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ADC Testing Algorithm for ENOB by Wavelet Transform using LabView Measurements and MATLAB Simulations

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Abstract: In this study, a new time frequency domain approach (well known as Wavelet Transform) will be applied to measure and analyze Analog-to-Digital Converters (ADC's) Effective Number of Bits (ENOB). In classical testing, ENOB is based on the Ratio of the Signal to Noise components (SNR) whose coefficients are driven via frequency domain that is fourier transform of the ADC's output signal and is extremely sensitive to noise. This makes ENOB estimation process longer and complex as the ADC's resolutions increases. In this research of evaluating non-ideal ADC's (real time testing), a new proposed evaluation method based on wavelet transform was used to estimate the worst case ENOB through the output signal dynamic range. Comparing with the classical testing methods, wavelet transform have shortened testing time and reduced computations complexity due to its special properties of multi-resolutions analysis. In addition, wavelet transform have improved ENOB estimation since, noise averaging is not part of testing algorithms. This method of wavelet transform improves the DSP testing for ADC's parameters.

Key words: Effective Number of Bits (ENOB), Discrete Wavelet Transforms (DWT), Analog-to-Digital Converters (ADCs), components, multi-resolutions, evaluating

INTRODUCTION

Mixed signal devices provide the ability of transforming information across Digital and/or Analog domains as desired (Mark, 2003; Burns *et al*., 2001). Therefore in choosing the right data acquisition board, conversion accuracy can be one of the most important factors. For proper system performance and digitizing accuracy, the output digitized data need to be close to the input signal. At most basic level, digitizer testing would seem simple matter, however, testing is extremely expensive and time consuming as indicated by Ramos *et al*. (2016), Gomez-Pau *et al*. (2015), Awada *et al*. (2010), Yamaguchi and Soma (1997), Marshall and Akujuobi (2002), Awada (2013), Cherubal and Chatterjee (2003) and Serra *et al*. (2005) for both static and dynamic parameter characterizations. Dynamic parameters of ADC's, based on FFT, provide specific information that shows the effect of noise and signal distortions, especially with applications of high-frequency signals. Depending on the quality of the digitizers and the continuous switching of signals between multiple channels, dynamic parameters such as ENOB can drop noticeably. For example, a 16 bit ADC's can drop to 12 bit or even fewer effective bits which drop the accuracy of system performance. Therefore, ENOB measurements can be one of the major dynamic error characteristics of any digitizer board but this measurement can be lengthy and complicated due to the large number of data samples acquired and the fact that it is heavily based on errors caused by noise (SNR).

As a result, significant research has been done to improve the testing techniques of ADC's parameters. Some focused on improving classical methods such as Fourier transform and Sinusoidal histogram in testing AC and DC performance (Cherubal and Chatterjee, 2003; Xu, 1999; Wagdy and Awad, 1991). However, while fourier transform is based on additive noise model and requires a large number of data samples (Yamaguchi and Soma, 1997; Marshall and Akujuobi, 2002), histogram testing for DC behaviors has most samples occur near the ends of histogram (large number of samples must be collected to increase the height of bins around the center) (Burns *et al*., 2001; Akujuobi, *et al*., 2007). Others have

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concentrated on new testing algorithms such as WT (Gomez-Pau *et al*., 2015; Yamaguchi and Soma, 1997; Marshall and Akujuobi, 2002; Akujuobi and Hu, 2002, 2003; Gandelli and Ragaini, 1996) in order to improve testing quality and duration. Through the simulation process (Awada, 2013), WT have shown improvements and very satisfactory results in term of accuracy and simplicity. As shown by Gomez-Pau *et al*. (2015) and Awada *et al*. (2010), WT were used in modeling ADC's testing at various numbers of bits for ENOB estimation. However, this research will explore the strength of this approach in real time testing.

In this study, wavelet based testing algorithms is proposed for evaluating an actual ADC's performance of instantaneous ENOB. Wavelet based digital signal processing have shown improvements in ADC's testing quality in both simulation and realistic performance. With the focus on shortening testing process, reducing sample size, simplifying testing complexity and improving ENOB estimation for higher resolutionsADC, wavelet computation efficient was very suitable for this application in contrast to the mean value measured by the conventional methods (Yamaguchi and Soma, 1997).

Effective Number of Bits (ENOB): The conventional method of testing ADC's effective bits is based on the ratio of the fundamental signal to the sum of all distortion and noise products in the output signal, after the DC term is removed. Therefore in testing for ENOB, clean analog sine-wave was used as stimulus input, since, perhaps it is the most popular method of evaluating ADC (Awada, 2013; Kollar and Blair, 2005). For an ideal ADC's output, signal (data) transformed into frequency domain will result in one spectral component. In real ADC's operation, quantization errors which cause nonlinearity effect on ADC's transfer function results into spectral frequencies other than the input frequency being tested. Quantization errors caused by IC internal or external noise (Burns *et al*., 2001) appear as random noise spread across the frequency spectrum of FFT, distort the conversion process and result in harmonic distortions and higher noise floor. The relation between nonlinearity, harmonics and noise floor are used to address ADC's ENOB and SNR.

The effective resolution of ADC's is one part in 2n (n is the ADC number of bits). For an ideal 12 bits ADC, 4096 unique digital codes are produced and the effective resolution is one part in 4096 codes as given by Mark (2003):

$$\text{dB} = -20\log\left(\frac{1}{2^n}\right) \quad (1)$$

ENOB can be expressed in term of SNR as:

$$\text{SNR} = \left(\left(\text{ENOB}\right)\times 6.02\right)+1.76)\text{dB} \quad (2)$$

By relating the noise ratio to ENOB and rearranging (Eq. 2), ENOB can be expressed as:

$$\text{ENOB} = \frac{\text{SNR}[\text{db}]-1.76}{6.02} \quad (3)$$

This method of estimating ENOB is extremely sensitive to errors caused by noise (Burns *et al*., 2001; Akujuobi and Hu, 2002) and requires a large number of samples. Therefore, the new proposed method of WT based testing can be especially suited for ENOB estimations with fewer samples.

In the next study, a brief description of the Discrete Wavelet Transform (DWT) illustrates the function and advantage of using DWT.

MATERIALS AND METHODS

Discrete wavelet transform: The objective of signal transformation is to have a different representation of a signal with no changes to the signal information. The Fourier transform which is based on summation series of sine and cosine waves, expresses signals in the frequency domain to determine frequencies in the signal with no time representations. Meanwhile in Wavelet transform, the objective is to achieve a localized space frequency with the ability to determine the position of frequency components (Kollar and Blair, 2005; Rioul and Vetterli, 1991; Adamou-Mitiche *et al*., 2016). Wavelet transforms have been used in various fields of signal processing (Awada *et al*., 2010; Rioul and Vetterli, 1991; Adamou-Mitiche *et al*., 2016) due to the functionality of multi-resolutions that allow pinpointing of signal components. With special properties of dilation and translation (Gomez-Pau *et al*., 2015; Awada *et al*., 2010; Kollar and Blair, 2005; Rioul and Vetterli, 1991; Adamou-Mitiche *et al*., 2016; Bayram and Seker, 2016; Silverman, 2000; Oliver *et al*., 2005), wavelets can create different scaled and shifted functions of signal transformation as in Fig. 1. In other words, unlike the Fourier transform, wavelet transform capability of dilation and translation allow the shift of a signal in the time domain (X-axis), rescaling (to expand or compress a signal on Y-axis) and produces flexible windows for analysis.

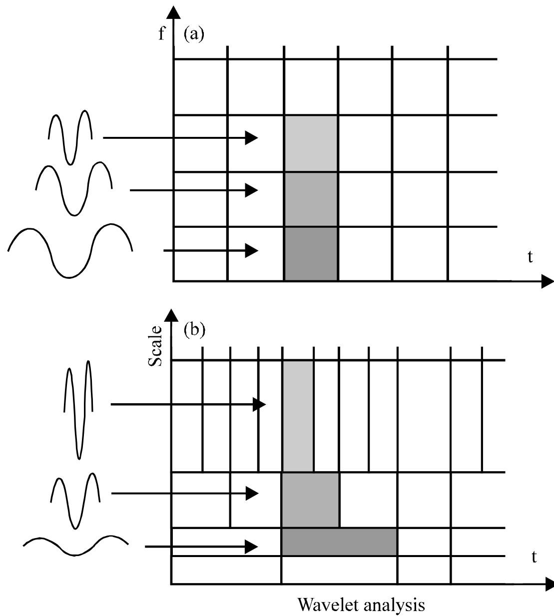

Fig. 1: a) Short-time fourier transform and b) Wavelet transform

Large scaling, allows us to see all information of the signal (the big picture), however in small scales wavelet shows signal details by zooming into the signal components.

To better understand wavelets, the Continuous Wavelet Transform (CWT) will be looked at first. In (Mallat, 1999), wavelet (Ψ) is a function of zero average as, i.e.:

$$\int_{-\infty}^{\infty} \psi(t)\,dt = 0 \tag{4}$$

where (Ψ) is base function known as mother wavelet used to drive wavelet transformation function through dilation (s) and translation (u) as:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{S}}\psi\left(\frac{t-u}{s}\right) \tag{5}$$

And since, wavelet merely performs a convolution operation with a given signal, Wavelet transform of continuous signal x(t) can be illustrated as:

$$Wx(u,s) = \int_{-\infty}^{\infty} X(t)\frac{1}{\sqrt{S}}\psi\times\left(\frac{t-u}{s}\right) \tag{6}$$

While DWT computation is based on predetermined low and high-pass filters for a particular wavelet function in most cases.

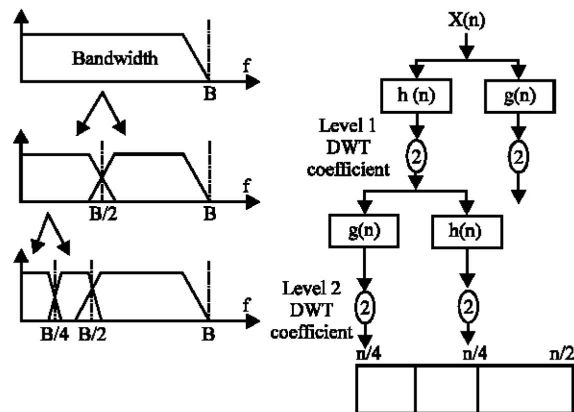

Fig. 2: Wavelet multilevel decomposition. Where, g(n) and h(n) are the Wavelet low and high-pass coefficients, respectively

In this research, DWT algorithm was used to analyze ADC output signal by first utilizing filter banks of high and low-pass and down-sampled by factor of 2 (decimation) in each scale (Gomez-Pau *et al*., 2015; Awada *et al*., 2010; Awada, 2003; Rioul and Vetterli, 1991) as shown in Fig. 2. The low-pass filter coefficient denoted by (g) produces approximation signal information while the high-pass filter coefficient denoted by (h) produces detail information.

By applying filtering and decimation factors of 2 at each decomposition level, frequency characterizations are passed and number of samples rate is reduced by half (half the frequency band). Starting withe the largest scale (the original signal), bandwidth becomes a multiple of half at the high and low-pass filters.

Wavelet-based estimation for ENOB: In this research, DWT was implemented to test high-speed 12 bits ADC (ADS5410). Testing procedures as in Fig. 3 and 4 was constructed based on single tone clean sine-wave.

Theoretically, by applying clean perfect sine wave, stimulus signal parameters such as (amplitude, frequency, phase, dc offset, etc.,) can be determined (Kollar and Blair, 2005) and the deviation of the ADC output signal from the ideal input signal is an effect of ADC performance. For an ideal ADC, the deviation is negligible (zero). However, realistic ADC performance produce quantization error that distort the output signal $\hat{X}[n]$ as:

$$\hat{X}[n] = X[n] + q \tag{7}$$

Where:

X [n] = Original value

q = Quantization error

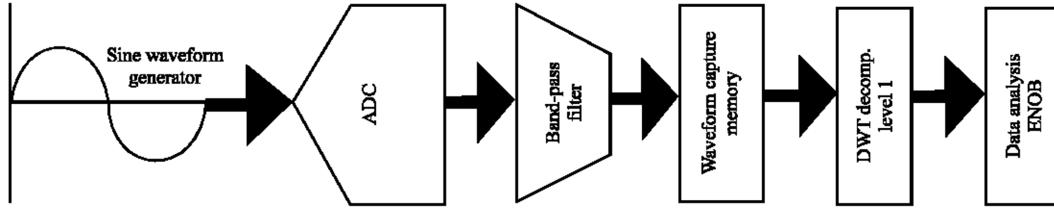

Fig. 3: Model setup for automated ADC wavelet test

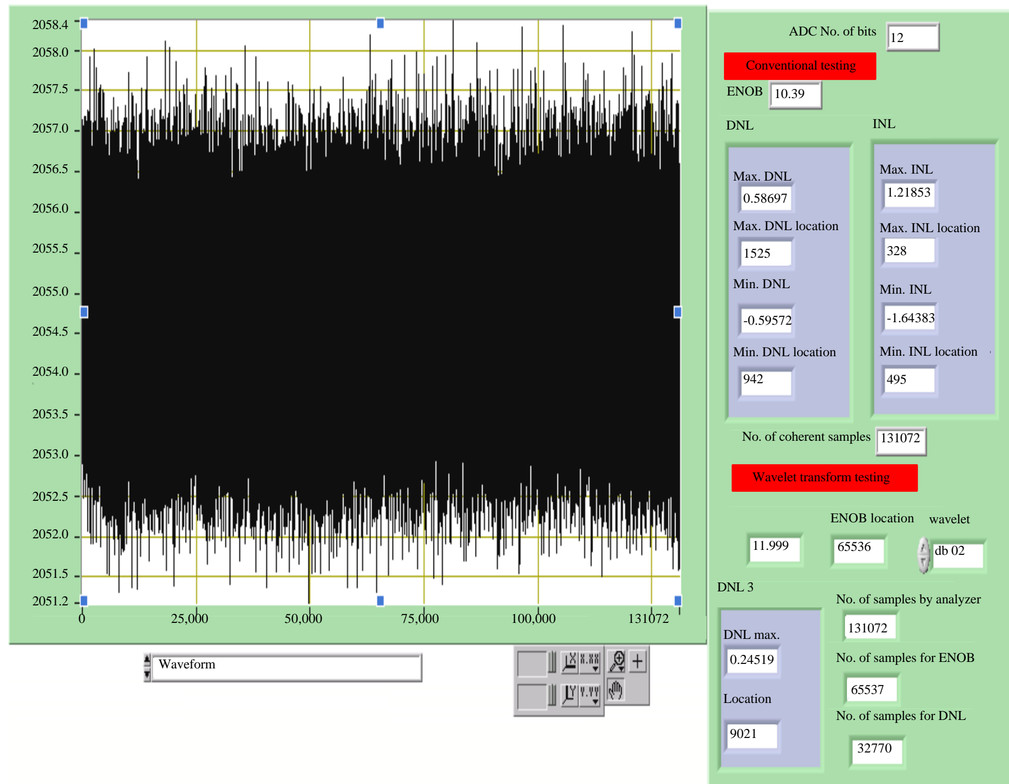

Fig. 4: Front panel of LabView ENOB calculation

By capturing ADC output data $\bar{x}[n]$ and appling DWT algorithms, using multi-resolution techniques, a combination of instantaneous low frequency (approximation coefficients S_n) and high frequency (detail coefficients d_n) are produced as shown in Eq. 8 and 9, respectively:

$$\begin{bmatrix} \vdots \\ S_{n-1,1} \\ S_{n-1,0} \\ S_{n-1,1} \\ \vdots \end{bmatrix} = \begin{bmatrix} \cdots\ \cdots\ \cdots & & \\ \cdots\ \tilde{h}_{-1}\ \tilde{h}_0\ \tilde{h}_1\ \tilde{h}_2 \cdots & & \\ & \cdots\ \tilde{h}_{-1}\ \tilde{h}_0\ \tilde{h}_1\ \tilde{h}_2\ \cdots & \\ & & \cdots\ \tilde{h}_{-1}\ \tilde{h}_0\ \tilde{h}_1\ \tilde{h}_2\ \cdots \\ & & \cdots\ \cdots\ \cdots \end{bmatrix} \begin{bmatrix} \vdots \\ S_{n,-1} \\ S_{n,0} \\ S_{n,1} \\ \vdots \end{bmatrix} \quad (8)$$

$$\begin{bmatrix} \vdots \\ S_{n-1,1} \\ d_{n-1,1} \\ S_{n-1,0} \\ d_{n-1,0} \\ S_{n-1,1} \\ d_{n-1,1} \\ \vdots \end{bmatrix} = \begin{bmatrix} \cdots\ \cdots\ \cdots & & \\ \cdots\ \tilde{h}_{-1}\ \tilde{h}_0\ \tilde{h}_1\ \tilde{h}_2 \cdots & & \\ \cdots\ \tilde{g}_{-1}\ \tilde{g}_0\ \tilde{g}_1\ \tilde{g}_2\ \cdots & & \\ & \cdots\ \tilde{h}_{-1}\ \tilde{h}_0\ \tilde{h}_1\ \tilde{h}_2\ \cdots & \\ & \cdots\ \tilde{g}_{-1}\ \tilde{g}_0\ \tilde{g}_1\ \tilde{g}_2\ \cdots & \\ & & \cdots\ \tilde{h}_{-1}\ \tilde{h}_0\ \tilde{h}_1\ \tilde{h}_2\ \cdots \\ & & \cdots\ \tilde{g}_{-1}\ \tilde{g}_0\ \tilde{g}_1\ \tilde{g}_2\ \cdots \\ & & \cdots\ \cdots\ \cdots \\ & & \cdots\ \cdots\ \cdots \end{bmatrix} \begin{bmatrix} \vdots \\ \vdots \\ \vdots \\ S_{n,-1} \\ S_{n,0} \\ S_{n,1} \\ \vdots \\ \vdots \\ \vdots \end{bmatrix} \quad (9)$$

From the high-pass filter, detail coefficients were obtained as:

$$\left(\cdots d_{n-1,-1}, d_{n-1,1}, d_{n-1,2}, d_{n-1,3}, d_{n-1,4}, d_{n-1,5}, d_{n-1,6}, d_{n-1,7}, \cdots,\right) \quad (10)$$

then down sampled by Eq. 2 (by taking the odd values as shown in Eq. 11) to end with half of the original data, i.e.:

$$\left(\cdots, d_{n-1,-1}, d_{n-1,1}, d_{n-1,3}, d_{n-1,5}, d_{n-1,7}, \cdots,\right) \quad (11)$$

As shown by Burns *et al.* (2001), the largest components of DWT high-pass coefficient at scale 1 defines the Dynamic Range (DR) that is used to estimate worst case ENOB. DR can be defined as (Burns *et al.*, 2001):

$$DR = -20\log_{10}\left[\frac{1}{\sqrt{2}}\left(\frac{\Delta}{2}\right)\right] = -20\log_{10}\left[\frac{1}{2^{\hat{B}-0.5}}\right][dB] \quad (12)$$

Where:

$\hat{B}$ = The Effective Number of Bits (ENOB)

Δ = Quantization step size

By rearranging Eq. 12, worst case instantaneous ENOB can be directly estimated as (Burns *et al.*, 2001):

$$\hat{B} = \frac{DR}{20\log_{10}(2)} - 0.5[bit] \quad (13)$$

Finally, applying labview testing and automation, ADC output signal was analyzed in DWT and computation algorithm was applied to obtain the worst case ENOB as in Fig. 4.

RESULTS AND DISCUSSION

Simulation and measurements: In addition to the actual lab testing and evaluation of DWT algorithms in estimating for the worst case ENOB, MATLAB simulation algorithm was implemented to verify the actual testing results. With no extraneous noise, ADCs (range from 6-18 bits) were tested based on FFT and DWT algorithms. Results are shown in Table 1 and illustrated in Fig. 5.

Meanwhile, an extraneous noise was introduced to the idealADCs output. A range of 10-14 bits ADCs were tested. Results of extraneous noise effects on ENOB measurements are shown in Table 2 and illustrated in Fig. 6.

As illustrated in Fig. 6, FFT tend to overestimate ENOB especially as ADCs number of bits increases. FFT test depend on noise summation (average) to all noises including quantization noise and very small noises (Awada *et al.*, 2010; Yamaguchi and Soma, 1997). This fact has higher effect on higher bits ADCs since quantization levels get smaller and any detection of noise offset ENOB estimation. Meanwhile, DWT tend to localize into ADCs output data as a result of multi-resolution property. This property allows obtaining the dynamic range of the output signal without noise summation.

Table 1: ENOB testing results (conventional method vs. wavelet) based on no extraneous noise simulation

	ADC (bits)						
DWT/FFT	6	8	10	12	14	16	18
haar	6.06	8.16	10.14	12.16	14.27	16.10	18.34
db4	5.97	7.9	10.17	11.92	13.97	16.02	18.00
db10	6.05	7.84	10.11	12.01	14.06	16.07	18.06
sym8	5.99	8.04	9.93	12.16	14.13	15.81	18.23
coif1	5.83	7.93	9.78	12.07	14.03	15.72	18.20
FFT	5.95	8.04	9.97	11.84	14.09	15.89	17.97

Table 2: ENOB testing results (conventional method vs. wavelet) based on extraneous noise simulation

	ADC (bits)		
DWT/FFT	10	12	14
haar	9.40	11.50	13.50
db4	9.00	11.00	13.00
db10	8.70	10.72	12.72
sym8	8.71	10.77	12.71
coif1	8.82	10.82	12.82
FFT	8.50	10.38	11.35

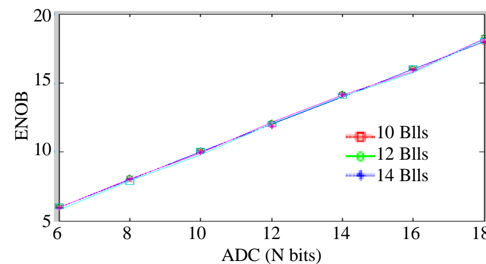

Fig. 5: ENOB at ideal ADC with no extraneous noise

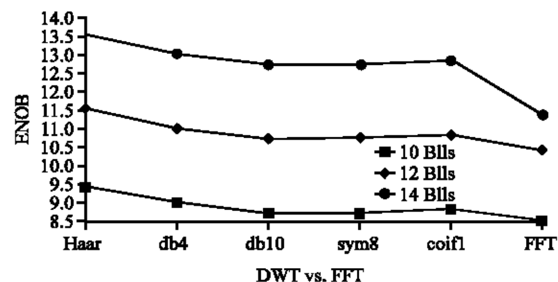

Fig. 6: ENOB at ideal ADC with extraneous noise

Actual testing setup and measurements by "LabView": Unlike text programming languages such as C++ for TRAN, Basic, etc., LabView is general purpose programming language based on graphical elements (Mallat, 1999). The graphical language of LabView reduces application development time and adds value by

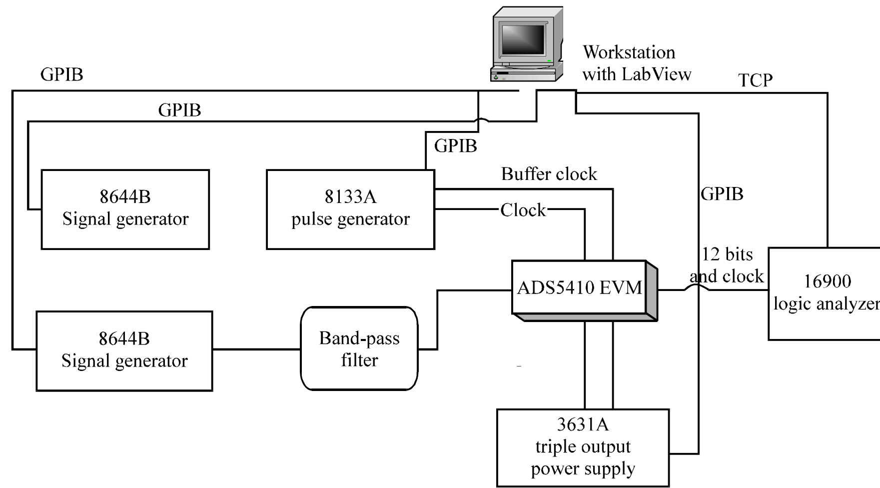

Fig. 7: ADC testing equipment's and layout

controlling other test equipment, acquire, analyzing and presenting data. Since, the adoption of PC for test measurements and analysis of captured data, LabView was ideal software for this testing application. VIs was developed for each specific function of this application and grouped to create one main VI to perform the controlling, compiling, analysis and presentation of tested data.

Testing setup and measurements: As shown in Fig. 7, signal generator, Agilent 8644B was used to produce a sine-wave of 10 MHz for testing purposes. The sine-wave was used as input signal to the EVM board through a band-pass filter. Meanwhile, a pulse generator, Agilent 8133A, provided sampling frequency clock as well as the buffer clock to the board that connects to the logic analyzer at 30, 40, 60 and 80 MHz. Triple output power supply (Agilent 3631A) provides a 3.3 V supply to the analog input of the ADS5410 EVM and a 1.8 V supply for the digital input of the board to drive the digital circuits. At the ADC output, Agilent 16900A logic analyzer, a key instrument in real time ADC testing was used to capture ADC discrete output data (Mallat, 1999).

All test equipment were controlled by and interacted through a work station PC and GPIB digital communication bus while a local area network was used to fetch the data to the work station. A picture of arranged bench prototype testing set-up is shown in Fig. 8.

Through LabView automation and control software, ADC output data were transformed and analyzed by FFT and DWT (such as Haar, db4, db10, coief1 and sym8) algorithms. A summary of ENOB estimated value is given in Table 3 and illustrated in Fig. 9.

Wavelet transforms have shown improvements in testing techniques by reducing number of sampling data

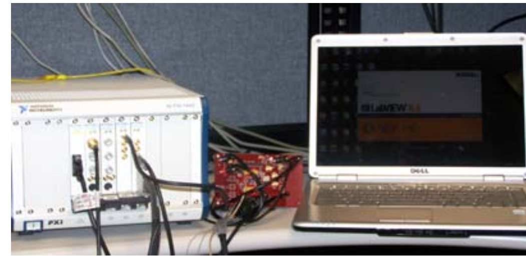

Fig. 8: Bench prototype testing set-up

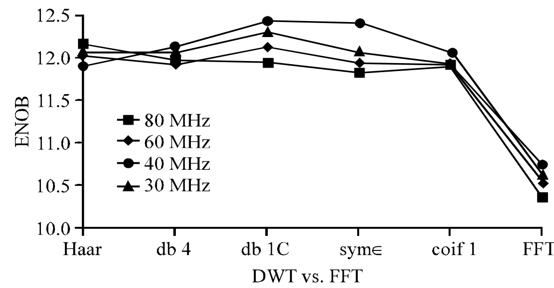

Fig. 9: ENOB testing results (conventional method vs. wavelet)

Table 3: ENOB testing results (conventional method vs. wavelet)

Sampling frequencies (MHz)	haar	db4	db10	sym8	coief1	FFT
80	12.14	11.95	11.93	11.80	11.88	10.31
60	12.03	11.90	12.12	11.92	11.91	10.71
40	11.90	12.13	12.43	12.40	12.06	10.62
30	12.05	12.06	12.30	12.05	11.92	10.52

and multiplication complexity. For example, 12 bits ADC requires 131072 data samples through conventional testing methods such as FFT to estimate for ENOB (Burns *et al*., 2001). However, as shown in Fig. 10, wavelet

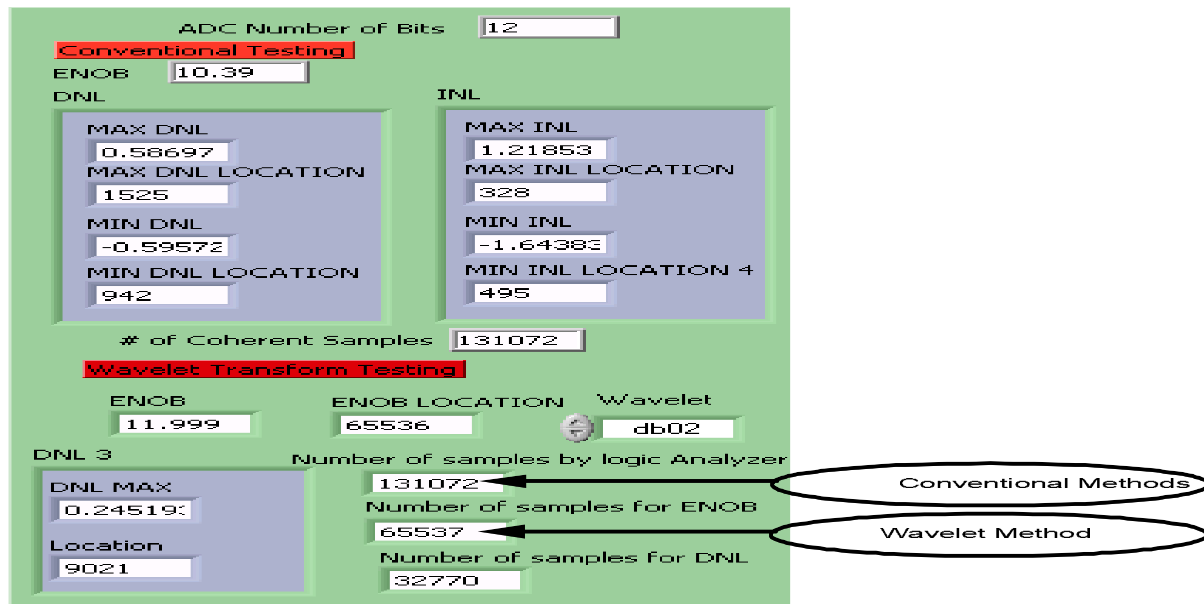

Fig. 10: Number of data samples collected (conventional method vs. wavelet)

transform algorithms decimate number of samples (bandwidth) by 50% (65536 samples) at high and low-pass filters to compute for ENOB. This feature of DWT reduces the data storage space requirements and shortens the testing time.

CONCLUSION

By implementing the wavelet transform, we were able to compare testing results of different types of wavelets to conventional methods such as FFT. It can be clearly observed that classical testing based on FFT sums all noises (large and small) over many sample point. As ADCs number of bits increases, quantization step sizes decrease and quantization noise has higher effect on ENOB estimation. Meanwhile, DWT provided well localized measurements of signal components and estimate ENOB based on the localized signal dynamic range. The real time testing using DWT was successful in measuring ADC performance without averaging noise. As a result, DWT can be used to reduce testing cost, duration and complexity based on the reduction of computed samples increases the accuracy of ENOB estimation especially for higher bits ADCs and its DSP algorithms can be implemented as built in self-test of ADC parameters based on the recursive feature.

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