Adaptive Channel Estimation in VLC for Dynamic Indoor Environment

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ABSTRACT
The channel of indoor VLC system is usually considered static for ease in most of the cases however in a real-world scenario, the changing effect due to people density, shadowing, dimming, background lights and interiors create dynamism in the VLC channel albeit with slow variation. Thus, the channel time-varying effect cannot be ignored entirely in modeling the VLC system. The impact of the dynamic channel can't be mitigated just by increasing LED transmission power. Fortunately, a possible alternative way is to estimate the channel state information (CSI) in dynamic VLC environment. This paper considers a dynamic VLC environment where a decrease in the normalized received power follows Rayleigh distribution. In this paper, we propose the estimation of the channel coefficients using variants of least mean square (LMS) algorithm such as normalized (NLMS), zero attracting (ZA-LMS), block (BLMS) and fast block (FBLMS). This paper tests the suitability of adaptive algorithms in terms of mean square error (MSE) and tap-weights convergence, computational complexity and the number of pilot symbols required in VLC dynamic channel. FBLMS and NLMS perform better in comparison to other algorithms as observed from results obtained. At lower people density in FBLMS and NLMS the difference in the number of MSE convergence samples is less compared to the higher people density as FBLMS converges faster to ideal zero MSE than NLMS.
Keyword: VLC, LMS, MSE, CSI.

1. INTRODUCTION

Nowadays, due to higher constraint in the radio frequency (RF) wireless spectrum, visible light communication (VLC) is considered to alleviate the burden of RF wireless communication. VLC can provide illumination and communications simultaneously which can complement conventional RF wireless communication. VLC offers huge unlicensed bandwidth; hence data can be transmitted at a very high rate which is an attractive and economical choice for network providers. It has many other advantages over RF communication such as more security and less power consumption supporting green communication [1]. Along with the above benefits, VLC does not meddle with the gadgets and environments sensitive to RF waves, for instance, inside planes, emergency clinics, refineries, gas and chemical chambers, and so forth. VLC works on less complex intensity modulation and direct detection (IM/DD) method, unlike traditional RF modulation and demodulation technique [2]. In VLC, the transmitters (Txs) are light emitting sources, and the receivers (Rxs) are light detectors. Usually, light emitting diodes (LEDs) act as Tx due to its low-cost and low energy consumption property and photo-detectors (PDs) as Rx. The light intensity of the LED varies by the input bits, and the PD detect these variations by generating the electrical signal with respective light responsivity.

The operation of any communication system is highly dependent on the channel behavior. VLC channels generally do not have the multipath fading effect. VLC channel may act as a frequency selective channel only when the LED modulation bandwidth exceeds B_c (channel coherence bandwidth), due to dispersion [3]. This uncertainty if not estimated correctly leads to an inaccurate analysis of the VLC communication system. In VLC, with changing Tx-Rx distances, different scenarios such as office, corridors, room, different people density with mobility and various furniture setup may lead to a noticeable ISI at higher data transmission rates [4]. These channel characteristics will distort the signal received at the receiver so it is important to accurately estimate the slow time-varying channel and compensate at the receiver for reliable communication. Therefore, channel estimation is required to impart channel information to the detector within coherence time [5]. Also, the maximum data transmission rate should be within the coherence bandwidth of the VLC dynamic channel. This paper analyses the suitability of the different types of LMS estimation algorithms for estimating the VLC dynamic channel for an indoor environment.

The rest of the paper is organized as follows. Section 2 describes the VLC dynamic channel considered in this paper. Section 3 presents various LMS based algorithms for channel estimation. Section 4 provides the simulation results with discussion on results. Finally, section 5 concludes the paper.

2. VLC CHANNEL MODEL

The indoor VLC channel DC gain for line of sight (LOS) and non-LOS (NLOS) link is as follows:

$$H_{LOS}(0) = \frac{(m+1)A}{2\pi D_d^2} \; cos^m(\theta)\, T_s(\phi)\, g(\phi) \cos(\phi) \tag{1}$$

$$H_{NLOS}(0) = \frac{(m+1)A}{2\pi^2 D_1^2 D_2^2}\ \rho dA_{wall}\ cos^m(\theta)\cos(\alpha)\cos(\beta)T_s(\phi)\ g(\phi) \tag{2}$$

where, $H_{LOS}(0)$ and $H_{NLOS}(0)$ is the VLC channel DC gain for LOS and NLOS link respectively. These gain equations follows only when ϕ (angle of incidence) is greater than 0 and less than equal to the receiver half angle FOV (ϕ_c). A is the area of the receiver, m is the Lambertian order of the transmitter, θ is the semi-angle at half illuminance of the transmitter, and D_d the distance between the Tx and the Rx. $T_s(\phi)$ is the optical filter, $g(\phi)$ is the concentrator gain, D_1 is the distance between Tx and the wall, D_2 is the distance between the wall and Rx, ρ is the reflection coefficient of the wall, dA_{wall} is the size of wall area, β is the irradiance angle and α is the receiving surface angle [6]. The total received power at the receiver considers both LOS and NLOS component. The received power P_{Rx} is expressed in (3) in terms of transmitted power P_{Tx} for q LEDs [6].

$$P_{Rx} = \sum_q \left(P_{Tx}\, H_{LOS}(0) + \int_{wall} P_{Tx}\, H_{NLOS}(0) \right) \tag{3}$$

The mobility of people within a room certainly affect the channel characteristics expressed in (1) and (2). The movement of the users inside a room can be modelled using effective people density (people/m^2). The authors in [4] take VLC channel based on (3) to simulate the effect of shadowing and blocking of the signal path due to obstacles present in the room. In the VLC channel with user movement, a decrease in the normalised received power can be empirically modelled to follow Rayleigh distribution given by the following equation:

$$p(x) = \frac{x}{\sigma^2}\exp\left(-\frac{x}{2\sigma^2}\right) \tag{4}$$

where, x is the decrease in normalised received power and σ represents the scale parameter. The scale parameter varies with the effective people density inside the room. For example, in a furnished room with effective people density of 1.11 people/m^2, σ is 1.77 and in the case of non-furnished room with effective people density of 0.17 people/m^2 and 0.37 people/m^2, σ is 0.98 and 1.33 respectively.

This work aims to look for the best suitable LMS algorithm for VLC dynamic channel estimation. The coherence time plays an important role in deciding the number of pilot symbols to estimate a channel. The coherence time of the channel can be calculated using the 50% coherence time formula $\tau_c = \frac{0.423\times c}{vf}$, where c is the speed of light and f is the transmitted signal frequency [7]. v, is the mobility of user which is considered maximum i.e. 5km/hr for a normal indoor office environment. The coherence bandwidth B_c of the VLC dynamic channel changes with people density due to change in the rms delay spread [4]. B_c puts an upper bound to f and data rate R_b for a flat channel. Taking $f = B_c$, the coherence time of the VLC channel can be calculated. For, an office room B_c changes from 25MHz to 19MHz for an empty room to highest people density (1.11people/m^2) considered in [4]. Hence, as the people density increase the coherence bandwidth B_c decreases, and the coherence time increases from 3.65s to 4.8s. Therefore, the number of samples (M) required to estimate the channel should satisfy, $M \ll (R_b \times \tau_c)$.

3. LMS ADAPTIVE ALGORITHM

This section describes the various adaptive filters based on least mean square algorithms to estimate the channel coefficients. The output of the adaptive filter is $y = w^H x$, where, w is the weight coefficient and x is the input signal. The error signal of a filter is $e(i) = d(i) - y(i)$, $d(i)$ is the desired response signal. The tap weights are time varying as they are functions of the time index i. The adaptive algorithms are simulated as adaptive filters of Q-tap. The $(i+1)th$ iteration i.e. $w(i+1)$ depends on $(i)th$ iteration tap-weight, w is increased and estimated in such a way that it minimises the error to ideal zero. μ as shown in (5, 6, 7, 8, 9) is the step-size parameter of the respective algorithms [8]. The basic LMS algorithm remain stable when $0 < \boldsymbol{\mu} < \frac{2}{tr[R]}$, where $tr[R]$ is the trace of the autocorrelation matrix $R = E\{x(i)x^H(i)\}$ [10]. For LMS upper bound on μ comes out to be 2. Further, for all other LMS variants used in this paper the upper bound on μ is greater than the basic LMS μ upper bound. The choice of step-size μ affects the MSE convergence of the adaptive algorithms, for each iteration larger μ causes more change in the tap-weights thereby reducing error more rapidly, however the reduced error fails to approach the ideal solution whereas, smaller μ changes the tap-weights very slowly to approach resulting error to an ideal solution but is computationally exhaustive and MSE converges to a higher M value [10]. For fair comparison, the value of M is taken at 1x10^{-3} MSE. μ is selected differently for different algorithms within the practical bounds so as to ensure MSE convergence at 1x10^{-3} and tap-weights stability at the least number of pilot symbols.

Least mean square (LMS): It is the most basic and commonly used algorithm. Tap-weights are constantly modified with $\boldsymbol{\mu} = 1$. The LMS algorithm adjusts w, so that e is minimized in the mean-square logic.

$$w(i+1) = w(i) + \boldsymbol{\mu} e(i)x(i) \tag{5}$$

Normalized LMS (NLMS): It considers the signal level variation at the filter input by selecting a normalised step-size parameter which results in stability and fast convergence. Here, $\boldsymbol{\mu}$ is chosen to be 0.1. δ is a small positive constant i.e., 0.1 and $\|x(i)\|$ is the Euclidean norm.

$$w(i+1) = w(i) + \frac{10\,\boldsymbol{\mu}}{\delta + \|x(i)\|^2}\, e(i)x(i) \tag{6}$$

Zero attracting LMS (ZA-LMS): It is a special case of the regularised LMS family [9] where it favours sparsity in the input signal. For signum function, $sgn(x) = 0$ if $x = 0$ and $sgn(x) = x/|x|$ if $x \neq 0$. $\rho = \boldsymbol{\mu\varepsilon}$ is the weight assigned to the penalty term, where $\boldsymbol{\mu}$ = 1.5 and $\boldsymbol{\varepsilon}$ (positive constant) = 0.002.

$$w(i+1) = w(i) + \boldsymbol{\mu} e(i)x(i) - \rho sgn(w(i)) \tag{7}$$

Block LMS (BLMS): In this case, the tap-weights updates on blocks. The kth block and the sample time i relates as, $i = kL + i,\ i = 0, 1, \dots L-1$ & , $k = 1, \dots L$ where $L = 10$ is the block length assumed in the algorithm. $\boldsymbol{\mu}$ = 0.5 is considered [10].

$$w(i+1) = w(i) + \boldsymbol{\mu} \sum_{j=0}^{L-1} x(iL+j)\, e(iL+j) \tag{8}$$

Fast block LMS (FBLMS): It is a computationally efficient BLMS algorithm where tap-weights are adapted in the frequency domain. For $W(i) = FFT([w^T(i),\ [0]_{m\times 1}^T\ ]^T)$, N-point FFT is used such that $N = 2m$. $\varphi(i)$ consists of the first m elements of $IFFT(X(i) \odot W(i))$, where $\odot$ is the Schur product operator. $X(i)$ is the FFT of $x(t)$, where $t = im - m, \dots, im + m - 1$ [10]. The block length is 120 and the step-size is 0.04. The tap-weights w from eq. 10 in the time domain are finally plotted with respect to number of samples.

$$W(i+1) = W(i) + \boldsymbol{\mu}\, FFT \begin{bmatrix} \varphi(i) \\ 0 \end{bmatrix} \tag{9}$$

$$w = IFFT(W) \tag{10}$$

The block diagram of the proposed work is shown in Fig. 1. To the best of authors' knowledge, the VLC dynamic channel has not yet been estimated in literatures till date with such varieties of LMS adaptive algorithms.

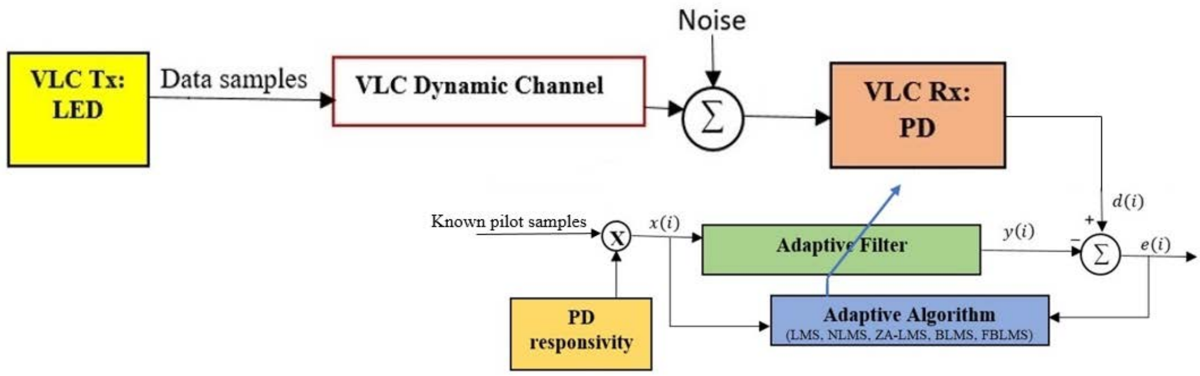

Figure 1. Block diagram of the proposed work.

4. RESULTS AND DISCUSSIONS

This paper presents simulation results of the proposed work inside a standard office room size of 6 m × 7 m × 3 m. LED is kept "ON" to send pilot samples as long array of "1s" after that data is modulated in OOK. The responsivity of the PD is considered 1 ideally. The increasing people density inside an office room increases the number of pilot symbols required to estimate the channel as seen in Fig. 2 (a, b, and c). The tap-weight convergence value of the filter also increases with increase in people density as observed in Fig. 3 (a, b, and c).

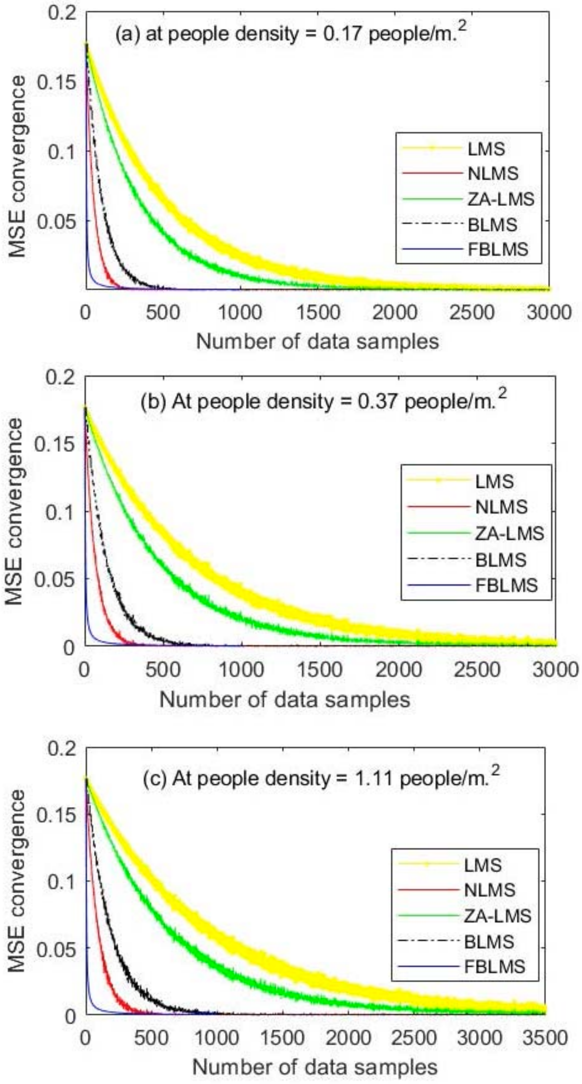

Figure 2. MSE convergence of the different channel estimations in VLC dynamic channel having people density (a) 0.17 people/m^2, (b) 0.37 people/m^2, (c) 1.11 people/m^2.

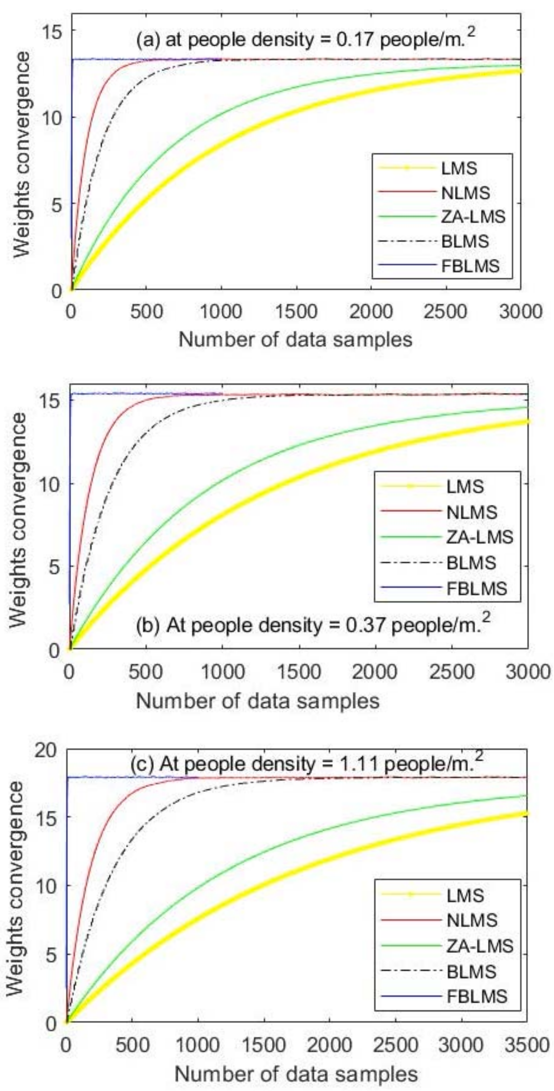

Figure 3. Filter weights convergence for different channel estimators in VLC dynamic channel having people density (a) 0.17 people/m^2, (b) 0.37 people/m^2, (c) 1.11 people/m^2.

Table 1 shows M, the number of data samples or iterations at which MSE is of order 1×10^{-3}. The disadvantage of the basic LMS algorithm is that it is sensitive to input signal $x(i)$ amplitude level which is responsible for higher values of M and T_R. ZA-LMS works better for sparse input signals which is not the case here. NLMS solves the problem of varying input by normalising with the power of the input, hence it gives better performance in this work. BLMS can perform like NLMS in terms of M if the step-size is increased to 1, it can perform better than NLMS if the block size increased to higher values but the fall in convergence is steep with higher error floor . Also, for tap-weights the convergence is very fast in FBLMS than any other algorithm due to estimation in blocks of samples in frequency domain. NLMS, BLMS, ZALMS and LMS tap-weights converges a little beyond their respective MSE convergence iteration number (referred as M in this paper) as they all are adapted in time domain. The computation complexity of the algorithms are quoted in the table and its ratio w.r.t. standard LMS algorithm is calculated for a filter of 120-tap weights and sample block length, L = 120. As L increases beyond 39, the frequency domain LMS becomes superior to conventional LMS [11]. It is observed from Table 1 that finally FBLMS is the best choice as MSE converges very fast, the change in M is not much with the change in people density and the computational complexity is the least [12]. Therefore, in a VLC dynamic channel where the people density will change significantly, taking M = 300 will estimate the varying channel accurately

Table 1. The number of MSE convergence iterations in estimating VLC channel with varying people density and the computation complexity of the respective estimation algorithms.

Adaptive Algorithms	People density (0.16 people/m^2)	People density (0.37 people/m^2)	People density (1.11 people/m^2)	Computational complexity for a block of L samples in one iteration*	Complexity ratio w.r.t. standard LMS
	M	*M*	*M*	Multiplication	*for Q=L=120*
LMS	2700	3000	3500	$(2Q+1) \times L$	1
NLMS	300	400	570	$(3Q+1) \times L$	1.5
ZA-LMS	1700	2450	3450	$(2Q+3) \times L$	1.008
BLMS	480	750	1000	$(2Q \times L+1)$	0.995
FBLMS	200	240	300	$10L \times \log_2(L) + 26L$	0.394

*In order to have fair comparison between all algorithms, the computational complexity per sample per iteration is converted to per block (L samples per block) per iteration for calculating complexity ratio [11]. Q is the number of taps in a filter.

5. CONCLUSION

VLC in an indoor office environment with dynamic channel characteristic requires a suitable adaptive filter to estimate the channel. The number of samples needed to estimate depends highly on people density in a dynamic VLC environment. FBLMS and NLMS have better error and tap-weights convergence with respect to number of samples. The difference in the number of samples for convergence at lower people density in FBLMS and NLMS is less. However, at increased people density FBLMS converges much faster to ideal zero MSE than NLMS. It is obvious from the results that FBLMS is the most computationally efficient algorithm among LMS, NLMS, ZA-LMS and BLMS for dynamic VLC channel considered in the paper. NLMS may be a better option if one wants to estimate channel in time domain only with a little bit more complexity.

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