

Performance Analysis of fixed point in Dense Communication System for Long Distance

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Abstract-Today a large amount of communication is taking place through wireless mediums, in form of cell phones and short distance communication. Here, the channel has a huge interference in the transmitted signal, thus this has to be studied using a statistical methodology. This forbids us from interpreting the received signal correctly. Telecom systems are hugely dependent on hardware, owing to their real-time servicing nature, in order to make the process convenient and cost effective, digital signal processing techniques have lately been employed. The technique discussed in this thesis is Fixed-Point DSP, where there are a limited number of bits available. Variation in quantization error will be studied with different bit widths and fractional bits. Upon Matlab implementation, it was noticed that least squares results depend more on the no. of integer bits as compared to the no. of fractional bits.

Keywords-Optical, EDFA, SOA, RAMAN

Introduction

Mathematical calculations have revealed that fixed points calculations cause larger quantization errors due to rounding off when compared to floating points operations [1-6]. The objective of this project has been to compare fixed point accuracies by using different bits, ranging inside the entire bit width [7-12]. The norm of matrices obtained in Fixed point representation are compared with the norm of matrices in Floating point representation. In this project, MATLAB simulator has been extensively used [13-16]. A great focus was put on the already derived fixed point toolbox (available as MATLAB package).

Fixed Point

It is a simple and convenient way of representing a fractional number, using a fixed number of bits. Here unlike floating point's numbers, the binary point is fixed at a particular position and it is ensured that it doesn't change. Fixed Point Numbers can be represented as per the Fig 1.

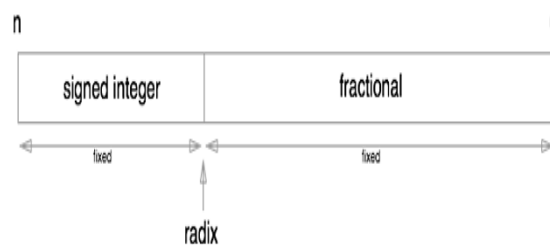


Fig. 1

Least Square Solution

Under the situations when, equation $\mathbf{Ax}=\mathbf{B}$, has no true defined solution, then it is attempted to estimate the value of 'x', which is nearest possible to the designated solution. The closest such vector will be the \mathbf{x} such that

$$Ax = \text{project } wB$$

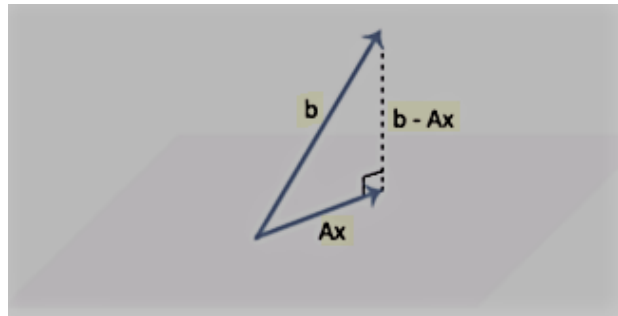


Fig. 2

The above requirement is met when the angle coincides between the Ax vector and the

Householder Decomposition Method

This is the method which is used to solve the Least Square Solution. Here matrix [A] is decomposed into Q*R

Q = Orthogonal matrix

R = Upper Triangular matrix

This decomposition can be easily performed with square matrix, whereas it is quite complicated in case of a rectangular matrix. Decomposition can be achieved by the help of Gram-Schmidt Process:-

$$\text{proj}_{\mathbf{u}} \mathbf{a} = \frac{\langle \mathbf{u}, \mathbf{a} \rangle}{\langle \mathbf{u}, \mathbf{u} \rangle} \mathbf{u}$$

then:

$$\begin{aligned} \mathbf{u}_1 &= \mathbf{a}_1, & \mathbf{e}_1 &= \frac{\mathbf{u}_1}{\|\mathbf{u}_1\|} \\ \mathbf{u}_2 &= \mathbf{a}_2 - \text{proj}_{\mathbf{u}_1} \mathbf{a}_2, & \mathbf{e}_2 &= \frac{\mathbf{u}_2}{\|\mathbf{u}_2\|} \\ \mathbf{u}_3 &= \mathbf{a}_3 - \text{proj}_{\mathbf{u}_1} \mathbf{a}_3 - \text{proj}_{\mathbf{u}_2} \mathbf{a}_3, & \mathbf{e}_3 &= \frac{\mathbf{u}_3}{\|\mathbf{u}_3\|} \\ &\vdots & &\vdots \\ \mathbf{u}_k &= \mathbf{a}_k - \sum_{j=1}^{k-1} \text{proj}_{\mathbf{u}_j} \mathbf{a}_k, & \mathbf{e}_k &= \frac{\mathbf{u}_k}{\|\mathbf{u}_k\|} \end{aligned}$$

We can now express the \mathbf{a}_i s over our newly computed orthonormal basis:

$$\begin{aligned} \mathbf{a}_1 &= \langle \mathbf{e}_1, \mathbf{a}_1 \rangle \mathbf{e}_1 \\ \mathbf{a}_2 &= \langle \mathbf{e}_1, \mathbf{a}_2 \rangle \mathbf{e}_1 + \langle \mathbf{e}_2, \mathbf{a}_2 \rangle \mathbf{e}_2 \\ \mathbf{a}_3 &= \langle \mathbf{e}_1, \mathbf{a}_3 \rangle \mathbf{e}_1 + \langle \mathbf{e}_2, \mathbf{a}_3 \rangle \mathbf{e}_2 + \langle \mathbf{e}_3, \mathbf{a}_3 \rangle \mathbf{e}_3 \\ &\vdots \end{aligned}$$

Fig. 3

The main class inside the program (“fp1”) comprises of all the key properties and functions. All the properties and functions given inside the main class are further divided into 3 categories each, which vary with different level of abstraction (user access). Every input data can be represented in the following form,

$$\begin{aligned} \text{data} &= \text{input} \cdot 2^{\text{fractional-width}} \\ \text{float} &= \text{data} \cdot 2^{-(\text{fractional-width})} \end{aligned}$$

Here the radix represents the fixed point. On the right of radix lies the fractional component, whereas on the left lies the integer component. Constant bit width poses a great challenge in depicting the signal precisely, due to this constraint the fractional bits are bound to be rounded off. This rounding off causes loss of information. Dashed line is 90 degrees, like shown in figure 2. If we summarize about Least Square Solutions, then we can say that it is the statistical procedure to derive a refined data set, by minimizing the number of extra points on the charts and other offset factors. Least square solutions are also used extensively in linear regression of data sets, and can be represented by the following equation,

$$b = Y(\text{dash}) - mX(\text{dash}),$$

$$X(\text{dash}) = (\sigma)_{x=0}^n x_i/n;$$

$$Y(\text{dash}) = (\sigma)_{y=0}^n y_i/n;$$

Simulation

The simulation was performed on the set of bit widths of 8,16,24,32 and the fractional widths being 0,4,8,12,16. The idea behind the entire simulation was to derive the difference between least square solution of floating points and Fixed points, with a random set 16*10 matrices of both variety.

Table.1

Variation of key values with changes in bit width and fractional width,

Bit Width	Fractional Width	Mean Value	Min Value	Max Value	Standard Deviation
8	0	113,87106	2,760488	251,89655	63,72847
8	4	12,70812	1,96578	19,74852	2,96458
8	8	1,94135	93,850	4,51072	48670
16	0	45,81905	2,24347	722,66578	82,84171
16	4	23145	6889	1,16934	15005
16	8	46,10689	1,58558	221,56608	59,18146
16	12	12,89856	1,73899	20,51874	2,99155
16	16	1,94612	68172	4,49945	50178
24	0	66,33105	2,69874	2020,59846	189,51745
24	4	23123	6876	1,16747	15019
24	8	1945	472	10700	15221
24	12	140	28	1309	111
24	16	47,40864	1,39787	221,74765	59,87437
32	0	66,33204	2,68802	2020,59997	189,54238
32	4	21145	6876	1,16824	15011
32	8	1942	459	10785	1287
32	12	137	1	44	5

Results

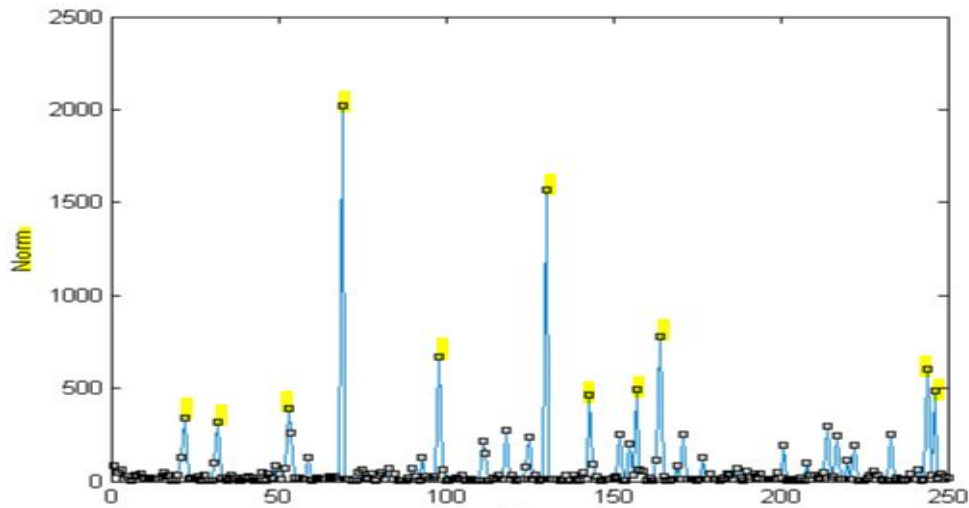


Fig. 4 Run, (Bit Width 24 & fractional width 0)

In fig. 4 it can be seen that norm values are drastically reduced. Values can be represented in decimals due to 4 fractional bits, which really increase precision. Also the rounding off error is considerably reduced.

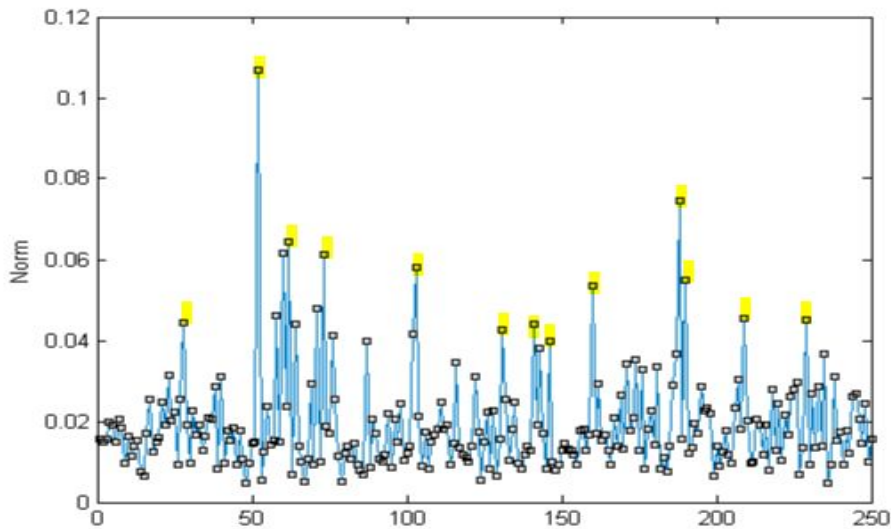


Fig. 5 Run, (Bit Width 24 & fractional width 8)

We have obtained very satisfactory and efficient results in Fig. 6, where fractional width is 16. It offers great precision and very low rounding off error. In the Fig 3 it can be observed that Norm values are extremely high, this can be attributed to lack of adequate fractional bits, causing rounding off errors.

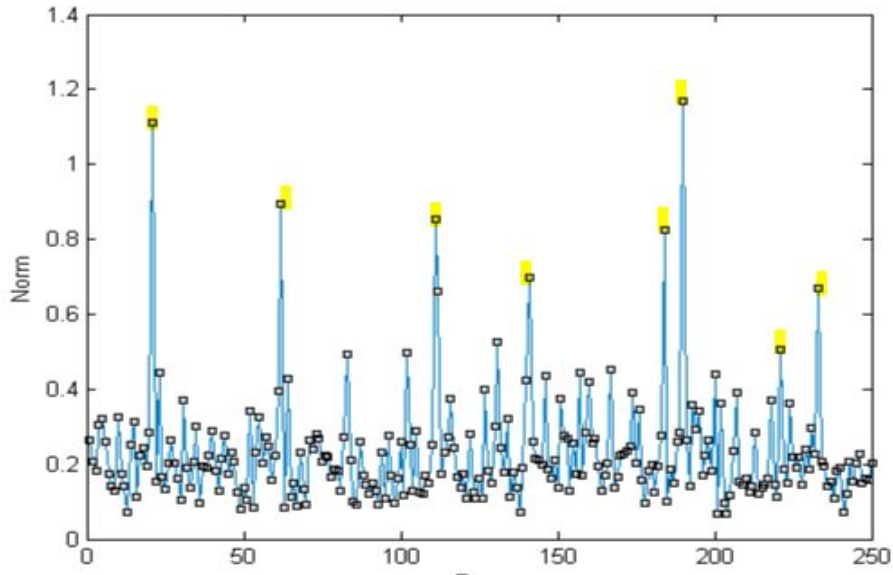


Fig .6 Run, (Bit Width 24 & Fractional width 4)

In Fig. 5 norms values have reduced down further. As we have 8 fractional bits, this enables us accommodate more decimal values and increasing the precision even further.

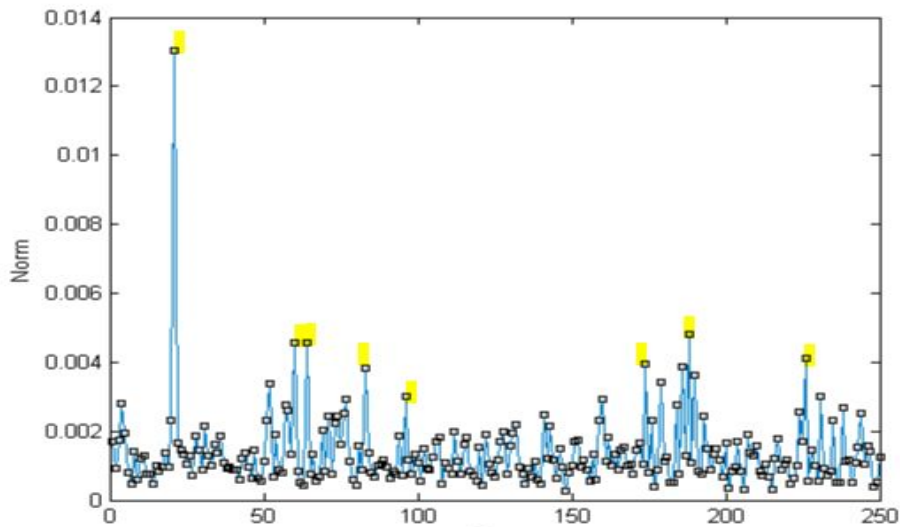


Fig. 7 Run, (Bit Width & fractional width 16)

Conclusion

The end of the simulation made in this project is that the fractional width ought to be extra than 0 due to rounding. The results are relying more on the number of integer bits, due to the need of double bit width in a multiplication. Some other ideas for destiny paintings are to make it feasible to boom the precision inside the arithmetic features. Another idea is to enforce an iterative technique for fixing least rectangular troubles. One approach that accomplishes this is the Gauss Seidel approach, which then ought to be in comparison to the Householder QR decomposition technique. If the fractional width is multiplied to minimize rounding errors, the bit width additionally needs to be improved to avoid saturation.

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