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Elevation and azimuth-aided channel estimation scheme for airborne hyperspectral data transmission

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Elevation and azimuth-aided channel estimation scheme for airborne hyperspectral data transmission

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Abstract. A channel-estimation (CE) scheme is proposed to estimate the complex amplitude, Doppler shift, angle-of-departure, and angle-of-arrival of the channel taps for sparse and doubly selective channels for hyperspectral image transmission from unmanned aircraft vehicles (UAVs) to ground stations. The proposed method is dubbed as compressed-sensing joint parameter estimation (CS-JPE) and finds the channel parameters matrix by employing a compressed-sensing (CS)-based method. Afterward, a modified version of the joint parameter estimation (JPE) is proposed as CS-JPE and is dubbed as M-CS-JPE, which employs the elevation-azimuth angles of the line-of-sight channel tap to estimate the channel parameters with higher accuracy and lower computational complexity compared to the CS-JPE scheme. For higher accuracy of the M-CS-JPE, an elevation-azimuth angle estimation is proposed and is dubbed as fractal-structure-array since it uses a fractal structure for the placement of the UAV antennas. The performance of the CE methods is appraised by simulating transmission of AVIRIS hyperspectral data via the communication channel and evaluating their accuracy for the classification after demodulation. Compared to the least-square method, the simulation results indicate up to 30-dB figure of merit in the bit-error-rate and 10 times improvement in the hyperspectral image classification fidelity. © 2018 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: 10.1117/1.JRS.12.046014]

Keywords: unmanned aircraft vehicle; elevation and azimuth angles; channel estimation; doppler shift; compressed sensing; orthogonal frequency division multiplexing.

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1 Introduction

The implementation of unmanned aerial vehicles (UAVs) for civilian applications such as remote sensing is growing. One of the most important remote sensing-based usages of the UAVs is the disaster area support. Along with the visible light cameras, UAVs can utilize hyperspectral imaging for monitoring the environment and find victims in the debris. In addition, UAVs can settle a temporary cellular communications network in the disaster area. The continuous surveillance of the disaster area by the transmission of hyperspectral images along with the transmission of communication systems data requires high-bandwidth communication systems, which should be able to transmit and receive the data with high fidelity.

Since orthogonal frequency division multiplexing (OFDM) has high-bandwidth efficiency and is robust to multipath effect, it has been applied for wideband terrestrial communications and can be a feasible candidate for UAV communications as well. On the other hand, the employment of massive multiple-input multiple-output (MIMO) utilizes channel diversity and increases the effective signal-to-noise ratio (SNR). However, using the massive MIMO-OFDM for UAV communications is challenging since the movement of UAVs imposes high Doppler shifts and makes the communication channel to be doubly selective (DS), i.e., both time and frequency selective, and therefore, destroys the orthogonality between the OFDM subcarriers and causes intercarrier interference (ICI).
In order to demodulate the MIMO-OFDM signal at the receiver and mitigate ICI, the knowledge of channel impulse response (CIR) is required at the receiver, and therefore, channel estimation (CE) is essential for MIMO-OFDM-based UAV communications. In addition to the high Doppler shift for UAV communications, the experimental results indicate that the tap delay line channel models for several vehicular communication systems are long and sparse. As a result, compressed-sensing (CS)-based CE approaches can be employed to estimate those sparse CIR channel models.

In order to be able to construct the frequency domain channel matrix for data demodulation, all the channel parameters, i.e., complex amplitude, Doppler shift, angle of departure (AoD), and angle of arrival (AoA), of the channel taps should be estimated. Several papers have considered the joint estimation of the channel parameters, however, no paper has considered the joint estimation of all the channel parameters in DS MIMO-OFDM channels. Those papers can be categorized into two groups regarding the problem that they considered. The first group of papers deals with the complex amplitude, AoD, and AoA estimation by the assumption that the channel is not DS, i.e., zero Doppler shift or very low Doppler shift. The second group of papers deals with the radar systems, and therefore, they do not consider the complex amplitudes’ estimation.

In this paper, a CS-based CE procedure is proposed, which is able to estimate all the channel parameters. Since the method performs joint parameter estimation (JPE), it is dubbed as compressed-sensing joint parameter estimation (CS-JPE). In this method, an over-complete matrix is defined which is obtained by quantizing all the possible Doppler shifts, AoDs, and AoAs. By considering the received pilots, a CS method such as orthogonal matching pursuit (OMP) is employed to obtain the nonzero elements of that over-complete matrix. The nonzero elements define the Doppler shifts, AoDs, and AoAs of the channel taps, whereas the value of those elements define the complex amplitudes. In the absence of any method that would be able to estimate all the channel tap parameters simultaneously, we employ the least square (LS) and linear minimum mean square error (LMMSE) methods of Ref. for comparison. Although running LS and LMMSE, we assume an ideal knowledge of the AoD and AoA of the channel taps.

Although the simulation results indicate more accurate performance of the CS-JPE method compared to the LS and LMMSE schemes, the performance of the CS-JPE scheme can be enhanced further if the Doppler shift of the channel taps are known a priori since it reduces the size of the over-complete matrix considerably. However, by knowing the speed of the UAV and carrier frequency, the AoD, which is the pair of the elevation-azimuth angles, of the channel taps is required to estimate the Doppler shifts. While the AoD of the nonlinear of sight (NLoS) channel taps is completely random, the AoD of the line of sight (LoS) tap can be obtained based on the UAV position. Since when beamforming is utilized the mean average power of the LoS channel tap is considerably larger than the mean average power of the NLoS channel taps, our simulation results indicate that even if the LoS tap’s Doppler shift is estimated accurately, the CE performance is enhanced significantly. As a result, we propose the modified version of the CS-JPE method and dubbed it as M-CS-JPE, in which, first the AoD of the LoS channel tap is estimated and is utilized to estimate the Doppler shift of the LoS channel tap. Afterward, the complex amplitude of the LoS channel tap would be estimated. The estimated elevation and azimuth angles can be employed for the estimation of UAVs attitudes, which are vital for the UAV control and displacement; therefore, we can consider that the elevation-azimuth estimation procedure does not add complexity to the CE process since those parameters were estimated priori for the sake of UAV attitude estimation.

In order to enhance the performance of the M-CS-JPE, we propose an elevation-azimuth estimation scheme in this paper. In this method, the receiver antennas are positioned according to a fractal structure on the UAV’s body. The proposed method applies the LS estimation method to estimate the spatial frequencies of the phase shifts from the received signals at the array of antennas. Afterward, the estimated special frequencies are utilized for estimating the elevation-azimuth angles of the UAV. The simulation results indicate that the proposed method estimates those angles more accurately compared to the method of Ref. which is one of the state-of-the-art elevation-azimuth estimation scheme. In order to increase the accuracy of elevation-azimuth estimation and make it more applicable for cellular communication systems, another step is added. The multiple signal classification (MUSIC) scheme is applied to search for more accurate
angles in the neighbor of the estimated angles from the previous step. The two-phase elevation-
azimuth estimation method is called fractal structure array (FSA) scheme. The proposed antenna
placement method plays the major rule in the performance of the FSA scheme. The simulation
results indicate that by increasing the size of the fractal structure, the elevation-azimuth pair is
estimated more accurately.

Finally, in order to evaluate the performance of our proposed CE procedures for hyperspec-
tral data transmission, we employed the spectral–spatial classification method of Ref. [4] to
analyze AVIRIS Indian Pines data set [3]. By the transmission of the hyperspectral images through
the communication channel, we can analyze the hyperspectral data under actual errors executed
by the communication systems, instead of adding random white noises to the data.

In summary, the contributions of this paper are:

- Proposing a method, CS-JPE, that is able to estimate complex amplitude, Doppler shift,
   AoD, and AoA of the channel taps jointly.
- Improving the CS-JPE method and propose the M-CS-JPE scheme, which utilizes the UAV
   attitudes to obtain the parameters of the LoS channel tap at the first step and estimate the
   parameters of the NLoS channel taps at the second step.
- Proposing the FSA method to obtain the elevation-azimuth angles.
- Simulating the whole system for hyperspectral image transmission and analysis.

The remainder of this paper is organized as follows. Section 2 describes the system model.
The CS-JPE and M-CS-JPE methods are elaborated in Secs. 3 and 4, respectively. The FSA
elevation-azimuth estimation method is discussed in Sec. 5. The computational complexity
analysis of the proposed methods is argued in Sec. 6. Section 7 presents the performance analy-
sis, and Sec. 8 concludes this paper.

Notations: upper (lower) boldface letters denote matrices (column vectors); (.)' denotes the
transpose of a matrix, (.)^-1 defines the inverse of a matrix, (.)^* denotes Hermitian conjugate
function, [.] defines the floor operator, E[.] defines the expected value, I defines the identity
matrix, O(.) expresses the order of computational complexity, and ⊗ denotes the Kronecker
product.

2 System Model

Assume that an OFDM signal with N subcarriers is transmitted through an MIMO system, in
which the UAV station (US) has NT transmitter antennas and the mobile station (MS) poses NR
receiver antennas. Similar to Ref. [3], we assume that for the transmission of each OFDM sub-
carrier, the US uses T time frames and at each frame it uses an individual beamforming vector. In
addition, each time frame is divided into S subframes and for each subframe, the MS uses an
individual combining vector to detect the transmitted signals. The coded transmitted signal at the
t’th time frame for the m’th subcarrier is defined as

\[ s_{m,t}(t) = P_m(t)s_m(t), \quad m = 1,2,\ldots,N, \]  

(1)

where \( s_m \) is the m’th OFDM symbol of the OFDM block, \( P_m(t) \) is the NT × 1 vector of the
digital precoding matrix for the m’th subcarrier. After the IFFT block, the cyclic prefix with
the length G, where \( G \geq L, L \) is the number of tapped delay line of the channel, is added
to the signal. Afterward, the time domain samples pass through the DS channel which at
time n by considering the concepts of Ref. [2] is defined as

\[ H_n = \sum_{l=0}^{L-1} \alpha_l a_{MS} f_l(\theta_l) a_{US}^T(\phi_l, \rho_l) e^{j2\pi f_l l T_s} \Lambda(n - lT_s), \]  

(2)

where \( \alpha_l, f_l, \theta_l, \) and \( \phi_l, \rho_l \) determine the l’th channel tap complex amplitude, l’th channel tap
Doppler shift, l’th channel tap AoA angle, and l’th channel tap AoD (elevation, azimuth) angles,
respectively. The total number of channel taps (L) is obtained by dividing the maximum delay
spread of the channel by the sampling time (T_s). The l’th tap antenna array vectors of the US and
MS are indicated by \( a_{US}(\phi_l, \rho_l) \) and \( a_{MS}(\theta_l) \), respectively, where by considering the linear array
with half a wavelength distance between the antennas, $a_{MS}(\theta_t) = [1 \ e^{j\pi \sin(\theta_t)} \ldots e^{jN_T \pi \sin(\theta_t)}]^T$ and $a_{US}(\phi_t, \rho_t)$ is defined in Sec. 3.

At the MS, first the cyclic prefix is removed from the received time domain data. Afterward, the DFT of the signal is calculated to obtain the frequency domain received symbols. At each frame, the MS uses $S$ combining $NN_T \times 1$ matrices, $c_s$, $s = 1, 2, \ldots, S$, to detect the transmitted signal. The $SN \times 1$ vector of all the received OFDM symbols at time $t$ can be expressed as

$$y(t) = H(t)s_{nt}(t) + w(t),$$

where $s_{nt}(t)$ is the $NN_T \times 1$ vector of the transmitted coded symbols at time $t$, $s_{nt}(t) = [s_{nt1}(t)^T, s_{nt2}(t)^T, \ldots, s_{ntN_T}(t)^T]^T$, $w(t)$ is the $SN \times 1$ vector of the additive white Gaussian noise at time $t$, $y(t) = [y_1(t), y_2(t), \ldots, y_SN_T(t)]^T$ and $y_m(t) = [y_{m1}(t), y_{m2}(t), \ldots, y_{m,N}(t)]^T$. The $SN \times NN_T$ frequency domain channel matrix at time $t$ is indicated by $H(t)$, where $H(t) = [H_1(t), H_2(t), \ldots, H_N(t)]^T$. The received vector for each subcarrier is expressed as

$$y_m(t) = H_m(t)s_{nt}(t) + w_m(t),$$

where $H_m(t)$ is a $S \times NN_T$ matrix, which is defined as

$$H_m(t) = C_h^T H_F(t) P_{RF}(t).$$

In Eq. (5), $C_h = [c_{v1}, c_{v2}, \ldots, c_{vS}]$ and it is an $NN_R \times S$ matrix, $P_{RF}(t)$ is the $NN_R \times NN_T$ matrix that defines the transmitted coded data from the $N_T$ transmitter antennas, and $H_F(t)$ is an $NN_R \times NN_T$ matrix that by considering Eq. (3) and the derivations of the elements of the channel matrix in Ref. 3 is defined as

$$\{[H_F(t)]_{m,v}\}_{1:NN_R, v(N_T-1)+1:NN_T} = \frac{1}{N} \sum_{l=0}^{L-1} a_{MS}(\theta_t) a_{US}^T(\phi_t, \rho_t) e^{j2\pi f_1lT_T} e^{-j2\pi ml} 1 - e^{j[2\pi l + \frac{\pi}{2}(m-v)]} \frac{1 - e^{j[2\pi l + \frac{\pi}{2}(m-v)]}}{1 - e^{j[2\pi l + \frac{\pi}{2}(m-v)]}},$$

where for each $m, v = 1, 2, \ldots, N$ and $\{[H_F(t)]_{m,v}\}_{1:NN_R, v(N_T-1)+1:NN_T}^T$ defines the $NN_R \times N_T$ sub matrix of $H_F(t)$ with the elements that are located between the $1$ to $NN_R$ rows and $v(N_T - 1) + 1$ to $vN_T$ columns.

As it is observed in Eq. (6), in the case of zero Doppler shift, only the $[H_F(t)]_{m,v}$ is nonzero and, therefore, $y_m(t)$ only depends on $s_{nt}(t)$ as

$$y_m(t) = C_h^T[H_F(t)]_{m,v}s_{nt}(t) + w_m(t).$$

When channel parameters are estimated, the $H(t)$ can be constructed according to Eq. (3), and the transmitted data can be estimated by the LS procedure as

$$\widehat{s}_{nt}(t) = \frac{y(t)}{\widehat{H}(t)},$$

or more accurately by minimum mean square error as

$$\widehat{s}_{nt}(t) = \widehat{H}(t)^* \times [\widehat{H}(t) \times \widehat{H}(t)^* + \sigma^2 I]^{-1} y(t),$$

where $\widehat{H}(t)$ and $\widehat{s}_{nt}(t)$ are the estimated frequency channel matrix and transmitted OFDM symbols, respectively, and $\sigma^2$ is the noise variance.

3 CS-JPE Scheme

Considering that the channel is sparse, we propose the following formulation in order to estimate the parameters of the channel by a CS-based method. First, we define the following matrices:

where \( \tilde{a}_{\text{MS}}(\theta_i) = C^T_i \tilde{a}_{\text{MS}}(\theta_i), \tilde{a}_{\text{US}}(\phi_1, \rho_1) = S^T_{\text{US}} \tilde{a}_{\text{US}}(\phi_1, \rho_1), S_{\text{US}} = [s_{\text{US}}(1), s_{\text{US}}(2), \ldots, s_{\text{US}}(T)] \) and \( q(l) = [e^{j2\pi f_0(T_l - \tilde{\theta}_s)}, e^{j2\pi (2f_0T_l - \tilde{\theta}_s)}, \ldots, e^{j2\pi (Nf_0T_l - \tilde{\theta}_s)}]. \)

Defining \( A, B, \) and \( C, \) and approximating the received signal by Eq. (10) and accepting the effect of the other subcarriers as the additive noise—this will be discussed more at the end of this section—the received signal for all the time frames can be expressed as

\[
Y_m = C(B \otimes A)^T + W_m = QD_a q^T(S^T_{\text{US}} \otimes C^T) + W_m.
\]

In order to obtain a sparse signal problem to be solved by a CS method, we discretize both the AoD–AoA and Doppler shift spaces. The AoD–AoA space is quantized into a \( N_{\text{AD}}^2 \times N_{\text{AA}}^2 \) grid, in which the \( N_{\text{AD}} \) has power 2 since both the elevation and azimuth angles should be defined for each channel tap. The resolution of the discretization for AoD and AoA are defined as \( r_1 = \left[ \frac{180}{N_{\text{AD}}^2} \right] \) and \( r_2 = \left[ \frac{180}{N_{\text{AA}}^2} \right], \) respectively. The nonzero element on that grid defines the AoD and AoA. The Doppler space is quantized into the \( D \) size vector with the \( r_3 = \left[ \frac{f_{\text{max}}}{D} \right] \) resolution, where \( f_{\text{max}} \) is considered to be the maximum possible Doppler Shift. Equation (11) can be redefined as

\[
Y^T_m = \bar{Q} \otimes [(R^T_x \otimes C^T)(\tilde{\gamma})] d + w_m,
\]

where \( \tilde{\gamma} \) is the \( N_{\gamma}N_{\text{E}} \times N_{\text{AD}}^2N_{\text{AA}}^2 \) over-complete matrix of \( \gamma \) that considers all the possible discretized array factor, \( \bar{Q} \) is the \( N \times 2LD \) over-complete matrix of \( Q \) that considers all the possible Doppler shifts \((-D \leq f_1 \leq D)\) and channel tap positions and is defined as

\[
\bar{Q} =
\begin{bmatrix}
    e^{-j2\pi D} & e^{-j2\pi D} & e^{-j2\pi D} & \cdots & e^{-j2\pi D} \\
    e^{-j2\pi D} & e^{-j2\pi D} & e^{-j2\pi D} & \cdots & e^{-j2\pi D} \\
    \vdots & \vdots & \vdots & \ddots & \vdots \\
    e^{-j2\pi D} & e^{-j2\pi D} & e^{-j2\pi D} & \cdots & e^{-j2\pi D} \\
\end{bmatrix}
\]

and \( d \) is a \( 2DLN_{\text{AD}}^2N_{\text{AA}} \times 1 \) vector that its nonzero elements define the AoDs, AoAs, and the Doppler shifts, and the value of the nonzero elements define the complex amplitudes. Since the matrix \( A, \) where \( A = \bar{Q} \otimes [(R^T_x \otimes C^T)(\tilde{\gamma})] \) is an \( NTS \times 2DLN_{\text{AD}}^2N_{\text{AA}} \) matrix, Eq. (12) cannot be solved by a linear algebraic method and a CS approach such as OMP should be applied for solving that equation.

Since the ICI of the OFDM subcarriers is mostly because of their adjacent subcarriers, in order to approximate Eq. (12) with Eq. (13) more accurately, one subcarrier guard interval is inserted before and after each pilot subcarrier. The pilots are scattered among the data according to the proposed method in Ref. [3] in order to increase the accuracy of the CS scheme. Note that in Ref. [2], the AoA and AoD have not been considered.

### 4 M-CS-JPE Scheme

Utilizing MIMO for special coding, the mean power of the LoS tap is significantly stronger than the NLoS taps, and therefore, it is valid to approximate that the received signal is just affected by the first channel tap. By the assumption that the \((\hat{\phi}_1, \hat{\rho}_1)\) and \(\hat{\theta}_i\) are the priori estimated AoD and AoA of the LoS channel tap, the received symbols can be approximated as
\[
Y_m = \alpha_1 \hat{q}(1) [\hat{a}_{US}(\hat{\varphi}_1, \hat{\rho}_1) \otimes \hat{a}_{MS}(\hat{\theta}_1)]^T + O.t_m, \quad (14)
\]

where \(O.t_m\) defines the additive noise and the effect of the NLoS channel taps on the received data and \(\hat{q}(1) = [e^{j2\pi f_1 T_s}, e^{j2\pi (2f_1 T_s - \frac{\pi}{2})}, \ldots, e^{j2\pi (N_f T_s - \frac{\pi}{2})}]\). As a result, \(\alpha_1\) is estimated by an LS procedure as

\[
\hat{\alpha}_1 = \{\hat{q}(1) [\hat{a}_{US}(\hat{\varphi}_1, \hat{\rho}_1) \otimes \hat{a}_{MS}(\hat{\theta}_1)]^T \} \cdot Y_m. \quad (15)
\]

Afterward, the estimated parameters of the LoS tap can be used for reducing its effect on the received data:

\[
\hat{Y}_m = Y_m - \hat{\alpha}_1 \hat{q}(1) [\hat{a}_{US}(\hat{\varphi}_1, \hat{\rho}_1) \otimes \hat{a}_{MS}(\hat{\theta}_1)]^T. \quad (16)
\]

The estimated \(\hat{Y}_m\) would be applied to the same procedure of Eqs. (11) and (12) to obtain the channel parameters of the NLoS taps.

Another modification can be utilized to improve the accuracy of estimating the parameters of the NLoS channel taps. In high Doppler shift conditions, if the Doppler shift resolution \(r_3\) is chosen small (fine resolution), the \(D\) would be large, and therefore, the size of the \(Q\) and \(A\) matrices would be large, which results in the degradation of the CS scheme accuracy and the increment of the computational complexity. On the other hand, if \(r_3\) is chosen large (coarse resolution), the quantization error for the estimated Doppler shifts would be high, which results in the CE accuracy degradation. Our proposed method is to choose \(r_3\) nonuniformly. It is specified in Ref. [21] that the Doppler spectrum of the UAVs has Jake distribution, which indicates higher probability for higher Doppler shifts. As a result, our proposed method considers higher \(r_3\) for lower Doppler shifts and lower \(r_3\) for higher Doppler shifts.

5 FSA Angle Estimation Procedure

It is assumed that the UAV can fly with any arbitrary pitch, roll, and yaw angles. As a result, the elevation and azimuth angles of the channel taps can have different values. The problem is to estimate the elevation and the azimuth angles of the LoS channel tap, \((\varphi_1, \rho_1)\) pair, from the received handshaking signals from the MS to US by the array of antennas that are located on the UAV.

Since the performance of the angle estimation highly depends on the antenna placement, we propose a structure for UAV antennas. The fractal structure with one repetition for locating the receiver antennas is depicted in Fig. 1. Similar to Ref. [18], the distance between each antenna to its adjacent antenna is \(\lambda/4\).

The spatial frequencies along the axes are indicated in Fig. 1 and are defined as

\[
\mu \equiv \tau_2 - \tau_1 = \frac{\pi}{2} \sin(\varphi_1) \cos(\rho_1), \quad (17)
\]

\[
\vartheta \equiv \tau_4 - \tau_1 = \frac{\pi}{2} \sin(\varphi_1) \cos(\rho_1 - 60 \ deg). \quad (18)
\]

**Fig. 1** Fractal structure with one repetition.
where \( \tau_i, i = 1, 2, 4 \) indicates the phase delay of the \( i \)'th antenna. For the structure of Fig. 1, the UAV array factor is obtained as

\[
a_{US}(\phi_1, \rho_1) = [1 \ e^{j\mu} \ e^{j2\mu} \ e^{jv} \ e^{j2v}]^T.
\]  

(19)

The number of antennas that are considered for massive MIMO is >6; therefore, more repetitions of the structure in Fig. 1 can be deployed for antenna locations. The second repetition of the fractal structure is depicted in Fig. 2.

For the structure of Fig. 2, the UAV array factor is obtained as

\[
a_{US}(\phi_1, \rho_1) = [1 \ e^{j\mu} \ e^{j3\mu} \ e^{j4\mu} \ e^{j(\mu+v)} \ e^{j(3\mu+v)} \ e^{j2v} \ e^{j(2\mu+2v)} \ e^{j(3\mu+3v)} \ e^{j4v}]^T.
\]  

(20)

### 5.1 Fractal Structure with One Repetition

Attitude estimation is performed in two steps: LS and MUSIC.

#### 5.1.1 Phase 1, LS

The sensor 1 is assumed to be the reference antenna; therefore, the following equations between the received symbols at the sensors are achieved:

\[
[E_2, E_3, E_5]^T = e^{j\mu}[E_1, E_2, E_4]^T,
\]  

(21)

\[
[E_4, E_5, E_6]^T = e^{j\theta}[E_1, E_2, E_4]^T,
\]  

(22)

where \( E_i, i = 1, 2, \ldots, 6 \) is the correlation of the received symbols at the \( i \)'th receiver antenna, which is obtained as

\[
E_i = \frac{1}{T} \hat{Y}_i^* \hat{Y}_i^*,
\]  

(23)

where \( \hat{Y}_i \) is the received symbol at the \( i \)'th receiver antenna. By applying the LS method for Eqs. (21) and (22), \( \mu \) and \( \theta \) are estimated. Afterward, using Eqs. (17) and (18), the elevation-azimuth pair is estimated and is indicated as \( (\hat{\phi}_1, \hat{\rho}_1) \).
5.1.2 Phase 2, MUSIC

At this stage, MUSIC method utilizes $(\widehat{\phi}_1, \widehat{\rho}_1)$ to obtain more refined estimation of the elevation and azimuth angles. We consider the following points for the implementation of the MUSIC method:

- Instead of searching the whole space for elevation and azimuth angles, only the neighboring values of $(\widehat{\phi}_1, \widehat{\rho}_1)$ would be considered; therefore, the computational complexity decreases considerably.
- Since two angles should be estimated by the MUSIC method, 1-D MUSIC does not result in a single pair of estimated angles. On the other hand, as the antennas are located on triangles not on uniform rectangular array, the 2-D music that is proposed in Ref. [24] would not be practical. As a result, we propose an implementation of the MUSIC by employing the received signals from the antennas that are located on the vertices of the outer triangle.
- For the estimation of $\mu$ and $\theta$, if the exact values of those parameters are small, the estimation error becomes smaller and $(\widehat{\phi}_1, \widehat{\rho}_1)$ angles would be estimated more accurately. As a result, if the distance between the antennas becomes smaller, those angles would be estimated more accurately; however, too small distance causes mutual effect on the antennas, and therefore, the distance between the sensors is set to $\lambda/4$ similar to Ref. [15]. On the other hand, for the MUSIC method, larger distance between the antennas results in better accuracy for angle estimation since the variation of the received signal’s phase for a certain variation in the angle would be larger, and therefore, angles would be estimated more precisely. In conclusion, we employ the received signal of the antennas that are located on the vertices of the outer triangle for the MUSIC procedure.

Each pair of the antennas on the vertices make an antenna array, and the received signal at each array is defined as

\[ X_{q,r} = a_{US_{q,r}}(\phi_1, \rho_1)S + Z_{q,r}, \quad (q, r) \in \{(1, 3), (1, 6), (3, 6)\}, \tag{24} \]

where $X_{q,r}$ is the $2 \times T$ matrix of the received symbols, and $Z_{q,r}$ is the $2 \times T$ matrix of the additive noise to the $r$'th and $q$'th sensors, and $a_{US_{q,r}}(\phi_1, \rho_1)$ is the $2 \times 1$ array steering vector, which is equal to $[1, e^{i2\phi}], [1, e^{i2\theta}], \text{ and } [e^{i2\phi}, e^{i2\theta}]$ for $(q, r)$ equal to $(1, 3), (1, 6),$ and $(3, 6),$ respectively.

Now, we define the MUSIC pseudospectrum as

\[ P_{MU}(\phi_1, \rho_1) = \prod_{(q, r) \in \{(1, 3), (1, 6), (3, 6)\}} \frac{1}{|a_{US_{q,r}}(\phi_1, \rho_1)V_{q,r}V_{q,r}^*a_{US_{q,r}}(\phi_1, \rho_1)|}, \tag{25} \]

where $V_{q,r}$ is the $2 \times 1$ least dominant eigenvector of the correlation matrix of the received symbols in the $(q, r)$'th array. The $a_{US_{q,r}}$ vectors can be written in terms of the $(\phi_1, \rho_1)$ that are in neighboring of $(\widehat{\phi}_1, \widehat{\rho}_1)$. The $(\phi_1, \rho_1)$ pair that maximizes $P_{MU}(\phi_1, \rho_1)$ defines the estimated elevation-azimuth angles and is indicated by $(\widehat{\phi}_1, \widehat{\rho}_1)_2$.

5.2 Fractal Structure with Two Repetitions

In the structure of Fig. 4, the number of equations that can be defined for the LS step is considerably higher compared to the structure of Fig. 1. By considering three set of antennas, $S_1 = \{1, 2, 3, 6, 7, 10\}, S_2 = \{3, 4, 5, 8, 9, 12\}, \text{ and } S_3 = \{10, 11, 12, 13, 14, 15\}$, $S_1$ can be mapped to $S_2$ and $S_3$ by $2\mu$ and $2\phi$ phase shifts, respectively. As a result, the equations that can be defined for the estimation of $\mu$ are obtained from the following four sets of equations:

\[
\begin{align*}
\left[ E_3, E_4, E_5, E_6, E_9, E_{12} \right]^T &= e^{i2\theta}[E_1, E_2, E_6, E_7] \\
\left[ E_4, E_5, E_6, E_9 \right]^T &= e^{i2\mu}[E_2, E_3, E_6, E_7] \\
\left[ E_{11}, E_{12}, E_{13} \right]^T &= e^{i2\phi}[E_{10}, E_{11}, E_{13}] \\
\left[ E_3, E_4, E_5, E_6, E_9, E_{12} \right]^T &= e^{i2\mu}[E_1, E_2, E_3, E_4, E_6, E_7, E_{10}]^T
\end{align*}
\]
Similar procedure can be applied for estimating $\theta$. This increment in the number of equations compared to Eqs. (21) and (22) enhances the performance of the LS procedure considerably. In addition, in the two repetition structures, phase 2 of the attitude estimation procedure, which is MUSIC, performs more accurately compared to the structure in Fig. 1 since the distance between the vertices have been doubled and a little amount of variation in the $(\phi_1, \rho_1)$ pair causes more change in the pseudospectrum. By employing more repetitions of the fractal structure, more accurate attitude estimation procedure would be achieved.

By the assumption that the MS adjust its phase array to obtain the maximum power from UAV, the AoA of the LoS tap is assumed to be 0 deg.

After the estimation of the elevation and azimuth angles, the Doppler shift of the LoS channel tap is estimated as

$$f_1 = \frac{V_U f_c \cos(\phi_1) \cos(\rho_1)}{V_p},$$  \hspace{1cm} (27)

where $V_U$ and $V_p$ are the UAV speed and wave propagation speed, respectively, and $f_c$ is the carrier frequency.

6 Computational Complexity Analysis

Each CE or elevation-azimuth estimation scheme has several steps and the total computational complexity is the summation of those steps. For the elevation-azimuth estimation, we compare our method with the hexagon-shaped seven element array (HSSEA), scheme of Ref. 18. As it is described in Ref. 25, the computational complexity of the OMP method is $O(K^2 S_M)$, where $K$ is the channel sparsity and $S_M$ is the number of the measurement matrix elements.

For the comparison with our CE methods, there is no CE scheme that would be able to estimate the complex amplitude, Doppler shift, AoD, and AoA of the channel taps for the DS MIMO channels simultaneously. As a result, we use the CS-based version of LS and LMMSE methods of Ref. 17 for the comparison. For running those methods, we assume an ideal knowledge of AoD and AoA of the channel taps.

6.1 Elevation-Azimuth Estimation Method

Tables 1 and 2 summarize the steps and the computational complexity of HSSEA and FSA methods, respectively. The reader is referred to Ref. 18 for the description of the HSSEA method.

<table>
<thead>
<tr>
<th>Step</th>
<th>Computational complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Construction of centro-Hermitian matrix</td>
<td>$O(4N_2^2 T + 4N_2 T^2)$</td>
</tr>
<tr>
<td>Calculating the autocorrelation of centro-Hermitian matrix</td>
<td>$O(T^2)$</td>
</tr>
<tr>
<td>Eigenvalue decomposition of the autocorrelation matrix</td>
<td>$O(6N_2^2 + 12N_2)$</td>
</tr>
<tr>
<td>Total</td>
<td>$O(6N_2^2 + 4N_2^2 T + (4N_2 + 1)T^2 + 12N_2)$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step</th>
<th>Computational complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS Eqs. (3) and (4)</td>
<td>$O(2M_p^2)$</td>
</tr>
<tr>
<td>Calculating the autocorrelation matrix Eq. (5)</td>
<td>$O(T^2)$</td>
</tr>
<tr>
<td>MUSIC Eq. (14)</td>
<td>$O[M_2^2(P_a + 3T)]$</td>
</tr>
<tr>
<td>Total</td>
<td>$O[2M_2^2 + T^2 + M_2^2(P_a + 3T)]$</td>
</tr>
</tbody>
</table>
The numerical values of the parameters in Tables 1 and 2 are as follows. Because of the hexagonal antenna structure for the HSSEA scheme, $N_a$ which is the number of transmitter antennas is equal to 7. By considering Eqs. (17) and (26), $M_p$, which defines the size of the LS procedure are 3 and 15 for the structure of Figs. 1 and 2, respectively. The number of antennas in each pair of array in the MUSIC phase is denoted by $M_a$, which is set to 2 in both Figs. 1 and 2 structures. The number of $(\varphi_1, \rho_1)$ pairs that the MUSIC method calculates the pseudospectrum for them is denoted by $P_a$, and it is set to $10 \times 10 = 100$ in this paper since after the estimation of $(\hat{\varphi}_1, \hat{\rho}_1)$, ±5 deg in the neighboring of the estimated angles are considered to be searched with the 0.1-deg resolution.

6.2 CE Methods

6.2.1 LS

This method only consists of two steps. First, the received $\mathbf{N} \times 1$ vectors of the pilots at $T$ time frames are divided into the vectors of the transmitted pilots and those $T$ vectors should be averaged for the sake of noise reduction. Afterward, the OMP is applied for CE. As a result, the computational complexity is obtained as $O(K^2N\bar{N} + T\bar{N} + T)$.

6.2.2 LMMSE

The first step of this approach is the LS scheme. Afterward, the autocorrelation of the time domain channel matrix should be calculated and multiplied to the estimated channel of the first step. Since the complexity of summation with the variance of noise matrix is $N\bar{N}$ and the complexity of matrix inversion is $N^3$, the total computational complexity is obtained as $O(K^2N\bar{N} + T\bar{N} + T + N\bar{N} + N^3)$.

6.2.3 CS-JPE

The size of the measurement matrix is $\bar{N}TS \times 2DLN^2_{AD}N_{AA}$. As a result, the total computational complexity is calculated as $O(2K^2\bar{N}TSDLN^2_{AD}N_{AA})$.

6.2.4 M-CS-JPE

As we discussed before, the complexity of estimating the elevation-azimuth angles of the LoS channel tap would not be considered as the whole computational complexity since the estimation of those angles is critical for UAV control. The steps of this method and the computational complexity of each step are presented in Table 3.

<table>
<thead>
<tr>
<th>Step</th>
<th>Computational complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS procedure for $\alpha_t$ estimation in Eq. (20)</td>
<td>$O(\mathbf{N}^3)$</td>
</tr>
<tr>
<td>Subtraction of two vectors in Eq. (13)</td>
<td>$O(\mathbf{N}TS)$</td>
</tr>
<tr>
<td>CS-JPE procedure for the estimation of the NLoS channel taps</td>
<td>$O[2(K - 1)^2\bar{N}TSDLN^2_{AD}N_{AA}]$</td>
</tr>
<tr>
<td>Total</td>
<td>$O[\mathbf{N}^3 + \bar{N}TS + 2(K - 1)^2\bar{N}TSDLN^2_{AD}N_{AA}]$</td>
</tr>
</tbody>
</table>
7 Performance Analysis and Results

In order to assess the performance of our elevation-azimuth estimation scheme and CE approaches and compare them with the other methods, Monte Carlo simulation is performed using MATLAB in this section.

7.1 Simulation Input Dataset

The AVIRIS Indian Pines hyperspectral data set is employed for the experiment. Figure 3(a) shows a complex of spectral bands in false colors and 3(b) shows 16 major classes of the land cover.

Each element of 220 frequency band matrices of the data cube is represented by 14 bits.

7.2 Data Transmission

Each frequency image is vectorized into a binary stream and transmitted to the OFDM modulation system applying QPSK modulation in each subcarrier. The communication system parameters are summarized in Table 4.

The maximum Doppler shift is calculated by setting the speed of the drone to 100 m/s, which is the maximum speed of the drones in a communication network. According to Ref. 26, the coherence time of the channel is obtained as $T_c = \frac{0.423}{f_{\text{max}}} = 253.29$ µs, which is larger than $T_c$.

![Fig. 3 AVIRIS Indian Pines data set: (a) false color composition and (b) ground truth as a collection of mutually exclusive classes.](image)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_s$</td>
<td>Sampling time</td>
<td>$10^{-7}$ s</td>
</tr>
<tr>
<td>$G$</td>
<td>Length of the cyclic prefix</td>
<td>16</td>
</tr>
<tr>
<td>$f_c$</td>
<td>Carrier frequency</td>
<td>5 GHz</td>
</tr>
<tr>
<td>$f_{D_{\text{max}}}$</td>
<td>Maximum Doppler shift</td>
<td>1.67 kHz</td>
</tr>
<tr>
<td>$N$</td>
<td>Number of subcarriers</td>
<td>128</td>
</tr>
<tr>
<td>$N_\pi$</td>
<td>Number of pilots</td>
<td>20</td>
</tr>
<tr>
<td>$N_a$</td>
<td>Number of transmitters/receivers antennas</td>
<td>6 or 15</td>
</tr>
<tr>
<td>$T$</td>
<td>Number of frames</td>
<td>17</td>
</tr>
<tr>
<td>$S$</td>
<td>Number of combining vectors</td>
<td>17</td>
</tr>
</tbody>
</table>
than the duration for transmission of $T$ OFDM blocks, $T \times (G + T) = 244.8 \mu s$, and therefore, the assumption of constant complex amplitude, Doppler shift, AoD, and AoA for all the channel taps during the transmission of $T$ frames is valid.

7.3 Channel Model

The channel model is selected from the Stanford University Interim (SUI) channel models. Those channels are proposed for three different continental US train types (A, B, and C). Since the height of the transmitter for channel sounding in that article was set to 30 m, the SUI channel models are appropriate for our proposed UAV to ground communication systems in the absence of an experimentally measured wideband air to ground tapped delay line channel model. Channel model SUI 3 is chosen for the simulation since it is measured in dense environments. Because of the beamforming, the model of SUI 3 that is measured with directional antennas is employed for our simulations. The power delay profile of SUI 3 channel model is summarized in Table 5.

Since the bandwidth of the communication system is set to 10 MHz, the length of the tap delay line channel model is 9.

7.4 Data Analysis Parameters

The $N_{AD}$ and $N_{AA}$ parameters are set to 180, while the $D$ is set to 1670, which results in $r_1 = r_2 = r_3 = 1$. In order to appraise the effect of the nonuniform Doppler shift quantization, two circumstances are considered for the M-CS-JPE scheme. In one condition, $D' = D = 1670$ and the method that is obtained in this situation is nominated as M-CS-JPE-uniform in the rest of this paper. In the other condition, $r_3$ is chosen nonuniformly. For 1 to 500 Hz, 500 to 1000 Hz, 1000 to 1670 Hz, $r_3$ is set to 50, 20, 10, and 1, respectively. As a result, $D' = 255$. The M-CS-JPE nomination refers to this second condition.

7.5 Computational Complexity Results

By considering the computational complexities that are defined in Tables 1 and 2, the $R_{EA} = \frac{\text{number of functions for elevation-azimuth estimation method}}{\text{number of functions for the HSSEA method}}$, versus $T$, for the FSA and MUSIC methods are depicted in Fig. 4. For the sake of brevity, the FSA method that utilizes one repetition or two repetitions of the fractal structure are called FSA-S1 and FSA-S2, respectively.

![Fig. 4 $R_{EA}$ versus $T$ for the elevation-azimuth estimation methods.](image-url)
As it is indicated in Fig. 4, the number of functions for running the FSA-S1 method is smaller than the HSSEA method for any $T$ and the number of functions for running the FSA-S2 method is smaller than the HSSEA method for $T > 10$. The number of functions for running the MUSIC method is considerably larger than the FSA-S1 and FSA-S2 methods for any number of $T$, and it is larger than the HSSEA method for $T < 63$.

By considering the computational complexities that are defined in Tables 1 and 2, the \( R_{EA} = \frac{\text{number of functions for CE method}}{\text{number of functions for the LS method}} \) versus $T$ are presented in Fig. 5. In this figure, the curve for LMMSE is not indicated since it is a straight line that its constant value is 100.

As it is observed in Fig. 5, the number of functions for running M-CS-JPE-uniform and M-CS-JPE methods is lower than the CS-JPE scheme, which indicates that the utilization of the elevation-azimuth angles of the LoS channel tap reduces the computational complexity. On the other hand, the lower number of function runs for the M-CS-JPE scheme compared to the M-CS-JPE-uniform method indicates the advantage of nonuniform Doppler shift quantization for computational complexity reduction.

### 7.6 Hyperspectral Image Analysis Scheme

The hyperspectral data classification method of Ref. 19 is utilized in this paper. That process employs subspace-based multinomial logistic regression procedure to learn the posterior probabilities and a pixel-based probabilistic support vector machine classifier to estimate the number of mixed components per pixels. Even under the presence of additive noise, the method is robust for mixed pixel characterization. At the last step, the Markov random field-based regularizer is used to increase the accuracy of the classification.

### 7.7 Performance Evaluation Criterions

We used several criterions to compare the performance of the elevation-azimuth estimation and CE schemes. In each run of the simulation, we calculate and plot the mean square error (MSE) for the channel parameters and bit error rate (BER) of data transmission versus SNR. For the assessment of the CE schemes for the transmission of the hyperspectral data, the overall accuracy (OA) of classification criterion is utilized, which is expressed by

\[
\text{OA} = \frac{1}{N_{\text{test}}} \sum_{n_c=1}^{N_{\text{class}}} m_{n_c,n_c},
\]

where the total number of test samples and the number of classification classes are indicate by $N_{\text{test}}$ and $N_{\text{class}}$, respectively, and the number of pixels that were correctly assigned to class $n_c$ is represented by $m_{n_c,n_c}$.  

![Fig. 5 $R_{CE}$ versus $T$ for the CE methods.](https://example.com/fig5.png)
7.8 Simulation Results

7.8.1 MSE results

The MSE of the elevation-azimuth estimation methods versus SNR is presented in Fig. 6. In this figure, the MSE curves for running only the MUSIC method for the fractal structure with one and two repetitions are not indicated since they completely match with the performance of the FSA-S1 and FSA-S2 methods, respectively. On the other hand, the LS-S1 is indicated in this figure, which represents the performance of the first phase of the FSA method, without applying the MUSIC phase and by the employment of the one repetition of the fractal structure.

As it is indicated in Fig. 6, the performance of the FSA method is considerably better than the performance of the HSSEA method even in the condition that only the first phase of the FSA method is applied. On the other hand, FSA-S2 performs better than the FSA-S1 specifically in low and medium SNR and it is concluded that in very high SNR values, it is not essential to employ higher repetitions of the fractal structure.

The MSE of the CE schemes for complex amplitudes' estimation versus SNR is indicated in Fig. 7.

![Fig. 6 MSE of the elevation-azimuth estimation methods versus SNR.](image)

![Fig. 7 MSE of the CE schemes for complex amplitudes' estimation versus SNR.](image)
As it is indicated in Fig. 7, our proposed methods perform better than the LS and LMMSE schemes although for the last two methods we considered an ideal knowledge of the AoD and AoA of the channel taps. The reason is that the LS and LMMSE schemes do not consider the Doppler shift effect. On the other hand, the M-CS-JPE-uniform and M-CS-JPE methods estimate the channel more accurately compared to the CS-JPE scheme although their computational complexity is lower.

7.8.2 BER results

The BER curves of data demodulation for different CE schemes are indicated in Fig. 8.

As it is observed in Fig. 8, the BER curves obey the same procedure as the MSE curves. Since the LS and LMMSE schemes do not consider the ICI effect, the superiority of our proposed methods to those two schemes for data demodulation is recognized better for the BER curves compare to the MSE curves. It is even recognized from Fig. 8 that the BER of the M-CS-JPE method at 0-dB SNR is lower than the BER of the LS method at 30-dB SNR, which indicates >30 dB figure of merit in SNR for the former method. In addition, although the LS and LMMSE methods would never reach to the BER of <1% OA for any SNR, our proposed methods are able to achieve <1% BER and M-CS-JPE method can obtain <0.1% BER.

7.8.3 Visual classification results

The effect of the different CE methods for data demodulation on the classified hyperspectral image at SNR = 10 dB is presented in Fig. 9.

As it is indicated in Fig. [1], our proposed methods perform better than the LS and LMMSE schemes although for the last two methods we considered an ideal knowledge of the AoD and AoA of the channel taps. The reason is that the LS and LMMSE schemes do not consider the Doppler shift effect. On the other hand, the M-CS-JPE-uniform and M-CS-JPE methods estimate the channel more accurately compared to the CS-JPE scheme although their computational complexity is lower.

Fig. 8 BER versus SNR.

Fig. 9 Classified hyperspectral image at SNR = 10 dB for: (a) LS, (b) LMMSE, (c) CS-JPE, and (d) M-CS-JPE.
The classification OA versus the number of training samples for CE methods for \( \text{SNR} = 10 \) and 30 dB are indicated in Fig. 10.

As it follows from Fig. 10, the classification accuracy curves for the different CE methods is higher for the methods and SNRs, which lead to lower BER. This indicates the importance of accurate CE and high-fidelity data demodulation for hyperspectral image classification. For the maximum number of training samples, the OA for LS method at \( \text{SNR} = 30 \) dB is \( \sim 0.07 \), whereas the OA for M-CS-JPE method at \( \text{SNR} = 30 \) dB is \( \sim 0.67 \), which indicates \( \sim 10 \) times improvement for the latter method. In addition, the only method that leads to the OA of \( >0.5 \) is M-CS-JPE method.

8 Conclusion

In this paper, we proposed a method, which is able to estimate the complex amplitude, Doppler shift, AoD, and AoA of the channel taps for UAV to ground channel model for MIMO-OFDM communication systems and hyperspectral data demodulation. The proposed method, CS-JPE, defines an over-complete grid for all the channel parameters and employs a CS method to estimate those parameters. The simulation results indicate that the CS-JPE method estimate the complex amplitudes of the channel more accurately compared to the conventional methods, i.e., LS and LMMSE, even when those conventional methods employ an ideal information of the AoD and AoA angles. Exploiting the elevation-azimuth angle of the LoS channel tap, we proposed the modified version if the CS-JPE dubbed as M-CS-JPE, which estimates the channel more accurately and with lower computational complexity compared to the CS-JPE scheme. For more accurate performance of the M-CS-JPE scheme, we proposed an elevation-azimuth estimation scheme dubbed as FSA which employs a fractal structure for angle estimation. Simulation results indicate that the proposed M-CS-JPE approach performs considerably better than the other schemes for the demodulation of the hyperspectral image data.

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