PSENSE: AN EFFICIENT AND PRACTICAL ANALOG-TO-INFORMATION PLATFORM USING COTS DEVICES

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ABSTRACT

A challenge in wireless sensing is to reduce power consumption during data transmission. Various methods aim at compressing amounts of data after sampling, which require additional computation energy or hardware. In this paper, pSense, a low complexity commercial off-the-shelf based (COTS-based) analog-to-information converter (AIC) platform is presented to minimize power consumption. A periodical pseudo-random down-sampling algorithm (PPRS) is employed to reduce energy consumption by controlling sampling numbers and features high scalability. Results show pSense can reconstruct signals within acceptable low error levels and having low energy consumptions.

INTRODUCTION

Researches[1] show original signals can be reconstructed with fewer sampling points required by Nyquist theorem when prior knowing sparsity of signals, namely compressed sensing (CS). Three types of CS hardware are proposed: digital CS, analog CS, and non-uniform-based (NUS) CS. For digital CS, a linear CS compression is applied in microprocessor after ADCs[2]. Power consumptions of ADCs are still significant because of using uniform sampling. For analog CS, the linear CS compression is implemented by customized analog circuits and occurs prior to ADCs, including serval analog AIC[3] for physiological sensing applications. The NUS-based AIC uses non-uniform sampling to randomly digitized signals by ADCs using different random patterns[4]. However, no NUS-based experiments are explored in practice.

In this paper, we present pSense, an efficient and practical AIC design, which features in following characteristics: (1) pSense is a low complexity COTS-based solution which can be easily adopted from the Nyquist sampling systems. (2) pSense provides high scalability when its size and frequency can be adjusted flexibly. (3) pSense achieves stable reconstruction performances with various types of signals. For example, for ECG signal, when compression ratio (CR) is 30, the percentage root-mean-square difference (PRD) will be lower than 10%. (4) pSense integrates an ultra-low power sampling module, where the energy consumption of the sampling module is as low as 0.24μW with a frequency of 125Hz, which is approximately equal to the performance of the existing CS analog front-end (AFE).

PSENSE ARCHITECTURE

Figure 1 demonstrates a flowchart of the proposed system. It mainly comprises two modules: a PPRS sampling module and a reconstruction module. The PPRS sampling module is responsible for collecting analog signals and transmitting captured signals to the next part. The pre-sampling matrix (PRBS: pseudo-random binary sequence) is generated and controls data samplings in the front-end. When the captured data are received by computer platform, a specific reconstruction process is conducted by using orthogonal matching pursuit (OMP) algorithm to get reconstructed original signals.

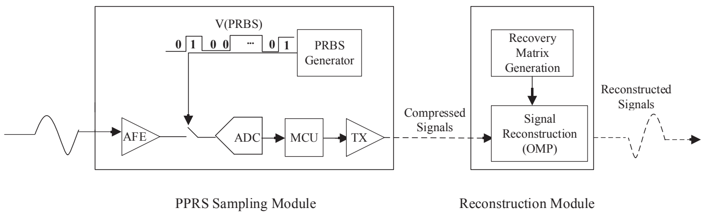


Figure 1: pSense framework overview

TABLE 1: OVERALL PERFORMANCE COMPARISON

Parameter	CS-AFE[5]	NUS[4]	digital CS[2]	The work
Supply(V)	0.9 - 1.2	0.9 - 1.2	0.6	1.2
Max Sig BW	1k	9.5M	20K	100K
Resolution(bit)	10	10	8	10
Power Power Consumption	1.8μw@1.2V-2K SPS	550μw@1.2V-9.5 MSPS	1.9μw @0.6V-20KSPS	0.16 - 0.24μw@125SPS 2.71 - 3.98μw@2K SPS

PPRS SAMPLING MODULE

The proposed front-end architecture showed in Figure 2 consists of two mains parts. The first part is a front sampling ADC, which could be a traditional commercial ADC device. It detects analog signals and quantizes them into digital data.

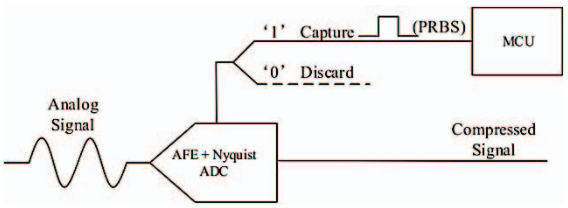


Figure 2: The sampling process is controlled by PRBS using a micro controller unit (MCU).

The second part is in a micro controller unit, whose function is to control the sampling process based on pre-sampling matrix. Therefore, the ADC will only sample analog signals at each specific time tick, which can significantly reduce power consumptions in the front end. A variable mark ratio pseudo random binary sequence (PRBS) *V[N]* is used, where the mark ratio is equal to *CR*. *V[N]* is used to perform sampling process as is shown in Algorithm 1. X[M] are captured samples, and *M* points are actual samples instead of *N*, defining as following equation (1):

$$CR = (1 - M/N) \times 100\%. \quad (1)$$

Algorithm 1 : Randomly Sampling algorithm

```
Initialize a counter and X[M]=0, input V[N].
for each interrupt do
    if( V[counter] == 1 ) then
        sampling and storing samples in X[M];
        counter ++ and M++;
    end else (V[counter] == 0)
        idle;
end for
```

SYSTEM IMPLEMENTATION

A prototype using COTS devices is shown in Figure 3. The bio-platform includes an Electrocardiograph (ECG) sampling device. The ECG sampling device consists of a medical analog front end (AFE), a low-power integrated industry-standard enhanced 8051 MCU and a low power ADC. This MCU core is employed to control the ADC to capture signals randomly. Power consumption (P) is calculated as following equation (2):

$$P = 83\mu A \times V_{DD} \times \frac{f_{sample}}{50k} \times \left(1 - \frac{CR}{100}\right). \quad (2)$$

where VDD is the supply voltage, f_{sample} is the sampling frequency. Its hardware characterizations are compared with proposed CS hardware architectures, such as CS AFE[5], NUS based CS[4]and digital CS[2] , and is shown in TABLE 1. Specifically, 83μA is the supply current of ADS7867 when VDD is 1.2V and f_{sample} is 50K sample per second (SPS). The power consumption performance is as good as the ASIC CS-AFE.

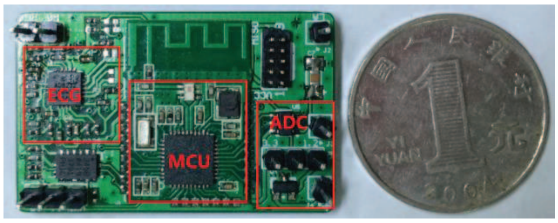


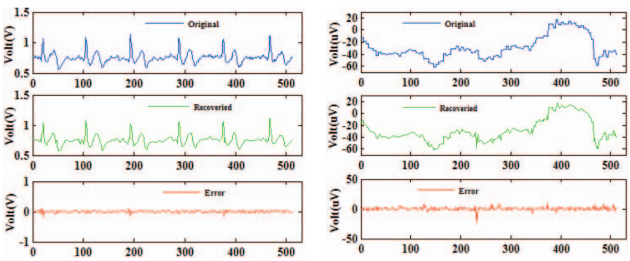
Figure 3: A photograph of prototype, including ECG AFE, ADC and a MCU. The board is small.

EVALUATION

Two sets of signals are used, which are manually collected signals (ECG signals) and online signal databases, i.e. Electro-Oculogram (EOG) signals from sleep heart health study (SHHS) polysomnography database. The PPRS acquisition process is simulated via MATLAB to obtain sampled signals, and recovery process was also operated on PC. The pSense platform is evaluated from accuracy, scalability and robustness. *CR* and percentage root-mean-square difference ($PRD, PRD = \frac{\|x-\bar{x}\|_2}{\|x\|_2} \times 100\%$) are deployed to quantify performances. *CR* evaluates energy savings performance, and *PRD* appraises quality of reconstructed signal $\bar{x}$.

Accuracy

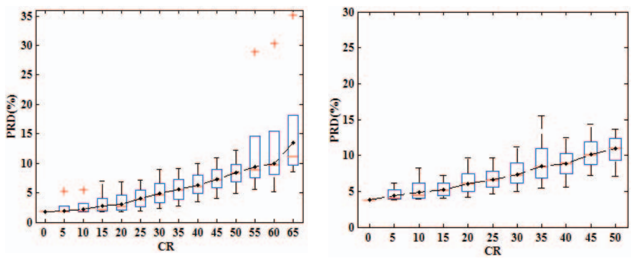
Comparing differences between original and reconstructed signals intuitively, we set $K = 50$, $CR = 30$, and using DWT-SYM8 basis, where K is the degree of sparsity. The original, reconstructed signals and the difference in Figure 4 are in the top, middle and bottom, respectively. In Figure 4(a), the heart rate pattern and typical ECG tracing (like the P wave) are clearly recovered. And the gap of EOG signals (Figure 4(b)) is relatively large. Thus, the recovery signal has high quality.



(a)ECG (b)SHHS EOG(L)

Figure 4: Visual comparison between original recovery signals. (a)ECG signals (b) EOG signals

The average results are from 100 repetitive experiments for a certain *CR*. As Figure 5(a) shows, when *CR* is less than 30, pSense achieves the average *PRD* lower than 10%. For EOG signal in Figure 5(b), when *CR* is less than 45, the average *PRD* is less than 10% in both cases.



(a)ECG (b)SHHS EOG(L)

Figure 5: PRDs for different CR (a) ECG signals (b) EOG signals

Scalability

pSense is a scalable AIC with only one sensing channel to deal with various applications based on PPRS algorithm. Compression Factor ($CF = 1/CR$) is used to describe the actual compressing ability of raw signals. In Table 2, the frame time and CS channels are limited in CS-AFE. If signals are with large sparse coefficient K (low sparsity),the actual required number of CS measurement channels can exceed the fixed number. Through CS-AFE cannot be used in such a case, pSense is applicable with its scalable frame time using one channel.

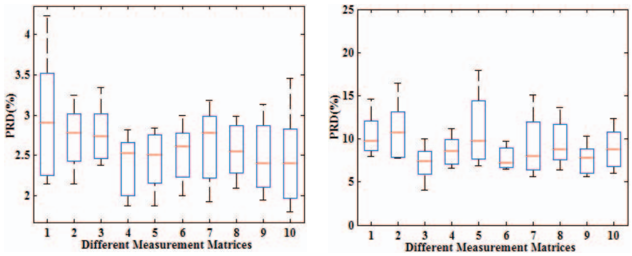
Robustness

The robustness of the platform is very important in practical use when measurement matrix is stored in the ROM of MCU and be tested using different sampling matrices.

Nine different ECG sequences are sampled at 125Hz, and they are simulated to be sampled and reconstructed by ten measurement matrices generated by PRRS algorithm on Matlab, similar with EOG sequences. In Figure 6, the *PRD* of the ECG sequences are distributed in the range of 1.5% to 4.5%. For EOG (L) signals, the distribution range is from 4% to 18%. The results show that for different sequences from the same signal type, the reconstruction performances under ten different random binary matrices are very close. Therefore, pSense is insensitive to different sampling matrices.

TABLE 2: SCALABLE PERFORMANCE COM-PARISON

Parameter	CS-AFE[5]	The work
Frame time(N_{cycles})	128/256/512/1024	Scalable
Channels (Rows)	1-64	1
CF	2-1024	Scalable



(a) ECG (b) SHHS EOG(L)

Figure 6: For different signal sequences, the performances of the same measurement are different.

CONCLUSION

In this paper, an efficient and practical analog-to-information platform using COTS devices is proposed. Without additional hardware is need, this platform can reduce energy consumption by applying a *PPRS* sampling method. ECG signals and other bio-signals from SHHS database are used for evaluating the performances. The experiment results show the original signals can be reconstructed stably and at an acceptable error level. The size of measurement matrix is scalability and the platform is not sensitive to the choice of base. So his method can be widely used in sampling various types of sparse signals.

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