

Efficient Variants of Square Contour Algorithm for Blind Equalization of QAM Signals

Ahmad Tariq Sheikh, Shahzad Amin Sheikh

Abstract—A new distance-adjusted approach is proposed in which static square contours are defined around an estimated symbol in a QAM constellation, which create regions that correspond to fixed step sizes and weighting factors. As a result, the equalizer tap adjustment consists of a linearly weighted sum of adaptation criteria that is scaled by a variable step size. This approach is the basis of two new algorithms: the Variable step size Square Contour Algorithm (VSCA) and the Variable step size Square Contour Decision-Directed Algorithm (VSDA). The proposed schemes are compared with existing blind equalization algorithms in the SCA family in terms of convergence speed, constellation eye opening and residual ISI suppression. Simulation results for 64-QAM signaling over empirically derived microwave radio channels confirm the efficacy of the proposed algorithms. An RTL implementation of the blind adaptive equalizer based on the proposed schemes is presented and the system is configured to operate in VSCA error signal mode, for square QAM signals up to 64-QAM.

Keywords—Adaptive filtering, Blind Equalization, Square Contour Algorithm.

I. INTRODUCTION

Modern communication systems employ Bandwidth Efficient techniques such as Quadrature Amplitude Modulation (QAM), in which both phase and amplitude of the sinusoidal signal are varied to transmit digital information. Since the signals are prone to distortion attributed to intersymbol interference (ISI) caused by multipath within time-dispersive channels. In order to mitigate the effects of ISI, adaptive equalization is one of the most widely used methods. Adaptive equalization can be implemented in several modes. If the methods applied to achieve channel equalization do not include transmission of training sequence, it is referred to as *blind equalization*. Many excellent tutorials exist on the subject of both trained [3, 4] and blind equalization [5, 6].

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The most early and widely used algorithm was the constant modulus algorithm (CMA), proposed independently by Goddard [1] and Treichler *et al.* [2]. The success of CMA was mainly due to its simple implementation structure, like the least mean square (LMS). But, the CMA is only amplitude dependent and lacks the phase information in cost function thus we need to incorporate a separate phase tracking loop at the output of the equalizer to recover and correct phase offset. Major modification to CMA was the multimodulus algorithm [7, 8] proposed by Yang *et al.*, achieving lower steady-state mean-squared error (MSE) and eliminating the need for separate phase tracking loop. The square contour algorithm (SCA) combined the benefits of Reduced Constellation Algorithm (RCA) [9] and CMA, proposed by Thaiupathump and Kassam [10]. This algorithm has a phase tracking loop embedded in its cost function and it achieves lower steady-state MSE as compared to its parent algorithms. *Hybrid Blind Equalization Algorithms* is another class of algorithms which augments the existing cost functions to enhance performance. Modification to SCA called the modified SCA (MSCA) was proposed in [11]. It augments the SCA and constellation matched error (CME) in its cost function. The MSCA achieved faster convergence rate and lower steady-state MSE as compared to SCA.

Motivated by the radius-adjusted approach [12] by Kevin Banovic, two new algorithms: the Variable step size Square Contour Algorithm (VSCA) and the Variable step size Square Contour Decision-Directed Algorithm (VSDA) are proposed. The proposed blind equalization algorithms achieve faster convergence rate and lower steady-state MSE when compared with existing SCA and MSCA. The rest of the paper is organized as follows; Section 2 discusses the generalized equalizer model, the square contour algorithm and the modified square contour algorithm. In section 3 proposed blind equalization algorithms are discussed. Selection of region parameters which correspond to varying step-sizes is discussed in section 4. Simulation results are given in section 5. Section 6 delineates the fixed-point and RTL simulation results. Finally, conclusions are made in section 7.

II. EQUALIZER MODEL

Consider the baseband representation for digital data transmission in Fig (1), where $s(n)$ are the independently identically distributed (i.i.d.) transmitted symbols, $v(n)$ is the additive white Gaussian noise (AWGN), $x(n)$ are the

equalizer inputs and $a(n)$ are the estimated outputs of the decision device. The equalizer's N -tap weight vector and input vector are defined as $W(n) = [w_0(n), w_1(n), \dots, w_{N-1}(n)]^T$ and $X(n) = [x(n), x(n-1), \dots, x(n-N+1)]$, respectively. Whereas $y(n) = W^T(n)X(n)$ is the equalizer output, $h(n)$ is the impulse

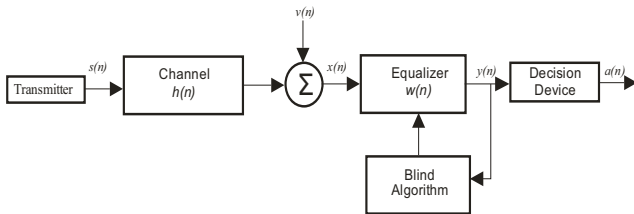


Fig. 1. Simplified baseband communication system

response of channel. The objective is to achieve an estimate of $s(n)$ using $y(n)$ without using a training sequence.

A. Square Contour Algorithm (SCA)

The SCA proposed by Thaiupathump and Kassam [10] minimizes the dispersion of the equalizer output around a square. By using a square zero-error contour, this algorithm combines the reliable convergence benefits of Constant Modulus Algorithm (CMA) [2] and the phase recovery feature of the Reduced Constellation Algorithm (RCA) [9]. The cost function of the square contour algorithm is given as

$$J_{SCA} = E\{(|y_{R,n} + y_{I,n}| + |y_{R,n} - y_{I,n}|)^p - R_{sca}^p\}^2 \quad (1)$$

For the case $p = 2$, the cost function then becomes

$$J_{SCA} = E\{(|y_{R,n} + y_{I,n}| + |y_{R,n} - y_{I,n}| - R_{sca})^2\} \quad (2)$$

Where R_{sca} is a real dispersion constant and is calculated assuming the perfect equalization i.e. $y(n) = s(n)$ and by setting the gradient $\nabla_w J_{SCA}$ to zero [10]:

$$R_{SCA} = \frac{E[(|s_{R,n} + s_{I,n}| + |s_{R,n} - s_{I,n}|) \cdot R']}{E[R']} \quad (3)$$

Where

$$R' = \{\text{sgn}[s_R(n) + s_I(n)] + \text{sgn}[s_R(n) - s_I(n)] - j(\text{sgn}[s_R(n) + s_I(n)] - \text{sgn}[s_R(n) - s_I(n)])\} \cdot s^*(n)$$

The tap update equation is obtained by differentiating the cost function in (2) with respect to the tap weights w and approximating the expectation with the instantaneous value yields

$$w(n+1) = w(n) - \mu e_{SCA} \cdot x^*(n) \quad (4)$$

where e_{SCA} is the SCA error term defined as [11]:

$$e_{SCA} = (|y_R(n) + y_I(n)| + |y_R(n) - y_I(n)| - R_{SCA}) \cdot \{\text{sgn}[y_R(n) + y_I(n)] + \text{sgn}[y_R(n) - y_I(n)] + j(\text{sgn}[y_R(n) + y_I(n)] - \text{sgn}[y_R(n) - y_I(n)])\} \quad (5)$$

The simulation results in [10] shows that the performance of SCA is better than its parent algorithms i.e. RCA and CMA for 16-QAM signal constellation. Moreover, like RCA and MMA, SCA is capable of recovering and correcting the phase offset due to square modulus, but the performance of MMA is superior to SCA in terms of convergence speed and constellation eye-opening. In order increase the convergence speed and other performance criterions, particularly the ISI suppression and constellation eye-opening, Thaiupathump et al. [11] proposed a modified version of SCA called Modified SCA (MSCA).

B. Modified Square Contour Algorithm (MSCA)

The modification to SCA called the Modified SCA (MSCA) was proposed by Thaiupathump et al. [11]. MSCA augments the SCA error function and Constellation Matched Error (CME) term. The CME term is designed to become zero at each constellation point, hence providing MSCA with an additional knowledge of constellation points allowing for greater reduction of MSE and convergence time. The MSCA cost function is defined as [11]:

$$J_{MSCA} = E\{(|y_R(n) + y_I(n)| + |y_R(n) - y_I(n)| - R_{sca}^2) + \beta \{g(y(n))\}\} \quad (6)$$

where β is the CME weighting factor and $g(y(n))$ is the sinusoidal CME term defined as [11]:

$$g(y(n)) = \left(\left(1 - \sin^{2n} \left(\frac{y_R(n)}{2d} \pi \right) \right) + \left(1 - \sin^{2n} \left(\frac{y_I(n)}{2d} \pi \right) \right) \right) \quad (7)$$

Here $2d$ is the minimum distance between QAM symbols. The MSCA error function is then given as [11]:

$$e_{MSCA}(n) = e_{SCA}(n) + \beta \eta(n) \quad (8)$$

where $\eta(n)$ is defined as [11]:

$$\eta(n) = \underbrace{\frac{d}{dx} g(x) \Big|_{x=y_R(n)}}_{\eta_R} + j \underbrace{\frac{d}{dx} g(x) \Big|_{x=y_I(n)}}_{\eta_I} \quad (9)$$

At the onset of equalization the convergence of MSCA is controlled by SCA error term, as CME doesn't provide the correct error information initially [11]. The β factor plays an important role in increasing or decreasing the convergence time of MSCA. It can be approximated using the bounds [11]:

$$\beta |\eta(n)|_{\max} < \max_{a \in \text{alphabet}} \left| 4 |s_R|^2 - R_{sca}^2 \right| \quad (10)$$

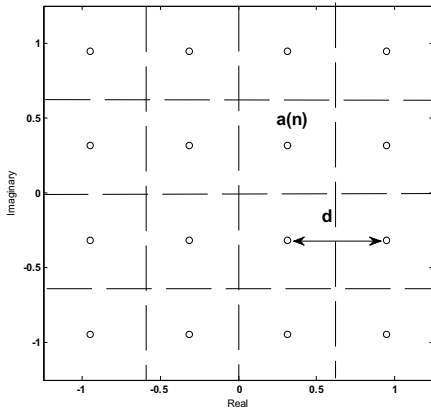
III. DISTANCE ADJUSTED APPROACH

Motivated by the radius adjusted approach [12], this section presents two new hybrid blind equalization algorithms based on a new variable step-size distance-adjusted approach. Static square contours are defined around an estimated symbol point in QAM constellation, in this way regions are created that can be mapped to variable adaptation phases. A region corresponds to a fixed step-size $\mu(n)$, and weighting factor $\lambda(n)$, that can be used to create a time-varying equalizer tap update base on the equalizer output distance, $d(n)$, which is defined as

$$d(n) = \frac{\left| (s_R(n) - y_R(n)) + (s_I(n) - y_I(n)) \right|}{2} + \frac{\left| (s_R(n) - y_R(n)) - (s_I(n) - y_I(n)) \right|}{2} \quad (11)$$

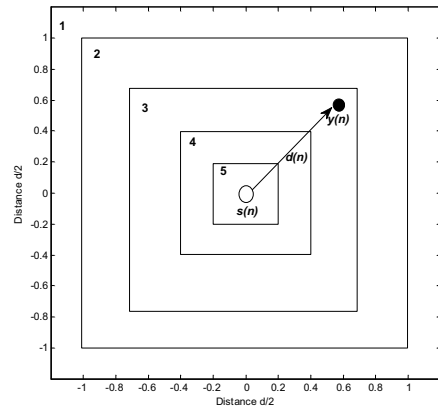
where $d(n)$ is the maximum distance between the equalizer output, $y(n)$, and its corresponding symbol estimate, $s_R(n) + js_I(n)$. The equalizer tap update consists of a linearly weighted sum of adaptation criteria that is scaled by a variable step size. The above equation can simply be written as:

$$d(n) = \max[|s_R(n) - y_R(n)|, |s_I(n) - y_I(n)|] \quad (12)$$



(a)

The general concept behind distance-adjusted approach is illustrated for 16-QAM in Fig 2. The equalizer output of fig 2(a) corresponds to $d(n)$ of fig 2(b), where sample square decision regions are superimposed over the original square decision region. Here, the outer regions of fig 2(b) correspond to adaptation phases with high MSE, while the inner regions correspond adaptation phases with low MSE. To improve the accuracy of the equalizer tap adjustment, regions are grouped into adaptation phases and then parameters $\mu(n)$ and $\lambda(n)$ are



(b)

Fig. 2. (a) Decision regions for symbol estimates in 16-QAM and (b) square decision regions centered on symbol estimate.

adjusted based on the characteristics of that phase. The convergence time can be reduced by applying large $\mu(n)$ in the outer region, thereby speeding up the initial convergence, while residual errors can be reduced by applying small $\mu(n)$ in the inner regions. Smooth transition between the error functions in hybrid approach is made by selecting a suitable value of $\lambda(n)$, where $\lambda(n) \in [0, 1]$.

IV. VARIABLE STEP-SIZE SQUARE CONTOUR ALGORITHM (VSCA)

The distance-adjusted variable step-size square contour algorithm (VSCA) augments the SCA cost function in (2) with a CME term and linearly weighs the respective terms based on the distance-adjusted approach. The sole objective is to decrease the convergence time, while obtaining low steady-state MSE and residual errors. The cost function that is minimized by VSCA is defined as

$$J_{VSCA} = \lambda(n) E \{ (|y_R(n) + y_I(n)| + |y_R(n) - y_I(n)|)^p - R_{sca}^p \}^2 + (1 - \lambda(n)) E \{ \beta g(y(n)) \} \quad (13)$$

where p is a positive integer, β is a weighting factor that trades off between the amplitude and constellation matched errors and $g(y(n))$ is the CME function, defined previously in (7). A stochastic gradient-descent algorithm that minimizes the J_{VSCA} is defined as,

$$\begin{aligned} w(n+1) &= w(n) + \mu (-\nabla_w J_{VSCA}) \\ &= w(n) - \mu(n) \{ \lambda(n) \{ (|y_R(n) + y_I(n)| + |y_R(n) - y_I(n)|)^p - R_{sca}^p \} \\ &\quad \cdot (|y_R(n) + y_I(n)| + |y_R(n) - y_I(n)|)^{p-1} \times \{ \text{sgn}[y_R(n) + y_I(n)] \\ &\quad + |\text{sgn}[y_R(n) - y_I(n)] + j(\text{sgn}[y_R(n) + y_I(n)] - \text{sgn}[y_R(n) - y_I(n)]) \} \} \\ &\quad + \{ (1 - \lambda(n)) \beta \eta(n) \} \} \cdot x^*(n) \\ &= w(n) - \mu(n) \underbrace{ \{ \lambda(n) e_{VSCA} + (1 - \lambda(n)) \beta \eta(n) \} }_{e_{VSCA}} \cdot x^*(n) \end{aligned} \quad (14)$$

Where $\eta(n) = \eta_R(n) + j\eta_I(n)$ is CME error signal and e_{vscd} is VSCA error signal, which is reduced to SCA error signal when $\lambda(n) = 1$ and to the CME error when $\lambda(n) = 0$. The CME function is obtained by taking the negative gradient of the CME function with respect to the equalizer tap coefficients and is given as in (9) and β is calculated using (10). During the initial stages of equalization, SCA algorithm with a large step-size is applied, thereby quickly decreasing the MSE. This allows the CME term to be included at an earlier stage blended with SCA error. The CME error is able to rapidly decrease the convergence time and MSE since it contains the knowledge about constellation points. Once the MSE has been reduced to the lower levels, CME updates with a small step-size are applied to the equalizer most of the time, thereby reducing the steady-state MSE and misadjustment. The use of fixed decision regions in VSCA serves a similar purpose as the weighting factor in MSCA. This would suggest that the distance-adjusted approach could replace the weighting factor in MSCA to achieve similar results with less complexity.

V. VARIABLE STEP-SIZE SQUARE CONTOUR DD ALGORITHM (VSDA)

The distance-adjusted variable step-size square contour decision-directed (VSDA) combines the SCA and DD cost functions respectively, and linearly weighs the respective terms based on the distance-adjusted approach. Again, the objective is to obtain reliable and automatic transfer to the DD mode, while decreasing the convergence time and obtaining low steady-state MSE and misadjustment. The cost function that is minimized by VSDA is defined as

$$J_{VSDA} = \lambda(n)E\{(|y_R(n) + y_I(n)| + |y_R(n) - y_I(n)|)^p - R_{SCA}^p\}^2 + \frac{1}{2}(1 - \lambda(n))E\{\hat{s}(n) - (y(n))^2\} \quad (15)$$

where p is a positive constant chosen to be '2', since it provides best compromise between performance and implementation complexity and $\hat{s}(n) = s_R(n) + js_I(n)$ denote the real and imaginary component of an estimated constellation point output from the slicer. A gradient-descent equalizer update algorithm that minimizes J_{VSDA} is defined as

$$w(n+1) = w(n) + \mu(-\nabla_w J_{VSDA})$$

$$= w(n) - \mu(n)\{\lambda(n)\{(|y_R(n) + y_I(n)| + |y_R(n) - y_I(n)|)^p - R_{SCA}^p\} \cdot (|y_R(n) + y_I(n)| + |y_R(n) - y_I(n)|)^{p-1} \times \{\text{sgn}[y_R(n) + y_I(n)] + \text{sgn}[y_R(n) - y_I(n)] + j(\text{sgn}[y_R(n) + y_I(n)] - \text{sgn}[y_R(n) - y_I(n)])\} + \{(1 - \lambda(n))\beta(\hat{s}(n) - y(n))\} \cdot x^*(n)\}$$

Similar to the VSCA, the equalizer taps of VSDA will initially be updated using a large step size most of the time, quickly reducing the MSE. Now, this allows the DD error to be included at an earlier stage combined with SCA error. Once the MSE has been reduced to the desired low levels, DD updates the tap weights afterwards.

VI. SELECTION OF REGION PARAMETERS

A simulation study was performed to relate the distance to different MSE intervals. This was accomplished to justify the mapping of adaptation regions to the square regions around an estimated symbol point. The SCA with small step size was applied to SPIB microwave channels # 1, 2, 5, 6, 9, 10, 12 and 13 [located at <http://spib.rice.edu>], and the mean and standard deviation for $d(n)$ was calculated for 50 realizations each of 16-QAM and 64-QAM per channel respectively. The results, which have been averaged over all channels and normalized with respect to $d/2$ are listed in table 1.

MSE Range (dB)	16-QAM		64-QAM	
	Mean	S.D.	Mean	S.D.
(-5, -7.5)	1.5290	1.0369	2.7464	2.4453
(-7.5, -10)	1.2383	0.7982	2.1576	2.0270
(-10, -12.5)	0.7919	0.3779	1.6824	1.5420
(-12.5, -15)	0.6259	0.2559	1.3355	1.1481
(-15, -17.5)	0.5175	0.2222	0.7969	0.4914
(-17.5, -20)	0.3804	0.1818	0.6446	0.2701
(-20, -22.5)	0.2484	0.1258	0.5283	0.2401
(-22.5, -25)	0.1728	0.0897	0.3692	0.1924

Table 1: Statistical properties of $d(n)$ as a function of MSE Range

It can be seen that the outer regions of fig 2(b) can be mapped to adaptation phases with high MSE, while inner regions can be mapped to adaptation phases with low MSE. At high values of MSE these statistics vary from channel to channel. However, simulation studies have shown that as the MSE approaches the minimum required to transfer to the DD algorithm, denoted by ξ_{DD} , the statistics are independent of channel, SNR and algorithm. When the MSE is above ξ_{DD} , $y(n)$ is inaccurate and therefore $\hat{s}(n)$ is unreliable, which leads to high mean and standard deviation of $d(n)$. However, when the MSE is below ξ_{DD} , the accuracy of $y(n)$ is improved and the reliability of $\hat{s}(n)$ is within that required for the convergence of DD algorithm. In this mode of operation $d(n)$ approximates the MSE, which is equivalent to the expected value of maximum distance from symbol point across the slicer. This essentially makes $d(n)$ a function of MSE, which is dependent upon the constellation.

The mean and standard deviation of $d(n)$ are plotted in figure 3 for 16-QAM and 64-QAM respectively using the statistics given in table 1. These figures can be used to obtain relative performance measures by extracting data from several intersecting lines. The maximum, minimum and mean values of $d(n)$ are denoted by $|d(n)|_{\max}$, $|d(n)|_{\min}$ and $|d(n)|_{ave}$, where $|d(n)|_{\min} \leq d(n) \leq |d(n)|_{\max}$ is the standard range. The horizontal line A_1A_2 represents ξ_{DD} , which is approximately -11.19dB and -17.40dB for 16-QAM and 64-QAM respectively [13]. The vertical line B_1B_2 is formed by the intersection of

line A_1A_2 with $|d(n)|_{\min}$, while C_1C_2 is formed by the intersection of line A_1A_2 with $|d(n)|_{\max}$.

Guidelines for parameter selection are given in table 2 which consist of five regions in order to allow greater flexibility and smoother transitions between errors and step sizes. Experimental results have shown that defining three to five regions is sufficient and the performance enhancement of anything above five regions is marginal. Regions 1-2 represent adaptation phases above ξ_{DD} , while regions 3-5 represent phases that are at or below ξ_{DD} . Similarly, $\lambda(n)$ is fixed intermediate value in the range $0 \leq \lambda(n) \leq 1$ in region 3, whose limits correspond to x in figure 4. This has been done to make sure the smooth transition between the error terms with in the respective error signals. $\lambda(n)$ can be quantized such that $\lambda(n) \in \{0,1\}$ to produce more efficient implementation. Simulation results have shown that $\mu(n)$ in region 1-2 control the initial rate of convergence, while $\mu(n)$ in regions 4-5 controls the misadjustment and convergence

Regions	Limits	$\mu(n)$	$\lambda(n)$
1	$d(n) \geq 1$	μ_{MAX}	1
2	$1 > d(n) \geq 0.7$	$\mu_{MAX} / 2$	1
3	$0.7 > d(n) \geq 0.4$	μ_{SCA}	$0 \leq \lambda(n) \leq 1$
4	$0.4 > d(n) \geq 0.2$	μ_{SCA}	0
5	$0.2 > d(n)$	μ_{MIN}	0

Table 2: Parameter Selection Guideline for VSCA and VSDA

time. The upper limit μ_{MAX} is derived empirically; it is based on the highest step-size value for which SCA algorithm performs well. While, the lower limit μ_{MIN} is also derived through extensive simulations, it is based on the smallest step-size value for which MSCA algorithm performs well. The above propositions are made on the fact that, initially, we want high convergence rate and since SCA error term will be updating the tap weights, step-size parameter will be kept high. When initial convergence is achieved the small step-size parameter is applied to the MSCA to further reduce the MSE and residual errors.

VII. SIMULATION RESULTS

Simulations were performed for 16-QAM and 64-QAM for SCA, MSCA, VSCA and VSDA respectively with SNR of 35dB. The channels impulse responses are $T/2$ -spaced microwave channels taken from SPIB, here T is the symbol period. The equalizers are chosen to be 16-tap $T/2$ -spaced finite impulse response (FIR) with center tap initialized to 1. Simulation parameters are given in table 3 for SCA, MSCA and in table 4 for VSCA and VSDA. Here β is calculated using (10) for VSCA. Two parameter values in second column of table 4 correspond to each of 16-QAM and 64-QAM, while

in third column two sets correspond to SPIB channel # 2 and 13 and in each set; parameters correspond to 16-QAM and 64-QAM. The values of $\lambda(n)$ are given for third region only, for other regions it is kept to be either 1 or 0. Simulation results are illustrated for SPIB microwave channel # 2 and 13. The MSE curves for these channels are illustrated in figure 4 for channel # 2 and in figure 5 for channel 13. The MSE curves for 16-QAM in channel 2 shows that the transient and steady-

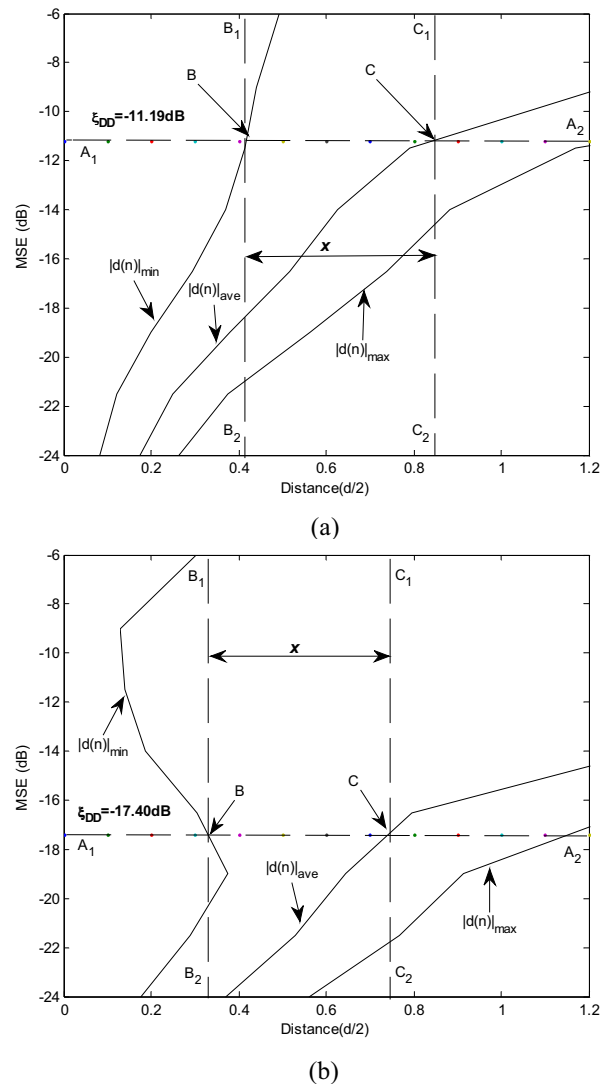


Figure 3: Statistical properties of $d(n)$ plotted as function of MSE range for (a) 16-QAM (b) 64-QAM

Channel	μ_{SCA}		μ_{MSCA}	
	16-QAM	64-QAM	16-QAM	64-QAM
2	3e-4	1.5e-4	3e-4	1.5e-4
13	3e-4	1.5e-4	3e-4	1.5e-4

Table 3: Step size parameters selected for SCA and MSCA

state performance of both VSCA and VSDA are similar. Both algorithms are able to achieve fast convergence time low steady-state MSE. The performance of VSDA is degenerated for channel 13 as clear from the MSE curves in figure 4. For 64-QAM the rate of convergence for VSDA drops off as the DD error term becomes the primary error signal. The steady-state behavior is same for both algorithms for channel 2; however, VSCA shows superior performance in terms of lower MSE for channel 13.

Method	β	μ_{MAX}	λ_3
VSCA	$0.9 \beta _{\max}$	$\{1.5 \times 10^{-3}, 3 \times 10^{-4}\}$	$\{0.1, 0.2\},$ $\{0.1, 0.1\}$
VSDA	$0.9 \beta _{\max}$	$\{1.5 \times 10^{-3}, 3 \times 10^{-4}\}$	$\{0.1, 0.4\},$ $\{0.6, 0.4\}$

Table 4: Simulation parameters for VSCA and VSDA for SPIB channel # 2 and 13

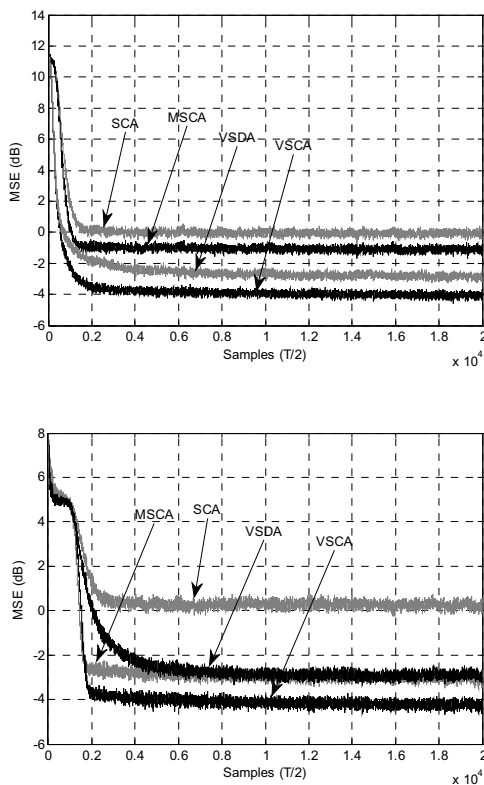


Figure 4: Simulation results for 16-QAM and 64-QAM using SPIB microwave channel # 2

VIII. DESIGN OF A COMPLEX BLIND EQUALIZER FOR QAM SIGNALS

This section discusses the design of a 16-Tap T/2-spaced blind equalizer for QAM signals. This section begins with the discussion of fixed-point simulations for VSCA. The architecture followed for implementation is the same as given

in [14]. The equalizer is implemented for VSCA only. It can be extended for other VSDA easily.

A. Fixed-point Analysis

The word-length and fractional word-length (FWL) for the fixed-point models of VSCA and VSDA were determined by fixed-point simulations that were completed using the fixed point toolbox of Matlab. The number system chosen for

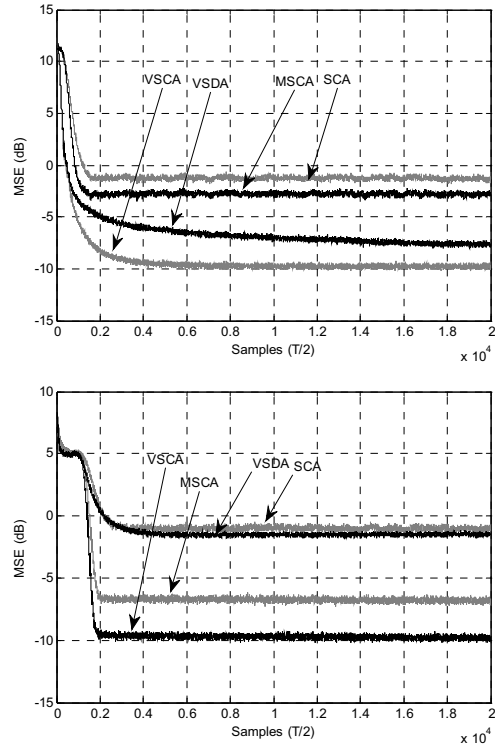


Figure 5: Simulation results for 16-QAM and 64-QAM using SPIB microwave channel # 13

implementation is the two's complement number system, which has a numeric range of $(-2^{IWL-1}, 2^{IWL-1} - 2^{-FWL})$ and a resolution of 2^{-FWL} , where the integer word-length is $IWL = WL - FWL$. Saturation is applied to handle overflow conditions, while truncation is applied instead of rounding. The input and output WL and FWL of the Blind equalizer are set to 16-bit and 12-bit, respectively, since 16-bit is a standard WL size. The error signal WL and FWL is held constant during fixed-point simulations at 16-bit and 12-bit, respectively. Fixed-point simulations are conducted with two different sets of WLs and FWLs for the tap coefficients, which are (20, 16)-bit and (22, 16)-bit. The performance gain between WLs of 20-bit and 22-bit tap coefficient is marginal. Therefore, the tap coefficient WL and FWL for this implementation are set to be 20-bit and 16-bit, respectively.

For VSCA error signal, the CME component is implemented using a LUT. The size of this LUT is determined by the precision of the input, which is set to a WL and FWL of 10-bit and 8-bit respectively. This results in a precision of $2^{-8} \approx 0.004$ which is sufficient for CME signal.

Fixed-point simulations for VSCA and VSDA are illustrated in figure 6 and 7, respectively. The fixed-point simulations were conducted SPIB microwave channel # 13. In all simulations, the results of the fixed-point algorithm are compared to their floating point counterparts. For 16-QAM the performance of fixed-point algorithms is almost identical to that of floating point. For 64-QAM VSCA shows increase in convergence time which is about 700 $T/2$ samples and 600 $T/2$ samples for VSDA. It should be kept in mind that as we increase the integer word length (IWL) of the coefficients the transient behavior of fixed-point algorithm becomes closer to the floating-point counterpart.

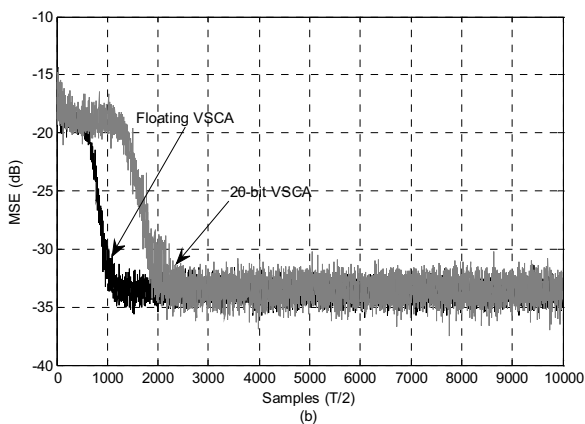
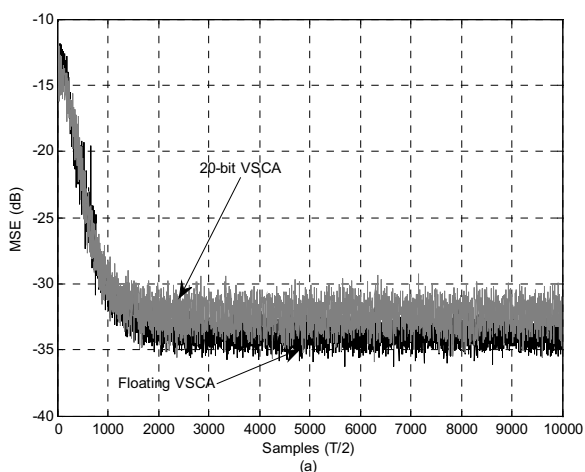


Figure 6: Fixed-point simulations of VSCA for (a) 16-QAM (b) 64-QAM using SPIB channel # 13

A. Blind Equalizer Implementation

The Blind equalizer is a complex 16-tap $T/2$ -spaced blind adaptive equalizer for QAM signals. The equalizer is implemented following the architecture discussed in [14] except for the error function block which here in our case incorporated SCA error function. The input, output and tap weights WL's are set as discussed in 6.1. The RTL implementation was done for VSCA only, but it can be extended easily for VSDA.

B. RTL Simulation Results

The functionality of the Blind equalizer at RTL level was verified using ModelSim 6.1f. The verification of each module was performed by creating a set of fixed-point inputs and expected outputs using fixed-point toolbox in Matlab. Exhaustive testing was performed in this way, thereby making sure that all the modules in the hierarchy were working correctly. The test vectors were saved to a stimulus file with a ".dat" extension and stimulus vectors were applied by the

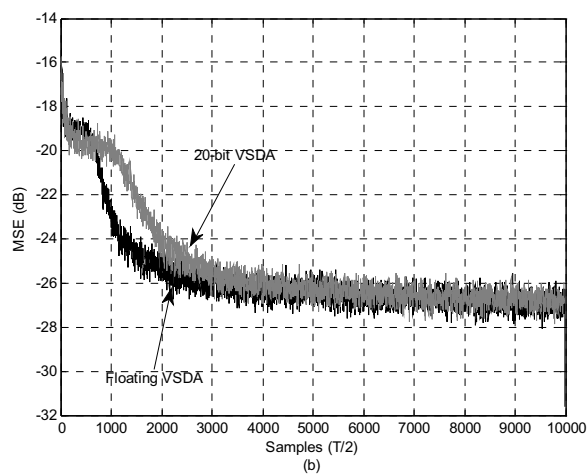
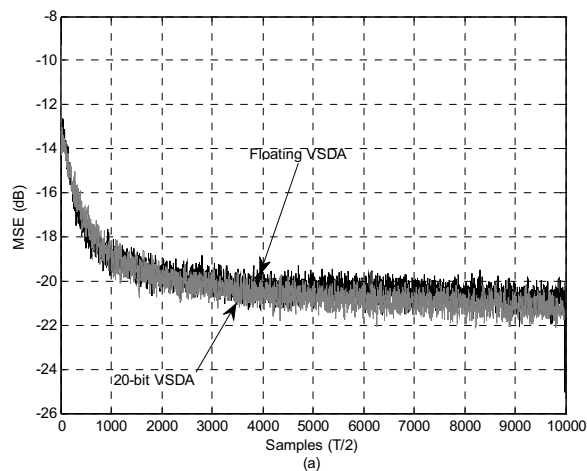
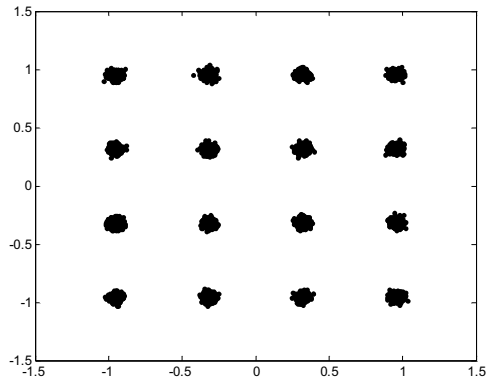


Figure 7: Fixed-point simulations of VSDA for (a) 16-QAM (b) 64-QAM using SPIB channel # 13

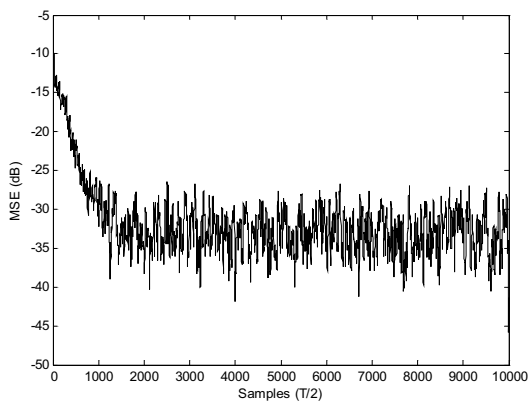
VHDL testbench using the *IEEE std_logic_textio* and *STD textio* libraries for text I/O. The stimulus data consisted of thousands of data vectors randomly generated using the Matlab fixed-point algorithms. The output of the RTL simulation was then written to a file in a Matlab format in order to produce graphical output. The final RTL results of Blind equalizer are shown in figure 8, for VSCA. These results are for a single realization and illustrate the instantaneous squared error across the slicer and the output signal constellation after convergence. The step-size parameter μ in error function block was chosen in the format $2e-x$, thereby making multiplication only a shifting operation. For VSCA the values of μ are given in table 5.

Method	QAM	μ
VSCA	16-QAM	$\{2e-8, 2e-9, 2e-10, 2e-10, 2e-11\}$
	64-QAM	$\{2e-9, 2e-10, 2e-11, 2e-11, 2e-12\}$

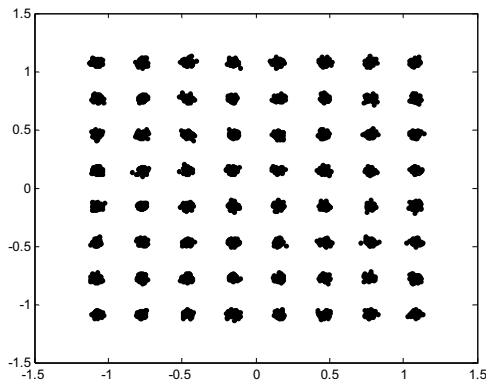
Table 5: Step size parameters selected for VSCA



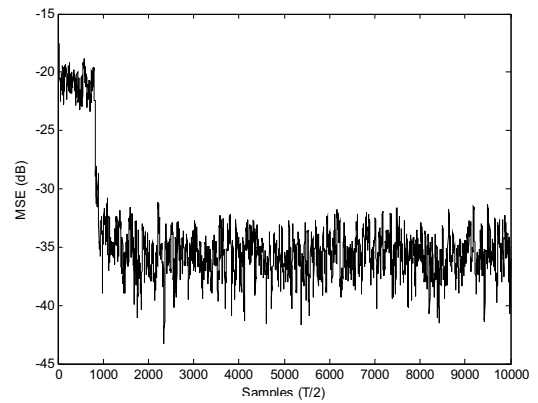
(a)



(b)



(c)



(d)

Fig. 8: RTL simulation results for VSCA (a) constellation eye-opening for 16-QAM (b) MSE plot for 16-QAM (c) constellation eye-opening for 64-QAM (d) MSE plot for 64-QAM using SPIB microwave channel # 13 performed in ModelSim 6.1f

IX. CONCLUSION

In this paper, a new distance-adjusted approach for blind equalization of QAM signals is introduced. Using this technique, two new algorithms are proposed, namely, VSCA and VSDA. A method to tune these algorithms has been developed based on the statistics of the distance. The proposed algorithms clearly outperform the SCA and MSCA in terms of convergence speed and MSE. Fixed point simulations demonstrate performance comparison between floating and 20-bit VSCA and VSDA. RTL implementation of 16-tap T/2 spaced equalizer carried out for 20-bit architecture using VSCA can achieve equalization up to 64-QAM.

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