This paper is available online at www.praiseworthyprize.org
International Journal on Communications Antenna and Propagation (I.Re.C.A.P.), Vol. 8, N. 3
ISSN 2039 – 5086
June 2018

A Primer on MIMO Detection Algorithms for 5G Communication Network

Olabode Idowu-Bismark, Okokpujie Kennedy, Francis Idachaba, Aderemi A. Atayero

Abstract – *In the recent past, demand for large use of mobile data has increased tremendously due to the proliferation of hand held devices which allows millions of people access to video streaming, VOIP and other internet related usage including machine to machine (M2M) communication. One of the anticipated attribute of the fifth generation (5G) network is its ability to meet this humongous data rate requirement in the order of 10s Gbps. A particular promising technology that can provide this desired performance if used in the 5G network is the massive multiple-input, multiple-output otherwise called the Massive MIMO. The use of massive MIMO in 5G cellular network where data rate of the order of 100x that of the current state of the art LTE-A is expected and high spectral efficiency with very low latency and low energy consumption, present a challenge in symbol/signal detection and parameter estimation as a result of the high dimension of the antenna elements required. One of the major bottlenecks in achieving the benefits of such massive MIMO systems is the problem of achieving detectors with realistic low complexity for such huge systems. We therefore review various MIMO detection algorithms aiming for low computational complexity with high performance and that scales well with increase in transmit antennas suitable for massive MIMO systems. We evaluate detection algorithms for small and medium dimension MIMO as well as a combination of some of them in order to achieve our above objectives. The review shows no single one detector can be said to be ideal for massive MIMO and that the low complexity with optimal performance detector suitable for 5G massive MIMO system is still an open research issue. A comprehensive review of such detection algorithms for massive MIMO was not presented in the literature which was achieved in this work.*

***Keywords**: Massive MIMO, Multiuser Detection, Optimum Detector, Linear/Non-linear Detector*

Nomenclature

CDMA	Code Division Multiple Access
IDD	Iterative Detector Decoder
LTE-A	Long Term Evolution-Advanced
M2M	Machine-to-machine
MAP	Maximum A posterior Probability
MCMC	Markov Chain Monte Carlo
MF	Matched Filter
MIC	Multistage Interference cancellation
MIMO	Multiple Input Multiple Output
ML	Maximum Likelihood
MMSE	Minimum Mean Square Error
MUD	Multi-User Detection
PDA	Probabilistic Data Association
PIC	Parallel Interference Cancellation
SDPR	Semi-Definite Programming Relaxation
SIC	Successive Interference Cancellation
ZF	Zero Forcing

I. Introduction

MIMO detection is concerned with many transmitted symbols jointly detected in a multipath communication channel. The problem of MIMO detection arises because of the non-orthogonality of the sub-channels of the multipath communication link connecting the transmitter to the receiver, such that the transmitted information signals from each different antenna superimpose and interfere with each other resulting in interference between the outputs [1], [2], therefore the separation of these signals at the receiver is termed detection [3].

According to [4] detection requires that the detector determines or estimates the value of the signal vector X which is transmitted as an output of the detector. In the case of [2], [5], [6], it says the fundamental duty of a MIMO detector is to decide the value of the input vector X based on the estimate of the channel matrix H and knowledge of signal vector Y received. In achieving the above, sophisticated signal processing algorithms are needed for the multiuser MIMO detection (MUD) even as the challenge of solving the detection dilemma increases as the number of transmit antennas increases to large numbers in massive MIMO systems. Current state of the art transmit and receive signal processing algorithms for MIMO detection has a computational cost

Available online by June 30th, 2018
https://doi.org/10.15866/irecap.v8i3.13731

that grows exponentially with the increase in the number of antennas as well as the modulation scheme which is not scalable in massive MIMO, consequently, novel low complexity with high performance solutions that scales with increasing antennas numbers in massive MIMO will have to be developed which will require significant research effort. This is of interest [7], [8].

The roots of many MIMO detection algorithms in the literature can be traced to algorithms for MUD in code division multiple access (CDMA) systems. Since MIMO systems and CDMA systems are both modelled with the same structural format (i.e. linear vector channel model).

The channel matrix of a CDMA system is made up of the normalized cross-correlations between the signature sequences of the active users, while in the case of MIMO system, the channel matrix is made up of the spatial signatures of the transmit and receive antennas connections. MIMO systems can therefore be represented by the linear vector channel model as shown below in equation (1):

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{V} \tag{1}$$

where $\boldsymbol{y}$ is the signal vector received, $\boldsymbol{x}$ is the transmit vector, $\boldsymbol{H}$ is the "channel matrix" and $\boldsymbol{V}$ is the noise vector with $\boldsymbol{V} \sim N(0, \sigma I)$ [8], [9].

There are two types of MIMO detection, these are coherent detection where the instantaneous value of the fading channel coefficients matrix called channel state information (CSI) is known. In the second type, the detection of $\boldsymbol{X}$ follows the non-coherent detection scheme where the knowledge of CSI is not available and MIMO detection therefore requires that the input or transmitted symbols are encoded such that block-by-block sequential detection are employed [2], [6]. Only the coherent detection techniques have been considered.

Various MIMO detectors existed for different applications need, these can be categorised into optimum versus suboptimum. The suboptimum detectors can be further classified as linear versus nonlinear. Fig. 1 is a flow chart of the various types and classification of MIMO detectors. Other classifications exist which includes hard-decision versus soft-decision, iterative versus non-iterative and coded versus un-coded [2], [10].

MIMO detection research has grown in two main directions of Linear and non-linear detection where, for linear detectors we have matched filter (MF), zero forcing (ZF), and minimum mean square error (MMSE) detectors, while non-linear detectors include Interference cancellation, Lattice-Reduction (LR), Probabilistic Data Association (PDA), Semi-definite Programming Relaxation (SDPR), and the Markov Chain Monte Carlo Method (MCMC) based detectors etc [11], see Fig. 1 The PDA, SDPR and the MCMC detectors are more suitable for massive MIMO system where both the transmit and or receive antennas are in hundreds [8].

This paper is structured as follows. Introduction deals with the various classes of state of the art detectors available while section II looked into the concept of optimum decision criteria and the optimum detectors. In section III it has been considered the linear sub-optimal detectors and looked at various non-linear sub-optimal detectors in section IV. In section V non-linear detectors suitable for massive MIMO have been studied and then summarized in section VI. In section VII conclusions can be read.

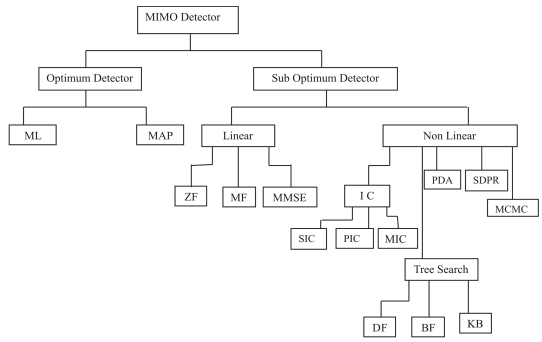

Fig. 1. MIMO Detection flow chart

II. Optimum Detectors

In this section, there is a primary look at the various algorithms used for detection in MIMO systems. The optimum decision criteria are usually set for optimum detectors/receivers when designing detection algorithms for wireless communications system because the classification of optimal detection algorithms is based on the precise or exact assumptions and set criteria of "performance" thus an optimal detection algorithm/receiver is that one that best perform under the given set of criteria/assumptions. Therefore if these criteria or assumptions changes, the classification as an optimal detection algorithm/receiver can as well change.

It is generally agreed that once the criteria/assumptions on which the theoretical analysis are based are conflicting with the situation of the practical location considered, the supposedly optimal detection algorithm/receiver designed is likely to have failed to offer valid results for the achievable practical performance envisioned [2]. It should be noted that the theoretically obtained optimal results by design are largely used as bound or standard on which any other results such as the practical experiment can be compared.

There are many standard criteria of performance for detectors or receivers, among them, of principal interest is the minimum error probability criterion, while the likelihood ratio as well as the hypothesis testing are also very important.

II.1. Maximum Likelihood Detector

According to [12], [13], [14] the ML detector when considering minimum error probability is optimal if all the vectors transmitted are similarly likely, and all available diversity are fully exploited. At the receiver, the detector finds an estimation of the transmitted symbol $\hat{\boldsymbol{x}}$ and it minimizes the average probability of error, p($\hat{\boldsymbol{x}} \neq$

$\boldsymbol{x}$) thus achieving optimum error-rate performance by solving the non-linear optimization problem of how to minimize the squared Euclidean space between the real received vector $\boldsymbol{y}$ and the hypothesized received signal $\boldsymbol{Hx}$ [8], [7] with the vector $\boldsymbol{x}$ constrained to the set A^{n_t}:

$$\hat{X}_{ML} = \underset{x \in A^{n_t}}{\operatorname{argmin}} \|\boldsymbol{y} - \boldsymbol{Hx}\|^2 \tag{2}$$

Computing the exact solution to the above optimization problem in equation (2) through an exhaustive search requires exponential complexity in n_T.

Therefore, this computation is possible only for small n_T.

Knowing the exact ML solution is desired since it serves as a benchmark to assess how various detectors perform relative to the optimum solution [12]. When n_T is large (tens to hundreds), computing the exact ML solution becomes infeasible due to the exponential complexity. Low complexity bounds on ML performance can help to address this issue [2], [15].

II.2. Maximum A Posterior Detector

In the Bayesian deduction, the maximum a posterior criterion is the optimum decision criterion that is used to minimize the error probability according to the received signals only as well as a specified set of hypotheses.[2].

This detector known as the Maximum A posterior Probability (MAP) detector according to its received observations compute the various a posterior probabilities of the received symbols and choose that transmitters symbols that has maximum a posterior probability. ML detectors considers purely the likelihood conditions however, the MAP detector looks at the a posterior probability, and the maximum a posterior probability minimizes the probability of errors which the ML does not. Thus the optimality of the ML Detector is lower than that of the MAP Detector.

The MAP detector is typically used in the iterative detector-decoder (IDD) forward-error-correction (FEC) coded receiver systems, in which the prior probabilities of the symbols transmitted, Pr(X), could be obtained by means of the iterative forward and backward exchange of information between the detector output signal and the channel decoder while the ML detector is typically used in uncoded FEC systems, in which case the transmitted symbols' prior probabilities are not available to the channel decoder [2].

III. Linear Detectors

The linear MIMO detectors operates on a linear conversion of the output signal vector $\boldsymbol{y}$, and are expected to generate soft estimates of the transmitted symbols through the linear conversion of the said received vector.

They are known for low complexity, but suffers significant performance loss when compared to the ML or MAP detectors. To obtain hard estimates, the assessment statistics of linear MIMO detectors may be written as $\tilde{\boldsymbol{x}} = \boldsymbol{Gy}$, where G is the linear conversion matrix which based on various criteria should be designed [2], [8].

III.1. MF Detector

The MF detector is a simple linear detector and computationally has the lowest complexity within the MIMO detector family. It also has optimal criterion for maximizing the received signal to noise ratio in the presence of additive stochastic noise.[2], [13] In detecting the symbol in a given stream, the MF detector treats the interference from other streams as merely noise.

Defining $\boldsymbol{h}_i$, i = 1, 2,…, N_T, to be the i^{th} column of the channel matrix $\boldsymbol{H}$, we can write our MIMO model equation in the form:

$$\begin{aligned} \boldsymbol{y} = \boldsymbol{Hx} + \boldsymbol{n} &= \sum_{i=1}^{n_t} \boldsymbol{h}_i x_i + \boldsymbol{n} \\ &= \boldsymbol{h}_k x_k + \sum_{i=1, i\neq k}^{n_t} \boldsymbol{h}_i x_i + \boldsymbol{n} \end{aligned} \tag{3}$$

where the first term in the equation (3) above is the component due to the k^{th} stream, and the second term is due to all streams other than the k^{th} stream, i.e., the second term is the interference term as far as the k^{th} stream is concerned. In detecting the k^{th} stream symbol $\boldsymbol{x_k}$, the MF detector simply ignores the second term as noise and obtains a soft estimate of $\boldsymbol{x_k}$ as:

$$\tilde{x}_k = \boldsymbol{h}_k^* \boldsymbol{y} \tag{4}$$

and a hard estimate is obtained by mapping to the closest symbol in the alphabet in terms of Euclidean distance. In vector form, the MF solution can be expressed as:

$$\tilde{\boldsymbol{x}}_{MF} = \boldsymbol{H}^H \boldsymbol{y} \tag{5}$$

i.e., the transformation matrix $\boldsymbol{G}_{MF} = \boldsymbol{H}^H$. Applying this to get $\hat{\boldsymbol{x}}$ requires a complexity of order $N_T \times kN_R$, which gives $\hat{\boldsymbol{x}} = (\boldsymbol{H}^{\mathrm{H}}\boldsymbol{H})\boldsymbol{x} + \boldsymbol{H}^{\mathrm{H}}\boldsymbol{n}$ which is very attractive.

However, its performance severely degrades with increasing N_T in systems with moderate to full loading, due to increased levels of un-cancelled interference from other streams.

III.2. ZF Detector

The zero forcing (ZF) detector is another linear detector where the linear transformation on the received vector is carried out by means of the pseudo-inverse of the $\boldsymbol{H}$ matrix. This is done by finding the minimum error solution to equation (2). The ZF which maximises the signal to interference ratio (SIR) of received vector is optimal in this regard [2], [12]. If it is assumed zero as noise vector, the MIMO model turns to an arrangement of linear equations and "finding the answers for N_T unknown variables based on KN_R linear equations" becomes the MIMO detection problem. Thus, if we have a square matrix $\boldsymbol{H}$ with $N_T = kN_R$ and of full rank, then $\mathbf{s} = \boldsymbol{H}^{-1}\boldsymbol{y}$ becomes the solution for this arrangement of linear equations. Again, if our matrix $\boldsymbol{H}$ satisfies the condition $kN_R > N_T$ and is of a full column rank of N_T, we then have the ZF solution in vector form as $\tilde{\boldsymbol{x}}_{ZF} = \boldsymbol{Q}_y$, where $\boldsymbol{Q}$ is the pseudo-inverse of $\boldsymbol{H}$, [16], [17], [18] i.e.:

$$\boldsymbol{Q} = (\boldsymbol{H}^H\boldsymbol{H})^{-1}\boldsymbol{H}^H \tag{6}$$

Since $\boldsymbol{QH} = \boldsymbol{I}_{\boldsymbol{N_T}}$, the transformation $\boldsymbol{Q}_y$ completely cancels the interference from other streams (hence the name zero-forcing or interference-nulling detector) [8], [2]. A drawback, however, is that noise is enhanced in the process of eliminating the interference completely.

The computational complexity in $\tilde{\boldsymbol{x}}_{ZF} = \boldsymbol{Q}_y$, is cubic in N_T because of the computation of the matrix inverse.

Therefore, the per-symbol complexity is N_T^2 which is one order more than that of the MF detector. While this quadratic per-symbol complexity of the ZF detector is still attractive for massive MIMO systems, its performance also degrades severely for large N_T at moderate to full loads [8], [9]. One of the problems of the ZF is that it does not consider the noise vector and has the potential to actually amplify noise. To solve this problem the literature propose the minimum mean square error (MMSE) detector.

III.3. MMSE Detector

The minimum mean square error (MMSE) detector considers the noise variance and solves the problem of noise amplification in ZF. In comparison to ZF, the MMSE provides a better equilibrium between the multi user interference (MUI) removal and noise amplification by mutually reducing the sum error enforced by the MUI and the noise.

Thus the MMSE performance is enhanced at low signal to noise ratios (SNRs) compare to the ZF. The MMSE is a linear detector whose conversion or transformation matrix is the matrix that brings to minimum the mean square error (MSE) between the transmit vector and the estimated vector (i.e., the transformed received vector). That is, the transformation matrix $\boldsymbol{G}_{MMSE}$ is given by the solution to the following minimization problem of equation (7) below [1], [18]:

$$\min_{G} E[\|\boldsymbol{x} - \boldsymbol{Gy}\|^2] \tag{7}$$

where the solution of the transformation matrix is given by equation (8) below:

$$\boldsymbol{G}_{MMSE} = (\boldsymbol{H}^H\boldsymbol{H} + \boldsymbol{\sigma}^2\boldsymbol{I}_{nt})^{-1}\boldsymbol{H}^H \tag{8}$$

where sigma square $\boldsymbol{\sigma}^2$ is the noise power and the MMSE solution is given by:

$$\tilde{x}_{MMSE} = \boldsymbol{G}_{MMSE}\boldsymbol{y}$$

The MMSE detector combines the best performance attributes of MF and ZF detectors. At high SNRs (i.e., small σ), MMSE behaves like ZF since the second term inside the inverse operation in the equation for $\boldsymbol{G}_{MMSE}$ above becomes negligible. At low SNRs, it behaves like MF because of the prominence of the diagonal entries of $\boldsymbol{H}^H\boldsymbol{H}$ as $\sigma \to \infty$. The MMSE detector strictly outperforms both the MF and the ZF detector over the entire range of SNRs. Based on the above, it should be noted that the MMSE solution needs knowledge of the noise variance $\boldsymbol{\sigma}^2$, which MF and ZF solutions do not need. Like the ZF detector, because of the matrix inversion involved in $\boldsymbol{G}_{MMSE}$, the per-symbol complexity of the MMSE detector is like the MF and ZF performances, the MMSE performance is also severely degraded for increasing N_T at medium to full loading [9], [12], [19].

IV. Non-Linear Detectors

The above linear detectors performance are close to ML performance when there is a channel condition number close to one, a situation where the MIMO channel is classified as "good". However, for "bad" or badly conditioned MIMO channel, the linear, suboptimal detectors performance is not so good because the channel matrix inverse does not exist or is not invertible. This necessitated the use of non-linear detectors. One way to mitigate against bad conditioned MIMO channel is to precondition the transmission by combining multiply signals over multiple streams in such a way that is it convenient for the receiver to decode and recover the signal as the channel is "conditioned" and the channel matrix thus exist or is invertible. Considering the ZF detector and assuming zero as noise vector, it will be $\boldsymbol{y} = \boldsymbol{Hx}$ and $\boldsymbol{x} = \boldsymbol{H}^{-1}\boldsymbol{y}$. However, $\boldsymbol{H}^{-1}$ may not be invertible, to ensure it is, the channel and by extension the channel matrix is conditioned. Using a 2 × 2 MIMO as an example, having $\boldsymbol{H} = \frac{1}{2}\begin{bmatrix}1 & 1\\1 & 1\end{bmatrix}$, this matrix is not invertible since the determinant is zero, but if the transmitter is preconditioned by transmitting the opposite of the signal on one antenna, it will be $\boldsymbol{H} = \frac{1}{2}\begin{bmatrix}1 & 1\\-1 & 1\end{bmatrix}$.

Here, the matrix determinant is one and it can be inverted.

IV.1. Interference Cancellation Aided MIMO Detectors

These are suboptimal detectors but they are non-linear. They are a good trade-off between the maximum likelihood detectors and the linear detectors but at a higher complexity [18]. The interference cancellation detectors are a bank of linear receivers (or detectors like the MMSE), where everyone of them individually detects one of the parallel data streams [9]. There are many variations of these detectors that includes the successive interference cancellation (SIC) detector, the parallel interference cancellation (PIC) detector, the multistage interference cancellation (MIC) detector as well as the feedback detector (DFD) [2]. A major disadvantage of this class of MIMO detectors is that they are prone to error propagation.

IV.1.1. Successive Interference Cancellation Detector

In successive interference cancellation (SIC) detector, the symbol estimation is done one at a time [1], [19], the filters used here are based on the linear detector filters and the key method of symbol detection is the layer peeling where the first symbol is detected using ZF, MF or MMSE (in which case it is called ZF-SIC etc) and the interference caused by this detected symbol is cancelled, or subtracted by means of any of the used linear detector filters in the next layer peeling [12], [18] in order to improve the SINR of the remaining data symbol in that time instance. This process is repeated on layer bases until the whole symbols are detected from the received signal [20], [19], [21].

In the SIC detection steps above, it is possible that the first detected symbol or stream is the strongest which is good or it could be the weakest in which case the detection is in error and is detrimental to the performance of the detector. This error of detecting the weakest stream first will be passed on to other layers impairing all subsequent symbol estimates. This impairment degrade the performance of the bit error rate (BER) of the SIC detector [2], [21], [19], [22]. According to [2], [19], this problem of passing the error detection to other layers is called error propagation. To reduce the effect of error propagation, we can order the signal detection by the greatest associated channel power first, and the weakest last, this will ensure that symbols with the strongest SINR are detected first and the SIC is less likely to make error in estimating them. This ordering by channel or symbol power is called ordered SIC (OSIC) or the VBLAST algorithm [19]. Decreasing signal-to-noise ratio (DSNR), the least mean-square-error (LMSE), the greatest signal-to-noise ratio (GSNR), and the increasing mean-square error (IMSE) are some of the ordering criteria for OSIC. In SIC, the detection reordering and the detection iteration linearly increases as the number of the symbols in the detected signal increases, consequently for a massive MIMO with high antenna dimension and high dimensional transmitted symbols, the SIC detection method on its own imposes a high complexity and does not scale well enough [2], however it still outperforms the linear detectors as shown in Fig. 2 where the ZF-SIC has a better BER at 10dB SNR compared to ZF and MF.

IV.1.2. Parallel Interference Cancellation Detector

As a substitute to the successive interference cancellation detector, the parallel interference cancellation detector (PIC) detects all symbols at the same time [2]. For each symbol a tentative or coarse estimation of the interfering symbols are obtained by means of say linear equalizer or based on a priori information from the channel decoder [23], after this stage kN_R (number of receive antennas) parallel filters are then applied such that each of the filter deduct the effect of all kN_R layers from each individual of the merged received signal. This iteration can be repeated severally before making a final decision on the transmitted symbol vector [2], [23], [24]. Because the interference cancellation is done simultaneously, the delay necessary for the removal of interference is really small, just a few bits in duration [22], [20], [24].

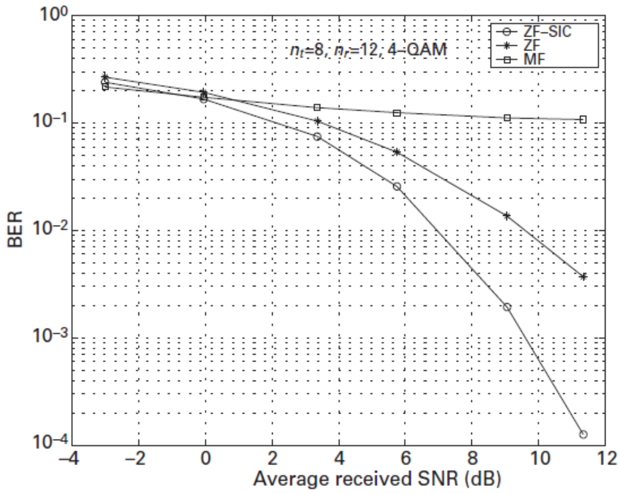

Fig. 2. BER performance comparison of ZF-SIC, ZF and MF detectors [8, ch 4]

The execution of the PIC detector using the above iterative deduction of the interference estimates can lead to an unfair decision statistic. The effect of this bias is very strong at the initial stage of the deduction or cancellation with the effect decreasing in the subsequent stages. The bias could results to erroneous cancellation at the initial stage and the effects of these errors will be seen at the next stages. There are various variations to the PIC detector as a result of efforts to solve the above problem, some of which are the Partial Parallel Interference Cancellation (PPIC) detector which multiplies the magnitude of the estimates by a partial cancellation factor which varies with the stage of cancellations and the system load, also there is the Subtracting PIC (SPIC) and the Hybrid PIC (H-PIC or SP-PIC) which is the combination of subtracting PIC and partial PIC [25].

IV.2. Tree-Search Based Detectors

The low complexity linear detectors as well as the interference cancellation based detection approach are poor in accuracy while the exhaustive search algorithm cannot meet the 4G/5G data rate requirement without hardware complexity [23]. The tree-search based detection method though suboptimal are very popular for their design flexibility in terms of achieving balance between optimal performance of the ML detectors and reduced complexity of the linear detectors [2]. According to [3], [23], [26]-[29] the approach represents the set of all likely transmitted symbol vectors V as a weighted tree structure, as shown in Fig. 3.

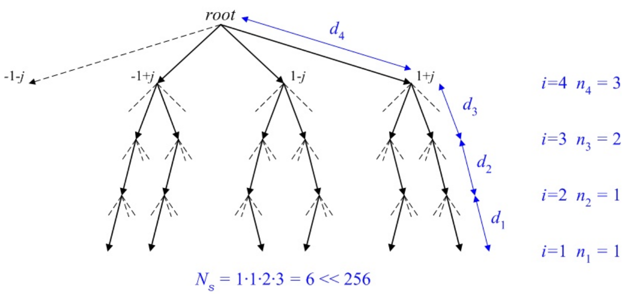

Fig. 3. Tree-Search Structure

The number of levels associated with the tree is defined by the amount of MIMO layers, which amount to the number of transmit antennas N_T if it is assumed spatial multiplexing using one transmit symbol stream per antenna. Each tree layer i comprises $2^{L(N_T-i}$ nodes and each of them represent a constellation symbol $x \in X$.

A set of child nodes called Q, descends from each parent node into the next layer (i.e. i−1 as you go downwards) with the tree root been defined by the topmost layer (where $i = N_T$), while the lowest layers (i.e. $i = 0$) are called leaf nodes (or leaves). Now each of the tree paths that is, the tree edges linking parent and child nodes from the root to a leaf node is weighted by a metric λ_0. Instead of searching the set V of all possible transmitted symbol vectors, tree-search based detection method consider only a subset $L \subset V$ of vector candidates. In other words a path from $i = (N_{T-1})$ to $i = 0$ denotes a total set of sent symbols x mapped to the leaves of the tree and from here, λ_0 can be calculated recursively using the layered branch metric. [23]. The task of the tree-search based detector is to determine the bits c most likely sent and also to calculate the reliability metrics for these bits. This action can be achieved by calculating the corresponding log-likelihood ratios (i.e. L-values) and also calculate λ_0 which is the distance metric for a set of received symbols y [29].

IV.2.1. The Sphere Detector

The tree-search based algorithm is used in the sphere detector (SD) which itself is a decoding scheme that is a variant of the ML decoder but possessing a lower complexity when compared with the ML decoder. The Breadth-first tree-search detector is one of the variants of the SD while others includes the Best-first tree search detector and the Depth-first tree-search detector (stack sequential detector) [27], [30], [31].

The idea behind the tree-search based sphere detection method is to reduce the computational complexity by solving equation (2) through enumerating or searching through only all points that are members of a hyper-sphere of radius R around the received signal point(s) $\boldsymbol{y}$, that is all points which satisfies the equation below [2], [32]:

$$\|\boldsymbol{y} - \boldsymbol{Hx}\|^2 \leq R^2 \tag{9}$$

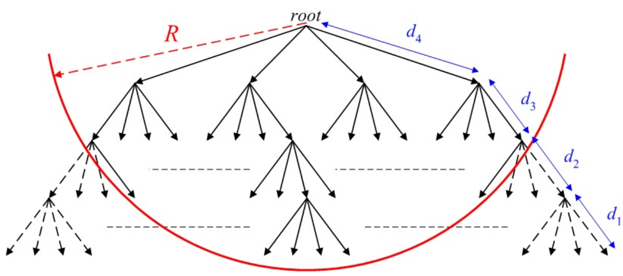

Fig. 4. Sphere Detector hyper-sphere of radius R diagram

According to [10] the SD put into consideration just a tiny group of vectors inside a specified sphere of radius R (Fig. 4) instead of all likely signal vectors transmitted, it then continues to adjust the radius of the sphere until only a lone vector within that sphere remains, this is the ML solution vector.

When there is no vector in the sphere, the radius is increased but decreased when there are more than one vectors inside the sphere.

According to [3] the above method known as the adaptive radius updating ends as soon as no other leaf node is reached as a result of reduction in the last updated radius. The rate of reduction of the radius moving from one leaf node to the next is a function of the channel matrix condition, since ill-conditioned matrices make the radius reduction process very slow.

The major advantage of the sphere detector is its simplicity of implementation, and its capability to ensure an optimal solution. However, a major disadvantage of the sphere detection algorithm is its inconsistent complexity that depends on channel conditions, where the worst-case complexity is exponential in the number of transmits antenna N_T indicating that it may not be good enough for massive MIMO application.

Also, due to the sequential tree-search like nature of the algorithm, it does not fit well for parallel implementation which is a necessity when N_T is large as in a massive MIMO situation.

However [2], [3] stated that recently L. G. Barbero and J. S Thompson proposed a suboptimal fixed-complexity SD for MIMO systems which makes the complexity fixed and also makes the structure very parallelizable, thus the fixed complexity sphere detector (FCSD) is able to offer a near ML performance using a complexity that is a square root of the transmit antennas N_T irrespective of the SNR encountered making the FCSD attractive for the achievement of a proficient hardware production as compared to the legacy exponential complexity SD.

IV.2.2. Lattice Reduction Based Detector

Sphere detection algorithms were designed to decrease the complexity of the maximum likelihood detector [33], [34], however the complexity of SD is not stable and varies due to channel realization and SNR (which is not good for practical implementation) and can thus sometimes be very high [35]. ZF and MMSE detector offers lower computation complexity, but with inferior performance when compared to ML, they also loses diversity as a result of their sensitivity to ill-conditioned channel matrices. Meanwhile Successive interference cancellation (SIC) detector perform decoding and interference signal subtracting one after the other instead of zero forcing [19], [21], thereby improving the signal-to-noise ratio (SNR) at each decoding stage and thus providing superior performance than linear detectors.

SIC based detectors also undergo diversity loss as linear detectors do, therefore to reduce the performance gap between ML detectors and linear detectors with low complexity, lattice reduction (LR) techniques have been introduced [36]. According to [37], the gap between the ML detector and the linear detectors is largely as a result of the ill-conditioned channel matrix $\boldsymbol{H}$. Thus the idea behind lattice reduction based detector according to [38], [39] is to transform the problem of ill-conditioned channel matrix into a domain where the effective channel matrix is better conditioned than the original one.

Therefore the use of LR-aided linear detectors is premised on the fact that if channel matrix H can be made as "close" as possible to orthogonal, then the decision region of linear detectors is then also "close" to that of the ML detector. Thus, to enhance the error performance of linear detectors, the lattice reduction method is employed to look for another more orthogonal basis $\widetilde{\boldsymbol{H}}$ that defines the same lattice as $\boldsymbol{H}$. There are various varieties of the LR algorithm but the most popular is the Lenstra-Lenstra-Lovasz (LLL) with two variants namely real-valued LLL and the complex-valued LLL [2], [40], [41].

LR in principle can combine with practically all the other detectors to enhance their performance, [2] such as in [42] where performance comparisons are made between LR-Aided receivers and other conventional receivers shows that LLL-MMSE outperforms ZF and MMSE receivers by 8.1 dB and 4.14 dB respectively at 0.01 BER. LLL-ZF outperforms ZF and MMSE receivers by 6.94 dB and 2.98 dB respectively at 0.01 BER. In Fig. 5, it can be seen LR-MMSE outperforming MMSE by 3.5dB at 0.01 BER. It is also noticed that as the channel is better conditioned, the SNR improves and the BER performance of LR-MMSE begins to increasingly outperform that of MMSE.

V. Detection Algorithms for Massive MIMO

When MIMO goes massive. the circulation of the singular values of the channel matrix tends towards a deterministic function. Also, less conditioned matrices begin to be incredibly well conditioned. As antenna numbers become large, some matrix operations such as inversions can be done faster, by the use of series expansion methods. The other consequence going massive is that thermal noise is zeroed out and the system is largely restricted by other cells interference [5], [43].

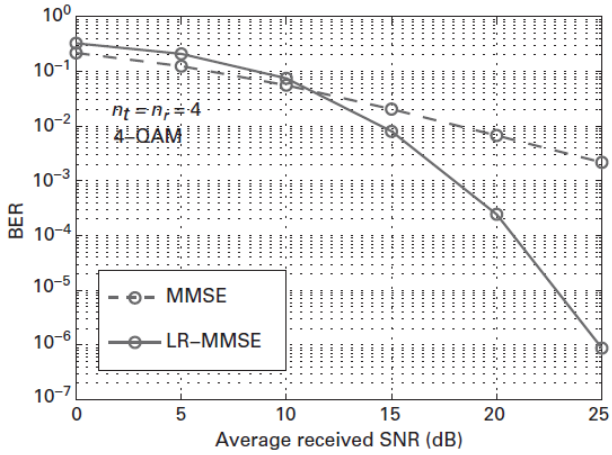

Fig. 5. BER performance comparison of MMSE and LR-MMSE Detectors [8, ch 4]

Favorable propagation, described as mutual orthogonality between the various UEs vector channels, is a key property of the radio channel exploited in achieving Massive MIMO benefits. It can be said that the channel offers favorable propagation if channel vectors $\boldsymbol{h}_k$ are paired wisely orthogonal i.e:

$$\boldsymbol{H}_i^H \boldsymbol{H}_j = \{0, i, j = 1,2 \ldots \ldots k, \text{and } i \neq j\}$$

and:

$$\boldsymbol{H}_i^H \boldsymbol{H}_j = \{\|\boldsymbol{H}_k\|^2 \neq 0, k = 1,2, k\}$$

It can also be assumed that the channel offers asymptotically favorable propagation if:

$$\frac{1}{M}(\boldsymbol{H}_k^H \boldsymbol{H}_j) \rightarrow 0 \text{ as M} \rightarrow \infty$$

where $k \neq j$ and M is the BS transmit antenna.

According to [44], [45], as N_T, $N_R \rightarrow \infty$ the circulation of the singular values of the random channel matrix $\boldsymbol{H}$ which are random begins to tends towards deterministic functions due to the Marcenko and Pastur law [2], that is as $\boldsymbol{H}$ becomes large its singular values becomes less responsive to the real distributions of the i.i.d entries of $\boldsymbol{H}$, hence the channel tends towards a more deterministic function.

Also as the magnitude of $\boldsymbol{H}$ grows, the diagonal entries of $\boldsymbol{H}^H\boldsymbol{H}$ becomes larger than the off diagonal entries such that some matrix operations such as the inversion requirement in ZF, MMSE and PDA detectors can be done faster with approximation using series expansion techniques for large dimension random matrices. The above behaviour of $\boldsymbol{H}^H\boldsymbol{H}$ is called channel hardening which makes linear detectors near optimal in massive MIMO. (The channel hardening experience of massive MIMO is useful for reducing CSI overhead and enhancing the development of low-complexity scheduling algorithms, although at the cost of limited scheduling gains) [45], [43]. Mathematically, channel hardening is represented as:

$$\left(\frac{1}{M}\right)\|\mathbf{H}_{\mathrm{k}}\|^2 = \left(\frac{1}{M}\right)\operatorname{tr}(\boldsymbol{R}) \rightarrow 0$$
$$M \rightarrow \infty$$

Another benefit of the Marcenko and Pastur law is that as $N_T \to \infty$ the channel matrix becomes very tall (or wide as $N_R \to \infty$) and $\boldsymbol{H}$ becomes well conditioned making even the simplest MF detector near optimal in performance for massive MIMO, though according to [46] for wide channel matrices when $NR \to \infty$ the scenario is described as overloaded systems, in which case the transmit antennas number is largely more than the receive antenna numbers (in the uplink), and hence, the channel's covariance matrix is rank-deficient and simple linear detector may not be near optimal as an iterative sphere detector (SD) was then proposed.

However, in non-cooperative multi-cell system, there is the challenge of pilot contamination due to the use of non-orthogonal pilot symbols in adjacent cells [47], [48], [49], this interference exist and persist even as $N_T, N_R \to \infty$ and becomes a major limiting factor for reaping the full benefits of massive MIMO, this accession was however disputed in [50] where the author proved that this is not correct and showed that using multi-cell MMSE precoding and combining with a small quantity of spatial channel correlation or large-scale fading variations over the antenna array, the spectral efficiency of massive MIMO increases without limit as the antenna number becomes large, even under pilot contamination.

Detection in massive MIMO needed to meet 5G requirement and must therefore meet the low complexity and superior near optimal performance for high data rate of the order of Gbps, let us therefore look at some of the detection algorithms with potential for meeting this requirement.

V.1. Probabilistic Data Association (PDA) Based Detector

PDA based detector was initially developed for target tracking in the 1970s [2], [37], [51]-[53].

When applied in digital communication, it is an alternative with reduced complexity for the a posteriori probability detector (MAP) [54]. According to [2], [53] in MIMO detectors using the PDA based algorithm, the probabilities of the prospective candidate symbols serves as the soft input soft output information and are estimated on a self-iterative process. The PDA has polynomial complexity that increases no faster than $(M_i N_{4_T})$ per symbol vector where M_i is the number of PDA iteration and N_T is the number of transmit antennas in MUD MIMO system or the number of users in a CDMA system.

The PDA algorithm achieves a near optimal performance particularly for CDMA system and it works well with FEC codes such as turbo codes, low density parity-check (LDPC) codes and convolutional codes [2], [52].

In [55] a hybrid PDA-SD algorithm was proposed which offers a computational complexity performance that is better than either of its constituent components.

It offers BER performance close to that of SD over a wide range of SNR at a significantly reduced computational cost which is better than what either PDA or SD could offer on stand alone. Fig. 6 shows the BER performance of the PDA detector in a V-BLAST MIMO system where the performance of the PDA detector increases with increase in the number of antennas using 4-QAM and 5 iterations.

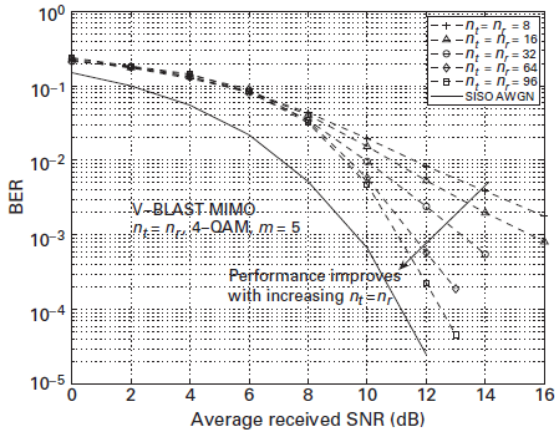

Fig. 6. BER performance of PDA Detector for $n_t = n_r$ = 8, 16, 32, 64, 96 antennas [8, ch 6]

V.2. Markov Chain Monte Carlo Detector

The MCMC detector is an alternative to sub-optimal non-linear detector, it is based on the proficient mining of the statistical inferences using Markov chains. The MCMC detector uses two different methods, i.e. on the Markov chain representation and the Monte Carlo integration.

While the previous is used to find the most likely detection candidates based on the related probability distributions, the latter is used to estimate the integral of interest on the basis of the detection candidates calculated by the Markov chain representation [56], [57], [61], [62]. According to [58], the MCMC simulation is a statistical tool used to draw samples from a random and possibly indefinite distribution. The MCMC detector is designed as a statistical search method called the Gibbs sampler (GS) which arbitrarily generate a small sample set that contains the most likely signal vectors transmitted [59].

TABLE I
PERFORMANCE COMPARISON FOR VARIOUS DETECTION ALGORITHMS

S/N	REFERENCE	DETECTION METHOD	PERFORMANCE	COMPLEXITY	MASSIVE MIMO APPLICATION
1	[8],[7],[12],[13],[14]	ML/MAP	Very good	Very high and grows exponentially as $N_T \to\infty$	Not good for Massive MIMO
2	[1],[8],[9],[12],[13],[16], [17], [18], [21]	Linear ZF, MF, MMSE	Performance is good but degrade with increase in N_T as well as in higher order modulation	Low even as $N_T \to\infty$	Complexity Good for Massive MIMO but BER/ sum rate performance is poor.
3	[1], [12], [18], [20], [21], [22], [19], [23], [24]	SIC	Perform well	High complexity as $N_T \to\infty$	Not good for massive MIMO
4	[27], [30], [31], [32], [9], [3]	SD	Perform well for higher order modulation at low to medium N_T degrade at large N_T.	Complexity varies with channel SNR and could be very high	Not good for Massive MIMO
5	[33], [34], [39], [35], [22], [21], [36], [37], [40], [38], [42]	LR	Good performance for small to medium N_T but degrade as $N_T \to\infty$	Low complexity but grows exponentially for small to large antennas.	Not very good for massive MIMO
6	[1], [43], [44], [45], [37], [46]	PDA	Very good performance	Low polynomial complexity	Good for Massive MIMO particularly when combined in a design with other detector like the SD or LR.
7	[47], [48], [49], [50], [51]	MCMC	Good performance at large N_T. Suffers from noise floor and performance may degrade as SNR increases.	Very low complexity	Good for Massive MIMO. Low performance in high SNR can be solved by combination with other detectors.

This technique is unlike the tree-search technique in two different ways, one it is a stochastic search method called Gibbs sampler and secondly, the complexity of the MIMO detector which is determined by the growth of the size of the list is not exponential with the number of bits per channel use [60], [63], [64]. The complexity actually grows slightly more rapidly than the linear while achieving outstanding performance with an incredibly small sample set. This makes the low-complexity MCMC detectors extremely attractive when the complexity of the optimal maximum a posteriori probability (MAP) detector grows exponentially with the number of antennas, constellation size, and channel memory. However, while MCMC MIMO detector achieves very good performance in low SNR (near capacity) regime, it suffers from a noise floor, and its performance may degrade as SNR increases [56], [58]-[60].

V.3. Future of Massive MIMO Detection Algorithm

Based on the requirement of the 5G detection algorithm, it is apparent that no single detector can meet this requirement, low complexity and near optimal performance detection algorithm with capacity for Gbps data rate is therefore an open research problem and researchers have sort to combine many detection algorithm in a design that can meet this requirement.

One of such is the Likelihood Ascent Search (LAS) based detector proposed by [1] referred to as the MF/ZF/MMSE-LAS detector, which was shown to have very good attributes in terms of both near capacity performance, high spectral efficiencies and low complexity achieving a 5.5dB of capacity and 24bps/Hz spectral efficiency for 16×16 STBC with 4QAM modulation scheme. Using an outer turbo code with rate -1/3 and BPSK, this detector working in a 600×600 antenna V-BLAST system achieves a spectral efficiency of 200bps/Hz and performs close to within 4.6dB of the theoretical capacity. This detector does not however work well in a rank deficient system. Below is the table for performance comparison of the various detection algorithms in Table I.

VI. Conclusion

This paper surveyed the various MIMO detection algorithms, it looked at the background of the development of MIMO algorithm along the coherent detection techniques where the instantaneous value of the fading channel coefficients matrix called channel state information (CSI) is known. It is then considered the optimal and the suboptimal detectors. The linear and non-linear suboptimal detectors were reviewed after which we looked at the MIMO detectors suitable for large scale antenna systems otherwise known as the massive MIMO system. The review shows no single one detector can be said to be ideal for massive MIMO and that the low complexity with optimal performance detector suitable for 5G massive MIMO system is still an open research issue.

Acknowledgements

We acknowledge and give thanks to Covenant University for the funding of this research work.

References

[1] K. Vishnu Vardhan, Saif K. Mohammed, A. Chockalingam, and

B. Sundar Rajan, Large MIMO Detection: A Low-Complexity Detector at High Spectral Efficiencies, (Parts of this paper appeared in *IEEE JSAC Special Issue on Multiuser Detection in Advanced Communication Systems and Networks*, vol. 26, no. 3, pp. 473-485, April 2008, and accepted in IEEE ICC'2008).

[2] Shaoshi Yang and Lajos Hanzo, Fifty years of MIMO detection: The road to large-scale MIMOs, *IEEE Communication Surveys & Tutorials*, Vol. 17, No. 4, Fourth Quarter 2015.

[3] Mirsad Čirkić, *Efficient MIMO Detection Methods*, PhD thesis Linköping University, SE-581 83 Linköping, Sweden ISBN: 978-91-7519-413-4 ISSN 0345-7524 Printed in Sweden by LiU-Tryck, Linkoping 2014.

[4] Markus Myllylä and Johanna Ketonen, MIMO detector algorithms and their implementations for LTE/LTE-A, *GIGA seminar* 11.01.2010.

[5] [5] Michael Wu, Bei Yin, Guohui Wang, Chris Dick, Joseph R. Cavallaro, and Christoph Studer, "Large-Scale MIMO Detection for 3GPP LTE: Algorithms and FPGA Implementations", *IEEE Journal of selected topics in signal processing*, 22 Mar 2014.

[6] A. Burg, M. Borgmann, M. Wenk, C. Studer, and H. Bölcskei, *Advanced receiver algorithms for MIMO wireless communications*, Integrated Systems Laboratory ETH Zurich 8092 Zurich, Switzerland.

[7] Rodrigo C. de Lamare and Raimundo Sampaio-Neto, *Detection and Estimation Algorithms in Massive MIMO Systems*, http://arxiv.org/abs/1408.4853v1, 21 Aug 2014.

[8] A. Chockalingam and B. Sundar Rajan, *Large MIMO Systems* By Cambridge University Press, 2014 Information on this title: www.cambridge.org/9781107026650

[9] Olabode B. Idowu-Bismark, Augustus E. Ibhaze, A. A. Atayero, MIMO Optimization Techniques and Their Application in Maximizing Throughput for 3GPP HSPA+' *Journal of Wireless Networking and Communications*, 2017.

[10] Young Soo Cho, Jaekwon Kim, Won Young Yang, Chung-Gu Kang, *MIMO-OFDM Wireless Communications with MATLAB.* IEEE PRESS John Wiley & Sons (Asia) Pte Ltd, 2010.

[11] Xiufeng Xie, Eugene Chai, Xinyu Zhang, Karthikeyan Sundaresan, Amir Khojastepour, and Sampath Rangarajan Hekaton: *Efficient and Practical Large-Scale MIMO*, a research project pp1-13, 2015.

[12] Dominik Seethaler, Harold Artés, and Franz Hlawatsch, Detection Techniques for MIMO Spatial Multiplexing Systems, *Elektrotechnik und Informationstechnik (e&i)*, vol. 122, no. 3, March 2005, pp. 91–96

[13] Bei Yin, *Low complexity detection and precoding for massive MIMO Systems: Algorithm, Architecture and Application*, PhD Thesis, Houston Texas, December, 2014.

[14] Shuangshuang Han, *Low complexity detection techniques for MIMO and cooperative networks*, PhD Thesis, 2013.

[15] Yasser Fadlallah, Abdeldjalil Aissa El Bey, Karine Amis Cavalec, Dominique Pastor. 'Low complexity detector for very large and massive MIMO transmission'. *SPAWC 2015: 16th IEEE International Workshop on Signal Processing Advances in Wireless Communications*, Jun 2015, Stockholm, Sweden. pp.251 - 255, 2015.

[16] Susmita Prasad, Samarendra Nath Sur, Lattice reduction aided detection techniques for MIMO systems, *International Research Journal of Engineering and Technology (IRJET)*, Volume: 03 Issue: 03/Mar/2016.

[17] Hidekazu Negishi, Wei Hou and Tadashi Fujino, An MMSE Detector Applying Reciprocal-Lattice Reduction in MIMO Systems, *The 2010 International Conference on Advanced Technologies for Communications*, ©2010 IEEE.

[18] Keke Zu, *Novel Efficient Precoding Techniques for Multiuser MIMO Systems*, Ph.D. Thesis, Communications Research Group Department of Electronics University of York. May 2013.

[19] Thomas Hesketh, Peng Li, Rodrigo C. de Lamare and Stephen Wales, Multi-Feedback Successive Interference Cancellation with Dynamic Lug-Likelihood-Ratio Based Reliability Ordering, *The Tenth International Symposium on Wireless Communication Systems* VDE VERLAG GMBH- Berlin 2013.

[20] Manatsavee B., Kazi Ahmed and Anil Fernando, *Performance of PIC, SIC and De-correlating Detectors for MUD Technique in WCDMA System*, 0-7803-8185-8/03/©2003 IEEE.

[21] Jianpang Chen, Zhan Zhang and Hidetoshi Kayama, Successive Interference Cancelling MIMO Signal Detection Method using Dynamic Multi-trace-likelihood Ordering Detection, *NTT DOCOMO Technical Journal* Vol. 10 No. 4, 2008.

[22] Andreas Wolfgang, Sheng Chen, Lajos Hanzo, Parallel Interference Cancellation Based Turbo Space-Time Equalization in the SDMA Uplink, *IEEE Transactions on Wireless Communications*, Vol. 6, No. 2, February 2007.

[23] Ester Pérez Adeva, *Efficient MIMO Sphere Detection: Algorithms and Architectures*, PhD Thesis 2015. Detailed bibliographic data are available on the Internet at http://dnb.dnb.de ISBN 978-3-938860-90-8

[24] Sanmati Jain, Prof. Sandeep Agrawal and Mrs Nilofar Khan, Estimation and Analysis of Parallel Interference Cancellation (PIC) Using AWGN Channel in DS-CDMA Receiver System, *International Journal of Innovative Research and Development*, Vol. 2 Issue 6 June, 2013.

[25] J. Ravindrababu, E. V. Krishna Rao and Y. Raja Rao, Interference cancellation in multi stage multi-user detection in DS-CDMA System using Hybrid technique, *WSEAS Transactions on Communications*, Issue 9, Volume 12, September 2013.

[26] Li Li, *Advanced Channel Estimation and Detection Techniques for MIMO and OFDM Systems*, PhD Thesis, June 2013. Department of Electronics, University of York.

[27] Yugang Jia, Christophe Andrieu, Robert J. Piechocki, and Magnus Sandell, 'Depth-First and Breadth-First Search Based Multilevel SGA Algorithms for Near Optimal Symbol Detection in MIMO Systems'. *Ieee Transactions On Wireless Communications*, Vol. 7, No. 3, March 2008.

[28] Ester Pérez Adeva, *Efficient MIMO Sphere Detection: Algorithms and Architectures*, PhD thesis, Internet: www.vogtverlag.de Dresden 2015.

[29] Björn Mennenga and Gerhard Fettweis, *Search Sequence Determination for Tree Search based Detection Algorithms*, Vodafone Chair Mobile Communication Systems Technische Universit¨at Dresden Dresden, Germany.

[30] Zhan Guo and Peter Nilsson, Algorithm and Implementation of the K-Best Sphere Decoding for MIMO Detection, *IEEE Journal on selected areas in Communications*, Vol. 24, No. 3, March 2006.

[31] Yugang Jia, Christophe Andrieu, Robert J. Piechocki and Magnus Sandell, Depth-First and Breadth-First Search Based Multilevel SGA Algorithms for Near Optimal Symbol Detection in MIMO Systems, *IEEE Transactions on Wireless Communications*, Vol. 7, No. 3, March 2008.

[32] Mohamed-Amine Arfaoui, Hatem Ltaief, Zouheir Rezki, Mohamed-Slim Alouini, and David Keyes, Efficient sphere detector algorithm for massive MIMO using GPU Hardware Accelerator, *Procedia Computer Science*, Pages 2169–2180, Volume 80, 2016.

[33] Deric W. Waters, *Signal Detection Strategies and Algorithms for Multiple-Input Multiple-Output Channels*, PhD Thesis, Georgia Institute of Technology December 2005.

[34] Volker Kühn, *Wireless Communications over MIMO Channels; Applications to CDMA and Multiple Antenna Systems*, Published by John Wiley & Sons Ltd, 2006.

[35] Qiaoyu Li, Jun Zhang, Lin Bai, and Jinho Choi, Lattice Reduction-Based Approximate MAP Detection with Bit-Wise Combining and Integer Perturbed List Generation, *IEEE Transactions on Communications*, vol. 61, no. 8, August 2013.

[36] Yiming Kong and Xiaoli Ma, Lattice Reduction Techniques in MIMO Systems with Correlated Channels, *Military Communications Conference* 2014 IEEE.

[37] Qi Zhou and Xiaoli Ma, Element-Based Lattice Reduction Algorithms for Large MIMO Detection, *IEEE Journal on Selected Areas in Communications*, Vol. 31, No. 2, February 2013.

[38] Hossein Najafi, and Mohamed Oussama Damen, Lattice-Reduction-Aided Conditional Detection for MIMO Systems, *IEEE Transactions on Communications*, vol. 62, no. 11, November 2014.

[39] Erik G. Larsson, MIMO Detection Methods: How They Work, *IEEE Signal Processing Magazine* pp1-6, May 2009.

[40] Huan Yao and Gregory W. Womell, *Lattice-Reduction-Aided Detectors for MIMO Communication Systems*, Dept. EECS and

Research Laboratory of Electronics MIT, Cambridge MA 02139, USA 0-7803-7632-3/2002 IEEE. 2002

[41] Susmita Prasad, Samarendra Nath Sur 'Lattice Reduction aided Detection Techniques for MIMO Systems, *International Research Journal of Engineering and Technology (IRJET)* Volume: 03 Issue: 03 Mar-2016. Pages 1496 – 1502

[42] Susmita Prasad, Samarendra Nath Sur, Lattice Reduction Aided Detection Techniques for MIMO Systems, *International Research Journal of Engineering and Technology (IRJET)*, Volume: 03 Issue: 03/ Mar-2016.

[43] Olabode Idowu-Bismark, Francis Idachaba and A. A. A. Atayero 'A Survey on Traffic Evacuation Techniques in Internet of Things Network Environment, *Indian Journal of Science and Technology*, Vol 10(33), 0.17485/ijst/2017/v10i33/112749, September 2017.

[44] Fredrik Rusek, Daniel Persson, Buon Kiong Lau, Erik G. Larsson, Thomas L. Marzetta, Ove Edfors, and Fredrik Tufvesson, *Scaling up MIMO: Opportunities and challenges with very large arrays*, a research project http://arxiv.org/abs/1201.3210v1 Jan 2012.

[45] Kan Zheng, Long Zhao, Jie Mei, Bin Shao, Wei Xiang, and Lajos Hanzo, Survey of Large-Scale MIMO Systems *IEEE Communication Surveys & Tutorials*, vol. 17, no. 3, Third Quarter 2015.

[46] A. Wolfgang, J. Akhtman, S. Chen, and L. Hanzo, Iterative MIMO Detection for Rank-Deficient Systems, *IEEE Signal Processing Letters*, vol. 13, no. 11, November 2006.

[47] Thomas L. Marzetta, Noncooperative Cellular Wireless with Unlimited Numbers of Base Station Antennas, *IEEE transactions on wireless communications*, vol. 9, no. 11, November 2010.

[48] Olakunle Elijah, Chee Yen Leow, Tharek Abdul Rahman, Solomon Nunoo, and Solomon Zakwoi Iliya, A Comprehensive Survey of Pilot Contamination in Massive MIMO-5G System, *IEEE Communications Surveys & Tutorials*, Vol. 18, No. 2, Second Quarter 2016.

[49] Lu Lu, Geoffrey Ye Li, A. Lee Swindlehurst, Alexei Ashikhmin, and Rui Zhang, An Overview of Massive MIMO: Benefits and Challenges, *IEEE journal of selected topics in signal processing*, vol. 8, no. 5, pp742-758 October 2014.

[50] Emil Bjornson, Jakob Hoydis, Luca Sanguinetti Massive MIMO has Unlimited Capacity, *arXiv*:1705.00538v2 [cs.IT] 4 May 2017.

[51] Justus Ch. Fricke, Magnus Sandell, JanMietzner and Peter A. Hoeher, Impact of the Gaussian Approximation on the Performance of the Probabilistic Data Association MIMO Decoder, *EURASIP Journal on Wireless Communications and Networking* 2005:5,796–800 c 2005 Justus Ch. Fricke etal.

[52] Shaoshi Yang, Tiejun Lv, Robert G. Maunder and Lajos Hanzo, Distributed Probabilistic-Data-Association-Based Soft Reception Employing Base Station Cooperation in MIMO-Aided Multiuser Multicell Systems, *IEEE Transactions on vehicular technology*, Vol. 60, No. 7, September 2011.

[53] Mohammed Saif Khan, *Low-Complexity detection and precoding in high spectral efficiency large-MIMO systems*, PhD Thesis, Electrical Communication Engineering Indian Institute of Science, Bangalore Bangalore – 560 012 (INDIA) March 2010.

[54] Justus Ch. Fricke et al Impact of the Gaussian Approximation on the Performance of the Probabilistic Data Association MIMO Decoder, *EURASIP Journal on Wireless Communications and Networking* 2005:5, 796–800.

[55] Georgios Latsoudas and Nicholas D. Sidiropoulos, A Hybrid Probabilistic Data Association-Sphere Decoding Detector for Multiple-Input–Multiple-Output Systems, *IEEE Signal Processing Letters*, vol. 12, No. 4, April 2005.

[56] Ashok Kumar, Suresh Chandrasekaran, A. Chockalingam and B. Sundar Rajan, *Near-Optimal Large-MIMO Detection Using Randomized MCMC and Randomized Search Algorithms*, 978-1-61284-231-8/11/ ©2011 IEEE.

[57] Lin Bai, Tian Li, Jianwei Liu, Quan Yu, and Jinho Choi, Large-Scale MIMO detection using MCMC approach with Blockwise Sampling, *IEEE Transactions on Communications*, vol. 64, no. 9, September 2016.

[58] Rong-Rong Chen, Ronghui Peng, and Behrouz Farhang-Boroujeny, *Markov Chain Monte Carlo: Applications to MIMO detection and channel equalization*, The University of Utah.

[59] Ronghui Peng, Koon Hoo Teo, Jinyun Zhang and Rong-Rong Chen, *Low-Complexity Hybrid QRD-MCMC MIMO Detection*, Mitsubishi Electric Research Laboratories http://www.merl.com, Globecom December 2008.

[60] Xuehong Mao, Peiman Amini and Behrouz Farhang-Boroujeny, *Markov Chain Monte Carlo MIMO Detection Methods for High Signal-to-Noise Ratio Regimes*, ECE department, University of Utah.

[61] Okokpujie, Kennedy, Obinna Okoyeigbo, J. E. Okhaifoh, Omoruyi Osemwegie, and Nsikan Nkordeh. Performance Analysis and Modeling of MIMO Systems. *International Journal of Applied Engineering Research* 11, no. 23 (2016): 11537-11541.

[62] Obinna, Okoyeigbo, Okokpujie Kennedy, Omoruyi Osemwegie, and Nkordeh Nsikan. Comparative Analysis of Channel Estimation Techniques in SISO, MISO and MIMO Systems, *International Journal of Electronics and Telecommunications*, vol. 63, no. 3 (2017): 299-304.

[63] Ndujiuba, Charles Uzoanya, Oluwadamilola Oshin, and Nsikan Nkordeh. MIMO deficiencies due to antenna coupling, *International Journal of Networks and Communications* 5, no. 1 (2015): 10-17.

[64] Ndujiuba, Charles U., Adebiyi A. Adelakun, and Oboyerulu E. Agboje. Hybrid Method of Analysis for Aperture-Coupled Patch Antenna Array for MIMO Systems, *International Journal of Electromagnetics and Applications* 5, no. 2 (2015): 90-97.

Authors' information

Olabode Idowu-Bismark is currently a PhD researcher in Covenant University, Ota, Ogun state Nigeria. He holds an M.Sc degree in Telecommunications Engineering from Birmingham University UK and a B.Eng Electrical and Electronics Engineering from the University of Benin, Nigeria. Olabode is a ZTE University China certified RF engineer and a certified Optical Fibre/Transmission engineer, he has worked in various companies including Logic Sciences Limited and Primotek Systems Limited as an engineer, senior engineer and a technical manager, a member of the IEEE his research interest is in the area of wireless mobile communication and the Internet of Things (IoT).

Kennedy Okokpujie holds a Bachelor of Engineering (B.Eng.) in Electrical and Electronics Engineering, Master of Science (M.Sc.) in Electrical and Electronics Engineering, Master of Business Administration (MBA) and Master of Engineering (M.Eng.) in Electronics and Telecommunication. He is currently on his Ph.D. in Information and Communication Engineering/ Lecturing with the Department of Electrical and Information Engineering at Covenant University, Ota, Ogun State, Nigeria. He is a member of the Nigeria Society of Engineers and the Institute of Electrical and Electronic Engineers (IEEE). His research areas of interest include Biometrics, Communication Engineering, Digital signal Processing, Cryptograph, Network security and Pravicy.

E-mail: kennedy.okokpujie@covenantuniversity.edu.ng

Engr.(Dr).**Francis E. Idachaba** is currently a Professor of Communication Engineering in the department of Electrical and Information Engineering in Covenant University Ota Ogun State. He obtained his PhD in Electronics and Telecommunication Engineering from the University of Benin in Edo State Nigeria. With over 15 years in the academia, he has within the last five years served as a research fellow in 2013 at the Massachusetts Institute of Technology in the US and as a Research Advisor with Shell Petroleum Development Company in Nigeria between 2010 to 2012. He has over 90 publications in both journals and conferences. . He is actively involved in the Internet of Things Research, 5G communications research and Smart Cities Research among other interests. He is a recipient of numerous awards among which include the SPE Faculty Enhancement Travel Grant for 2014 and 2015.He is a member of the Society of Petroleum Engineers, the Nigerian Society of Engineers and a Registered Engineer in Nigeria.

A. A. Atayero is The Covenant University Professor of Communication Engineering and current Vice-Chancellor of the University. Professor Atayero has a Bachelor of Science Degree in Radio Engineering and a Master of Science Degree in Satellite Communication Systems in 1992 and 1994 respectively. He earned his PhD from the Moscow State Technical University of Civil Aviation (MSTUCA) in 2000. Atayero is a Fellow of the Science Association of Nigeria (FSAN) as well as a Senior Research Fellow of the International Association of Research Scholars and Administrators. Engineer Atayero is a COREN Registered Engineer and member of the Institute of Electrical and Electronic Engineers (IEEE) and other professional bodies. He has published over a hundred scientific papers in International peer-reviewed journals and proceedings. He is on the editorial board of several international scientific and engineering Journals. Atayero is a recipient of various awards and scholarships including the '2009 Ford Foundation Teaching Innovation Award'. His current research interests are in various aspects of Communication Engineering, including (but not limited to): Wireless Sensor Networks, Wireless (Mobile) Communications, Internet of Things (IoT), Smart Cities, and Cyber Physical Systems.