

VIRTUAL PILOT SIGNALS FOR MIMO-OFDM SYSTEMS FOR ITERATIVE CHANNEL ESTIMATION

RAGA DIVYA

PG Scholar, Dept. of ECE, Chadalawada Venkata Subbaiah College of Engineering, Tirupati, A.P. **E-Mail:** raga476@gmail.com

DR.V.THRIMURTHULU

Professor, Dept.of ECE, Chadalawada Ramanamma Engineering College, Tirupathi, A.P. **E-Mail:** vtmurthy.v@gmail.com

MS. G. DILLI RANI

Asst. Professor, Dept .of ECE, Chadalawada Ramanamma Engineering College, Tirupathi, A.P. **E-Mail:**gdillirani@gmail.com

ABSTRACT:

The number of transmit and receive antennas in multiinput multi-output (MIMO) systems is increasing rapidly to enhance the throughput and reliability of nextgeneration wireless systems. Benefits of large size MIMO systems, however, can be realized only when the quality of estimated channels is ensured at the transmitter and receiver side alike. In this paper, we introduce a new decision-directed channel estimation technique dealing with pilot shortage in the MIMO-OFDM systems. The proposed channel estimator uses soft symbol decisions obtained by iterative detection and decoding (IDD) scheme to enhance the quality of channel estimate. Using the soft information from the decoders, the proposed channel estimator selects reliable data tones, subtracts interstream interferences, and performs re-estimation of the channels. We have analyzed the optimal data tone selection criterion, which accounts for the reliability of symbol decisions and correlation of channels between the data tones and pilot tones. From numerical simulations, We have shown that the proposed channel estimator achieves considerable improvement in system performance over the conventional channel estimators in realistic MIMO-OFDM scenarios.

Index Terms: Channel estimation, decision directed channel estimation, iterative detection and decoding, joint channel estimation and detection, multi-input multi-output (MIMO), orthogonal frequency division multiplexing (OFDM).

I. INTRODUCTION

Multi-Input multi-output orthogonal frequency division multiplexing (MIMO-OFDM) is a technology widely used in various commercial systems including 3GPP long term evolution (LTE), and IEEE wireless LAN standard. Recently, MIMO-OFDM systems with large number of antennas, referred to as massive MIMO, are of great interest to further improve throughput and reliability of next generation wireless systems. One of major issues in realizing the massive MIMO-OFDM systems is that the amount of pilot signals needed for channel estimation is proportional to the number of the transmit antennas. When the number of transmit antennas is large, pilot signals occupy significant portion of downlink resources, eating out the data throughput significantly. One can consider the reduction of pilot signal density but this is undesirable since it will simply cause the degradation of channel estimation quality, affecting link performance and data throughput eventually.

When the pilot resources are depleted, one can naturally consider the option of using the data signals for the channel estimation purpose. This approach, often referred to as decision-directed channel estimation (DD-CE), uses the decided (sliced) data symbols in the reestimation of channels. There have been a number of approaches related to DD-CE techniques. These include maximum a posteriori (MAP) based channel estimation, expectation maximization (EM)-based joint detection and channel estimation, Kalman filter based soft decision channel estimator. and channel estimation with interference suppression in MIMO channels. Two main concerns of the DD-CE for the MIMO-OFDM systems, not thoroughly addressed in the previous efforts, are the reliability of the detected data symbols and the interstream interference caused by the MIMO transmission.

First, the quality of the estimated channel would not be appealing if the soft statistics of the data tones used for channel re-estimation are not reliable. Second, unlike the pilot symbols, the data symbols in the MIMO-OFDM systems are transmitted simultaneously through multiple transmit antennas so that channel estimation is interfered by the data symbols coming from

ANVESHANA'S INTERNATIONAL JOURNAL OF EMERGING TRENDS IN ELECTRONICS TECHNOLOGY, SOFTWARE ENGINEERING AND COMPUTATIONAL INTELLIGENCE



ANVESHANA'S INTERNATIONAL JOURNAL OF EMERGING TRENDS IN ELECTRONICS TECHNOLOGY, SOFTWARE ENGINEERING AND COMPUTATIONAL INTELLIGENCE

other transmit antennas. Clearly, proper control of these interstream interferences is crucial for effective decision-directed channel estimation.

The primary goal of this paper is to demonstrate that the selective use of data signals, in conjunction with the state of the art iterative detection and decoding (IDD) technique, its the effective means to improve channel estimation quality of the MIMO-OFDM systems. The proposed scheme selects the reliable data tones (henceforth referred to virtual pilots) among all possible data tones, purifies the chosen virtual pilots via interstream interference cancellation, and then performs soft-decision-directed channel estimation. By employing deliberately chosen virtual pilot signals as well as the pilot signals, channel estimation quality and sub sequent detection and decoding quality can be improved substantially.

It is to be noted that when the observation of (reliable) data tones is added to the observation of the pilot tones (see Fig 1), the channel estimator can capture time-frequency variations of channels better and also filter out the interference and noise more effectively. In analysis, we show that data tones our maximizing both the reliability of soft decisions (derived from the a posteriori log-likelihood ratio of data tone) and the correlations of channel gains between pilot tones and data tones improves the channel estimation quality substantially. We also show from numerical simulations in realistic MIMO-OFDM scenarios that the proposed method outperforms the conventional channel estimation methods in terms of the MSE and link level BER performance.

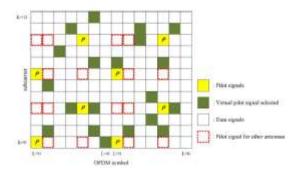


Fig 1: Illustration of virtual pilot signal selection and soft decision-directed channel estimation.

II. CHANNEL ESTIMATION USING VIRTUAL PILOT SIGNAL

In this section, we discussed the channel estimation algorithm that exploits the virtual pilot signals as well as pilot signals in the reestimation of channels. Fig 2 depicts the block diagram of the proposed scheme. Firstly, a posteriori LLRs, obtained by adding anextrinsic LLRs of the MIMO detector and a prior LLRs of the decoder, is converted to the soft symbols. Next, among data tones available in the window, virtual pilot signals are chosen. Virtual pilot signals used for the channel estimation should meet two conditions. First, the quality of virtual pilot signals should be good enough to be used for channel estimation. To meet this condition, clearly, the magnitude of a posteriori LLRs should be large. Second, the channels for the virtual pilot signals should be highly correlated with those for the pilot signals since otherwise virtual pilot signals would not be helpful in improving the quality of channel estimates.

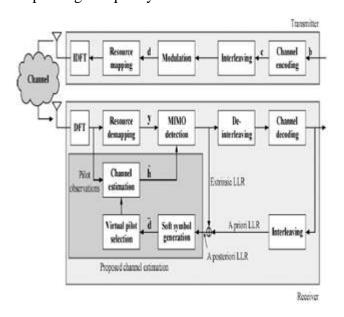


Fig 2: Block diagram of the proposed channel estimation scheme using virtual pilot signals.

Using the selected virtual pilot signals together with the original pilot signals, channel is re-estimated and the newly generated channel estimate is used for the MIMO detection in the next iteration. The proposed algorithm is repeated until suitably chosen termination condition is satisfied.

ANVESHANA'S INTERNATIONAL JOURNAL OF EMERGING TRENDS IN ELECTRONICS TECHNOLOGY, SOFTWARE ENGINEERING AND COMPUTATIONAL INTELLIGENCE EMAIL ID: anveshanaindia@gmail.com, WEBSITE: www.anveshanaindia.com VOLUME 1, ISSUE 1 (2017, JAN/FEB)

ANVESHANA'S INTERNATIONAL JOURNAL OF EMERGING TRENDS IN ELECTRONICS TECHNOLOGY, SOFTWARE ENGINEERING AND COMPUTATIONAL INTELLIGENCE

A. Channel Re-Estimation Using Virtual Pilot Signal

Let N_d be the number of the virtual pilot signals used for the channel estimation, then the virtual pilot observations are expressed as

IJETETSECI

$$y_0^{(r)} = \sum_{i=0}^{T-1} \sqrt{\eta_{d,i}} g_0^{(r,i)} d_0^{(i)} + v_0^{(r)}$$
(1)

$$y_{Nd-1}^{(r)} = \sum_{i=0}^{T-1} \sqrt{\eta_{d,i}} g_{Nd-1}^{(r,i)} + v_{Nd-1}^{(r)}$$
(2)

Where $y_j^{(r)}$ and $v_j^{(r)}$ are the observation and noise received at the r-th received antenna, $g_j^{(r)}$ is the channel gain from the i-th transmit antenna to the r-th receive antenna, $d_j^{(r)}$ is the data signal from the i-th transmit antenna, and $\eta_{d,i}$ is the transmitted power of the data symbols at -th transmit antenna. A vector form of the virtual pilot observations is

$$y_r = \sum_{i=0}^{T-1} \sqrt{\eta_{d,i}} D_i, g_i + v_r \qquad (3)$$

Where

 $y_r = \left[y_0^{(r)}, \dots, y_{N_{d-1}}^{(r)}\right]^T$, respectively. We note that in contrast to the pilot symbols P_t in (8), the data symbols in $\{D_i\}_{i=0}$.

Unknown in a priori to the receiver and hence should be chosen among all available data tones. By stacking pilot observation vector Zr and virtual pilot observation vector Yr, we obtain the observation vector for the channel estimation

$$\begin{bmatrix} Z_r \\ y_r \end{bmatrix} = \begin{bmatrix} \sqrt{\eta_{d,i}}, P_t h_{r,t} \\ \sum_{i=0}^{T-1} \sqrt{\eta_{d,i}}, D_i, g_{r,i} \end{bmatrix} + \begin{bmatrix} n_r \\ v_r \end{bmatrix}$$
(4)
$$\begin{bmatrix} \sqrt{\eta_{d,i}}, P_t h_{r,t} \\ \sqrt{\eta_{d,i}}, D_i, g_{r,i} \end{bmatrix} + \begin{bmatrix} \sum_{i=0, i \neq t}^{T-1} \begin{bmatrix} 0 \\ \sqrt{\eta_{d,i}}, D_i, g_{r,i} \end{bmatrix} + \begin{bmatrix} n_r \\ v_r \end{bmatrix}$$
(5)

Recall that $h_{r,t}$ and $g_{r,t}$ are the channel vectors for the pilot and data signals, respectively. Note that the second term in the right-hand side is the signal not coming from the transmit antenna and hence becomes the interferences in channel estimation of the -the transmit antenna. Since the estimation of channels using this interference-corrupted observation vector is undesirable, using newly updated soft information of data symbols, we cancel the interferences

$$\begin{bmatrix} \tilde{z}_r\\ \tilde{y}_r \end{bmatrix} = \begin{bmatrix} z_r\\ y_r \end{bmatrix} - \begin{bmatrix} \sum_{i=0,i\neq t}^{T-1} \begin{bmatrix} 0\\ \sqrt{\eta_{d,i}}, D_i, g_{r,i} \end{bmatrix}$$
 (6)

Where the estimation of the interstream interferences $\sqrt{\eta_{d,i}D_i}\hat{g}_{r,i}$ is constructed from the soft estimate of the data symbols $\overline{D}_i(\triangleq diag(\left[d_0^{-(i)}, \dots, d_{N_{d-1}}^{-(i)}\right]^T))$ and the channel estimate $\hat{g}_{r,i}$ obtained from the previous iteration. To be specific, if $L(c_{j,0}^{(i)}), \dots, L(c_{j,Q-1}^{(i)})$ are the a posteriori LLRs of Q bits mapped to a data symbol $d_j^{(i)}$ then the first order moment of $d_j^{(i)}$ is

$$\bar{d}_{j}^{(i)} = E\left[d_{j}^{(i)}\right] = \sum_{\theta \in \theta} \theta \prod_{m=0}^{Q-1} \Pr\left(c_{j,m}^{(i)}\right) = \sum_{\theta \in \theta} \theta \prod_{m=0}^{Q-1} \frac{1}{2} \left(1 + c_{j,m}^{(i)} \tanh\left(\frac{1}{2}L\left(c_{j,m}^{(i)}\right)\right)\right)$$
(7)

Where the set Θ includes all possible constellation points. In a similar way, the second order moment of is $d_j^{(i)}$ computed as

$$\begin{split} \bar{\lambda}_{j}^{(i)} &= E\left[\left|d_{j}^{(i)}\right|^{2}\right] = \sum_{\theta \in \theta} \theta \prod_{m=0}^{Q-1} \Pr\left(c_{j,m}^{(i)}\right) = \\ \sum_{\theta \in \theta} \theta \prod_{m=0}^{Q-1} \frac{1}{2} \left(1 + c_{j,m}^{(i)} \tanh\left(\frac{1}{2}L\left(c_{j,m}^{(i)}\right)\right) \right] \end{split}$$

(8) This shows that the proposed channel estimator subsumes the conventional MMSE channel estimator when the soft symbol information is unavailable. It is worth mentioning that the channel estimates the function of the covariance matrix and the soft symbol estimate. As the soft symbol estimate becomes more accurate, therefore, we expect better channel estimation performance.

B. Virtual Pilot Signal Selection Criterion

From our discussion thus far, it is clear that the choice of virtual pilot signals directly affects the quality of channel estimation. Perhaps an ideal way is to compare the performance metric (typically expressed in terms of MSE) for all possible choices of the virtual pilot signals and then choose the set of data tones (say data tones) minimizing the MSE. Since this approach is computationally demanding and hence not so

ANVESHANA'S INTERNATIONAL JOURNAL OF EMERGING TRENDS IN ELECTRONICS TECHNOLOGY, SOFTWARE ENGINEERING AND COMPUTATIONAL INTELLIGENCE

AIJETETSECI VOLUME 1, ISSUE 1 (2017, JAN/FEB)

(ISSN-XXXX-XXXX) ONLINE

ANVESHANA'S INTERNATIONAL JOURNAL OF EMERGING TRENDS IN ELECTRONICS TECHNOLOGY, SOFTWARE ENGINEERING AND COMPUTATIONAL INTELLIGENCE

practical, we instead consider an approach of computing the MSE using only one virtual pilot tone. In this approach, a single data observation together with pilot observations is used to compute the MSE of the data tone. Once the MSE is computed, we choose -best candidates (data tones) with the smallest MSE as virtual pilots. For hypothetical selection of the -the data tone, the MSE metric is defined as

$$\phi(n) \triangleq E \left\| \left[\frac{\mathbf{h}_{r,t}}{g_n^{(r,t)}} \right] - \left[\frac{\mathbf{h}_{r,t}}{\hat{g}_n^{(r,t)}} \right] \right\|^{-1}$$
(9)

$$= \operatorname{tr}\left(\operatorname{Cov}\left(\left[\begin{array}{c}\mathbf{h}_{r,t}\\g_n^{(r,t)}\end{array}\right] - \widetilde{\Omega}_{r,t}\widetilde{\Sigma}_{r,t}^{-1}\left[\begin{array}{c}\mathbf{z}_r\\\tilde{y}_n^{(r)}\end{array}\right]\right)\right)$$
(10)

$$= \operatorname{tr}\left(\operatorname{Cov}\left(\begin{bmatrix}\mathbf{h}_{r,t}\\g_{n}^{(r,t)}\end{bmatrix}\right) - \operatorname{Cov}\left(\widetilde{\Omega}_{r,t}\widetilde{\Sigma}_{r,t}^{-1}\begin{bmatrix}\mathbf{z}_{r}\\\widetilde{y}_{n}^{(r)}\end{bmatrix}\right)\right)$$
(11)

$$= \operatorname{tr}\left(\operatorname{Cov}\left(\begin{bmatrix}\mathbf{h}_{r,t}\\g_n^{(r,t)}\end{bmatrix}\right) - \widetilde{\Omega}_{r,t}\widetilde{\Sigma}_{r,t}^{-1}\widetilde{\Sigma}_{r,t}\widetilde{\Sigma}_{r,t}^{-1}\widetilde{\Omega}_{r,t}^{H}\right) (12)$$

$$= \operatorname{tr}\left(\operatorname{Cov}\left(\begin{bmatrix}\mathbf{h}_{r,t}\\g_n^{(r,t)}\end{bmatrix}\right) - \widetilde{\Omega}_{r,t}\widetilde{\Sigma}_{r,t}^{-1}\widetilde{\Omega}_{r,t}^{H}\right), \quad (13)$$

Where

$$\begin{split} \widetilde{\Omega}_{r,t} &= \operatorname{Cov}\left(\begin{bmatrix} \mathbf{h}_{r,t} \\ g_n^{(r,t)} \end{bmatrix}, \begin{bmatrix} \mathbf{z}_r \\ \widehat{y}_n^{(r)} \end{bmatrix} \right) \\ &= \begin{bmatrix} \sqrt{\eta_{p,t}} C_{h_t,h_t} \mathbf{P}_t^H & \sqrt{\eta_{d,t}} C_{h_t,g_t} \left(\overline{d}_n^{(t)} \right)^* \\ \sqrt{\eta_{p,t}} C_{g_t,h_t} \mathbf{P}_t^H & \sqrt{\eta_{d,t}} C_{g_t,g_t} \left(\overline{d}_n^{(t)} \right)^* \end{bmatrix} \end{split}$$
(14)

And

$$\begin{split} \widetilde{\Sigma}_{r,t} &= \operatorname{Cov}\left(\begin{bmatrix} \mathbf{z}_{r} \\ [\widetilde{y}_{n}^{(r)} \end{bmatrix} \right) \\ &= \begin{bmatrix} \eta_{p,t} \mathbf{P}_{t} C_{h_{t},h_{t}} \mathbf{P}_{t}^{H} + I & \sqrt{\eta_{p,t} \eta_{d,t}} \mathbf{P}_{t} C_{h_{t},g_{t}} (\overline{d}_{n}^{(t)})^{*} \\ \sqrt{\eta_{p,t} \eta_{d,t}} \overline{d}_{n}^{(t)} C_{g_{t},h_{t}} \mathbf{P}_{t}^{H} & \sum_{i=0}^{T-1} \eta_{d,i} \lambda_{n}^{(i)} + 1 \end{bmatrix}, \end{split}$$
(15)

In the high signal to noise ratio (SNR) regime

$$\phi(n) \approx \Psi + \frac{\left(1 - \frac{1}{\xi} \eta_{d,t} |\overline{d}_n^{(t)}|^2\right) \left(1 - \|C_{h_t,g_t}\|^2\right)}{1 - \frac{1}{\xi} \eta_{d,t} |\overline{d}_n^{(t)}|^2 \|C_{h_t,g_t}\|^2} = \Psi + \frac{1}{\frac{1}{1 - \frac{1}{\xi} \eta_{d,t} |\overline{d}_n^{(t)}|^2} + \frac{1}{1 - \|C_{h_t,g_t}\|^2} - 1}$$
(16)

Noting that is not related to the data tone selection, one can observe that the data tone minimizing is one maximizing the denominator of the second term in (16). In light of this, the resulting cost metric becomes

$$\tilde{\phi}(n) \triangleq \frac{1}{1 - \frac{|\overline{d}_{n}^{(t)}|^{2}}{\sum_{i=0}^{T-1} \eta_{d,i} \lambda_{n}^{(i)} + 1}} + \frac{1}{1 - \|C_{h_{t},g_{t}}\|^{2}} \qquad (17)$$

The proposed scheme is a cubic function in the number of all pilot signals being used (real virtual pilot signals). In and a real implementation, therefore, we need to choose the number of the virtual pilots so that the resulting system does not violate the computational requirements.

III.SIMULATIONS

In this section, we compare the performance of the proposed channel estimation technique with the conventional approaches through numerical simulations.

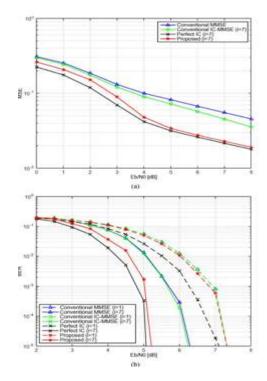


Fig 3: Performance of the conventional and proposed scheme for MIMO systems: (a) MSE and (b) BER.

ANVESHANA'S INTERNATIONAL JOURNAL OF EMERGING TRENDS IN ELECTRONICS TECHNOLOGY, SOFTWARE ENGINEERING AND COMPUTATIONAL INTELLIGENCE

EMAIL ID: <u>anveshanaindia@gmail.com</u>, WEBSITE: <u>www.anveshanaindia.com</u>



VOLUME 1. ISSUE 1 (2017, JAN/FEB)

(ISSN-XXXX-XXXX) ONLINE ANVESHANA'S INTERNATIONAL JOURNAL OF EMERGING TRENDS IN ELECTRONICS TECHNOLOGY, SOFTWARE ENGINEERING AND COMPUTATIONAL INTELLIGENCE

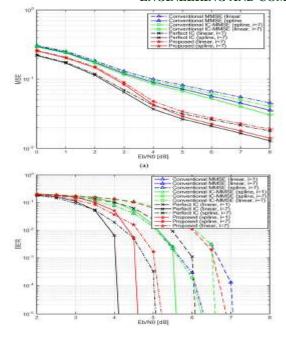
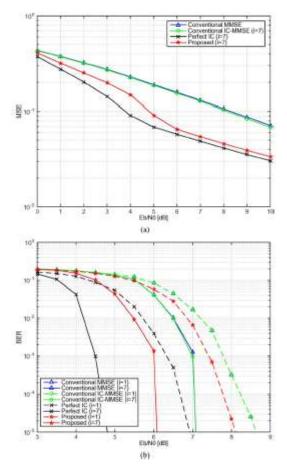
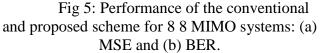


Fig 4: Performance of the conventional and proposed scheme with spline cubic interpolation: (a) MSE and (b) BER.





VI. CONCLUSIONS

In this paper, we proposed a new channel estimation algorithm to deal with the pilot shortage problem in MIMO-OFDM systems. By using the *reliable* data tones highly correlated with the pilot signals for the channel estimation, the proposed method achieves better channel estimation quality at data tone and eventual performance improvement. While our focus in this work was primarily on the OFDM based MIMO system, the main concept can be readily applied to non-OFDM various wireless systems such as single-carrier MIMO systems, channel interference-limited estimation under environments (e.g., hot spots). Also, the extension of the proposed scheme to the multiuser MIMO (MU-MIMO) scenario employing demodulation reference signals (DM-RS) is an interesting direction worth investigation.

Since the DM-RS, used for the demodulation of MU-MIMO in LTE-Advanced systems, is present only for the user being serviced, it is compactly assigned to the small number of resource blocks. Besides, since the DM-RS is mainly targeted for the demodulation of data symbols for MU-MIMO scenario, the pre-coding has been used to remove the inter user interference. Due to these reasons, we expect that the residual interference in the received signal at data tones would be smaller than the residual interference (interstream interference) for the single-user MIMO (SU-MIMO) system and the proposed scheme might provide better gain than what SU-MIMO offers. We leave these interesting explorations for our future work

ACKNOWLEDGMENT

I would like to thank to Dr.V. Thrimurthulu, for his outstanding support and also we would like to express gratitude to my guide G.Dilli Rani for their technical advice.

REFERENCES

[1] J. Gao and H. Liu, "Decision-directed estimation of MIMO time-varying Rayleigh fading channels," IEEE Trans. Wireless Commun., vol. 4, pp. 1412-1417, Jul. 2005.

ANVESHANA'S INTERNATIONAL JOURNAL OF EMERGING TRENDS IN ELECTRONICS TECHNOLOGY, SOFTWARE ENGINEERING AND COMPUTATIONAL INTELLIGENCE

EMAIL ID: anveshanaindia@gmail.com , WEBSITE: www.anveshanaindia.com

ALJETETSECI

VOLUME 1, ISSUE 1 (2017, JAN/FEB)

(ISSN-XXXX-XXXX) ONLINE

ANVESHANA'S INTERNATIONAL JOURNAL OF EMERGING TRENDS IN ELECTRONICS TECHNOLOGY, SOFTWARE

ENGINEERING AND COMPUTATIONAL INTELLIGENCE [2] C. Georghiades and J. Han, "Sequence estimation in the presence of random parameters via EM algorithm," IEEE Trans. Commun., vol. 45, pp. 300-308, Mar. 1997.

[3] H. Zamiri-Jafarian and S. Pasupathy, "EM-based recursive estimation of channel parameters," IEEE Trans. Commun., vol. 47, pp. 1297-1302, Sep. 1999.

[4] C. H. Aldana, E. de Carvalho, and J. M. Cioffi, "Channel estimation for multicarrier multiple input single output systems using the EM algorithm," IEEE Trans. Signal Process., vol. 51, pp. 3280-3292, Dec. 2003.

[5] J. Ylioinas and M. Juntti, "Iterative joint detection, decoding, and channel estimation in Turbo-Coded MIMO-OFDM," IEEE Trans. Veh. Technol., vol. 58, pp. 1784-1796, May 2009.

[6] S. Song, A. Singer, and K. Sung, "Soft input channel estimation for turbo equalization," IEEE Trans. Signal Process., vol. 52, pp. 2885-2894, Oct. 2004.

[7] R. Otnes and M. Tuchler, "Soft iterative channel estimation for turbo equalization: Comparison of channel estimation algorithms," in Proc. Int. Conf. Commun. Syst., Singapore, Nov. 2002, pp. 72-76.

[8] D. Yoon and J. Moon, "Soft-decision-driven channel estimation for pipelined turbo receivers," IEEE Trans. Commun., vol. 59, pp. 2141–2151, Aug. 2011.

[9] M. Munster and L. Hanzo, "Parallel-interferencecancellation-assisted decision-directed channel estimation for OFDM systems using multiple transmit antennas," IEEE Trans. Wireless Commun., vol. 4, pp. 2148-2162, Sep. 2005.

[10] M. Jiang, J. Akhtman, and L. Hanzo, "Iterative joint channel estimation and multi-user detection for multipleantenna aided OFDM systems,



AUTHORS

Raga Divya is currently pursuing M.Tech degree .in Digital Electronics & Communication Systems at Chadalawada Venkata Subbaiah College of Engineering Tirupathi (A.P), India. She received her B.Tech degree in Electronics & Communication Engineering from JBTUA, A.P her area of Engineering from JBTUA, A.P, India Her area of research is Wireless communication Design.



V. Dr. Thrimurthulu is currently working as Professor and Head of ECE Department at CR Engineering College, Tirupathi, India. He received his Graduation in Electronics & Communication of Electronics Institute &

Engineering from Telecommunication Engineering, New Delhi and M.E (Microwaves and Radar Engineering) from University College of Engineering, Osmania University, Hyderabad. He has done his Ph.D in Philosophy from Central University. He has done his research work on Ad-Hoc Networks. He has presented and published more than 20 papers in various National & International Journals



Ms.G.DilliRani is currently working as Assistant Professor in the Department of Electronics & Engineering Communication at Chadalawada Ramanamma Engineering College, Tirupati, India

.She has 7 years of teaching experience. Her's extensive education includes B.Tech from SIET Puttur, from JNTU Hyderabad University, plus M.Tech in SIET Puttur, A.P, India. She is making research in the field of Biomedical Signal Processing.