems and multicarrier CDMA systems
12. Multiple output selection-LAS algorithm in large MIMO systems
13. A family of likelihood ascend search multiuser detectors
14. Layered tabu search algorithm for large-MIMO detection and a lower bound on ML performance
15. MIMO detection for high-order QAM based on a Gaussian tree approximation
16. Low complexity detection in large-dimension MIMO-ISI channels using graphical Models
17. Channel hardening exploiting message passing for large MIMO
18. Improved large MIMO detection with damped belief propagation
19. A novel Monte-Carlo-sampling-based receiver for large-scale uplink multiuser MIMO systems
20. Element based lattice reduction algorithm for large MIMO system

Firmly grounded in framework of statistical learning theory, Support Vector Machine (SVM) has become a powerful tool to solve real world supervised learning problems such as classification, regression and prediction. SVM method is a nonlinear generalization of Generalized Portrait algorithm developed by Vapnik in 1960s [1][2], which can give good generalization performance to unseen data [3].

Research and industry interest of SVM boosted since 1990s, promoted by related works of Vapnik and co-workers at AT&T Bell laboratory[4][5][6][7][8][9]

Moreover, the kernel based methods [3] carries out nonlinear learning task by mapping input data sets into high dimensional feature space, then replacing inner product of feature mappings by computational inexpensive kernel functions discarding the actual structure of the feature space. This rational is supported mathematically by Reproducing Kernel Hilbert Space (RKHS).

Based on the same regularized risk function principle, *ϵ*-Support Vector Regression (epsilon-SVR) [6][10] was developed.

Like SVM, epsilon-SVR solving original optimization problem by transforming it into Lagrange dual optimization problem, which can be solved by Quadratic Programming (QP), Sequential Minimal Optimization (SMO) algorithm was proposed as a fast algorithm to solve this QP problem by decompose the it into sub QP problems and solve them analytically [11], therefore, the computational intensive numerical method can be avoided. A more general method is decomposition solver, which refers to a set of algorithms that separate the optimization variables (Lagrange multipliers) into two sets W and N, W is the work set and N contains the remaining optimization variables. In each iteration, only the optimization variables in work set is optimized while keeping other variables fixed. SMO algorithm is an extreme case of decomposition solver. An important issue of decomposition solver is the choice of work set, one strategy is to choose Karush–Kuhn–Tucker (KKT) condition violators, and final converge can be guaranteed [12]. SMO algorithm restricts the size of work set to 2, because of linear constraint in dual problem that inducted by offset. In [13], a method to train SVM without offset was proposed, with the comparable performance to the SVM with offset. The authors work demonstrates that with the combination of two single optimization variable work set selection strategies which requires searching time O(n) and update a work set size of two in each iteration, this method can achieve a iteration time as few as that searching over all pairs of optimization variables which requires O(n2) searching times.

Until now, although the mathematical foundation of kernel based methods is RKHS which is defined in complex domain, the most of practitioners are dealing with real data set. In communication and signal processing area, the channel gains, signals, waveforms etc. are all represented in complex form. Recently, a pure complex SVR$SVM based on complex kernel was proposed in [14], which can process the complex data set purely in complex domain. The simulation of channel realization and equalization in [14] demonstrate a better performance as well as reduced complexity comparing to simply split learning task into two real case by real kernel.

Based on this work, we construct a prototype of a complexity-performance controllable detector for large MIMO based on dual channel complex SVR. The detector can work in two parallel real SVR pipeline which can be solved independently. Moreover, only real part of kernel matrix is needed in both channel. This means a large amount of computation can be reduced.

Based on the discrete time MIMO channel model, In our regression model, this CSVR-detector

is constructed without offset, Therefore, for each real SVR without offset, in principle, only one variable is needed to be updated in each iteration, In our prototype, we propose a sequential single optimization variable searching strategy that find two optimization variable sequentially, which can approximate the optimal double optimization variables searching strategy.

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