Intermediate Report Nr. 3

Bernhard Geiger

March 27, 2009

1 Influence of Integration Offset

Facilitating the ED outputs to aproximate the compound response $\Phi_{mp}(t)$ with a series of weighted sinc-functions has the advantage that leading edge detection can be performed on a continuous-time signal which was not possible by operating on the ED outputs directly. Therefore, the well-known uncertainty regarding the determination of the LE (or, MES) within the integration interval is not existent here. Previously, if the leading edge was assumed to be located at the center of the integration interval (and, if the integration interval indeed contains the leading edge), there still was a minimum achievable mean absolute error (MAE) of $\frac{T_i}{4}$. This error of course increases if a wrong output sample is chosen, which is likely in the LE detection case.

Using parallel structures where $T_s \neq T_i$ it is possible to reduce this minimum MAE further while still operating directly on the ED output samples. Still, due to the discrete nature of the output samples and the resulting uncertainty concerning the actual time of arrival (TOA), the minimum error is still non-zero, increasing in steps if a wrong sample is chosen to represent the LE or the MES.

Interpreting the ED outputs as Nyquist-rate samples of the compound response (which obviously only holds if integration and sampling periods are short enough) and interpolating intermediate values the detection error is merely determined by the approximation error. Although this approximation error is closely related to the choice of T_s and T_i, there is no limitation on the minimum achievable error due to discretization.

What still has to be taken into account is the influence of the integration start time, or, the integration offset. As it is obvious, by shifting the integration period relative to the maximum energy peak there may be cases where the input to the energy detector is more steady than in other cases. In such cases, Urkowitz's approximation holds better, which can influence approximation error and, consequently, detection error. Therefore one has to consider that the integration offset *has* some influence on the performance of the intended ranging method. Still, this influence cannot be mitigated by any measure, because it adheres to the same kind of uncertainty resulting in the minimum MAE of $\frac{T_i}{4}$ for operating on ED output samples – there is no possibility to determine the integration offset, as there is no possibility to determine where exactly within the integration period the leading edge is situated.

I run a series of simulations over 100 channels, each with a Ricean k factor of 0.2 and an RMS delay spread of 10 ns. This time, I used a smaller value for oversampling which had the effect of decreased performance. Still, on average, performance for approxmation and detection should be similar as derived in IR2, which is illustrated in Tab. 1. However, the overall performance changes with the

T_s ns	T_i ns	Q_2 dB	MAE-MES ns	MAE-LE ns
1.00	1.00	-20.99	0.32	0.18
1.25	1.25	-18.11	0.47	0.27
2.00	2.00	-12.25	1.00	0.62
2.50	2.50	-10.49	1.34	0.88

Table 1: Average Performance over Integration Offset

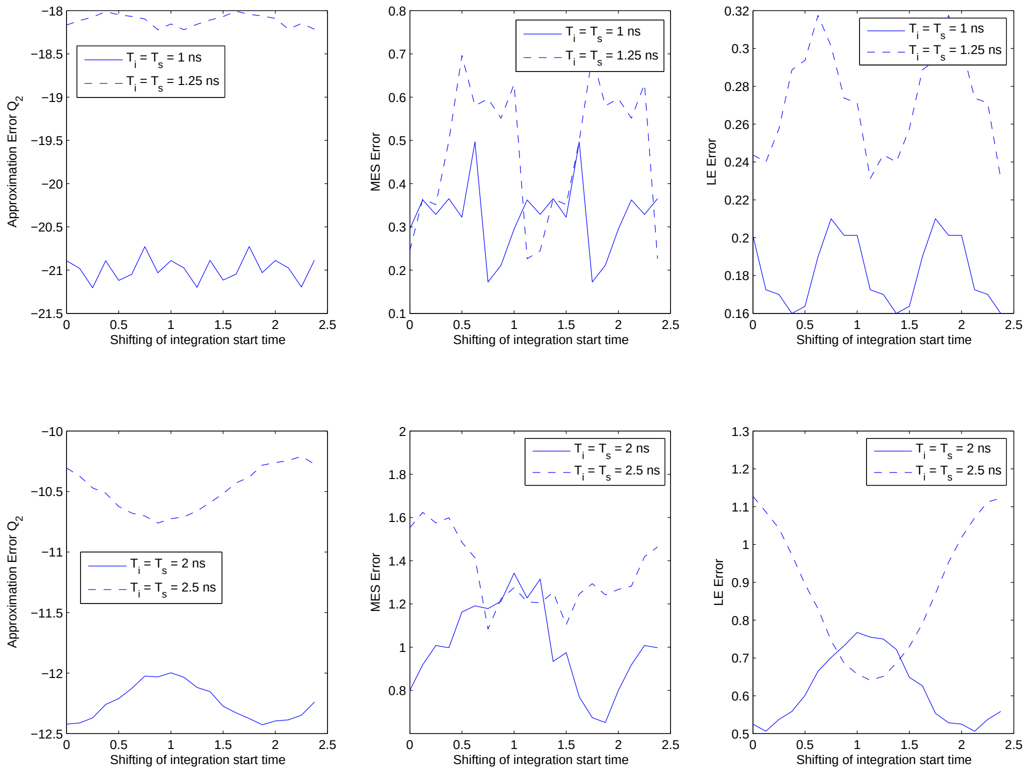

Figure 1: Influence of Integration Offset

integration offset, as expected. Naturally, these changes are periodic with $T_i = T_s$, as it can be seen in Fig. 1[1]. Comparing these results to the best results obtained in my previous work one can clearly see the benefit of a sinc-interpolation: Even with an integration period of 2 ns better results could be achieved for leading edge detection than for directly operating on ED outputs spaced with only 1 ns (where the minimum error was around 1 ns). If this still applies in the presence of noise has to be found out[2].

[1]How this behaves for $T_i \neq T_s$ would be interesting to find out!

[2]Another interesting thing to find out would be effects of the oversampling factor `tx.OS`, which was reduced to 16 in this simulation and therefore led to a higher approximation and detection error. Especially with noise it would be interesting if, w.r.t. the variance of the ED outputs, the noise has to be scaled somewhat.

1.1 Application for ranging

As said before, by using sinc-interpolation we can reduce the uncertainty caused by the non-zero integration interval. The minimum mean absolute error is now less than $\frac{T_i}{4}$. Such an error was artificially created by adding a (uniformly) random $\pm\frac{T_i}{2}$ to the time vector running along the ED output samples. This, however, cannot be done here without seriously decreasing performance of the ranging algorithm employing sinc-interpolation – a reduced random time vector has to be added, and it has to be found out if such a time vector is still uniformly distributed within $\pm\frac{T_u}{2}$, where T_u is the amount of uncertainty when searching for MES or for a certain threshold[3].

Furthermore, it turned out that the error occurring during LE detection is not zero-mean. This is most likely due to the fact that the slope of the leading edge is steeper than it can be modelled with sub-sampled sinc-pulses. Therefore, the approximation of the leading edge crosses the threshold earlier than the actual leading edge, whereas the difference reduces with increasing thresholds. This information can be exploited to improve ranging accuracy, since this systematic bias can be equalized that way.

A series of 1000 simulations with a Ricean k-factor of 0 and 0.8, respectively, and an RMS delay spread of 5 ns was performed. Each time the 10% and 90% quantile of the error values were computed, indicating the range of uncertainty T_u. Furthermore, for LE detection also the mean error was computed, which can be used to correct ranging measurements partly. MES error was almost zero-mean each time, so I didn't record any values for that. Have a look at Tab. 2 for further reference

		k=0		k=0.8	
	ζ	OS=16	OS=8	OS=16	OS=8
		10% to 90% quantile			
MES	1	-0.775..0.5375	-0.5656..0.5906	-0.425..0.475	-0.257..0.4313
LE	0.2	-1..0	-0.9..0.025	-0.975..-0.55	-0.844..-0.5625
LE	0.3	-0.825..0.037	-0.7375..0.1094	-0.85..-0.37	-0.694..-0.419
LE	0.4	-0.75..0.125	-0.65..0.225	-0.7..-0.25	-0.5875..-0.2875
LE	0.5	-0.725..0.4	-0.525..0.347	-0.575..-0.125	-0.4625..-0.169
LE	0.6	-0.5..0.5875	-0.4625..0.4875	-0.475..-0.05	-0.3313..0.0063
		Mean error			
LE	0.2	-0.5326	-0.4852	-0.7588	-0.7075
LE	0.3	-0.4424	-0.3752	-0.6108	-0.5578
LE	0.4	-0.3070	-0.2546	-0.4845	-0.4272
LE	0.5	-0.1509	-0.12	-0.3588	-0.2941
LE	0.6	-0.0123	0.0323	-0.2234	-0.1506

Table 2: Uncertainty for different thresholds

[3] I will try to find the accurate distribution of the uncertainty as well as a function for modelling T_u dependent on ζ, which most likely will lead to an update of this document. So far, I would like to model MAE for MES and LE only, where LE is defined as the point where the slope exceeds 20% of the peak