



Convergence analysis of RMSE optimization power adaptation algorithms for wireless image transmission

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ABSTRACT

Convergence plays an important role in optimization of error. In this paper, Convergence is analyzed in terms of power with respect to Root Mean Square Error. Power Adaptation Algorithms are implemented on image transmission and the convergence is analysed. Distance Based Power Adaptation Algorithm outperforms compared with the other algorithms.

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Introduction

Multimedia communication deals with the services of discrete media data such as text, graphics and continuous media data like audio and video, over digital networks. It involves software and hardware design for capturing, processing, storing, disseminating, editing, reusing, and managing different types of digital media sources over a diversity of devices and transmission media to assure different application requirements. These systems are paying much attention during the last few years in the society all together and in the information technology field [1]. To facilitate access to information such as audio and video data, techniques are to be developed that allow handling of audio-visual information in computer and communication systems. Multimedia transmission has to handle a range of compressed and uncompressed signals such as data, text, image, audio, and video. The system has to become accustomed to the worst channel conditions also, as the error rates are high on wireless channels [2].

Typical systems for multimedia applications like video, image, audio etc., have to be transmitted by means of wireless channels. In the future there will be much interest to make a variety of applications available in the mobile environment. Therefore, future mobile systems are expected to provide a raw channel accessible for the bits. This channel is characterized by low delay, frequent bit errors and high Bit Transmission Rate (BTR), as interleaving and channel coding is not applied. Using the channel conditions the applications can be adjusted individually to the transmission condition in terms of BTR, BER and delay. Error robust applications, including error robust source coding, adapted channel coding, or combined source and channel coding and decoding, might be used on this end-to-end connection [3].

The reliability of the information used in channel decoders gets lost, as only binary 0 and 1, but no soft information is available. Additionally, unnecessary bandwidth extension is added due to improved error robustness for all connections in between, as the complete redundancy is transported end to end. For common services like speech or video transmission, source and channel coding might be adapted for each point-to-point transmission. Both source and channel coding modules are included in the same processing block in order to optimize the overall performance. Adaptation to different sources and channels is nearly impossible or at least not optimized. This procedure is the most bandwidth efficient [4-8].

System Model

Efficient use of power in multimedia communications is becoming more and more critical and complex, particularly when multimedia signal processing is integrated. Since high capacity wireless systems are interference-limited, it is essential to adjust power of the transmitted bits to ensure signal integrity.

The system used is a typical QPSK digital communication system for multimedia transmission. The signal is sampled, quantized and then coded into binary bits for transmission. Initially source encoding is applied to transform the image to digital form using a conventional method (Fig 1.1). Then signal is sampled, quantized, and then coded into binary bits for transmission over the QPSK system. Each sample is coded into M bits. The power adaptation algorithms are applied to the coded bit stream after source coding. The data is first de-multiplexed into N parallel streams, with each stream having the bits of similar importance from different samples; i.e. Most Significant Bit (MSB) are grouped together, then next MSB etc. All bits in the same stream from different pixels having the same significance are assigned the same amount of energy.

The primary task of a source coding is to represent a signal with the minimum number of binary symbols without exceeding an acceptable level of distortion, which is determined by the application [9-10]. Gray coding is used in the simulation of the proposed algorithms.

The process by which information symbols are mapped to alphabetical symbols is called source coding. The mapping must be performed in such a manner that it guarantees the exact recovery of the information symbol back from the alphabetical symbols otherwise it will destroy the basic theme of the source coding. It is the process of removing redundancy from the source symbols, which essentially reduces data size. Source coding is a vital part of any communication system as it helps to use transmission bandwidth efficiently. Two types of source coding techniques are characteristically named:

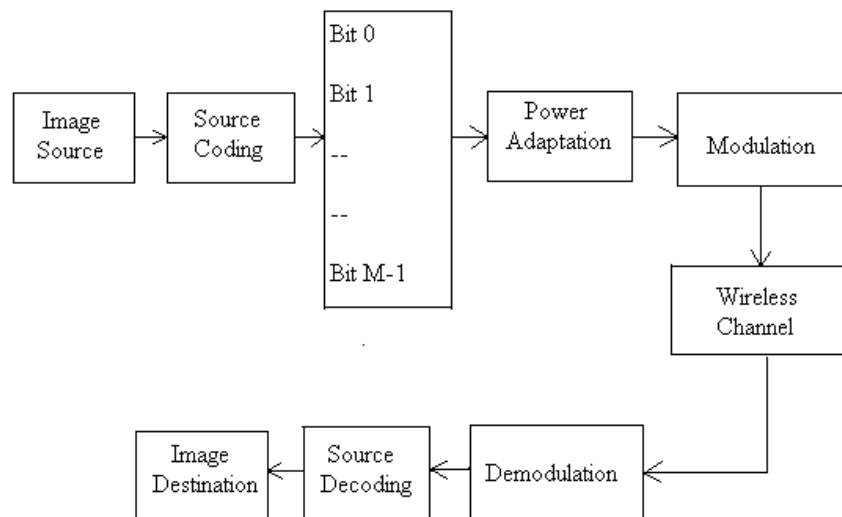


Fig. 1.1 Block diagram showing system model

The conditional probability of error of $\mathbf{b}[1]$ is the same, regardless of which symbol is conditioned on. Moreover, exactly the same analysis holds for $\mathbf{b}[2]$, except that errors are caused by the noise random variable \mathbf{N}_s . We therefore obtain that

$$p_b = p_1 = p_2 = Q\left(\sqrt{\frac{2E_b}{N_0}}\right) \quad (1.1)$$

The fact that this expression is identical to the bit error probability for binary antipodal signaling is not a coincidence. QPSK with Gray coding can be thought of as two independent BPSK systems, one signaling along the I component, and the other along the Q component. Gray coding is particularly useful at low SNR (e.g., for heavily coded systems), where symbol errors happen more often. For example, in a coded system, fewer bit errors are to be passed up to the decoder for the same number of symbol errors.

In Gray Coding a 2^n -ary constellation is considered in which each point is represented by a binary string = (b_1, \dots, b_n) . The bit assignment is said to be Gray coded if, for any two constellation points b and b' which are nearest neighbors, the bit representations b and b' differ in exactly one bit location.

In nearest neighbors approximation for BER with Gray coded constellation the i^{th} bit b_i in an n -bit Gray code for a regular constellation with minimum distance d_{\min} is considered. For a Gray code, there is at most one nearest neighbor which differs in the i^{th} bit, and the pair wise error probability of decoding to that neighbor is $Q\left(\frac{d_{\min}}{2\sigma}\right)$. Therefore the BER is given by

$$P(\text{bit error}) \approx Q\left(\sqrt{\frac{\eta_p E_b}{2N_0}}\right) \text{ with Gray coding} \quad (1.2)$$

Where $\eta_p = \frac{d_{\min}^2}{E_b}$ is the power efficiency.

Gray coding may not always be possible. Indeed, for an arbitrary set of $M = 2^n$ signals, we may not understand the geometry well enough to assign a Gray code. In general, a necessary (but not sufficient) condition for an n -bit Gray code to exist is that the number of nearest neighbors for any signal point should be at most n .

Power Adaptation

In wireless communications, several power adaptation techniques and algorithms are proposed, which uses the channel quality measurements to adjust the power levels of the transmitted data. These are either centralized or distributed algorithms. The scope of this thesis considers only some of the important distributed power adaptation algorithms for analysis and evaluation.

The rate of convergence and MSE are two important performance metrics. Rate of convergence is the number of iterations the algorithm takes to obtain a steady state level. Some algorithms perform better in terms of rate of convergence and the other with respect to MSE. The goal of using the power adaptation algorithms is to optimize the total transmitted power in the system while minimizing the MSE maintaining faster convergence.

In the field of power adaptation in cellular systems, initially, centralized algorithms based on balancing of the received power levels were proposed. Since the centralized algorithms were not practically realizable, distributed algorithms, also aiming at balancing the power levels, have been substituted. To match the demanding QoS requirements, many more algorithms were proposed with multiple and fixed step power adaptation.

All these algorithms were proposed based on the E_b/N_0 , MSE, BER and PSNR etc. But there are few works which could bring out the essence of all the power adaptation algorithms based on their performance. In, the algorithms are based on their rate of convergence and probability of error Compared quite a number of algorithms based on the rate of convergence but with a generalized gain matrix, solely for the purpose of comparing the algorithms.

The optimized (dynamic) power adaptation algorithms being proposed in this work evaluates and adjusts the transmitted power to the signal strength and quality by a power regulation process that regulates the transmitted power directly to the required optimum transmitted power. It is necessary to adapt the powers in a distributed fashion, and these distributed algorithms can be seen as local adaptation loops.

Power adaptation in systems is principally used to maintain an established quality and to improve bandwidth utilization. There are two main types of quality based power adaptation algorithms that have been extensively deliberated in the literature and implemented in practice. They are MSE based algorithms and BER based algorithms. There are several practical issues in the algorithms that have been proposed in the literature yet to be addressed. The most vital issue in the MSE based algorithms is how to determine the Marked MSE parameter and how to derive good BER estimators of the rare occurrences of erroneous bits in the BER based algorithms. Another problem that is mutual by both algorithm types is the functional relation between the BER and the MSE. This relationship is essential as one may serve as an adaptation value and the other as an adaptation objective. To further enhance the performance of the system, an effective connection algorithm is developed based on the new minimum power adaptation algorithm. Determining the MSE Marked adaptation parameter (in MSE or BER based algorithms) involves more than just a static transformation between the

BER and the MSE. Since the actual MSE value is a stochastic process in nature, its variation and time correlation must be accounted for.

Power adaptation is proved to be a potential technique for resource adaptation, which balances the power levels of all the transmitters and receivers in the system. It also shows promising results in the capacity enhancements. Rate of convergence and PSNR are important performance parameters. Measure of the rate of convergence gives the responsiveness of an algorithm. PSNR represents the qualitative measure.

With the objective of serving as much data as possible in a communication system, it is important to utilize the available bandwidth efficiently. The main issue in this work is methods to assign appropriate transmission powers to the bits, with the intention of maximizing the capacity, while providing sufficient transmission quality to the data.

Some of the power adaptation algorithm performs well in rather ideal cases, but in real systems there are a number of effects that hamper the performance. They are:

Measuring adapted power signal takes time, which result in time delay. The possible output powers of the transmitter are constrained due to physical limits and quantization. Furthermore, different external constraints such as the use of maximum power on specific channels affect the output power.

The signals needed for Adaptation may not be available and have to be estimated.

Quality is a subjective measure, and relevant objective measures have to be employed.

Most of the optimized power adaptation methods either used simulations or energy-distortion curves to estimate the distortion at the transmitter at various power configurations. The entire process increases the computational complexity of the optimization process, making it infeasible for real-time image and video transmission.

The power adaptation methods should take into account the effects of channel changes during an image/video transmission.

Theoretically, power adaptation can be formulated and solved as a convex optimization problem. In real life power adaptation is far more complex. This is due to relative movement of the bits, lack of instantaneous information regarding individual bit conditions and limited data capacity.

These algorithms are iterative and generally each algorithm converges to the Minimum MSE value after certain number of iterations. The iterations taken to converge to the Minimum value depends on the responsiveness of the algorithm.

Optimization Using Power Adaptation

The power adaptation algorithms minimize the interference experienced by the channel such that the minimum MSE requirement of the data is satisfied. Further, from analysis of the optimization of power adapted to the bits, it is observed that both MSE and BER are necessary to achieve optimization.

Initially, the RMSE is estimated and is mapped into its corresponding Marked RMSE. It is then used to update the powers using the iterations shown in the algorithms. By using P_{\min} and P_{\max} , the powers can be updated in a manner that difference between successive power values will not exceed a given optimum power.

The most critical issue in the MSE based algorithm is to determine the Marked RMSE. It is only a parameter to maintain a low BER which the decoder can cope with. From this exact reason, BER-based algorithms make more sense as the estimated objective function at time t is used to control the objective function at time $(t + dt)$. However, it may not necessarily imply higher bandwidth utilization. More critical is the fact that erroneous bits are rare and therefore BER is hard to estimate.

The proposed methods cannot guarantee the given BER constraint which is well known as an essential QoS requirement in data transmission. Since reliable data transmission usually resorts to stringent BER constraints and the available transmit power is limited, the transmit power adapted to each bit should be minimized while meeting the given BER constraints. Thus, BER-constraint based power adaptation is an important element and plays an important role in image transmission system.

While meeting the BER constraint, the proposed methods efficiently reduces the transmit power in statistical sense. Such reduction in average transmit power is useful for improving the system performance. Moreover, from an implementation point of

view, the required amount of transmit power to meet the BER constraint on each bit should be determined before the adaptation operations. However, the threshold in the static scheme will change with the variation of channel fading models and cannot be estimated before the adaptation operations.

In a multimedia system, for an image with M number of bits per sample, the powers transmitted by the bits are $\mathbf{P} = [\mathbf{P}_1, \mathbf{P}_2, \dots, \dots, \mathbf{P}_M]$ and the respective RMSEs at the bits are $\mathbf{RMSE} = [\mathbf{RMSE}_1, \mathbf{RMSE}_2, \dots, \dots, \mathbf{RMSE}_M]$. Let RMSEM be the Marked RMSE. The MSE is given by

$$MSE = \sum_{j=0}^{2^M-1} (x_j - \hat{x}_j)^2 p(x_j) \quad (1.5)$$

\hat{x}_j - Estimate of the j^{th} sample x_j reconstructed after detection of the M bits

$p(x_j)$ - Apriori probability that the j^{th} sample transmitted.

The possible received sequence of M bits will be one of the other $2^M - 1$ combinations. The probability that i^{th} sample with a decimal value of (i) is reconstructed is given by

$$P_i(k) = \prod_{k=0}^{M-1} [p_k \vartheta(k) + (1 - p_k) \widetilde{\vartheta(k)}] \quad (1.6)$$

p_k - Probability that the k^{th} bit is in error

$\vartheta(k)$ Equal to zero if the indices of i and k are same and the value will be equal to 1 if the indices are different

$\widetilde{\vartheta(k)}$ - Binary inversion of $\vartheta(k)$

The MSE for the above case is calculated as

$$MSE = \frac{1}{\sqrt{2^M - 1}} \sum_{k=0}^{M-1} P_i(k) \quad (1.7)$$

MSE for other samples can be obtained following a similar procedure and the average MSE can be calculated by averaging over all possible samples. It is possible to show that, on average, all MSE values are approximately the same and hence equation (1.5) will be average MSE [74 - 77]. The probability of the k^{th} bit to be in error for the AWGN case is given by

$$PE_k = Q\left(\sqrt{2 \frac{E_b}{N_o}}(k)\right) \quad (1.8)$$

Based on the above analysis different adaptation algorithms are proposed and applied for image transmission over wireless channels. All these algorithms are aimed at minimizing the MSE while considering the permissible BER. The proposed algorithms are:

1. Minimum Power Adaptation Algorithm (MPAA)
2. Maximum Power Adaptation Algorithm (MAPAA)
3. Balanced Power Adaptation Algorithm (BPAA)
4. Distance Based Power Adaptation Algorithm (DBPAA)

Minimum Power Adaptation Algorithm (MPAA)

In this algorithm, minimum information of the channel is sufficient to adjust the transmitting power. However, a normalization procedure is required in each iteration to determine transmitting power. The RMSE is updated by choosing the minimum of the normalized RMSE value among the marked RMSE and the RMSE of the previous iteration. The new power level in each iteration is calculated by the product of the previous power level and the updated RMSE calculated, for a given marked RMSE. This method does not have any feedback mechanism that makes the proposed algorithm a good choice for multimedia systems. The power adaptation is performed according to the following steps explained below:

Algorithm Steps:

1. Initialize number of iterations, N

2. Initialize number of bits, M
3. Initialize power step size to ΔP .
4. Initialize PAPR_{\max} .
5. Initialize power of all M bits to '1'
6. Define two bits, R is recipient power and C is contributing power ,

For $j = 1$ to M bits

Compute RMSE.

Update power of all the bits using

$$P_i^{n+1} = \text{RMSE}_i^n \times P_i^n \quad (1.9)$$

$$\text{where } \text{RMSE}_i^n = \frac{\text{MIN}(\text{RMSE}_i^n, \text{RMSE}_M)}{\text{RMSE}_i^n} \quad (1.10)$$

P_i^{n+1} = Power allocated in the $n+1$ state

P_i^n = Power allocated in the n state

RMSE_i^n = Root mean square error of i^{th} bit in n^{th} iteration

RMSE_M = Marked Root Mean Square Error

End

7. Calculate the power of each bit and keep changing the power of the two bits R and C , until the minimum value of MSE is set up while the PAPR is kept less than PAPR_{\max} .
8. Reiterate the step 6 with the bit C incremented by one until all least significant bits are used.
9. Plot RMSE, BER and PSNR against E_b/N_0 .

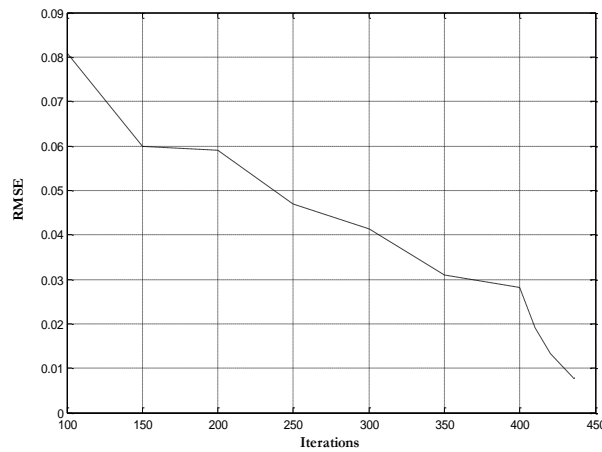


Fig.1.5. RMSE Convergence of MPAA

Maximum Power Adaptation Algorithm (MAPAA)

MAPAA is an improved version of the MPAA algorithm. The previous algorithm considers the minimum of the basic information, whereas this algorithm differs from it in its consideration of the maximum value of the same. Here the new power level is calculated by the product of the previous power level and the maximum value ratio of RMSEs. All the constraints of MPAA are also satisfied by MAPAA.

The power adaptation is done according to the following steps:

Algorithm Steps:

1. Initialize number of iterations, N
2. Initialize number of bits, M
3. Initialize power step size to ΔP .
4. Initialize PAPR_{\max} .

5. Initialize power of all M bits to '1'.
6. Define two bits, R is recipient power and C is contributing power ,
For $j = 1$ to M bits

Compute RMSE.

Update power of all the bits using

$$P_i^{n+1} = RMSE_i^n \times P_i^n \quad (1.11)$$

$$\text{where } RMSE_i^n = \frac{\max(RMSE_i^n, RMSE_M)}{RMSE_i^n} \quad (1.12)$$

P_i^{n+1} = Power allocated in the $n+1$ state

P_i^n = Power allocated in the n state

$RMSE_i^n$ = Root mean square error of i^{th} bit in n^{th} iteration

$RMSE_M$ = Marked Root Mean Square Error

End

7. Calculate the power of each bit and keep changing the power of the two bits R and C , until the minimum value of MSE is set up while the PAPR is kept less than $PAPR_{\max}$.
8. Reiterate the step 6 with the bit C incremented by one until all least significant bits are used.
9. Plot RMSE, BER and PSNR against E_b/N_0 .

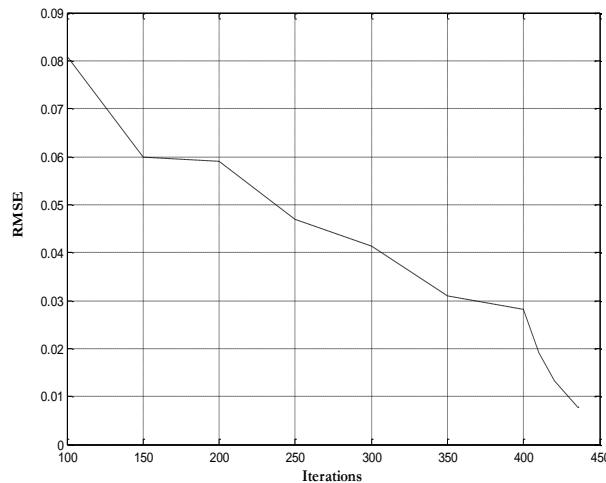


Fig.1.9. RMSE Convergence of MAPAA

Balanced Power Adaptation Algorithm (BPAA)

This algorithm calculates the optimal transmission power adapted for each bit within the bits per pixel taking into account all the neighboring bits, the powers are balanced in this algorithm as it takes the advantage of the both MPAA and MAPAA. The algorithm sets upper and lower threshold level to stabilize the power. If the power of the bits in any iteration is greater than the upper threshold level, then MPAA is executed and if the power in any iteration is less than the lower threshold level, then MAPAA is executed. This algorithm also assures all the properties of the MPAA and MAPAA. The convergence of BPAA depends on the careful selection of the upper and lower threshold power levels.

Algorithm Steps:

1. Initialize number of iterations, N
2. Initialize number of bits, M .
3. Initialize power step size to ΔP .
4. Initialize $PAPR_{\max}$.
5. Initialize power vector to all ones
6. Define two bits, R is recipient power and C is contributing power ,

For $j = 1$ to bits

Update power of all the bits using

$$RMSE_i^n = \frac{\min(RMSE_i^n, RMSE_M)}{RMSE_i^n} \dots \dots \dots P_i^n \geq p_u$$

$$= \frac{\max(RMSE_i^n, RMSE_M)}{RMSE_i^n} \dots \dots \dots P_i^n \geq p_l$$

$$= RMSE_i^n - 1 \dots \dots \dots p_u \leq p \leq p_l \quad (1.11)$$

$$\text{Where } RMSE_i^n = \frac{\max(RMSE_i^n, RMSE_M)}{RMSE_i^n} \quad (1.14)$$

P_i^{n+1} = Power allocated in the $n+1$ state

P_i^n = Power allocated in the n state

$RMSE_i^n$ = Root mean square error of i_{th} bit in n_{th} iteration

$RMSE_M$ = Marked Root Mean Square Error

End

7. Calculate the maximum power of each bit.
8. Reiterate the step 6 with the bit C incremented by one until all least significant bits are used
9. Calculate the minimum MSE.
10. Plot RMSE, BER and PSNR against E_b/N_0 .

The proposed scheme works iteratively to find the optimum combination of powers transmitted for individual bits to minimize the mean square error for better image quality. Most significant bits should always be allocated most of the power transmitted. However, other bits of less significance may be sent with less power. Fig.1.14 shows the RMSE convergence of this algorithm.

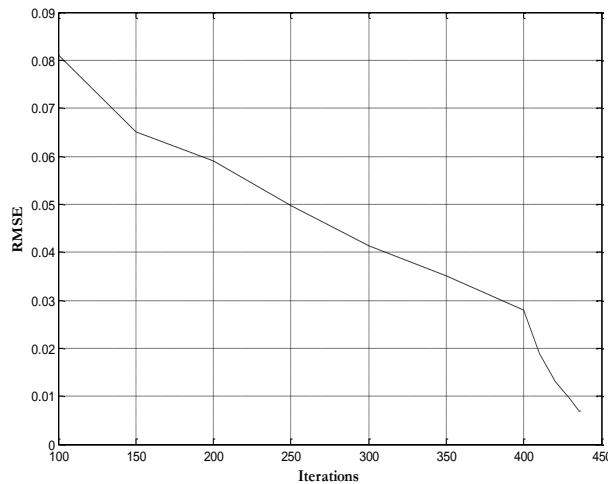


Fig.1.11. RMSE Convergence of BPAA

Distance-Based Power Adaptation Algorithm (DBPAA)

Fast convergence can be achieved by making the iteration step smaller, and by designing iteration with faster convergence property. DBPAA is one of the fast convergence power adaptation algorithms that address the problem of MSE balancing in a complete manner.

The DBPAA uses the distance between reference bit and each other bit indicating the pixel of the image to allocate transmitted power to each of the bits. In order to avoid having very small transmitted powers for bits close to the maximum bit, bits whose distance is less than a certain threshold value d_{min} , the same transmitted power is allowed. Thus, more transmitted power is to be allocated to bits which are far from their corresponding reference bit.

The DBPAA algorithm computes the transmitted power of bit according to the following equation:

$$p_m = kx_i^n \quad (1.15)$$

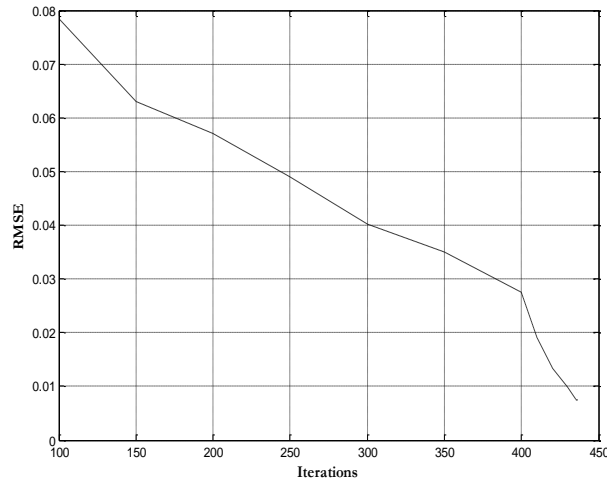


Fig 1.17 RMSE Convergence of DBPAA

$$\text{where } x_i^n = \begin{cases} \frac{d_{bb}}{R}, & \text{if } d_{bb} > d_{min} \\ \frac{d_{min}}{R}, & \text{if } d_{bb} \leq d_{min} \end{cases} \quad (1.16)$$

k = positive constant

n = real positive value

R = maximum distance between the bits of the power vector

d_{bb} = distance between bit and its assigned reference bit.

Algorithm Steps:

1. Initialize number of iterations
2. Initialize number of bits
3. Initialize d_{min} , R , k , n
4. Initialize power vector to all ones
5. Initialize $PAPR_{max}$
6. Initialize power step size to ΔP .

For $j = 1$ to bits

If $d_{bb} \leq d_{min}$

$$p(j) = k (d_{min}/R)^n$$

else

$$p(j) = k(d_{bb}(j)/R)^n$$

End

7. Define two bits, R is recipient power and C is contributing power

For $j = 1$ to bits

Update power of all the bits using

$$P_i^{n+1} = RMSE_i^n \times P_i^n \quad (1.17)$$

$$\text{Where } RMSE_i^n = \frac{\max(RMSE_i^n, RMSE_M)}{RMSE_i^n} \quad (1.18)$$

P_i^{n+1} = Power allocated in the $(n+1)^{th}$ state

P_i^n = Power allocated in the n^{th} state

$RMSE_i^n$ = Root mean square error of i^{th} bit in n^{th} iteration

$RMSE_M$ = Marked Root Mean Square Error

End

8. Calculate the maximum power of each bit.
9. Reiterate the step 5 with the bit C incremented by one until all least significant bits are used.
10. Calculate the minimum MSE.
11. Plot RMSE, BER and PSNR against E_b/N_o .

Conclusion

The proposed algorithms almost show better performance over conventional algorithms in terms of almost all the quantitative parameters used for representing the performance of the image transmission process. DBPA algorithm performs best among all the proposed power adaptation algorithms.

The performance of the algorithms and hence the reliability of the information (image) can be further improved by using channel coding. Hence it is intended to employ coding along with the power adaptation algorithms for image transmission

References

- [1] T. Wiegand and H. Schwarz. Source Coding: Part I of Fundamentals of Source and Video Coding, Foundations and Trends in Signal Processing, Vol. 4. Foundations and Trends in Signal Processing, 2011.
- [2] S. Akram Bin and Mohammed El-Tarhuni, "Combined Power Allocation and Coding For Compressed Image Transmission", IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC'06), pp. 1 - 5, September 2006.
- [3] S. Akram Bin and Mohamed El-Tarhuni, "Optimizing Bit Energy and Channel Coding for Image Transmission", 10th IEEE Singapore International Conference on Communication systems (ICCS), pp. 1 - 5, October 2006.
- [4] Akram Bin Sediq and Mohamed El-Tarhuni, "MMSE Power Allocation for Image and Video Transmission over Wireless Channels," 16th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Vol. 2, pp. 1060 - 1064, September 2005.
- [5] A.B. Sediq and El-Tarhuni, "Power Allocation and Coding for Compressed Image Transmission", 17th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), pp. 1 - 5, September 2006.
- [6] Mohamed El-Tarhuni, Mohamed Hassan and Akram Bin Sediq, "A Jointly Optimized Variable M-QAM and Power Allocation Scheme for Image Transmission", Journal of Computer Networks and Communications, pp. 1 - 14, November 2011.
- [7] Mohamed El-Tarhuni, Mohamed Hassan, and Akram Bin Sediq, "A Joint Power Allocation and Adaptive Channel Coding Scheme for Image Transmission over Wireless Channels", International Journal of Computer Networks & Communications (IJCNC), Vol. 2, No. 1, pp. 85 - 99, May 2010.
- [8] N.Arzu Karaer, Costas N. Georghiades, "Optimum Bit-by-Bit Power Allocation for Minimum Distortion Transmission", IEEE International Conference on Communications (ICC '06), Vol. 4, pp. 1616 - 1621, June 2006.
- [9] Bin Sediq, A., El-Tarhuni M., "Reduced-Complexity Power Allocation and Modulation Scheme for Image Transmission over Wireless Channels", 9th International Symposium on Signal Processing and Its Applications (ISSPA), pp. 1 - 4, February 2007.
- [10] Saina Lajevardi, "Image Transmission over AWGN/Fading Channels Using OFDM and Performance analysis", Project Report, Eastern Mediterranean University, June 2008.