

Received March 6, 2022, accepted March 18, 2022, date of publication March 23, 2022, date of current version April 6, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3161618

Power of Error Correcting Codes for SFBC-OFDM Classification Over Unknown Channels

MOHAMED MAREY¹, (Senior Member, IEEE), AND HALA MOSTAFA², (Member, IEEE)

¹Smart Systems Engineering Laboratory, College of Engineering, Prince Sultan University, Riyadh 11586, Saudi Arabia

²Department of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, Riyadh 11671, Saudi Arabia

Corresponding author: Mohamed Marey (mfmmarey@psu.edu.sa)

ABSTRACT The development of intelligent radios in wireless applications is mainly driven by the growing need for higher data rates, along with constrained spectrum resources. An intelligent radio is one that can autonomously assess the communication environment and automatically update the communication parameters to achieve optimal performance. The problem of determining the type of space-frequency block coding (SFBC) for orthogonal frequency division multiplexing (OFDM) transmissions is one of the main tasks of an intelligent receiver. Previous approaches to this problem are restricted to uncoded communications; nevertheless, existing systems typically utilize error-correcting codes. This study develops a maximum-likelihood (ML) classifier that discriminates among SFBC-OFDM signals using the soft outputs of a channel decoder. The mathematical analysis shows that the maximization of the likelihood function can be carried out by employing an iterative expectation-maximization (EM) procedure. A channel estimator is also included in the proposed classifier as a vital step. The findings show that the classification performance of the proposed algorithm is considerably better than the classical classifiers reported in the literature, at the cost of an acceptable increase in computing complexity.

INDEX TERMS Signal classification, SFBCs, EM algorithm.

I. INTRODUCTION

The analysis of a received signal with the aim of determining its parameters is commonly referred to as signal classification (SCL). This is a fundamental process of intelligent radios that adjust their broadcast settings based on channel circumstances [1]. SCL algorithms are used to retrieve these settings from the received signal as a feasible alternative of sending those attributes via separate routes. This maximizes the transmission data rate and conserves spectral resources while maintaining a target quality of service. Historically, SCL has been utilized in the military to detect and analyze unknown signals originating from unfriendly transmissions. The advent of intelligent radios has heightened further curiosity in SCL within the framework of civilian implications [2].

There has been a significant amount of research on SCL for single-input single-output systems over single-carrier (SC) and multi-carrier (MC) broadcasts. This encompasses

a variety of classification problems such as modulation types [3]–[6], error-correcting codes [7], [8], and SC against MC emissions [9], [10]. Recently, the configuration of space block coding (SBC) has become one of the most important signal parameters that needs to be estimated for multi-input multi-output (MIMO) systems [11]. Numerous studies have been addressed this problem for single-carrier and multi-carrier systems. Maximum-likelihood (ML) and feature-based (FB) are two of the most common strategies for signal classification. Under the hypothesis that multiple signals are received, the former strategy computes the probability function of the received signal, and the choice is taken relying on this function's maximum. The ML solution is optimum in terms of enhancing the probability of classification according to detection theory, but at the expense of computing complexity. The FB strategy bases its classification judgment on the contrasts in the features of the candidate signals. This kind of feature exhibits distinct properties for each individual signal and is often picked on an as-needed basis.

The associate editor coordinating the review of this manuscript and approving it for publication was Mostafa Zaman Chowdhury.

An ML method is designed for blind space-time block codes (STBC) classification, knowing synchronization and channel characteristics [12]. Correlation functions are used to recognize STBC signals using a binary search tree algorithm [13]. Second-order cyclostationarity [14] and fourth-order moment [15] are utilized to differentiate between STBC signals in the presence of various transmission impairments. Classification algorithms in [16] are suggested to discriminate between Alamouti (AL) and spatial multiplexing (SM) STBC signals over frequency-selective fading channels. Binary hypothesis tests are sketched in [17]–[19] to identify STBC signals over orthogonal frequency-division multiplexing (OFDM) transmissions. Recent years have seen a rise in the use of deep learning in signal classification systems [20]. A potential weakness of these algorithms is that they need a vast volume of data for training to operate properly. Gathering training data from a source isn't always an option. An illustration of this may be found in military classification systems. Classifiers have the additional drawback of often being implemented on small portable devices with little processing power. As a consequence, if retraining becomes required, it will be very challenging. This highlights the need for non-deep learning classification algorithms.

To the best of the author's knowledge, all the previously reported studies are devoted to uncoded emissions running in a blind context. However, existing systems typically utilize error-correcting codes and adopt reference signals (pilots) to ensure stable communications. While blind approaches are appropriate for military use, civilian applications need the use of both blind and data-aided techniques [1]. In this work, we introduce a new approach to classify SBC signals taking benefits of the existence of error-correcting codes. More specifically, we focus on classifying space-frequency block coding (SFBC) signals for OFDM transmissions. The main contributions of this work lie in the following aspects.

- 1) Error-correcting codes have been intensively studied for MIMO-OFDM communication systems. Examples include low-density parity-check (LDPC) codes [21], turbo codes [22], and convolutional codes [23]. They also have been adopted in many practical MIMO-OFDM systems such as 5G, LTE, WiMAX, and IEEE 802.11x WiFi systems [24]. In the previously mentioned works, the primary purpose of using error-correcting codes is to correct errors caused by noise and/or to further improve the estimation accuracy of channel and synchronization parameters. This work is the first of its kind in exploring the capability of error-correcting codes to classify between different types of SFBC-OFDM signals.
- 2) The soft information of a channel decoder is employed repeatedly to enhance the classification performance of the proposed method using ML principles and an expectation-maximization (EM) technique [25]. Furthermore, in the event that channel state information is not obtainable at the receiver, we offer a channel

estimation method to be implemented into the proposed classifier.

- 3) The proposed classification algorithm runs with any error-correcting code as long as its decoding process is soft-decision based [26].
- 4) The proposed classification algorithm is broad in the sense that it can be used with any number of space-frequency codes with no code parameters limits. Four codes are provided as examples for the sake of conceptual clarity and simulations. These codes include AL and SM codes which have been adopted in several wireless standards, such as 5G, LTE, WiMAX, and IEEE 802.11x WiFi systems [24]. It is worth mentioning that many research works in the literature classify only between AL and SM codes [15], [16], [18], [19], [27].
- 5) It is well known that most wireless transmissions rely on pilots to estimate synchronization and channel parameters [24]. We utilize these pilots to provide initial estimates of the first iteration. In this context, we refer to the proposed classification algorithm as a semi-blind procedure. The proposed iterative algorithm has the advantages of both blind and data-aided techniques in the sense that it has magnificent classification performance with a minor throughput loss. The key idea is that the output information of a channel decoder is exploited to compute the a posteriori expectations of the transmitted symbols, which are employed as if they were pilot symbols.

The work is structured as follows. The signal model and problem formulation are described in Section II. The ML classification algorithm is created in Section III. Simulation results are presented in Section IV. Finally, the study is concluded in Section V.

II. SIGNAL MODEL AND PROBLEM FORMULATION

SFBC-OFDM signals are considered with N subcarriers, ν cyclic prefix (CP) samples, F transmit antennas, and a single receive antenna. The conceptual block diagram of a transmitter is presented in figure 1. A sequence of information bits is protected by a channel encoder and an interleaver. A digital modulator maps the coded bits into data symbols, belonging to an M -point constellation Ω . A few pilots are stacked with data symbols forming a vector $\mathbf{A} = [a_0, a_1, \dots, a_{N_d-1}]$ of length N_d . Here, there are no constraints on the type of channel coding, interleaver, mapping strategy, pilots distribution, and constellation set Ω . The elements of the vector \mathbf{A} are further split into several blocks of length P . Using a predefined $F \times Q$ code matrix $C(\mathbf{a}^{(p)})$, the encoder of SFBC spans the p th block, $\mathbf{a}^{(p)}$, over Q adjacent subcarriers to be sent via F transmit antennas. For illustration, the code matrices of SM($P = 2, Q = 1, F = 2$), AL($P = 2, Q = 2, F = 2$), SF3($P = 3, Q = 4, F = 3$), and SF4($P = 4, Q = 8, F = 4$) are [28]

$$C^{(\text{SM})}(\mathbf{a} = [a_0 \ a_1]) = [a_0 \ a_1]^T, \quad (1a)$$

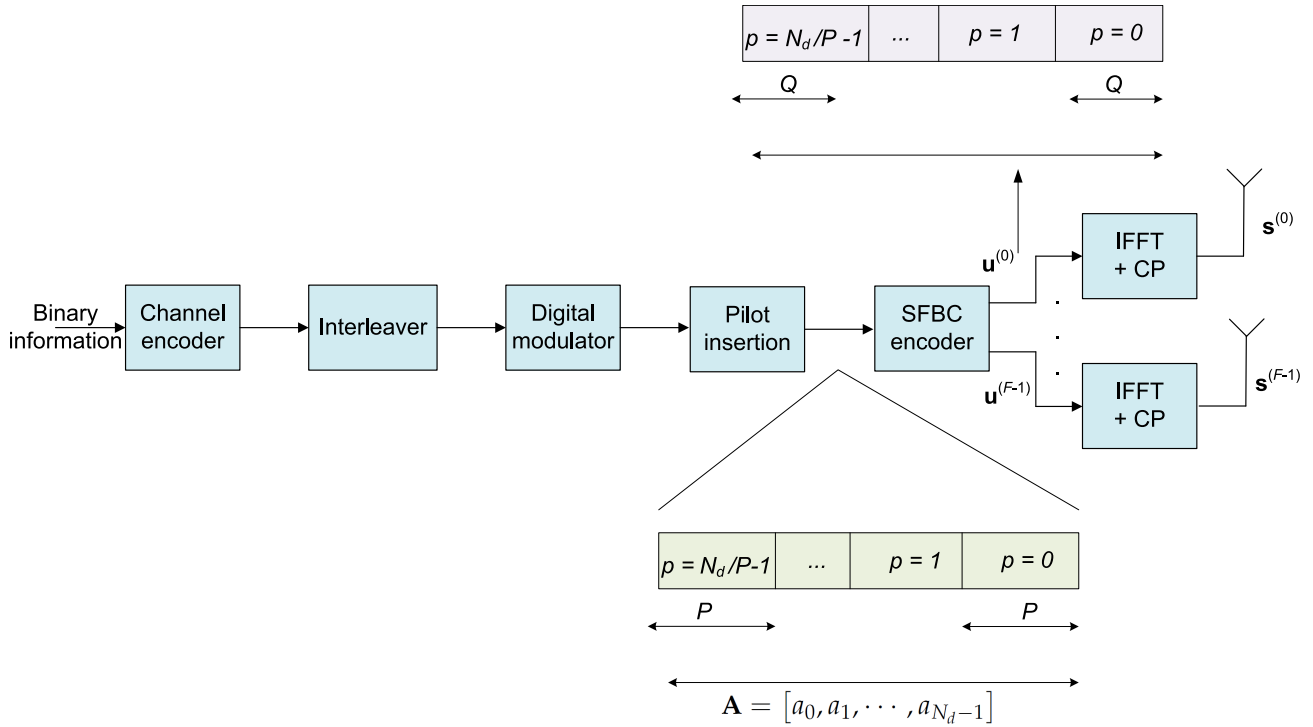


FIGURE 1. Block diagram of a SFBC-OFDM transmitter.

$$C^{(AL)}(\mathbf{a} = [a_0 \ a_1]) = \begin{bmatrix} a_0 & a_1 \\ -a_1^* & a_0^* \end{bmatrix}^T, \quad (1b)$$

$$C^{(SF3)}(\mathbf{a} = [a_0 \ a_1 \ a_2]) = \begin{bmatrix} a_0 & a_1 & a_2 \\ -a_1^* & a_0^* & 0 \\ a_2^* & 0 & -a_0^* \\ 0 & -a_2^* & a_1^* \end{bmatrix}^T, \quad (1c)$$

$$C^{(SF4)}(\mathbf{a} = [a_0 \ a_1 \ a_2 \ a_3]) = \begin{bmatrix} a_0 & a_1 & a_2 & a_3 \\ -a_1 & a_0 & -a_3 & a_2 \\ -a_2 & a_3 & a_0 & -a_1 \\ -a_3 & -a_2 & a_1 & a_0 \\ a_0^* & a_1^* & a_2^* & a_3^* \\ -a_1^* & a_0^* & -a_3^* & a_2^* \\ -a_2^* & a_3^* & a_0^* & -a_1^* \\ -a_3^* & -a_2^* & a_1^* & a_0^* \end{bmatrix}^T, \quad (1d)$$

where T and $*$ refer to the matrix transpose and complex conjugate operations, respectively. In (1a)-(1d), we omit the block index p for notation convenience. At each transmit antenna branch, a vector $\mathbf{u}^{(f)}$ of length N is constructed by concatenating all the outputs of SFBC encoder, where $N = \frac{Q N_d}{P}$. Then, an OFDM symbol is created by using an N -point inverse fast Fourier transform (IFFT), and the last ν samples are appended as a cyclic prefix. Mathematically, the n th time-domain sample broadcasted from the f th transmit antenna is expressed as

$$s^{(f)}(n) = \frac{1}{\sqrt{N+\nu}} \sum_{k=0}^{N-1} u^{(f)}(k) e^{j2\pi nk/N}, \quad n = 0, \dots, N+\nu-1 \quad (2)$$

where $u^{(f)}(k)$ is the k th element of the vector $\mathbf{u}^{(f)}$. It is worth noting that the samples $s(n)$ for $n = 0, \dots, \nu - 1$ constitute the cyclic prefix part of the OFDM signal. Here, we take advantage of the IFFT algorithm's cyclic shift feature, which demonstrates that $s(n) = s(N + n)$ [18], [29]. Denoting β as the employed SFBC type, where $\beta \in \{\text{SM}, \text{AL}, \text{SF3}, \text{SF4}\}$, we attach β to the transmit vector $\mathbf{s}^{(f)}$ to emphasize that its structure is dependent on β . The transmission matrices of those codes are shown in (1a-1d). The transmit signal $\mathbf{s}^{(f)}(\beta) = [s^{(f)}(0), \dots, s^{(f)}(N+\nu-1)]$ is subject to the adverse effect of an L -path channel model, $\mathbf{h}^{(f)} = [h^{(f)}(0), \dots, h^{(f)}(L-1)]$. Accordingly, the received signal can be expressed in vector notation as

$$\mathbf{r} = \sum_{f=0}^{F-1} \mathbf{s}^{(f)}(\beta) \star \mathbf{h}^{(f)} + \mathbf{n}, \quad (3)$$

where \star denotes the convolution operation and \mathbf{n} is the additive white Gaussian noise (AWGN) vector. Using the received signal \mathbf{r} , our aim is to determine the type of the transmit SFBC signal by exploiting the presence of error-correcting codes.

III. ML CLASSIFICATION ALGORITHM

For the sake of mathematical simplicity, we represent (3) in matrix notation as

$$\mathbf{r} = \sum_{f=0}^{F-1} \mathbf{S}^{(f)}(\beta) \mathbf{h}^{(f)} + \mathbf{n}, \quad (4)$$

where $\mathbf{S}^{(f)}(\beta)$ is an $(N + L - 1) \times L$ matrix with its element at row w_1 and column w_2

being given as

$$S_{w_1, w_2}^{(f)} = \begin{cases} s^{(f)}(w_1 - w_2) & \text{for } w_1 = 0, \dots, N + L - 1 \\ 0 & \text{for } w_2 = 0, \dots, L - 1, w_1 \geq w_2, \end{cases} \quad (5)$$

and $s^{(f)}(w_1 - w_2)$ is the $(w_1 - w_2)$ th element of the vector $\mathbf{s}^{(f)}(\beta)$. There are several methods for performing linear convolution of (3), including graphical and numerical approaches. The matrix multiplication employed in (4) is one of those approaches that has been widely utilized in the wireless communications literature [29]. A more compact form of (4) is given as

$$\mathbf{r} = \mathbb{S}(\beta)\mathbf{H} + \mathbf{n}, \quad (6)$$

where $\mathbb{S}(\beta) = [\mathbf{S}^{(0)}(\beta), \dots, \mathbf{S}^{(F-1)}(\beta)]$ and $\mathbf{H} = [\mathbf{h}^{(0)}, \dots, \mathbf{h}^{(F-1)}]^T$.

The ML estimate of β can be expressed as

$$\hat{\beta} = \arg \max_{\beta} \log \Pr(\mathbf{r} | \mathbb{S}(\beta), \mathbf{H}), \quad (7)$$

and

$$\Pr(\mathbf{r} | \mathbb{S}(\beta), \mathbf{H}) \propto \exp\left(-\|\mathbf{r} - \mathbb{S}(\beta)\mathbf{H}\|^2 / \sigma_n^2\right), \quad (8)$$

where $\|\cdot\|$ refers to the norm operation. Since the receiver has no prior knowledge about the transmission matrix and channel conditions, a direct design of a ML algorithm proves infeasible. In practice, the ML estimates of $\mathbb{S}(\beta)$ and \mathbf{H} can be calculated by using an EM-based iterative procedure which involves two steps: the expectation (E-step) and the maximization (M-step).

The E-step computes the conditional expectation of the log-likelihood function of $[\mathbf{r}, \mathbb{S}(\beta)]$ with respect to $\mathbb{S}(\beta)$ given the i th estimates of the unknown parameters. Mathematically, we write

$$\begin{aligned} \mathcal{E}(\beta, \mathbf{H} | \hat{\beta}(i), \hat{\mathbf{H}}(i)) &= \mathbb{E} \left[\log \Pr(\mathbf{r}, \mathbb{S}(\beta) | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i)) \right] \\ &= \int_{\mathbb{S}(\beta)} \log \Pr(\mathbf{r}, \mathbb{S}(\beta) | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i)) \\ &\quad \times \Pr(\mathbb{S}(\beta) | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i)) d\mathbb{S}(\beta), \end{aligned} \quad (9)$$

where $\mathbb{E}[\cdot]$ denotes the statistical average operation. Using (8) into (9) with ignoring the irrelevant factors of $\|\mathbf{r}\|^2$ and σ_n^2 that have no influence on the optimization task, the E-step is expressed as

$$\mathcal{E}(\beta, \mathbf{H} | \hat{\beta}(i), \hat{\mathbf{H}}(i)) \propto -\mathbf{H}^H \Lambda(\beta) \mathbf{H} + 2\Re \left\{ \mathbf{r}^H \Phi(\beta) \mathbf{H} \right\}, \quad (10)$$

where $(\cdot)^H$ is the Hermitian transpose of a matrix, $\Re\{\cdot\}$ is the real part of a complex number,

$$\Lambda(\beta) = \int_{\mathbb{S}(\beta)} \mathbb{S}^H(\beta) \mathbb{S}(\beta) \Pr(\mathbb{S}(\beta) | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i)) d\mathbb{S}(\beta), \quad (11)$$

and

$$\Phi(\beta) = \int_{\mathbb{S}(\beta)} \mathbb{S}(\beta) \Pr(\mathbb{S}(\beta) | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i)) d\mathbb{S}(\beta). \quad (12)$$

The M-step updates the estimates as

$$\left[\hat{\beta}(i+1), \hat{\mathbf{H}}(i+1) \right] = \arg \max_{\beta, \mathbf{H}} \mathcal{E}(\beta, \mathbf{H} | \hat{\beta}(i), \hat{\mathbf{H}}(i)). \quad (13)$$

To simplify the implementation of the two-dimensional optimization problem shown in (13), we consider the following approach. For each value of β , \mathbf{H} is updated by maximizing (10) as

$$\hat{\mathbf{H}}(i+1, \beta) = (\Lambda(\beta))^{-1} (\Phi(\beta))^H \mathbf{r}. \quad (14)$$

Using (10) and (14) into (13), the updated value of β is expressed as

$$\begin{aligned} \hat{\beta}(i+1) &= \arg \max_{\beta} \left\{ -\hat{\mathbf{H}}^H(i+1, \beta) \Lambda(\beta) \hat{\mathbf{H}}(i+1, \beta) \right. \\ &\quad \left. + 2\Re \left\{ \mathbf{r}^H \Phi(\beta) \hat{\mathbf{H}}(i+1, \beta) \right\} \right\}. \end{aligned} \quad (15)$$

The final channel update is

$$\hat{\mathbf{H}}(i+1) = \hat{\mathbf{H}}(i+1, \hat{\beta}(i+1)). \quad (16)$$

The following practical issues are of interest:

- 1) Based on (2), one can show that

$$\begin{aligned} \mathbb{E} \left[s^{(f)}(n) | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i) \right] \\ = \frac{1}{\sqrt{N+v}} \sum_{k=0}^{N-1} \mathbb{E} \left[u^{(f)}(k) | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i) \right] e^{j2\pi nk/N}, \end{aligned} \quad (17)$$

where

$$\begin{aligned} \mathbb{E} \left[u^{(f)}(k) | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i) \right] \\ = \sum_{\varpi \in \Omega} \varpi \Pr(u^{(f)}(k) = \varpi | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i)). \end{aligned} \quad (18)$$

In practice, at the receiver, $\mathbb{E} \left[s^{(f)}(n) | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i) \right]$ can be used to create the matrix of $\Phi(\beta)$, instead of the unknown transmitted sample $s^{(f)}(n)$. In addition, due to the presence of an interleaver, $\Lambda(\beta)$ can be easily computed as $\Phi^H(\beta)\Phi(\beta)$.

- 2) As observed from (18), computing $\Pr(u^{(f)}(k) = \varpi | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i))$ is crucial for the proposed classifier. This probability can be estimated from the channel decoder outputs of any error-correcting coding system, provided that the decoder is able to produce soft information outputs. More details on this issue are provided in [30]. The key question is how the decoding mechanism works with various SFBC signals. We develop two execution possibilities for that kind of challenge. A design principle of parallelism is adopted as shown in figure 2 where each decoding process is associated with a particular SFBC signal. Bit metric computations shown in figure 2 are conducted as reported in [31]. The iterative feedback is provided to the channel estimators via these processes. This means

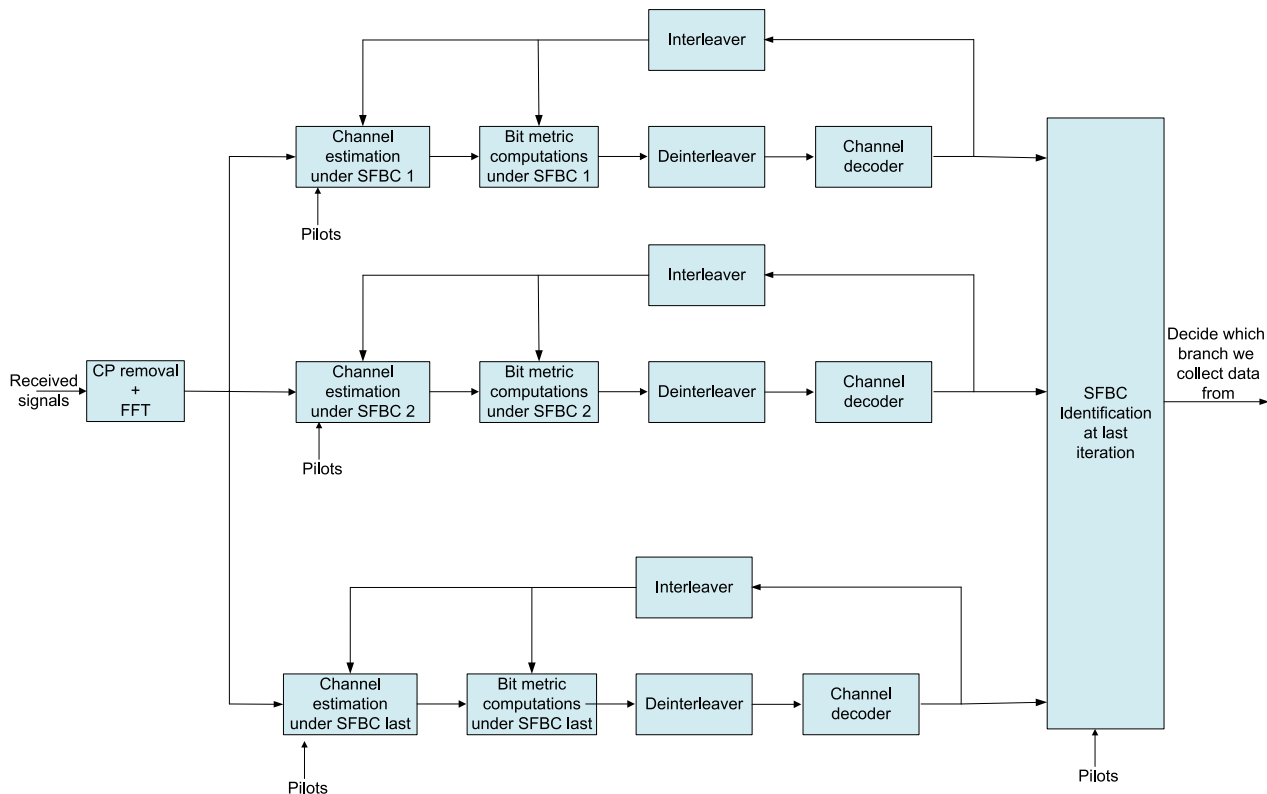


FIGURE 2. The conceptual block diagram of the first proposed receiver structure.

that each estimator serves a specific possible SFBC signal. The proposed SFBC classifier makes a final judgment on the transmit SFBC signal throughout the last round, and then the soft outputs supplied by the relevant decoder are exploited to retrieve the transmitted information. Current technology seems to be appropriate for this approach, with great achievements in the creation of parallel decoders [32]. The second technique is characterized as a sequential combination of the channel estimator, the SFBC classifier, and the decoding process that continually swaps their outputs as indicated in figure 3. When the suggested SFBC classifier alters its selection during the loops, the decoding process should be rebooted to modify its a prior knowledge. Additional memory is necessary for storing and retrieving the decoder outputs to shorten the execution time of this scheme. This enables a fast update for the decoding process when switching between various SFBC signals.

- 3) The presented algorithm’s computing cost is measured in terms of the number of floating operations (flops), with the multiplication and addition of two complex-valued numbers taking 6 and 2 flops, respectively [33], [34]. Furthermore, we claim that the multiplication of two complex-valued matrices with sizes $\vartheta_1 \times \vartheta_2$ and $\vartheta_2 \times \vartheta_3$ demands $8\vartheta_1\vartheta_2\vartheta_3$ flops, the addition of two complex-valued matrices, each has size of $\vartheta_1 \times \vartheta_2$ involves $2\vartheta_1\vartheta_2$ flops, and the inverse of a complex-valued matrix with size $\vartheta_2 \times \vartheta_2$ necessitates

ϑ_2^3 flops. Applying these findings into (14) and (15), we can show that the required number of floating-point operations (flops) per iteration is given by

$$\rho = \sum_{F \in \{2,2,3,4\}} 24L^2F^2(N + \nu + L - 1) + 4L^3F^3. \tag{19}$$

A comparison between the proposed algorithm and the state of art algorithms in terms of computational complexity, delay, and requirement of training mode is presented in Table 1. Here, Z is the number of receive antenna elements, Υ is the number of OFDM symbols, and \mathcal{X} is the duration of an OFDM symbol. One observes that the computational complexity of the proposed algorithm is higher than others. However, the proposed algorithm’s practical implementation looks to be feasible with the advanced technologies. As an example, Altera’s 14 nm Stratix 10 FPGA series can generate up to 10 Teraflops per second [35]. For numerical illustration, consider $N = 512$, $L = 6$, $\nu = 7$, and a processor of 10 Teraflops per sec then $\rho = 20.5(10)^6$ flops. This requires a processing time of $2.05\mu\text{sec}$ which appears negligible for practical applications. In addition, the proposed algorithm is superior to others in terms of delay. This is because the proposed algorithm relies on one OFDM symbol; however, the others need Υ OFDM symbols. For example, the algorithm in [27] needs at least 500 OFDM symbols in order to provide a satisfactory performance. Also, the proposed

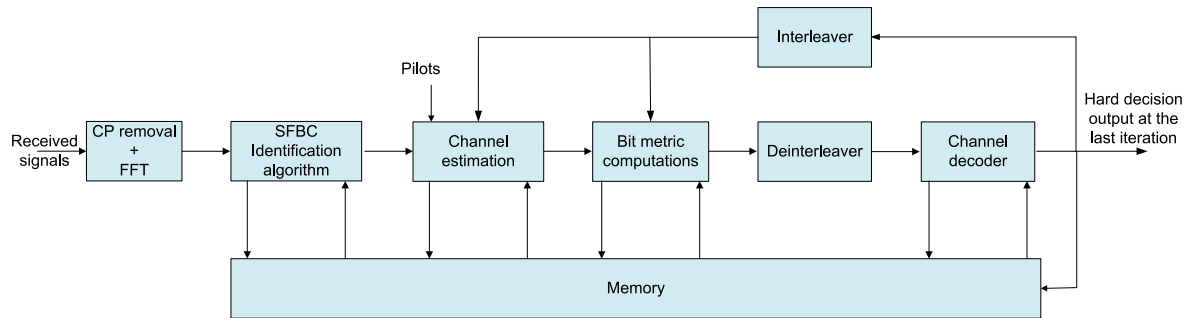


FIGURE 3. The conceptual block diagram of the second proposed receiver structure.

algorithm does not require a training mode which is needed for machine learning algorithms. As indicated in [36], a large number of samples is required to train the reported support vector machine algorithm. Furthermore, the proposed algorithm is capable of operating with either a single or multiple antenna receiver, while others request a multi-antenna receiver. Moreover, the proposed algorithm surpasses its competitors in terms of classification performance by a substantial margin as shown in the next section. It should be noted that there has been supplemental complexity involved in the proposed receiver in the form of hardware components needed for adopting a bank of channel decoders, as implied in the first approach, or a storage memory, as clarified in the second alternative.

- 4) The first round of estimations is acquired from (15) and (16) by using a couple of pilot symbols with the unknown data symbols being replaced with zeros. With iterations, the soft outputs produced by the channel decoder is exploited to deliver $\Pr(u^{(f)}(k) = \varpi | \mathbf{r}, \hat{\beta}(i), \hat{\mathbf{H}}(i))$ which is used to derive the proposed classifier.

IV. SIMULATION RESULTS

Monte Carlo simulations are carried out to evaluate the classification performance of the proposed algorithm. Unless otherwise, we consider an OFDM system with $N = 512$ and $\nu = 7$. The subcarriers are modulated by 512 data symbols, each of which is chosen at random from a 16-QAM constellation. The SFBC set under consideration is {SM, AL, SF3, SF4}. In addition, a turbo code is employed with rate 1/3, including two recursive systematic convolutional encoders with 16-state, rate 1/2, and generator polynomials of $(31)_8$ and $(33)_8$ [37]. Scattered pilots of size 16 symbols are adopted to initialize the proposed classifier. The wireless connection between each broadcast and receive antenna is assumed to be frequency-selective with a length of $L = 6$ and a power delay profile being given as $\sigma_h^2(l) = \eta \exp(-l/6)$, where η is selected such that each sub-carrier has the same level of energy [30]. The probability of false classification P_f is used as a performance measure,

$$P_f = 1 - [Pr(SM|SM) + Pr(AL|AL) + Pr(SF3|SF3) + Pr(SF4|SF4)]. \quad (20)$$

Figure 4 illustrates the performance of the proposed classifier as a function of signal-to-noise ratio (SNR) at different iterations. The proposed classifier has a significant classification performance improvement with iterations. At the first iteration, the proposed classifier has limited performance in categorizing the SFBC signals. This is because we rely on a few pilot data symbols. Starting from the second iteration, the proposed classifier exploits the soft information produced by the channel decoder to refine the classification process. The results agree with the theoretical findings that with iterations, the outputs of the channel decoder become more authentic, improving the classification performance. It is worth mentioning that the proposed algorithm iterates until the estimates have converged or a certain stopping criterion has been met. With the aid of figure 5, which shows the classification performance as a function of iteration number, one observes that there is no notable progress beyond iteration five.

Figure 6 shows the classification performance of the proposed algorithm in two scenarios at 16-QAM and 64-QAM modulation formats. Here, the number of iterations has been set at five. The first scenario assumes having perfect knowledge about the channel parameters, while the second one relies on the proposed channel estimator shown in (16). We note that the difference between the two scenarios is less than 1 dB. This confirms the success of the proposed receiver design. It is vital to note that having less than 1 dB between ideal and real estimators is widespread in coded communications as reported in [38].

Figure 7 illustrates the classification performance of the proposed algorithm for different modulation formats including 16-QAM, 64-QAM, 256-QAM, 512-QAM, and 1024-QAM, at $SNR = 20$ dB. The results indicate that the usage of the higher-order modulation format results in a degradation in the classification performance. This is because the soft information outputs of the channel decoder are less reliable with having a higher-order modulation format which in turn limits the achievable classification performance.

In order to simplify the mathematical developments, we discussed the proposed algorithm in the case of having a single receive antenna element. However, the proposed algorithm can be easily extended to any number of receive antenna elements. The difference is the computations of the a posteriori expectations of the transmitted symbols in the case of having multiple receive antenna elements. For more details

TABLE 1. A comparison between the proposed algorithm and the state of art algorithms. Here, $\Upsilon = 50$, $Z = 2$, $N = 512$, $\nu = 7$, and $\text{card}(\tau) = 7$. τ is a time lag vector as defined in [27].

Algorithm	Computational complexity	Number of flops	Delay	Training mode
Proposed	$\sum_{F \in \{2,2,3,4\}} 24L^2F^2(N + \nu + L - 1) + 4L^3F^3$	$20.5(10)^6$	\mathcal{X}	No
[27]	$8YNZ(Z - 1)$	$0.4(10)^6$	$\Upsilon\mathcal{X}$	Yes
[36]	$0.75N(64Z^3 + 32Z^2\Upsilon)$	$2.95(10)^6$	$\Upsilon\mathcal{X}$	No
[39]	$4Y(N + \nu)Z(Z - 1)(\text{card}(\tau) + 1)$	$1.7(10)^6$	$\Upsilon\mathcal{X}$	No

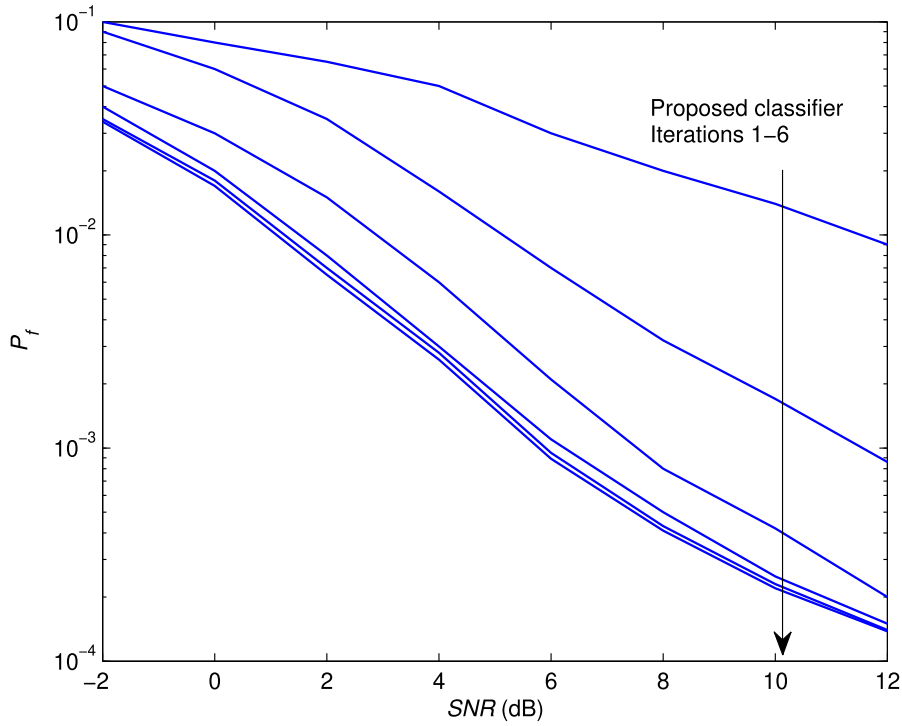


FIGURE 4. P_f as a function of SNR.

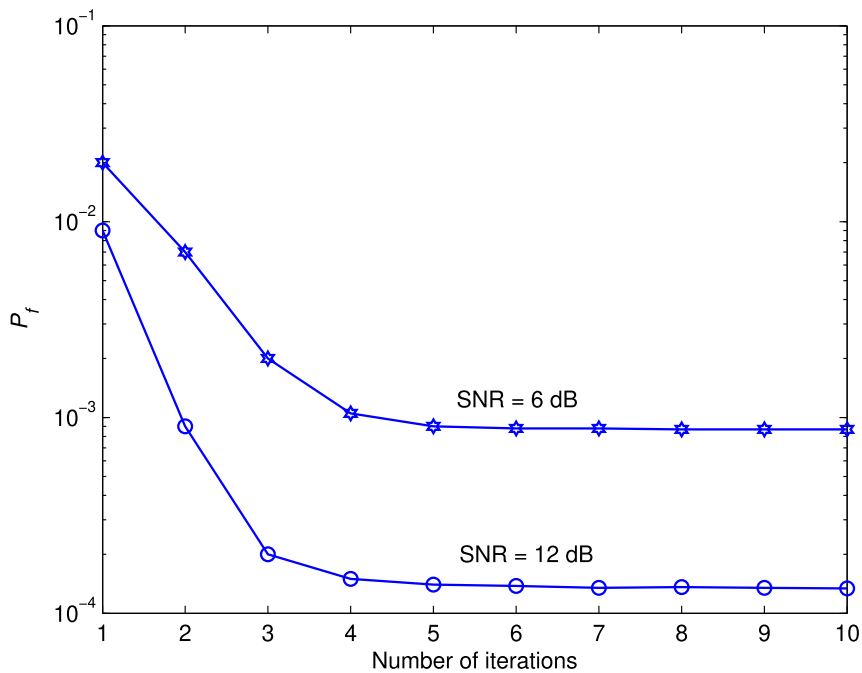


FIGURE 5. P_f as a function of iteration number.

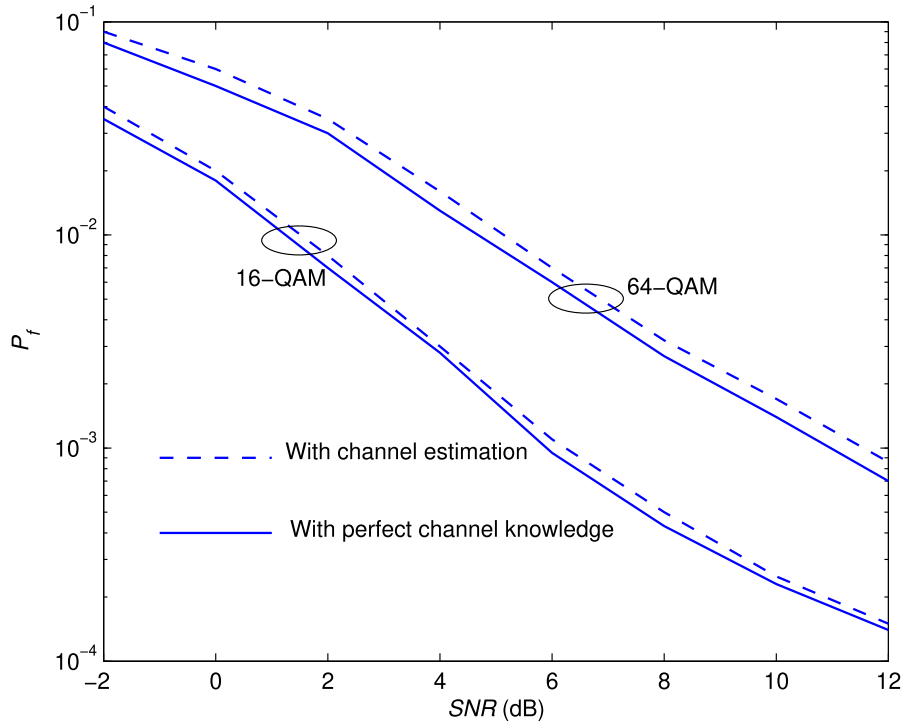


FIGURE 6. P_f with and without channel knowledge.

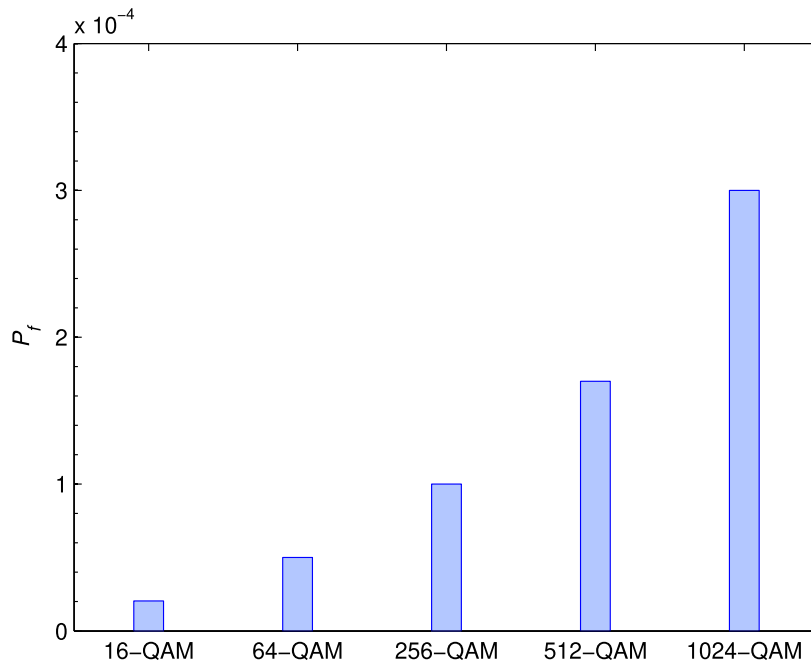


FIGURE 7. P_f at different modulation formats, $SNR = 20$ dB.

on these computations, we refer to [33]. Figure 8 shows the classification performance with a receiver equipped with $Z = 1, 2,$ and 3 antenna elements, and the number of iterations is five. Also, we show the performance in the case of employing another recursive systematic convolutional code with rate $1/2$, 16-state, and a generator polynomial of $(31)_8$ [37]. Moreover, we illustrate the performance of the algorithms reported in [27], [36], [39] for the sake of

comparison. The results show that the classical classifiers are not able to achieve a satisfactory performance even at high values of SNR . This is because they were designed to operate blindly without the help of pilots symbols. It is well-known that blind classification algorithms suffer from shortened classification performance, even with increasing the number of the processed samples. However, pilots-based classification algorithms provide outstanding classification

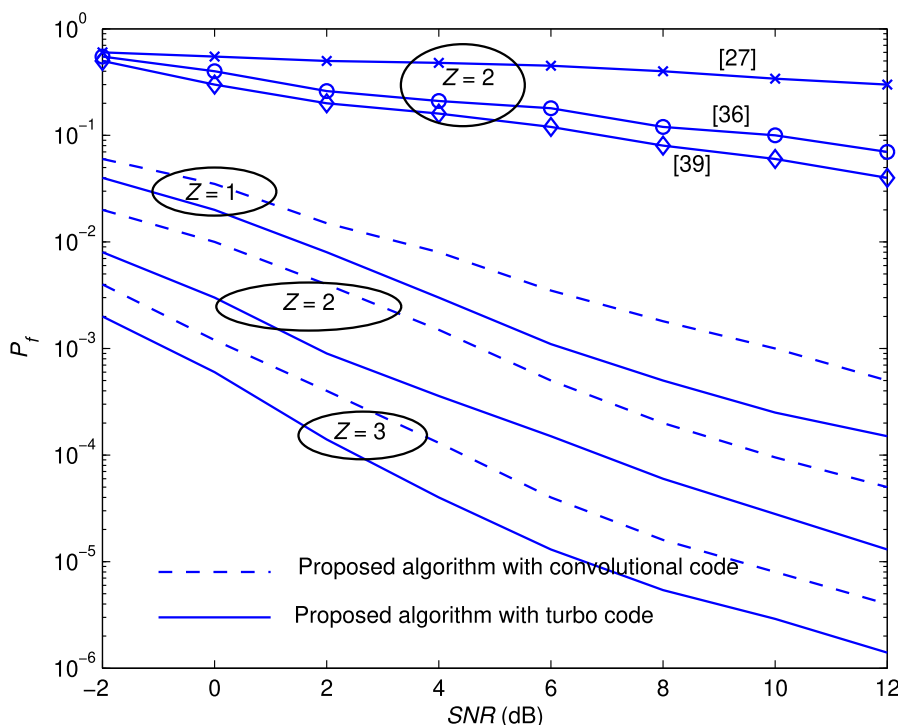


FIGURE 8. P_f in conjunction with turbo and convolutional codes at different receive antenna elements, Z .

performance at the cost of shortened throughput. In the sense that it has impressive classification performance with a small throughput loss, the proposed algorithm has the advantages of both blind and data-aided techniques. The central idea is to use the output information of a channel decoder to compute the a posteriori expectations of the transmitted symbols, which are then adopted as pilot symbols.

Also, the classification performance improves with increasing Z . This is because the reliability of the a posteriori expectations of the transmitted symbols enhances as Z grows. If both codes have the same settings for code rate and constraint length, it is well-known that turbo codes provide more accurate a posteriori expectations of the sent symbols than convolution codes [37]. Because of this, findings show that the turbo code outperforms the convolutional code, as seen in the results.

V. CONCLUSION

The classification of SFBC signals was discussed for OFDM transmissions in the context of error-correcting codes. Starting from the ML principles, we derived a classification algorithm using an EM procedure. The outputs of a channel decoder were iteratively utilized to improve the classification performance of the proposed algorithm. Additionally, we develop a channel estimation approach to supply the proposed classifier. The results indicated that the proposed classifier achieved superiority compared to the traditional classifiers reported in the literature in terms of classification performance and delay at the cost of an acceptable increase in computational complexity. The proposed algorithm has shown to be an efficient technique for SFBC classification

in MIMO systems; nevertheless, more study is essential to adapt the algorithm to massive MIMO technology.

ACKNOWLEDGMENT

Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2022R137), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia. The authors would like to acknowledge the support of Prince Sultan University for paying the Article Processing Charges (APC) of this publication.

REFERENCES

- [1] O. A. Dobre, "Signal identification for emerging intelligent radios: Classical problems and new challenges," *IEEE Instrum. Meas. Mag.*, vol. 18, no. 2, pp. 11–18, Apr. 2015.
- [2] A. Ivanov, K. Tonchev, V. Poulkov, and A. Manolova, "Probabilistic spectrum sensing based on feature detection for 6G cognitive radio: A survey," *IEEE Access*, vol. 9, pp. 116994–117026, 2021.
- [3] M. Marey and H. Mostafa, "Turbo modulation identification algorithm for OFDM software-defined radios," *IEEE Commun. Lett.*, vol. 25, no. 5, pp. 1707–1711, May 2021.
- [4] M. Marey and H. Mostafa, "Code-aided modulation classification algorithm for multiuser uplink SC-FDMA systems," *IEEE Wireless Commun. Lett.*, vol. 10, no. 5, pp. 1023–1027, May 2021.
- [5] M. Marey, H. Mostafa, S. A. Alshebeili, and O. A. Dobre, "Iterative modulation classification algorithm for two-path successive relaying systems," *IEEE Wireless Commun. Lett.*, vol. 10, no. 9, pp. 2017–2021, Sep. 2021.
- [6] M. Marey and O. A. Dobre, "Blind modulation classification for Alamouti STBC system with transmission impairments," *IEEE Wireless Commun. Lett.*, vol. 4, no. 5, pp. 521–524, Oct. 2015.
- [7] Z. Wu, L. Zhang, Z. Zhong, and R. Liu, "Blind recognition of LDPC codes over candidate set," *IEEE Commun. Lett.*, vol. 24, no. 1, pp. 11–14, Jan. 2020.
- [8] T. Xia and H.-C. Wu, "Novel blind identification of LDPC codes using average LLR of syndrome a posteriori probability," *IEEE Trans. Signal Process.*, vol. 62, no. 3, pp. 632–640, Feb. 2014.

- [9] A. Punchihewa, Q. Zhang, O. A. Dobre, C. Spooner, S. Rajan, and R. Inkol, "On the cyclostationarity of OFDM and single carrier linearly digitally modulated signals in time dispersive channels: Theoretical developments and application," *IEEE Trans. Wireless Commun.*, vol. 9, no. 8, pp. 2588–2599, Aug. 2010.
- [10] Q. Zhang, O. A. Dobre, Y. A. Eldemerdash, S. Rajan, and R. Inkol, "Second-order cyclostationarity of BT-SCLD signals: Theoretical developments and applications to signal classification and blind parameter estimation," *IEEE Trans. Wireless Commun.*, vol. 12, no. 4, pp. 1501–1511, Apr. 2013.
- [11] L. Yuan, Z. Zheng, N. Yang, and J. Zhang, "Performance analysis of short-packet non-orthogonal multiple access with Alamouti space-time block coding," *IEEE Trans. Veh. Technol.*, vol. 70, no. 3, pp. 2900–2905, Mar. 2021.
- [12] V. Choqueuse, M. Marazin, L. Collin, K. C. Yao, and G. Burel, "Blind recognition of linear space-time block codes: A likelihood-based approach," *IEEE Trans. Signal Process.*, vol. 58, no. 3, pp. 1290–1299, Mar. 2010.
- [13] V. Choqueuse, K. Yao, L. Collin, and G. Burel, "Hierarchical space-time block code recognition using correlation matrices," *IEEE Trans. Wireless Commun.*, vol. 7, no. 9, pp. 3526–3534, Sep. 2008.
- [14] M. Marey, O. A. Dobre, and R. Inkol, "Classification of space-time block codes based on second-order cyclostationarity with transmission impairments," *IEEE Trans. Wireless Commun.*, vol. 11, no. 7, pp. 2574–2584, Jul. 2012.
- [15] Y. A. Eldemerdash, M. Marey, O. A. Dobre, G. K. Karagiannidis, and R. Inkol, "Fourth-order statistics for blind classification of spatial multiplexing and Alamouti space-time block code signals," *IEEE Trans. Commun.*, vol. 61, no. 6, pp. 2420–2431, Jun. 2013.
- [16] M. Marey, O. A. Dobre, and B. Liao, "Classification of STBC systems over frequency-selective channels," *IEEE Trans. Veh. Technol.*, vol. 64, no. 5, pp. 2159–2164, May 2015.
- [17] M. Marey, O. A. Dobre, and R. Inkol, "Blind STBC identification for multiple-antenna OFDM systems," *IEEE Trans. Commun.*, vol. 62, no. 5, pp. 1554–1567, May 2014.
- [18] Y. A. Eldemerdash, O. A. Dobre, and B. J. Liao, "Blind identification of SM and Alamouti STBC-OFDM signals," *IEEE Trans. Wireless Commun.*, vol. 14, no. 2, pp. 972–982, Feb. 2015.
- [19] E. Karami and O. A. Dobre, "Identification of SM-OFDM and AL-OFDM signals based on their second-order cyclostationarity," *IEEE Trans. Veh. Technol.*, vol. 64, no. 3, pp. 942–953, Mar. 2015.
- [20] Y. Kumar, M. Sheoran, G. Jajoo, and S. K. Yadav, "Automatic modulation classification based on constellation density using deep learning," *IEEE Commun. Lett.*, vol. 24, no. 6, pp. 1275–1278, Jun. 2020.
- [21] K. Wang, H. Shen, W. Wu, and Z. Ding, "Joint detection and decoding in LDPC-based space-time coded MIMO-OFDM systems via linear programming," *IEEE Trans. Signal Process.*, vol. 63, no. 13, pp. 3411–3424, Jul. 2015.
- [22] I. Shubhi and Y. Sanada, "Joint turbo decoding for overloaded MIMO-OFDM systems," *IEEE Trans. Veh. Technol.*, vol. 66, no. 1, pp. 433–442, Jan. 2017.
- [23] X. Zhang, P. Xiao, D. Ma, and J. Wei, "Variational-bayes-Assisted joint signal detection, noise covariance estimation, and channel tracking in MIMO-OFDM systems," *IEEE Trans. Veh. Technol.*, vol. 63, no. 9, pp. 4436–4449, Nov. 2014.
- [24] W. Stallings, *5G Wireless: A Comprehensive Introduction*. Reading, MA, USA: Addison-Wesley, 2021.
- [25] T. Moon, "The expectation maximization algorithm," *IEEE Signal Process. Mag.*, vol. 13, no. 6, pp. 47–60, Nov. 1996.
- [26] Z. Yang, Y. Fang, G. Zhang, F. C. Lau, S. Mumtaz, and D. B. D. Costa, "Analysis and optimization of tail-biting spatially coupled protograph LDPC codes for BICM-ID systems," *IEEE Trans. Veh. Technol.*, vol. 69, no. 1, pp. 390–403, Jan. 2020.
- [27] M. Marey and O. A. Dobre, "Automatic identification of space-frequency block coding for OFDM systems," *IEEE Trans. Wireless Commun.*, vol. 16, no. 1, pp. 117–128, Jan. 2017.
- [28] V. Tarokh, H. Jafarkhani, and A. R. Calderbank, "Space-time block codes from orthogonal designs," *IEEE Trans. Inf. Theory*, vol. 45, no. 5, pp. 1456–1467, Jul. 1999.
- [29] M. Marey and O. A. Dobre, "Iterative receiver design for uplink OFDMA cooperative systems," *IEEE Trans. Broadcast.*, vol. 62, no. 4, pp. 936–947, Dec. 2016.
- [30] M. Marey, M. Guenach, and H. Steendam, "Code-aided channel tracking and frequency offset-phase noise elimination for multi-carrier systems," *IEEE Signal Process. Lett.*, vol. 15, pp. 657–660, 2008.
- [31] A. Chindapol and J. Ritcey, "Bit interleaved coded modulation with iterative decoding and 8psk signaling," *IEEE Trans. Commun.*, vol. 50, no. 8, pp. 1250–1257, Aug. 2002.
- [32] A. Li, P. Hailes, R. G. Maunder, B. M. Al-Hashimi, and L. Hanzo, "1.5 Gbit/s FPGA implementation of a fully-parallel turbo decoder designed for mission-critical machine-type communication applications," *IEEE Access*, vol. 4, pp. 5452–5473, 2016.
- [33] M. Marey, H. Mostafa, O. A. Dobre, and M. H. Ahmed, "Data detection algorithms for BICM alternate-relaying cooperative systems with multiple-antenna destination," *IEEE Trans. Veh. Technol.*, vol. 65, no. 5, pp. 3802–3807, May 2016.
- [34] H. Mostafa, M. Marey, M. H. Ahmed, and O. A. Dobre, "Simplified maximum-likelihood detectors for full-rate alternate-relaying cooperative systems," *IET Commun.*, vol. 7, no. 17, pp. 1899–1906, Nov. 2013.
- [35] *Stratix 10: The Most Powerful, Most Efficient FPGA for Signal Processing*. Accessed: May 2015. [Online]. Available: <https://www.intel.com/content/dam/www/programmable/us/en/pdfs/literature/backgrounders/stratix10-floating-point-backgroundunder.pdf>
- [36] M. Gao, Y. Li, O. A. Dobre, and N. Al-Dhahir, "Blind identification of SFBC-OFDM signals based on the central limit theorem," *IEEE Trans. Wireless Commun.*, vol. 18, no. 7, pp. 3500–3514, Jul. 2019.
- [37] V. Lottici and M. Luise, "Embedding carrier phase recovery into iterative decoding of turbo-coded linear modulations," *IEEE Trans. Commun.*, vol. 52, no. 4, pp. 661–668, Apr. 2004.
- [38] M. Guenach, M. Marey, H. Wymeersch, H. Steendam, and M. Moeneclaey, "Turbo estimation and equalization for asynchronous uplink MC-CDMA," *IEEE Trans. Wireless Commun.*, vol. 7, no. 4, pp. 1217–1226, Apr. 2008.
- [39] M. Gao, Y. Li, O. A. Dobre, and N. Al-Dhahir, "Blind identification of SFBC-OFDM signals using subspace decompositions and random matrix theory," *IEEE Trans. Veh. Technol.*, vol. 67, no. 10, pp. 9619–9630, Mar. 2018.



MOHAMED MAREY (Senior Member, IEEE) received the M.Sc. degree in electrical engineering from Menoufia University, Egypt, in 1999, and the Ph.D. degree in electrical engineering from Ghent University, Belgium, in 2008. From 2009 to 2014, he was a Research Associate and a Visiting Professor with the Faculty of Engineering and Applied Science, Memorial University, Canada. He is currently a Full Professor with the Faculty of Electronic Engineering, Menoufia University. He is on a sabbatical leave in order to join the Smart Systems Engineering Laboratory, Prince Sultan University, Saudi Arabia, as a Research Laboratory Leader. He authored the book *Multi-Carrier Receivers in the Presence of Interference: Overlay Systems* (VDM Publishing House Ltd., 2009) and around 100 scientific papers published in international journals and conferences. His research interests include wireless communications and digital signal processing, with a particular focus on smart antennas, cooperative communications, signal classification for cognitive radio systems, synchronization and channel estimation, multiple-input multiple-output antenna systems, multicarrier systems, and error correcting codes. He was a recipient of the Young Scientist Award from the International Union of Radio Science, in 1999. He is currently serving as an Editor of IEEE OPEN JOURNAL OF THE COMMUNICATIONS SOCIETY.

HALA MOSTAFA (Member, IEEE) received the Ph.D. degree in electrical engineering from the Faculty of Engineering and Applied Science, Memorial University, Canada, in 2014. From 2014 to 2015, she was a Research Scientist with Memorial University. She is currently an Assistant Professor with the Information Technology Department—College of Computer and Information Sciences—Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia. Her research interests include wireless communications, with a particular focus on smart antennas and wireless sensor networks.