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MULTI-RESOLUTION BASED DISCRETE WAVELET TRANSFORM FOR ENHANCED SIGNAL COVERAGE PROCESSING AND PREDICTION ANALYSIS

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ABSTRACT

Wavelet transform methods are extensively employed to transform signal dataset into different components for effective spatial signal power processing and modelling. In this work, a distinctive multi-resolution discrete wavelet transform algorithm is explored for enhanced processing and decomposition of measured signal power coverage data acquired from operation LTE cellular communication networks. The effectiveness of Symlets (sym) and Daubechies (db) wavelets under five decomposition levels are analyzed based on five quantitative evaluation parameters: root mean square error (RMSE), signal to error reconstruction ratio, (SRER), Pulse amplitude demodulation (PAD), Coefficient of correlation (R) and standard deviation (STD). The results that multi-resolution based processed signal with sym3 wavelet under decomposition level 4 is best compared to others, in terms of the computed statistical indices. The above best performance with sym3 can be attributed to their excellent denoising property of the entire symlets wavelet family. Besides, the obtained results reveal that the choice of wavelet thresholding technique and level of decomposition also significantly impact the sensitivity and reliability of data-driven predictive analytics with adaptive polynomial.

Keywords**:** Signal processing, Multi-resolution decomposition**,** thresholding technique, data-driven predictive analytics

INTRODUCTION

Signal processing is a subcomponent of information, mathematics and electrical engineering which mainly deals with the analysis, synthesis, and transformation of signals. For instance, signal processing techniques can be employed to enhance signal transmission reliability and communication quality; and that can be achieved by detecting and extracting the desired components of interest in measured signal data.

Information about spatial signal attenuation processing is of pronounced importance in signal coverage predictive analysis, modelling and management because it reflects the exact field strength in cellular network planning processes. Measurement, analysis and extrapolative forecasting of spatial signal attenuation and field strength coverage are intricate processes owing to their nonlinear and stochastic properties.

Conventional techniques for spatial signal processing, using Fourier transform and serial correlation analysis, deals with only stationary and temporal signal processing in frequency domain. Compared to the above conventional techniques, wavelet transform (WT) provides superior support for multi-spatial scale signal analysis and non-stationary signal representation with a good resolution, and so has become a potent processing tool in signal coverage predictive analysis, modelling and management. Another key superiority WT has over the Fourier transform is the usage of robust shifting window of adaptable width for signal enhanced processing along all scale (i.e. frequency) bands (Ojuh and Isabona, 2018; Isabona and Ojuh, 2017). WT can decompose a signal dataset to various scales with characteristic frequency bands (i.e. scales, such that, at every scale), the locus of signals features are determined approximately.

One of the upmost operative uses of WT in signal processing is denoising, (i.e. lessening or removing noise in a signal). The WT-based technique can yield much better denoising quality than traditional methods. Moreover, the WT-based process preserves the original information of a signal after denoising.

There exist two main types of wavelet transforms. They are the continuous wavelet transform (CWT) and discrete wavelet transform (DWT). In statistical and realistic practical settings, data scientists are more largely entranced with discretely sampled functions, compared to the continuous functions. Thus, in this paper, the emphasis is only on the DWT functions. In functional and numerical analysis, DWT is a distinctive wavelet transform wherein the wavelets are discretely assessed and sampled both in frequency and location information. The Haar, Daubechies, Coilets and Symlets are all examples of DWT. A fast wavelet decomposition and reconstruction algorithm was first introduced in 1988 by Stephane Mallat (Mallat, 1988). For a DWT algorithm, is a classical scheme in the signal processing community, the Mallat explores two channel sub-bandcoder to process signal using conjugate quadrature filters.

Principally, the focus of this research work is to explore DWT en route for enhanced processing of one dimensional measured noisy signal data acquired from operation LTE cellular communication networks. Other authors (Lahmiri and Boukadoum, 2015; Rajbhandari, Ghassemlooy and Angelova, 2009; Galiano, and Velasco, 2015, Wang, Wan, Wong, and

Zhang, 2016; Wu, Shen, and Zhou, 2013; Sharmila and Geethanjali, Lahmiri, 2014; Gautier, Arndt and Lienard, 2007), have also carry out some similar researches on signal processing by means of wavelet transform analysis method. But unlike those previous researches, this work explores more practical signal processing procedures which includes decomposition, thresholding and reconstruction using the MATLAB software.
In addition, the effect of the enhanced processed signal data on signal power coverage prediction accuracy at different data points is also investigated using adaptive polynomial predictive fitting.

PROPOSED METHODOLOGY

Signal Data Collection

The base station transceiver (also known as NodeB) explored for signal data collection process belong to major commercial telecom service provider operating Port Harcourt City, Nigeria. The NodeB engineering parameters collection are listed in Table 1. The field test tools employed for signal data collection round the NodeB are:
Pilot Pionner scanner
HP Laptop empowered by TEMS
TEMS pocket Samsung mobile phone
DC/AC converter
Geography positioning system (GPS)
Dongle

With the aid of the above field drive test tools, signal measurements were conducted along different routes round the NodeB cell sites, in active mode for six months. The acquired signal type is called Reference Signal Receive Power (RSRP). Shown in figure 1 is the illustrative diagram of the mobile terminal transmitting set-up to NodeB during data collection. The acquired signal, can be analyzed using a set of wavelet functions through different resolution process as described below in section 2.2.

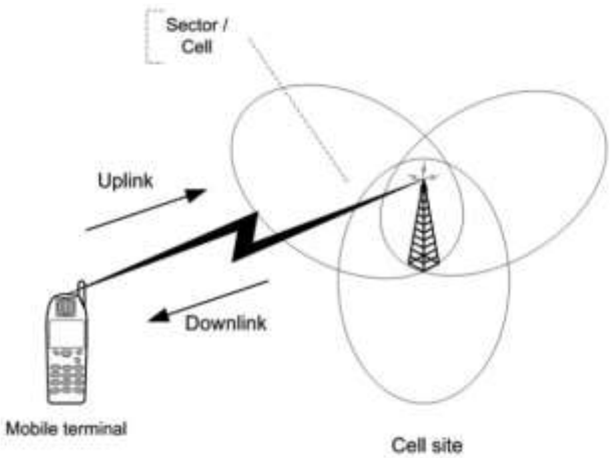

Fig. 1: Mobile Terminal Transmitting Configuration during Field Drive Test

Table 1: NodeB Engineering Parameters

Parameter	Value
Antenna Height	40m
Uplink operating frequency	900MHz
Downlink operating frequency	900MHz, frequency band 2600MHz.
Transmit power	20W (43dB)
Sectorial type	3

Multi-resolution DWT decomposition and reconstruction methodology

The term' wavelet' term describes a wave based window function in correspondence to main frequency f_0. The classical continuous wavelet transform is defined as:

$$W[\tau,\mu]=\frac{1}{\sqrt{\mu}}\int x[t]\psi[t]\left[\frac{t-\tau}{\mu}\right]dt \quad (1)$$

where:
$\psi(t)$ = mother wavelet function
τ =translator factor
μ =scale factor (which is the inverse of f_0)
$\frac{1}{\sqrt{\mu}}$ = signal energy normalization factor

In terms of DWT setting, the parameters τ and μ take on discrete values. The coefficients of $x(t)$ in equation (1) can be expressed as:

$$W[k]=(x*\psi)[k]=\sum_{-\infty}^{\infty}x[k]\psi[n-k] \quad (2)$$

where k is the translation parameter, and n is an integer.

This work explores multi-resolution DWT decomposition and reconstruction methodology for the enhancement of measured LTE signals under noisy conditions. The proposed methodology is based on Mallat transform algorithm (Mallat, 1988). For DWT, the Mallat algorithm involves processing the reference signals using conjugate quadrature filters to produce signal wavelet approximation and detailed coefficients. The block diagram of Figure 2 reveals the various steps employed to implement the proposed methodology.

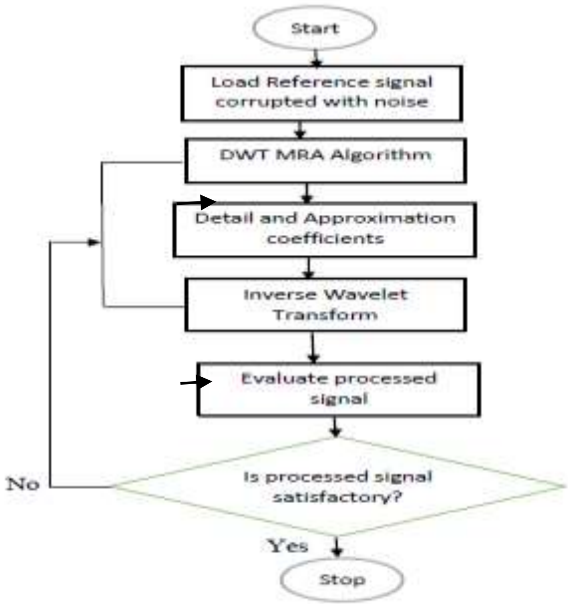

Fig. 2: Block diagram for the Enhanced for the Signal data denoising with WDT

The measured noisy signals is the reference signal data. For a signal sample of length L, the DWT comprises of $\log_2 L$ steps. The first stage entails the convolving of the signal sample simultaneously with both low-pass filter and high-pass filter to provide a number of approximation coefficients and detail coefficients correspondingly. The filter output of low-pass filter and the high-pass filter can be expressed as:

$$W_{low}[n] == \sum_{-\infty}^{\infty} x[k]g[2n-k] \qquad (3)$$

$$W_{high}[n] == \sum_{-\infty}^{\infty} x[k]h[2n-k] \qquad (4)$$

After that, part of the signal samples are removed via a process termed down sampling. The signal decomposition is repeated over several levels to further upturn the frequency resolution. Figure 3 illustrates 5 decomposition levels and all the filters possesses a function for sub-sampling of the signal by 2.

$g(n)$ and $h(n)$ are dependent on each other by:

$$g[L-1-n] = (-1)^n . h(n) \qquad (5)$$

where L is the length of the filter.

Next step is the reconstruction of the signal and it can be expressed by:

$$x(n) = \sum_{k=-\infty}^{\infty} \left(W_{lhigh}[n]x[k].g[-n+2k]\right) + \left(W_{l\,ow}[k].h[-n+2k]\right) \qquad (6)$$

The reconstruction is implemented using Inverse Discrete Wavelet Transform (IDWT).

Whereas decomposition consist of convolution followed by dint of down sampling, reconstruction involves up sampling followed by means of convolution. Up sampling defines the signal lengthening process by injecting zeros amid the signal data points.

While carrying out the reconstruction, both the detail coefficients, cD and approximation coefficients, cAn are first up sampled. While the detail coefficients are convolved using a high pass filter, the approximation coefficients are convolved using the low-pass filter. Both sets of convolved data are then combined to obtain the next level of approximation coefficients, cA,-1

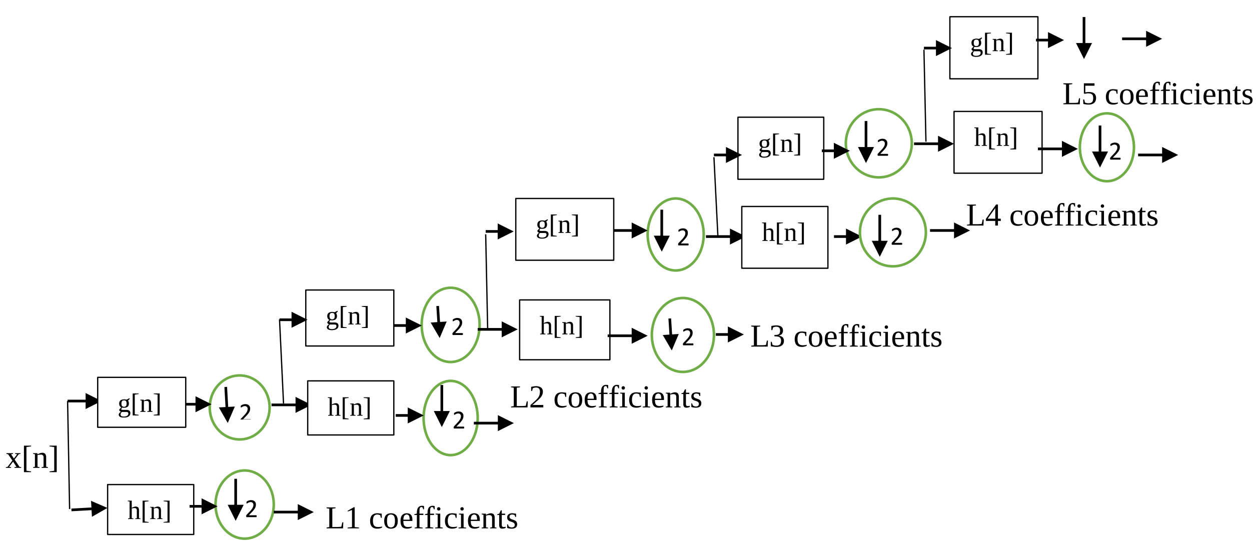

Fig. 3: A Filter bank illustration of different level Decomposition with DWT

There exist a number of wavelet families, among the key ones are Haar, Daubechies, Coilets, Symlets, Biorthogonal, Reverse Biorthogonal, and discrete FIR Mayer wavelet. A brief description of the most frequently used ones in literature are summarized in Table 2.

In this work, based on recommendation in (Renisha and Jayasree, 2015), only Symlets and Daubechies are investigated with decomposition level N varied from 1 to 5.

Table 2: Orthogonal Wavelet Families and their key Features

	Orthogonal Wavelet	Features	wname
1	Coiflet	wavelets and Scaling function possess same vanishing moment number	'coifN' for N = 1, 2, ..., 5
2	Symlet	Nearly linear phase; Least asymmetric. The Symlets wavelets possess minimal phase.	'symN' for N = 2, 3, ..., 45
3	Daubechies	Energy is concerted nigh the start of their support; Nonlinear phase. Daubechies wavelets family possess maximal phase	'dbN' for N = 1, 2, ..., 45
4	Haar	A special case of Daubechies; Symmetric; particularly very valuable for edge detection	'haar' ('db1')

Wavelet Thresholding: Hard thresholding and Soft thresholding

Wavelet thresholding process is one of the utmost signal processing methods (Isabona and Ojuh, 2017; To, Moore and Glaser, 2009). A typical wavelet-based signal processing method includes thresholding of wavelet coefficients using either hard thresholding or soft thresholding (Ojuh and Isabona, 2018; Isabona and Ojuh, 2017).

Hard thresholding describes the standard wavelet processing method of setting the components with specified absolute values lower or smaller than the actual threshold to zero (Donoho and Johnstone., 1994). Correspondingly, in soft thresholding, each detail coefficient is set in such a way that specified absolute value lower than a certain threshold is zeroed firstly, then again, the outstanding signal coefficients are moved to zero by means of the scale of threshold level (Donoho and Johnstone., 1994).

PERFORMANCE MEASURES OF SIGNAL QUALITY

The performance of the proposed enhanced signal processing technique based on DWT is evaluated using the following quantitative performance measures:

Root Mean Square Error

This performance measure defines the 'mean of error squares' and it is obtained mathematically using the formula:

$$RMSE = \sqrt{\sum_{k=1}^{N}[x(n) - x'(n)]^2} \qquad (7)$$

where $x(n)$ and $x'(n)$ express the reference signal and denoised signal. The constant N indicates the signal sample number.

Standard Deviation

Standard deviation (STD) is calculated as:

$$STD = \sqrt{\left(\frac{1}{N}\sum_{n=1}^{N}\left|x(n) - x'(n)\right| - MAE\right)^2} \qquad (8)$$

$$MAE = \frac{1}{N}\sum_{n=1}^{N}\left|x(n) - x'(n)\right| \qquad (9)$$

Correlation coefficient

Correlation coefficient, R is defined by:

$$R = \frac{\sum_{q=1}^{N}\left(x(n) - \hat{x}(n)\right)\left(x(n) - \hat{x}(n)\right)}{\sqrt{\left[\sum_{n=1}^{N}\left[\left(x(n) - \hat{x}(n)\right)^2\right]\right]\left[\sum_{q=1}^{N}\left[\left(x(n) - \hat{x}(n)\right)^2\right]\right]}} \qquad (10)$$

Signal to Reconstruction Error Ratio

Signal to Reconstruction Error Ratio (SRER) is determined as:

$$SRER = \frac{\sum_{n=1}^{N} x^2(n)}{\sum_{k=1}^{N}\left(x(n) - x'(n)\right)^2} \qquad (11)$$

Pulse Amplitude Distortion

Pulse Amplitude Distortion (PAD) is calculated as:

$$PAD(\%) = \frac{x_{\max} - x'_{\max}}{x_{\max}} \qquad (12)$$

where X_{max} and X'_{max} express the amplitude of reference signal and amplitude of denoised signal, respectively.

RESULTS AND DISCUSSION

This section contains the performance evaluation results of the proposed enhanced signal processing technique based on DWT and the discussion of results. The DWT program scripts and implementation is actualized in Matlab 2015a software. In general, an enhanced processed signal should result in low RMSE value, low PAD value, low STD value, high SRER value and high R value (Ojuh and Isabona, 2018; Obahiagbon and Isabona, 2018; Ebhota, Isabona and Srivastava, 2018)

The processed signal data at different levels (scales) is to enable us grasp the seeming morphology trend plus details. For illustrative examples, the processed measured reference signal dataset using sym2 and "db2" wavelets at different levels up to 5, are shown in Figures 4 and 5, and each figure contains 5 detailed sub-signals components indicated by D1, D2, D3, D4, D5 and 1 approximate sub-signal indicated by A5. Lower detail levels (i.e. D levels) possess higher frequencies, which characterize the swiftly changing component of the dataset. On the other hand, the higher D levels possess lower frequencies, which stand for the steadily changing component of the signal data. The A5, which is the approximation components characterize the slowest changing constituents of signal dataset. The results in Tables 3 to 6 represents the overall performance of the processed signals using ''sym'' and ''db'' under soft and hard thresholding to produce signal at different decomposition levels. Since noise is often categorized as the high frequency fluxes, it is expected that thresholding the high fluctuating frequency components by DWT at different levels reduces noise, thus preserving the low frequency components which represent the relevant information

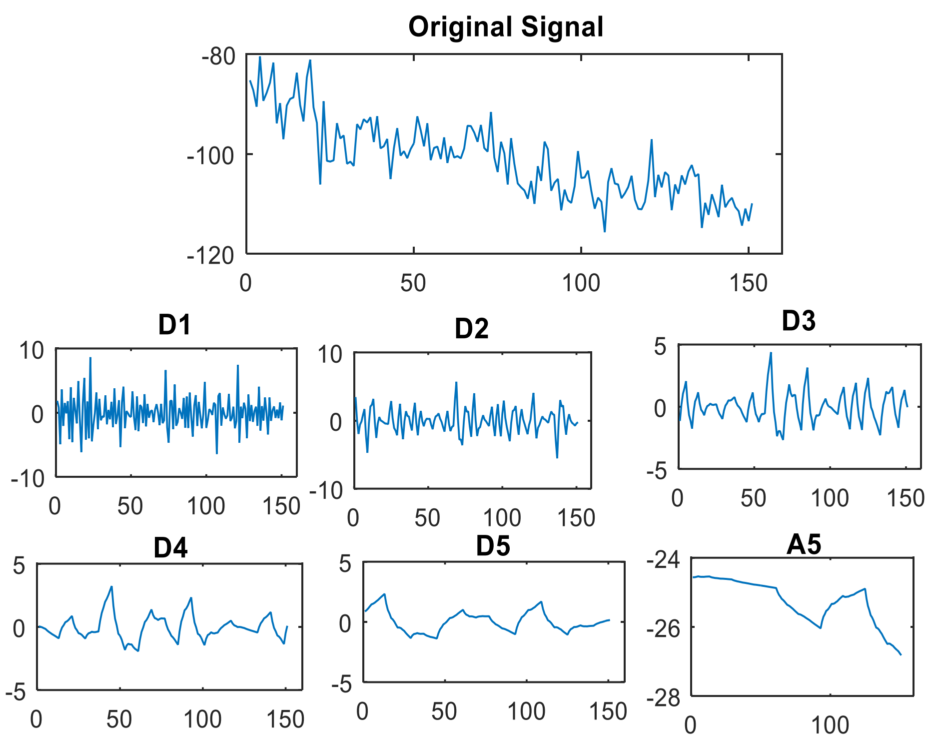

Fig. 4: level decomposition with sym2 wavelet

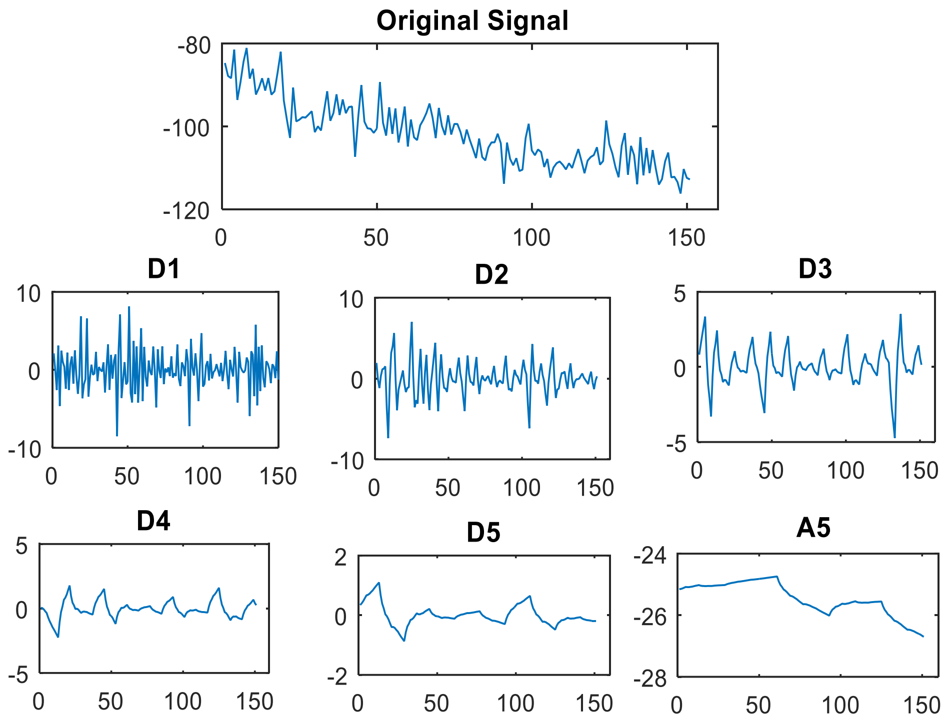

Fig. 5: level decomposition with db2 wavelet

Table 3: Processed Signal at different Decomposition Levels for Symlet wavelet family with Hard Thresholding

Wavelet Type	Decomposition Level	PAD	RMSE	SRER	STD	R
Sym1	1	2.26	1.18	60.45	0.83	0.9882
	2	4.64	2.13	55.37	1.24	0.9618
	3	5.69	2.43	54.21	1.42	0.9453
	4	5.49	2.86	52.81	1.60	0.9223
	5	8.59	3.47	51.09	1.95	0.8928
Sym2	1	5.63	2.22	54.98	1.36	0.9565
	2	4.96	2.15	55.26	1.25	0.9599
	3	4.55	1.99	66.95	1.18	0.9655
	4	6.98	2.68	53.36	1.63	0.9387
	5	4.32	11.74	57.05	1.03	0.9742
Sym3	1	5.96	2.20	55.07	1.36	0.9605
	2	4.51	1.95	56.10	1.13	0.9651
	3	6.82	2.99	52.41	1.69	0.9243
	4	4.82	2.08	55.54	1.22	0.9618
	5	9.13	2.73	53.20	1.66	0.9362
Sym4	1	4.67	1.78	56.87	1.07	0.9711
	2	2.15	0.97	62.18	0.63	0.9919
	3	4.64	1.59	57.91	1.02	0.9782
	4	4.55	1.89	56.36	1.12	0.9710
	5	7.89	2.75	53.13	1.63	0.9399
Sym5	1	2.22	0.97	62.16	0.64	0.9925
	2	5.12	2.28	54.75	1.34	0.9540
	3	4.89	1.92	56.22	1.16	0.9681
	4	2.16	0.96	62.23	0.55	0.9923
	5	4.97	1.92	56.24	1.07	0.9226

Table 4: Processed Signal at different Decomposition Levels for dB wavelet family with Hard Thresholding

Wavelet Type	Decomposition Level	PAD	RMSE	SRER	STD	R
db1	1	3.02	1.40	59.00	0.98	0.9844
	2	7.73	2.78	53.03	1.62	0.9321
	3	5.05	2.42	53.23	1.45	0.9479
	4	6.23	2.44	54.19	1.41	0.9526
	5	8.63	3.46	51.15	2.16	0.8952
db2	1	6.63	2.32	54.57	1.41	0.9529
	2	6.95	2.53	53.84	1.54	0.9455
	3	5.40	2.06	55.60	1.19	0.9648
	4	5.51	1.96	56.10	1.27	0.9691
	5	6.24	2.65	54.43	1.66	0.9419
db3	1	4.09	1.61	57.78	1.05	0.9779
	2	6.29	2.49	53.98	1.45	0.9443
	3	7.83	2.72	53.18	1.69	0.9409
	4	5.73	2.14	55.32	11.30	0.9614
	5	4.61	2.06	55.62	1.11	0.9642
db4	1	2.37	1.14	60.72	0.71	0.9893
	2	3.45	1.39	59.04	0.81	0.9827
	3	5.50	2.02	55.77	1.22	0.9632
	4	3.83	1.71	57.27	0.97	0.9743
	5	6.44	2.24	54.91	1.41	0.9579
db5	1	4.65	1.99	55.95	1.18	0.9664
	2	7.06	2.54	53.81	1.45	0.9469
	3	5.99	2.53	53.81	1.52	0.9418
	4	6.25	2.27	54.79	1.36	0.9557
	5	7.62	2.76	53.10	1.60	0.9336

Table 5: Processed Signal at different Decomposition Levels for Symlet wavelet family with Soft Thresholding

Wavelet Type	Decomposition Level	PAD	RMSE	SRER	STD	R
Sym1	1	5.69	2.31	54.62	1.41	0.9516
	2	7.10	2.71	53.26	1.60	0.9388
	3	8.00	2.79	53.03	1.63	0.9370
	4	7.65	3.11	52.07	1.86	0.9140
	5	9.12	4.22	49.41	2.53	0.8359
Sym2	1	4.68	2.01	55.86	1.16	0.9655
	2	5.37	2.17	55.22	1.18	0.9605
	3	5.33	2.48	54.04	1.42	9509
	4	7.29	2.66	53.41	1.66	0.9410
	5	8.63	2.88	52.71	1.69	0.9295
Sym3	1	3.36	1.86	56.51	1.06	-.9722
	2	8.65	3.02	52.23	1.79	0.9215
	3	7.71	2.73	53.17	1.63	0.9379
	4	6.78	2.46	54.06	1.48	0.9502
	5	4.51	2.71	53.27	1.58	0.9338
Sym4	1	4.47	2.06	55.61	1.22	0.9647
	2	5.54	2.14	53.31	1.24	0.9623
	3	8.13	3.22	57.64	1.92	0.9116
	4	4.62	2.37	54.41	1.27	0.9493
	5	8.24	3.12	51.78	1.98	0.9058
Sym5	1	4.70	2.16	55.24	1.28	0.9597
	2	4.41	2.04	55.74	1.16	0.9646
	3	8.48	2.35	50.94	2.12	0.8959
	4	6.65	2.74	53.14	1.67	0.9318
	5	6.94	2.63	53.54	1.64	0.9466

Table 6: Processed Signal at different Decomposition Levels for Daubechies (db) wavelet family with Soft Thresholding

Wavelet Type	Decomposition Level	PAD	RMSE	SRER	STD	R
db1	1	6.05	2.48	54.00	1.55	0.9495
	2	5.61	2.26	54.82	1.30	0.9563
	3	5.21	2.28	54.73	1.28	0.9573
	4	8.11	2.72	50.23	1.68	0.9280
	5	9.93	3.73	50.33	2.28	0.8689
db2	1	4.39	1.96	56.07	1.12	0.9648
	2	6.30	2.59	53.65	1.58	0.9422
	3	5.99	2.44	54.17	1.49	0.9494
	4	6.81	2.70	53.70	1.65	0.9341
	5	6.78	3.13	52.00	1.91	0.9161
db3	1	5.40	2.28	54.75	1.43	0.9548
	2	5.90	2.34	54.53	1.43	0.9500
	3	6.23	2.58	53.68	1.52	0.9457
	4	6.15	2.28	54.74	1.43	0.9560
	5	9.48	3.22	51.75	1.95	0.9124
db4	1	4.46	2.24	54.92	1.22	0.9561
	2	5.84	2.26	54.84	1.95	0.9550
	3	5.35	2.20	55.04	1.29	0.9578
	4	7.36	2.83	52.88	1.71	0.9337
	5	8.73	3.67	50.62	2.43	0.8920
db5	1	6.27	2.29	54.70	1.37	0.9669
	2	4.43	2.03	55.73	1.13	0.9678
	3	4.22	1.82	56.69	1.02	0.9718
	4	4.60	2.08	55.54	1.21	0.9556
	5	9.91	3.16	51.93	1.92	0.9186

Specifically in terms of SRER performance indicator, the plotted graphs in Figures 7 to 9 are provided to reveal the decomposition level and wavelet family type that yielded the best result during the entire signal processing exercise. From the results, we can see that best processed signal is obtained at level 3 using sym2 wavelet under soft thresholding with SRER of 66.95dB. This is followed wavelet db1 at level 4 under soft thresholding with SRER of 60.72dB. The figures also show the worst processed signal results are obtained under hard thresholding.

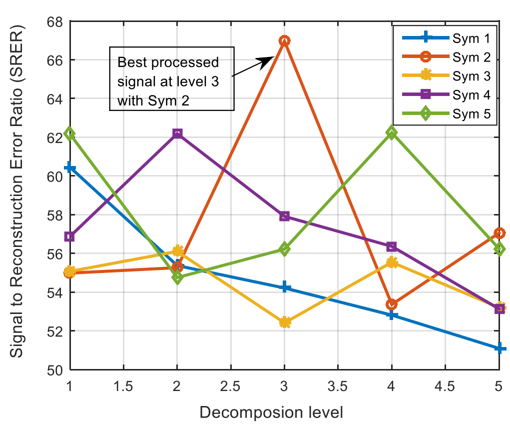

Fig. 6: Processed signals using Symlet wavelet under soft thresholding

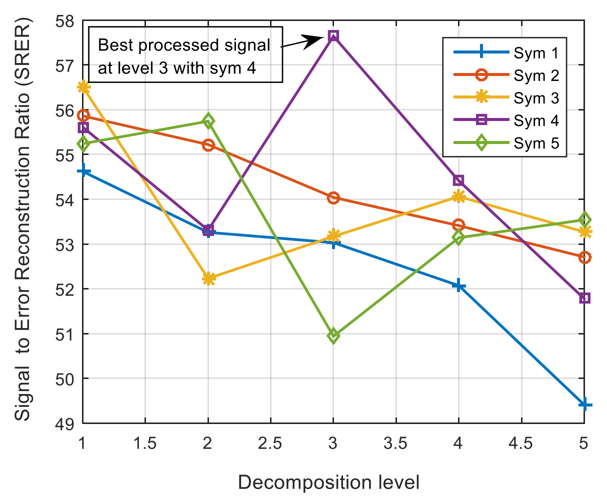

Fig. 7: Processed signals using Symlet wavelet under hard thresholding

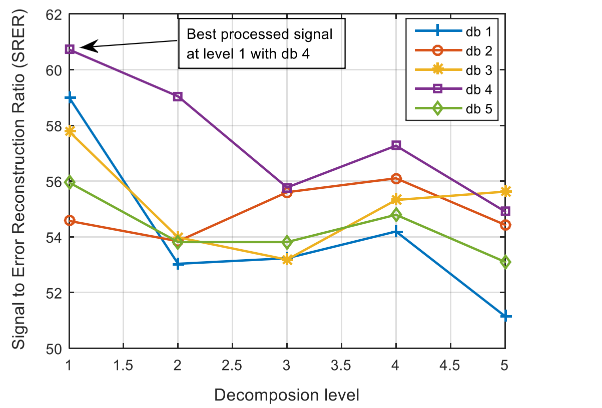

Fig. 8: Processed signals using dB wavelet under soft thresholding.

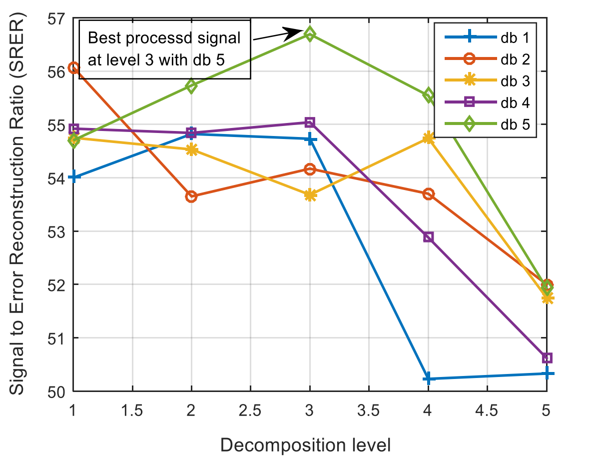

Fig. 9: Processed signals using db wavelet under hard thresholding

The Effect of Processed Signal Power Coverage prediction Accuracy

The next drive is to examine the effect of the processed signal on signal power coverage prediction accuracy over the different data points. To accomplish this, the adaptive polynomial predictive fitting tool in MATLAB (R2015a) program is explored.

The plotted graphs in figures 10 and 11 display the prediction accuracy of the adaptive polynomial on the processed and unprocessed signal power coverage for the best two wavelet families and decomposition levels in figures 6 and 8, respectively. The resultant prediction accuracy of adaptive polynomial on the signal power in their processed and unprocessed state are provided for performance comparison using PAD, RMSE, SRER and STD respectively. It is clear from the summarised results in Table 7 that processed signal data attained the optimal prediction performance with adaptive polynomial in terms.

Table 7: Adaptive Polynomial Prediction Performance with Processed and Unprocessed Signal Data

Level	Performance measure	Processed signal prediction results	Unprocessed signal prediction results
1	PAD	15.16	23.14
	RMSE	4.85	8.81
	SRER	47.56	42.38
	STD	2.84	4.42
2	PAD	13.08	22.76
	RMSE	5.45	9.35
	SRER	46.54	41.86
	STD	3.21	4.95

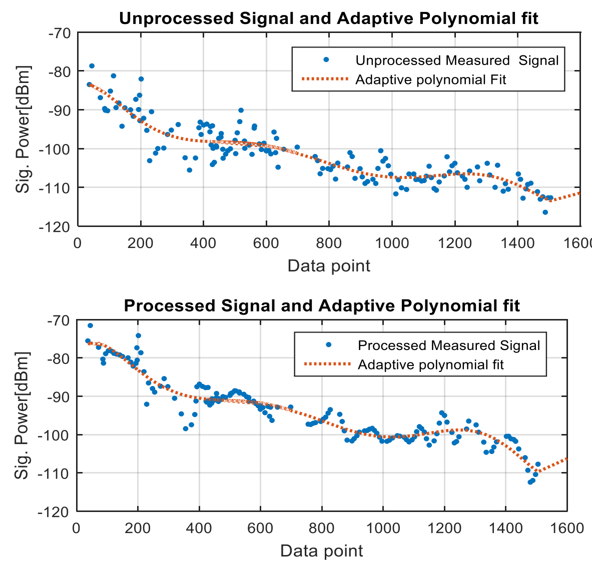

Fig. 10: Best Adaptive Polynomial Fit at Decomposition Level 2 for Sym 4 wavelet family with Hard Thresholding

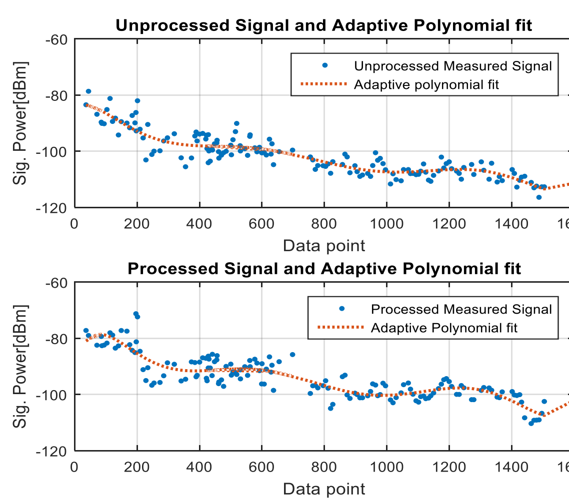

Fig. 11: Best Adaptive Polynomial Fit at Decomposition Level 1 for db 4 wavelet family with Hard Thresholding

CONCLUSION

Extracting relevant information from acquired measured field test signal dataset at mobile equipment terminal over a telecommunication network is an important step toward efficient signal coverage processing and predictive analytics in cellular network planning process. Wavelets serve as a powerful tool to accomplish the above task. The capability of wavelet to decompose a signal into different resolutions (levels or scales) is very crucial for effective denoising, and it can impact the analysis of the signal considerably.

In this work, the multi-resolution DWT based signal processing technique have been explored to identify deterministic components of spatial signal dataset and also provide a means of reliably signal coverage predictive analysis. From the results (in Tables 2 to 4 and figures 5 to 6), we can deduce that the processed signal under decomposition level 4 with sym3 wavelet is better than others, in terms of RMSE, SRER, R, PAD, and STD statistics. Hence, decomposition level 4 with sym3 wavelet is chosen as the best one for enhanced signal coverage processing and prediction analysis in this case. Another vital facts gotten from the obtained results is that an appropriate decomposition level should be tactfully and cautiously chosen when carrying out wavelet-based data processing. This is because it impact the accuracy of the wavelet decomposition results, which in turn has pronounced effect on any data-driven predictive analytics.

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