Proceedings of the International Conference on Intelligent Computing and Communication for Smart World (I2C2SW-2018)
14-15 December 2018

Area Efficient Implementation of Adaptive Filters using High Level Transformation

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***Abstract*—Signals carry important information about the behaviour of system under study. Generally, background noises present in the environment corrupt the signal. Raw signals comprise of signal of interest with extraneous noises present in them. Thus, it is very important to remove the noises and retrieve the signal of interest. Adaptive filters play an important role in manipulation of the information present in the signal. This paper presents an effort to implement the associativity technique in the adaptive filter design. The proposed architecture is used to reduce the area of the structure. The designed architecture with RLS, Affine Projection (AP) and Kalman filtersdepicts improvement in SNR and VLSI implementation promises to be effective design in terms of area reduction.**

Keywords—Adaptive filter, RLS, Affine, Associativity, SNR

I. Introduction

Transmission or acquisition of signals is often being corrupted by various noises that are present in the atmosphere. Generally, background noises present in the atmosphere degrade the quality of the speech and signal transmitting systems. Be it a biosignal or a speech signal, both of them suffer from the degradation of the signal quality when it undergoes any disturbance. Hence it is of much importance to cancel the noises present, and thereby improving the quality of the system. Adaptive Noise Cancellation (ANC) is an alternative technique of estimating signals corrupted by additive noise or interference.

The extraction of relevant information present in the input signal is facilitated by mapping the input signal to the output signal through a device called filter. Filters may be time-invariant or time-variant. Based on the application, the choice of appropriate filer structure that defines the algorithm and its implementation forms should be chosen carefully. Fixed filters require a complete description of the input and reference signal so as to provide a good performance. In practice, the environment is not well defined. When the environment is not well defined, it becomes necessary to model the signal and design a filter. Signal modeling and its implementation leads to higher cost. Under such circumstances, employing an adaptive filter promises to be a better solution. When the information about the signal is not known a priori, adaptive filter is required. The adaptive filters are time-varying as their parameters are continually changing in order to meet performance requirement.

In [3], a concept of usage of Recursive Least Square algorithm to remove the extraneous noise is described. The filtered noise was completely subtracted from the "noisy input signal” and finally the "Error Signal" contained the original signal. In [8]-[10], comparison based on the performance metric called the signal to ratio for different Adaptive Algorithms is demonstrated in denoising ECG with Power Line Interference (PLI) noise and speech signal. In [13]-[14], adaptive filter algorithms designed for noise cancellation and its performance is discussed.

II. Adaptive FILTER FOR NOISE CANCELLATION

Fig.1 shows the block diagram representation of Adaptive filter for Noise Cancellation application.

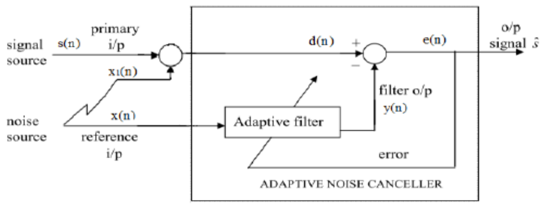

Fig. 1. Adaptive Noise Canceller

The block diagram of adaptive noise canceller consistes of two inputs.One,the primary input is the combination of original signal s and corrupted by noise n uncorrelated with the signal. The adaptive algorithm receives a reference noise n_0 which is uncorrelated with the signal but correlated in some way with the noise n. The noise n_0 is given as an input to a filter to produce an output $\hat{n}$ which is a close estimate of primary input noise. The obtained filter output is subtracted from the contaminated signal to produce the signal $\hat{s}$, which is the system output.

III. RLS Algorithm

Recursive Least Square algorithm is an adaptive algorithm that acts recursively and finds the filter coefficients used to minimize a weighted linear least squares cost function.New samples are iterated for the solution can be calculated in recursive form, for the least-squares problem, that results in the RLS algorithm. They have faster convergence speed even when the eigen value spread of the input signal correlation matrix is large suitable for time-varying environment. The algorithm is given below,

(i) Initialize Weights:

$$w(0) = 0 \quad (1)$$

(ii) Initialize Inverse Correlation Matrix:

$$P(0) = \delta^{-1} I \quad (2)$$

(iii) Computation of Gain Vector:

$$\pi(n) = P(n-1)u(n) \quad (3)$$

$$k(n) = \frac{\pi(n)}{\lambda + u^t(n)\pi(n)} \quad (4)$$

(iv) Error Estimate Computation:

$$e(n) = d(n) - w^t(n-1)u(n) \quad (5)$$

(v) Compute Inverse Correlation Matrix:

$$P(n) = \lambda^{-1}p(n-1) - \lambda^{-1}k(n)u^t(n)P(n-1) \quad (6)$$

(vi) Updating the Coefficients:

$$W(n) = w(n-1) + k(n)e(n) \quad (7)$$

IV. AFFINE PROJECTION ALGORITHM

The affine projection algorithm is an algorithm for adaptive filtering, which is closely related to the Normalized least mean squares algorithm(NLMS). It was first invented by Yamada et al. in 1982. The algorithm is given below,

(i) Compute the error estimate:

$$e(n) = d(n) - w(n-1)u^T(n) \quad (8)$$

(ii) Update the coefficients:

$$w(n) = w(n-1) + (\square.u(n))[u^T(n)u(n) + \delta I{-}1.e(n) \quad (9)$$

Where,

e(n) - error signal,

d(n) - desired signal,

w(n) - the weight coefficient,

u(n) - reference noise signal,

δ is the regularization parameter,

μ is the stepsize parameter.

Fast convergence is obtained in affine projection algorithm than NLMS adaptive filter.

V. KALMAN ALGORITHM

The estimates and uncertainities of the current state variables are produced by kalman filtering operation. It does not need any additional past information[18]. Updation if estimates happens when the outcome of the next measurement is observed. Here the estimates with higher certainty are given more weight.

Step 1: Compute Kalman gain

$$g(m+1) = \frac{k(t)u(t+1)}{u^H(t+1)k(t)u(t+1)} + Q_M \quad (10)$$

Step 2: Filtered output

$$y(t+1) = u^H(t+1)w(t+1) \quad (11)$$

Step 3: Error estimation

$$e(t+1) = d(t+1) - y(t+1) \quad (12)$$

Step 4: Update the coefficient

$$w(t+1) = w(t) + e(t+1)g(t+1) \quad (13)$$

Step 5: Compute correlation matrix

$$k(t+1) = k(t) - g(t+1)u^H(t+1)k(t) + Q_P \quad (14)$$

where $Q_M = \delta^{-1}I_M$ and $Q_P = \delta^{-1}\lambda$

Complexity of Kalman algorithm is low compared to RLS and Affine since matrix operations are not required[19].

VI. ASSOCIATIVITY TECHNIQUE

The proposed method aims at implementation of technique called associativity in adaptive filters. Associativity postulates that, in the set over an algebraic structure defined using an operation +, for every *a, b,* and c, which are elements of the set, it holds that a + (b + c) = (a + b) + c.

A System generator design in Xilinx for general FIR filter of order 4. is shown in Fig.2.

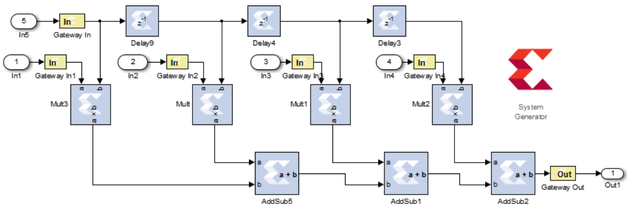

Fig.2. FIR filter with order 4

The critical path of designed FIR filter is given below,

$$T_{c1} = T_{mult} + 3T_{add} \quad (15)$$

where,

T_{c1} represents the critical path of FIR filter

T_{mult} represents multiplier unit delay

T_{add} represents adder unit delay

In order to enhance the filter performance, 4-tap FIR filter with associativity technique is designed in Xilinx System generator as shown in Fig.3.

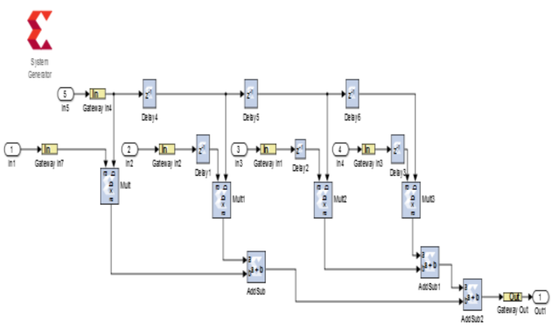

Fig.3. Design of FIR filter using Associativity

The critical path of designed associativity FIR filter is given below,

$$T_{c2}=T_{mult} + 2T_{add} \quad (16)$$

where,

T_{c2} represents the critical path of 4-tap associativity FIR filter.

T_{mult} represents the multiplier delay.

T_{add} represents the delay of adder.

Thus, it is evident that the critical path of FIR filter with associativity technique is greatly reduced to (T_{mult} + $2T_{add}$).

VII. RESULTS AND DISCUSSION

The structures are designed for RLS, AP and Kalman filters of different taps without and with Associativity.The designed architecture for different algorithms are simulated and implemented in Virtex FPGA. The application targetted is denoising ECG signal.Adaptive filters design without associativity technique is shown in Fig. 4.

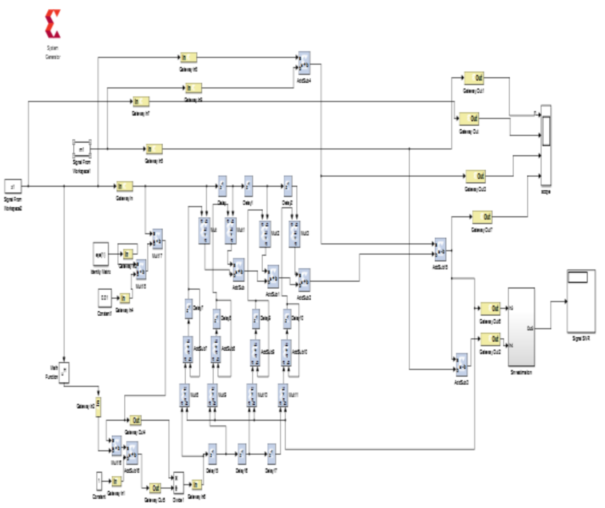

Fig. 4. RLS filter without Associativity technique of order 4

A. *ECG signal denoising*

The architecture designed is experimented for ECG signal denoising. ECG signal corrupted with the Power Line Interferene (PLI) noise is considered as the input signal. The reference input to adaptive algorithm is PLI Noise. The denoised ECG signal is obtained by subtracting the filter output from the input.The Fig.4, Fig.6 and Fig.8 shows the System generator design for RLS,AP and Kalman filters of order 4 without Associativity technique respectively.

As shown in Fig.4, the simulation of the 4-tap RLS filter without Associativity technique for denoising ECG signal is carried out with with the following specifications: Filter order N=4,forgetting factor λ=1, Small positive constant δ= 0.01 and iterations= 4000. The input ECG signal is taken from MIT-BIH database (100.dat). The first 4000 samples are taken to the process and simulated in MATLAB. Then this signal is used in System generator by using signal from workspace block. The PLI noise generated in MATLAB is given as reference input to the filter using signal from workspace block.

In the Fig.5, Fig.7 and Fig.9 the first subplot refers the original ECG signal (Rec.No.100), the next subplot corresponds the PLI noise, the subplot III depicts the contaminated ECG, the subplot IV points the denoised ECG signal obtained using RLS, AP and Kalman filters of tap length 4 without Associativity respectively.

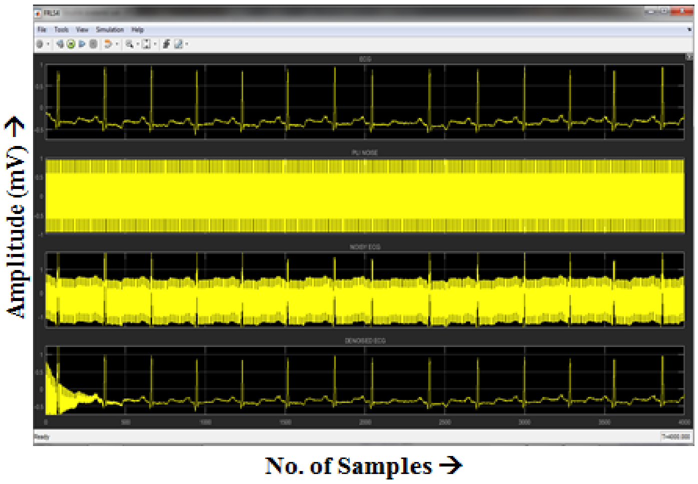

Fig. 5. Denoised ECG signal with RLS filter without Associativity technique

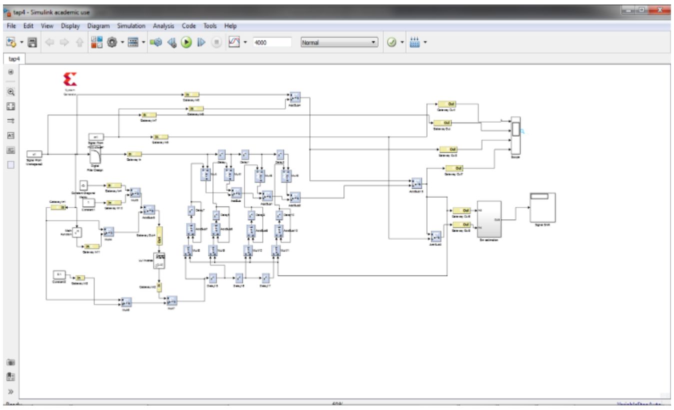

Fig. 6. AP filter without Associativity technique

B. *Adaptive filters design with Associativity technique for denoising ECG signal.*

The proposed designs RLS, AP and Kalman filter structures with Associativity are designed in Xilinx System generator.

C. *Perfomance Metrics-Signal to Noise Ratio*

SNR for RLS with and without Associativity for different ECG database records is,TABLEI refers to the SNR comparison for existing RLS and proposed RLS with associativity by using different ECG database records reveals that SNR is not degraded for the proposed architecture.

From the above TABLE.I, it is clear that the SNR value for 8-tap RLS design is improved when compared to the SNR of 4-tap RLS design.

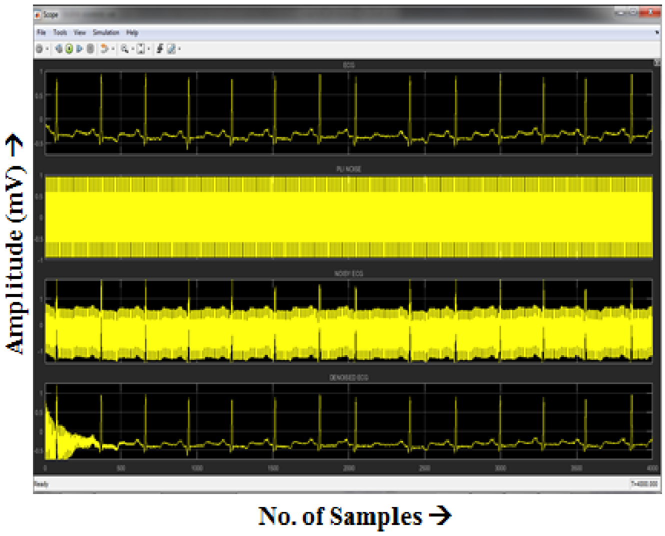

Fig. 7. Output of denoised ECG signal with AP filter without Associativity technique

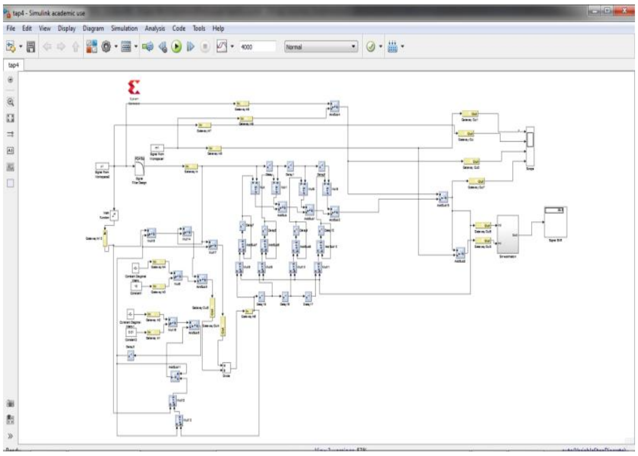

Fig. 8. Kalman filter without Associativity technique

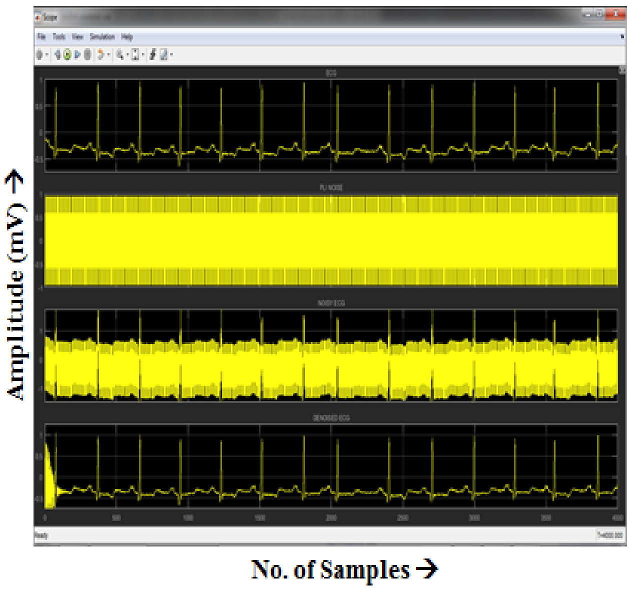

Fig. 9. Denoised output of ECG signal with Kalman filter without Associativity technique

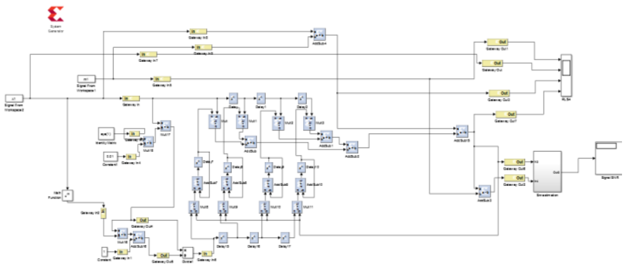

Fig. 10. RLS filter with Associtivity technique

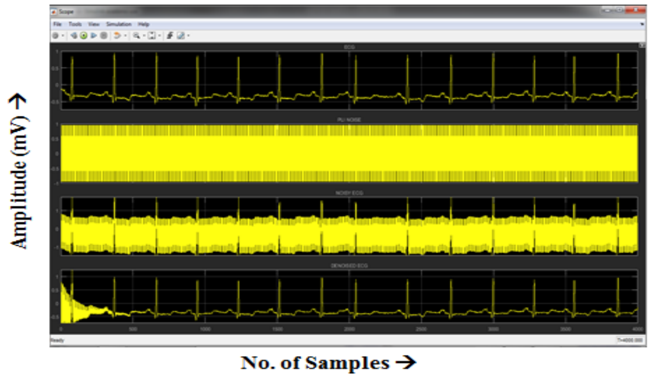

Fig. 11. Denoised ECG signal - RLS filter with Associativity technique

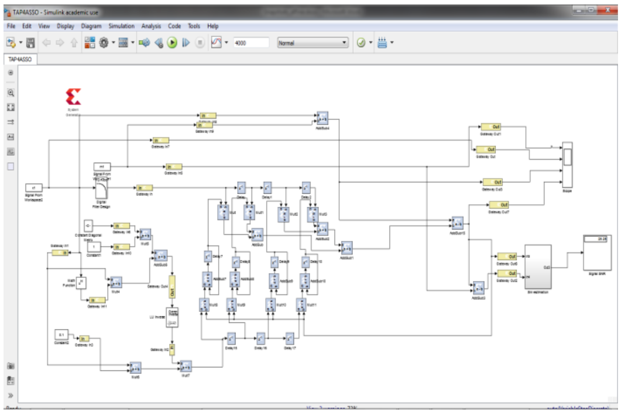

Fig. 12. AP filter with Associtivity technique

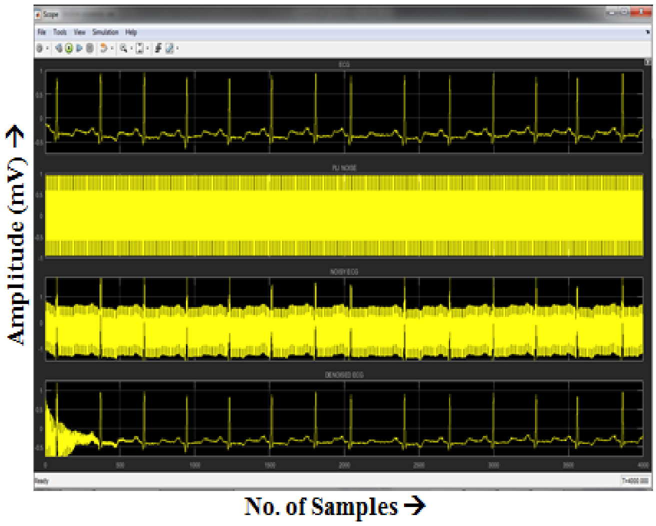

Fig. 13. Denoised output of ECG signal for AP filter with Associativity technique.

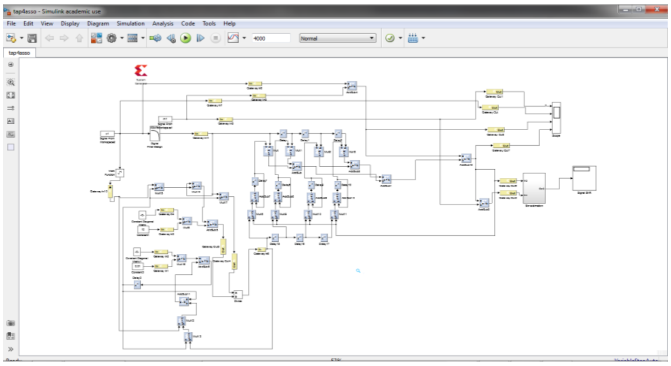

Fig. 14. Kalman filter with Associtivity technique

D. *Area Comparision*

Area comparison for RLS, AP and Kalman with and without Associativity for different order of the filters are, In TABLEIV, V and VI shows the comparison of area for RLS, AP and Kalman without and with associativity by using different order of the filters. It is evident from theresults that the area is reduced in the associativity technique with the reduction in delay.

TABLE I. COMPARISON OF SNR FOR RLS FILTERS

INPUT ECG SIGNAL	SIGNAL TO NOISE RATIO (dB)							
	FILTER LENGTH -4		FILTER LENGTH -8		FILTER LENGTH -16		FILTER LENGTH -32	
	RLS	RLS WITH ASSOCIATIVITY	RLS	RLS WITH ASSOCIATIVITY	RLS	RLS WITH ASSOCIATIVITY	RLS	RLS WITH ASSOCIATIVITY
100.dat	23.48	23.48	29.68	29.68	32.82	32.82	32.3	32.3
101.dat	23.96	23.96	30.17	30.17	33.29	33.29	32.67	32.67
105.dat	24.37	24.37	30.6	30.6	33.7	33.7	33	33
108.dat	22.29	22.29	28.48	28.48	31.68	31.68	31.38	31.38
200.dat	27.14	27.14	33.38	33.38	36.29	36.29	34.95	34.95
203.dat	27.96	27.96	34.22	34.22	37.06	37.06	35.46	35.46
208.dat	30.26	30.26	36.53	36.53	39.14	39.14	36.9	36.9
228.dat	20.71	20.71	26.83	26.83	30.08	30.08	30.05	30.05

TABLE II. COMPARISON OF SNR FOR AP FILTERS

INPUT ECG SIGNAL	SIGNAL TO NOISE RATIO (dB)							
	FILTER LENGTH -4		FILTER LENGTH -8		FILTER LENGTH -16		FILTER LENGTH -32	
	AP	AP WITH ASSOCIATIVITY	AP	AP WITH ASSOCIATIVITY	AP	AP WITH ASSOCIATIVITY	AP	AP WITH ASSOCIATIVITY
100.dat	39.81	39.81	41.14	41.14	44.45	44.45	46.02	46.02
101.dat	33.88	33.88	37.78	37.78	53.25	53.25	57.04	57.04
105.dat	36.72	36.72	38.22	38.22	51.08	51.08	56.06	56.06
108.dat	27.29	27.29	29.04	29.04	42.15	42.15	54.67	54.67
200.dat	39.51	39.51	41.27	41.27	54.16	54.16	56.52	56.52
203.dat	35.16	35.16	44.2	44.2	51.04	51.04	54.14	54.14
208.dat	46.22	46.22	50.71	50.71	58.73	58.73	59.53	59.53
228.dat	28.2	28.2	29.65	29.65	33.75	33.75	41.81	41.81

TABLE III. COMPARISON OF SNR FOR KALMAN FILTER

INPUT ECG SIGNAL	**SIGNAL TO NOISE RATIO (dB)**							
	FILTER LENGTH -4		**FILTER LENGTH -8**		**FILTER LENGTH -16**		**FILTER LENGTH -32**	
	KALMAN	**KALMAN WITH ASSOCIATIVITY**	**KALMAN**	**KALMAN WITH ASSOCIATIVITY**	**KALMAN**	**KALMAN WITH ASSOCIATIVITY**	**KALMAN**	**KALMAN WITH ASSOCIATIVITY**
100.dat	38.12	38.12	40.88	40.88	53.03	53.03	53.19	53.19
101.dat	28.5	28.5	34.08	34.08	37.94	37.94	39.11	39.11
105.dat	31.95	31.95	37.86	37.86	44.74	44.74	58.24	58.24
108.dat	23.22	23.22	26.57	26.57	30.58	30.58	32.61	32.61
200.dat	35.93	35.93	37.64	37.64	38.68	38.68	42.57	42.57
203.dat	47.26	47.26	49.59	49.59	52.74	52.74	54.27	54.27
208.dat	40.94	40.94	46.17	46.17	53.02	53.02	54.45	54.45
228.dat	24.87	24.87	28.1	28.1	32.08	32.08	33.83	33.83

TABLE IV. AREA COMPARISION FOR RLS FILTER

Filter Length/ Parameter	**FILTER ORDER 4**		**FILTER ORDER 8**		**FILTER ORDER 16**		**FILTER ORDER 32**	
	RLS	**RLS WITH ASSOCIATIVITY**	**RLS**	**RLS WITH ASSOCIATIVITY**	**RLS**	**RLS WITH ASSOCIATIVITY**	**RLS**	**RLS WITH ASSOCIATIVITY**
Number of Slice LUTs	**616**	**609**	**1040**	**1034**	**1918**	**1906**	**4559**	**3980**
Number of Slice Registers	98	98	184	184	396	396	766	766
Minimum period(ns)	26.155	23.963	33.357	26.046	47.867	27.977	78.136	30.932
Minimum input arrival time before clock (ns)	27.017	24.729	34.399	26.537	48.729	28.452	78.998	31.344
Maximum output required time after clock (ns)	20.907	18.697	28.289	21.142	42.619	23.073	71.327	24.800
Total delay (ns)	**25.718**	**24.187**	**33.100**	**25.582**	**48.430**	**28.497**	**77.136**	**30.162**

TABLE V. AREA COMPARISION FOR AP FILTER

Filter Length/ Parameter	**FILTER ORDER 4**		**FILTER ORDER 8**		**FILTER ORDER 16**		**FILTER ORDER 32**	
	AP	**AP WITH ASSOCIATIVITY**	**AP**	**AP WITH ASSOCIATIVITY**	**AP**	**AP WITH ASSOCIATIVITY**	**AP**	**AP WITH ASSOCIATIVITY**

Number of Slice LUTs	**647**	**645**	**1075**	**1069**	**1953**	**1941**	**5018**	**4406**
Number of Slice Registers	98	98	186	186	394	394	762	762
Minimum period (ns)	26.155	24.878	33.537	26.046	47.867	27.977	78.130	30.931
Minimum input arrival time before clock (ns)	29.348	29.346	34.344	28.751	48.674	29.353	78.397	34.685
Maximum output required time after clock (ns)	20.907	19.630	28.289	21.142	42.619	23.073	71.325	24.801
Total delay (ns)	**21.714**	**20.183**	**29.096**	**21.578**	**43.426**	**23.493**	**72.132**	**25.158**

TABLE VI. AREA COMPARISION FOR KALMAN FILTER

Filter Length/ Parameter	**FILTER ORDER 4**		**FILTER ORDER 8**		**FILTER ORDER 16**		**FILTER ORDER 32**	
	KALMAN	**KALMAN WITH ASSOCIATIVITY**	**KALMAN**	**KALMAN WITH ASSOCIATIVITY**	**KALMAN**	**KALMAN WITH ASSOCIATIVITY**	**KALMAN**	**KALMAN WITH ASSOCIATIVITY**
Number of Slice LUTs	**790**	**788**	**1222**	**1212**	**2093**	**2089**	**6309**	**5732**
Number of Slice Registers	120	120	208	208	416	416	784	784
Minimum period (ns)	26.155	24.878	33.537	26.046	48.296	27.977	78.136	31.529
Minimum input arrival time before clock (ns)	27.045	25.514	34.427	26.565	49.186	28.480	79.027	31.970
Maximum output required time after clock (ns)	23.524	23.524	28.289	23.524	43.048	23.524	71.327	26.966
Total delay (ns)	**24.391**	**24.391**	**29.179**	**24.391**	**43.938**	**24.391**	**72.218**	**27.093**

VIII. CONCLUSION AND FUTURE SCOPE

This paper presented the implementation of architectural modification using Associativity technique in various adaptive filters like RLS,Affine and Kalman for adaptive filter for noise cancellation application in biomedical signal. The designed structures are simulated in Xilinx System generator and MATLAB Simulink environment. Perfomance analysis was carried out by SNR estimation. The performance of the filter circuit in terms of area and delay is verified by implementing in Xilinx Virtex 5 FPGA kit. From the analysis, it is observed that the associativity technique results in 12.7%, 12.19% and 9.14% reduction in area and 35.97% , 32.67% and 30.84% reduction in delay for RLS, AP and Kalman algorithms than the normal structure.

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