Digital Signal Processing of Pad Sensors

Schematic Layout

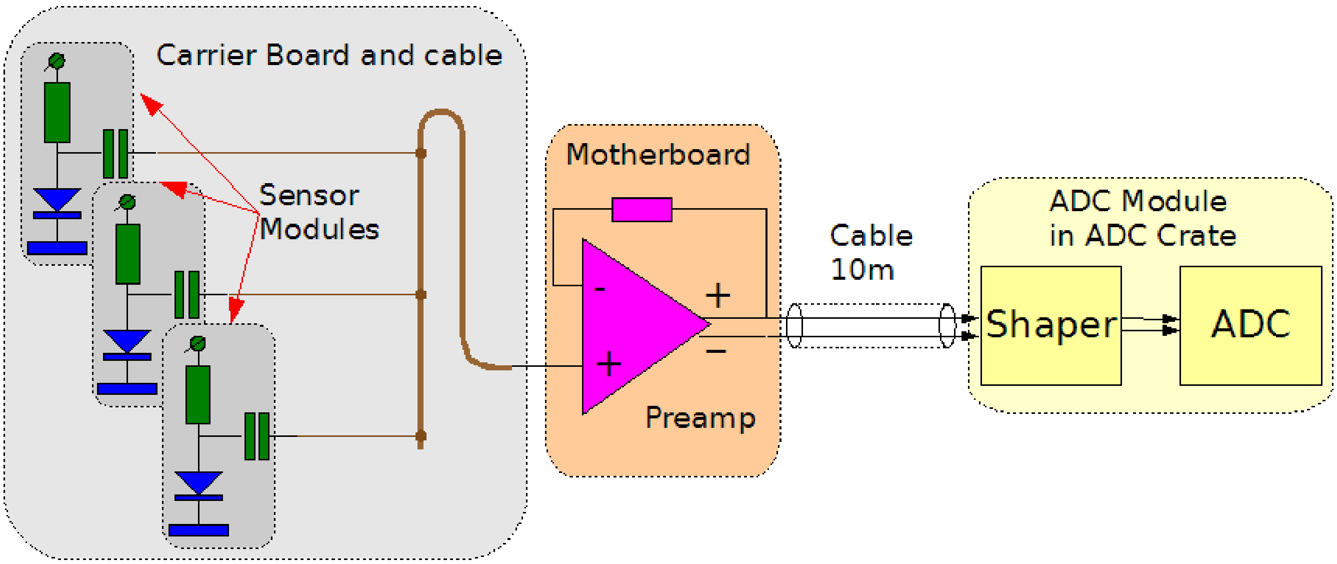

Fig 1: Schematic layout of the NCC pad sensor readout chain.

The signal at the input of the shaper is proportional to the current pulse at the sensor. Since we measure the charge deposited in the sensor, the output signal of the channel should be integral of the current pulse.

Terminology

We are following the terminology as it explained in [AD].

Noise-Free (Flicker-Free) Code Resolution

The *noise-free code resolution* of an ADC is the number of bits of resolution beyond which it is impossible to distinctly resolve individual codes. This limitation is due to the effective input noise (or input-referred noise) associated with all ADCs, usually expressed as an rms quantity with the units of *LSBs rms*. Multiplying by a factor of 6.6 converts the rms noise into a useful measure of peak-to-peak noise - the actual uncertainty with which a code can be identified - expressed in *LSBs peak-to-peak*. Since the total range (or span) of an *N*-bit ADC is 2^N LSBs, the total number of *noise-free counts* is therefore equal to:

$$\text{Noise-free counts} = \frac{2^N}{\text{peak-to-peak input noise (LSBs)}}$$

The number of noise-free counts can be converted into *noise-free (binary) code resolution* by calculating the base-2 logarithm as:

$$\text{Noise-free code resolution} = \log_2(\text{Nose-free counts})$$

The ratio of the full-scale range to the *rms* input noise (rather than peak-to-peak noise) is sometimes used to calculate resolution. In this case, the term *effective resolution* is used. Note that under identical conditions, *effective resolution* is larger than *noise-free code resolution* by $\log_2(6.6)$, or approximately 2.7 bits.

$$\text{Effective resolution} = \log_2\left(\frac{2^N}{\text{rms input noise (LSBs)}}\right)$$

Effective resolution = Noise-free code resolution + 2.7 bits

Effective Resolution or Noise-Free Code Resolution should not be confused with **Effective Number of Bits (ENOB)**

Because of the similarity of the terms, *effective number of bits* and *effective resolution* are often assumed to be equal. This is not the case.

Effective number of bits (ENOB) is derived from an FFT analysis of the ADC output when the ADC is stimulated with a full-scale sine-wave input signal. The root-sum-of-squares (RSS) value of all noise and distortion terms is computed, and the ratio of the signal to the noise-and-distortion is defined as SINAD, or *S/(N+D)*. The theoretical SNR of a perfect *N*-bit ADC is given by:

SNR = 6.02 + 1.76 dB

ENOB is calculated by substituting the ADC's computed SINAD for *SNR* in Equation 5 and solving equation for *N*.

ENOB = (SINAD-1.76dB)/6.02

The Noise-free code resolution is best applicable for pulse measurements while ENOB – for frequency domain systems.

Noise Sources

input-referred noise - modeled as a noise source connected in series with the input of a noise-free ADC.

quantization noise – errors due to digitization of continuous values.

The input-referred noise in a well designed system (good ADC, layout, grounding and decoupling) is approximately Gaussian.

The quantization noise can also be considered as a random noise in most cases.

The quantization error cannot be treated as random in one important case when the analog signal remains at about the same value for many consecutive samples and the input-referred noise is less than one LSB. Instead of being an additive random noise, the quantization error now looks like a thresholding effect or weird distortion.

In our application the input-referred noise is larger than LSB, therefore we can treat all ADC-related noise as random.

Optimal Digitization of The Pulse With Known Shape

The effect of input noise can be reduced by digital averaging. If noise is random then averaging over N samples improves the signal-to-noise ratio $\sqrt{N}$ times.

Using optimal digital filtering will further increase signal-to-nose ratio, effectively increasing the dynamic range of the system at the expense of overall output sampling rate.

In this section we describe three types of optimal FIR (Finite Impulse Response) filters applied to a system with random noise.

Different filters are "best" (optimal) in a different ways [SMITH].

The **moving average filter** is optimal in the sense that it provides the fastest step response for a given noise reduction. For our application we will consider **sliding integrator** instead of moving average since we need to integrate the input signal.

The **matched filter**. The idea behind the matched filter is *correlation.* The amplitude of each point in the output signal is a measure of how well the filter kernel *matches* the corresponding section of the input signal. The output of a matched filter does not necessarily look like the signal being detected. The matched filter is optimal in the sense that the top of the peak is farther above the noise than can be achieved with any other linear filter. (To be perfectly correct, it is only optimal for *random white noise*).

The **Wiener filter** (named after the optimal estimation theory of Norbert Wiener) separates signals based on their frequency spectra. The gain of the filter *at each frequency* is determined by the relative amount of signal and noise *at that frequency*:

Assume the ADC takes **n** samples of signal $\mathbf{S_i}$ with known shape $\mathbf{F_i}$. Assume the white noise at the ADC input has level of **Vn**.

Sliding Integrator

Output amplitude: $Aa = a \cdot \sum_{i=1}^{n} F_i$ where *a* is a conversion coefficient of the ADC.

Output Noise: $Na = \sqrt{n} \cdot Vn$

Signal-to-Nose ratio: $SNa = \frac{a}{Vn} \cdot \frac{1}{\sqrt{n}} \cdot \sum_{i=1}^{n} F_i$

Matched Filter

Filter coefficients (weights) are proportional to the signal shape $W_i = w * F_i$. the *w* is an normalizing coefficient.

Output amplitude: $Am = a \cdot \sum_{i=1}^{n} F_i \cdot W_i$ $Am = a \cdot w \cdot \sum_{i=1}^{n} F_i^2$

Output noise: $Nw = Vn \cdot w \cdot \sqrt{\sum_{i=1}^{n} F_i^2}$

Signal-to-Nose ratio: $SNw = \frac{a}{Vn} \cdot \sqrt{\sum_{i=1}^{n} F_i^2}$

Signal-to-Noise improvement

Interesting to note that

$SNa = \frac{a}{Vn} \cdot \sqrt{n} \cdot \langle Fi \rangle$ $\langle F_i \rangle$ is the mean of the signal shape function.

$SNm = \frac{a}{Vn} \cdot \sqrt{n} \cdot \sqrt{\langle Fi^2 \rangle}$ $\langle F_i^2 \rangle$ is the mean of the squared signal shape function.

The improvement factor of using matching filter over sliding integrator:

$\frac{SNm}{SNa} = \frac{\sqrt{\langle F_i^2 \rangle}}{\langle F_i \rangle} = \sqrt{1 + \frac{sigma^2}{\langle F_i \rangle^2}}$ the *sigma* is the variance of the signal shape function.

Examples:

1) When the signal shape is flat then, obviously, is no improvement: $\frac{SNm}{SNa} = 1$

2) For linear shape: $\frac{SNm}{SNa} = \sqrt{\frac{2 \cdot (2 \cdot n + 1)}{3 \cdot (n+1)}}$, *n* is the number of samples; for large *n* it reaches $\sqrt{\frac{4}{3}}$ = 1.1547

For unipolar shapes the improvement is small (less than $\sqrt{n}$) since the variance cannot be bigger then the mean. For bipolar signals the improvement could be very large since the mean of the signal shape could be arbitrary small.

In our application we are using low pass pass filter (4^{th} order Bessel), it will be always negative overshoot in the output pulse shape.

Optimal Digitization for Readout Channel of NCC Pad Sensor

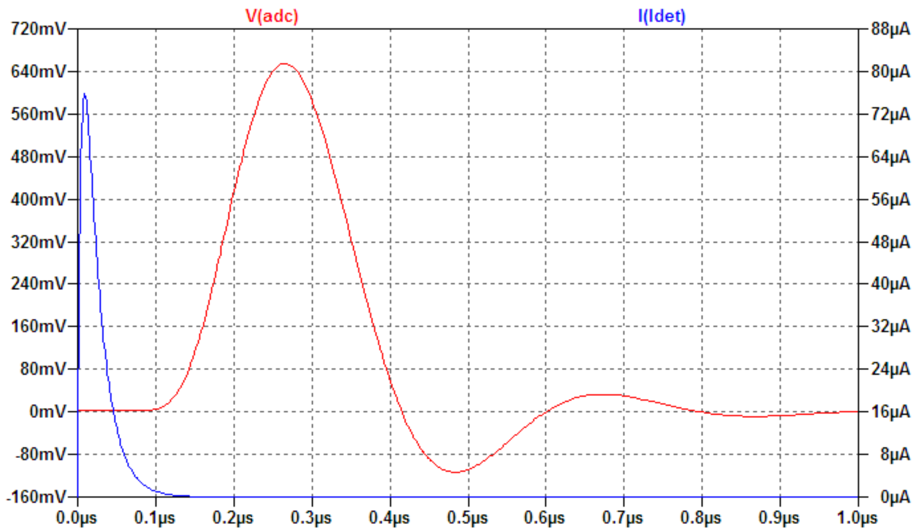

Fig 2: LTSPICE simulation of the readout chain for NCC pad sensors. Detector signal (blue) and the output of the filter (red) are shown.

Selection of the Sampling Rate and the Length of the Filter

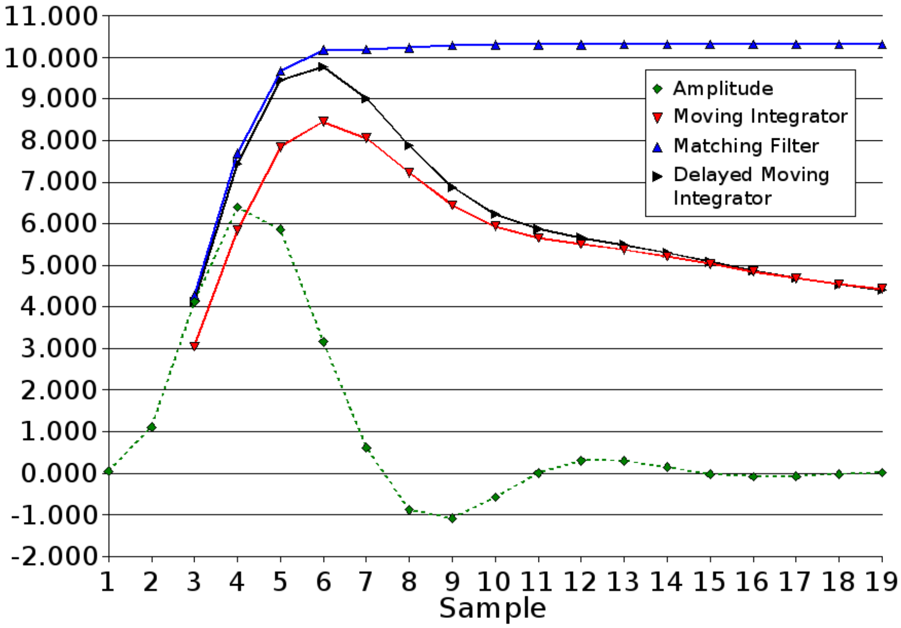

Fig 3: Signal-to-noise ratio (solid lines) for sliding integrator (red) and for matching filter (blue) versus number of samples for random noise with rms=1. The thin black - for moving , delayed by two samples. The signal amplitude is green dotted line. The sampling rate is 20MHz.

- The signal-to-noise ratio of the original signal has maximum of 6.4 at sample 4.
- the matching filter reaches maximum of 10.2 (1.59 times better than original signal) at sample 6.
- the sliding integrator reaches maximum of 8.4 (1.32 better than original signal) at sample 6.
- the 4-sample moving delayed by two samples performs as good as matching filter, it has maximum of 9.8 (1.52 times better than original signal).

Conclusion:

The sliding integrator with integration time of 200 ns around the signal peak is near optimal for the signal shape shown on Fig. 3. This filter improves signal to noise ratio by the factor of $0.76*\sqrt{N}$.

For example:

- If we use 4-sample with 20MHz ADC then signal-to-noise improvement will be 1.53.
- If we use 4 times faster ADC (80 Mhz) with the same noise-free code resolution and use 16-sample integration then we will gain another factor of two in signal to noise ratio and total improvement will be 3.06.

References

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