DeconvolutionOfEnergyPlaneSignalsInNEW

September 7, 2016

1 Deconvolution of the Energy plane signals

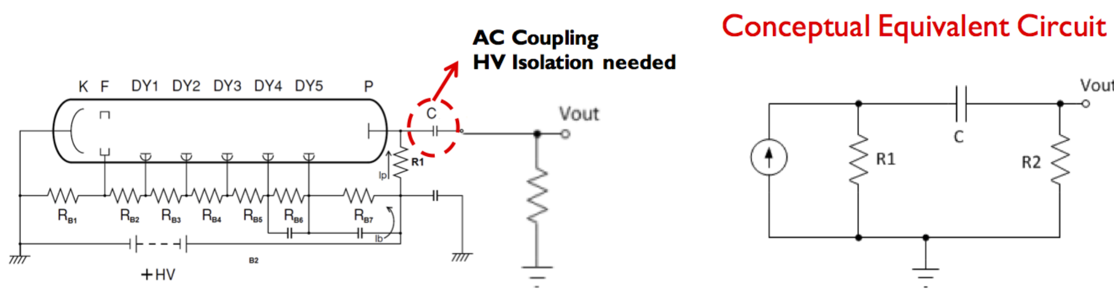
```
In [9]: %matplotlib inline
```

```
In [4]: from IPython.display import Image
```

1.1 PMT connection mode

```
In [5]: Image(filename='images/fee.png')
```

Out[5]:



$$\frac{V_{out}}{I_i} = \left({}^{R_2}/_{R_1}\right)\frac{(R_2 + R_1)Cs}{(R_2 + R_1)Cs + 1}$$

1.2 CR diferentiator

```
In [6]: Image(filename='Images/RC-circuit.png')
```

Out[6]:

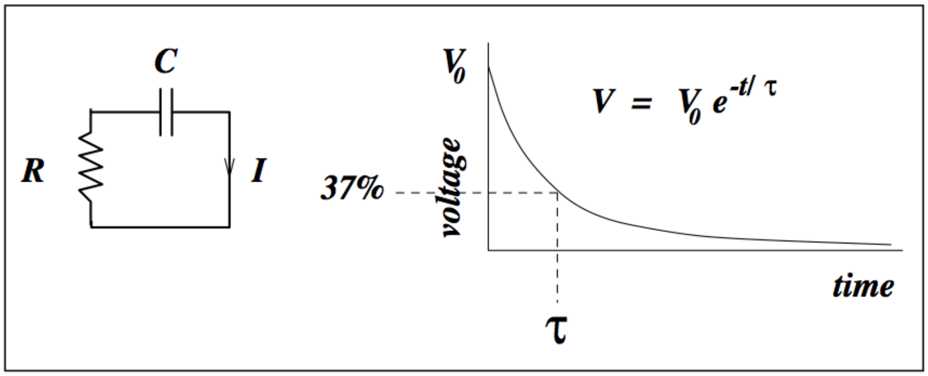


Figure 2.2 Discharge of a capacitor across a resistor.

$$C\frac{\mathrm{d}V}{\mathrm{d}t} = I = -\frac{V}{R} \tag{2.1}$$

To solve Equation (2.1): Rewrite it as $\frac{\mathrm{d}V}{\mathrm{d}t} + \frac{V}{\tau} = 0$, where $\tau = RC$.

Multiply by $e^{t/\tau}$: $e^{t/\tau}\left(\frac{\mathrm{d}V}{\mathrm{d}t} + \frac{V}{\tau}\right) = \frac{\mathrm{d}}{\mathrm{d}t}\left(Ve^{t/\tau}\right) = 0$.

Integrate: $\left(Ve^{t/\tau}\right) = K$ and, if $V = V_0$ at $t = 0$, $K = V_0$. Hence,

the solution to Equation (2.1) is:

$$V = V_0 e^{-t/RC} \tag{2.2}$$

where V_0 is the initial voltage across the capacitor.

In [7]:
```
Image(filename='Images/CR-differentiator.png')
```

Out[7]:

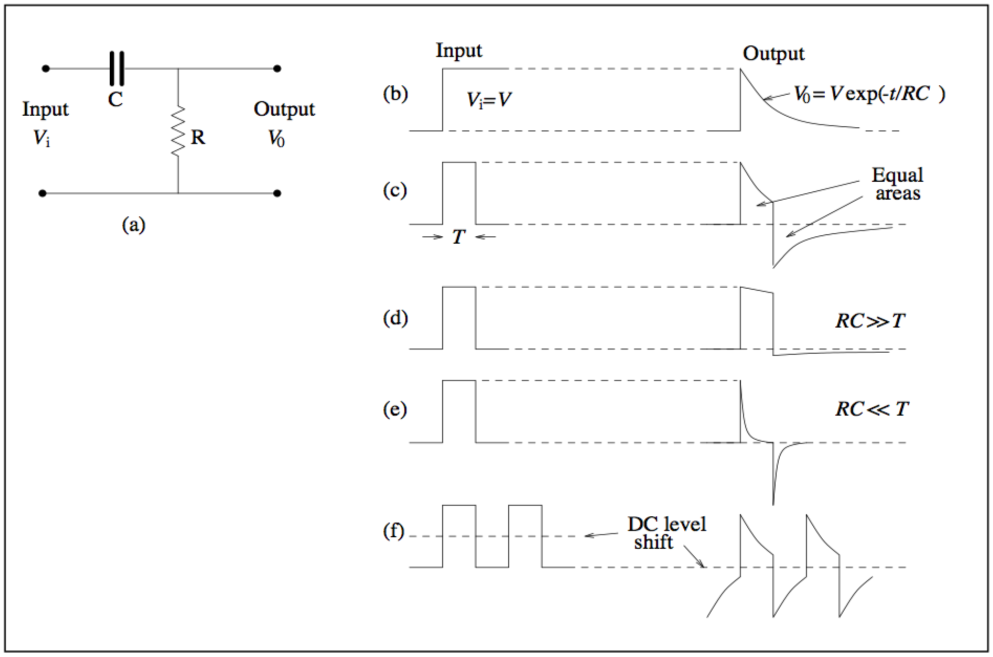
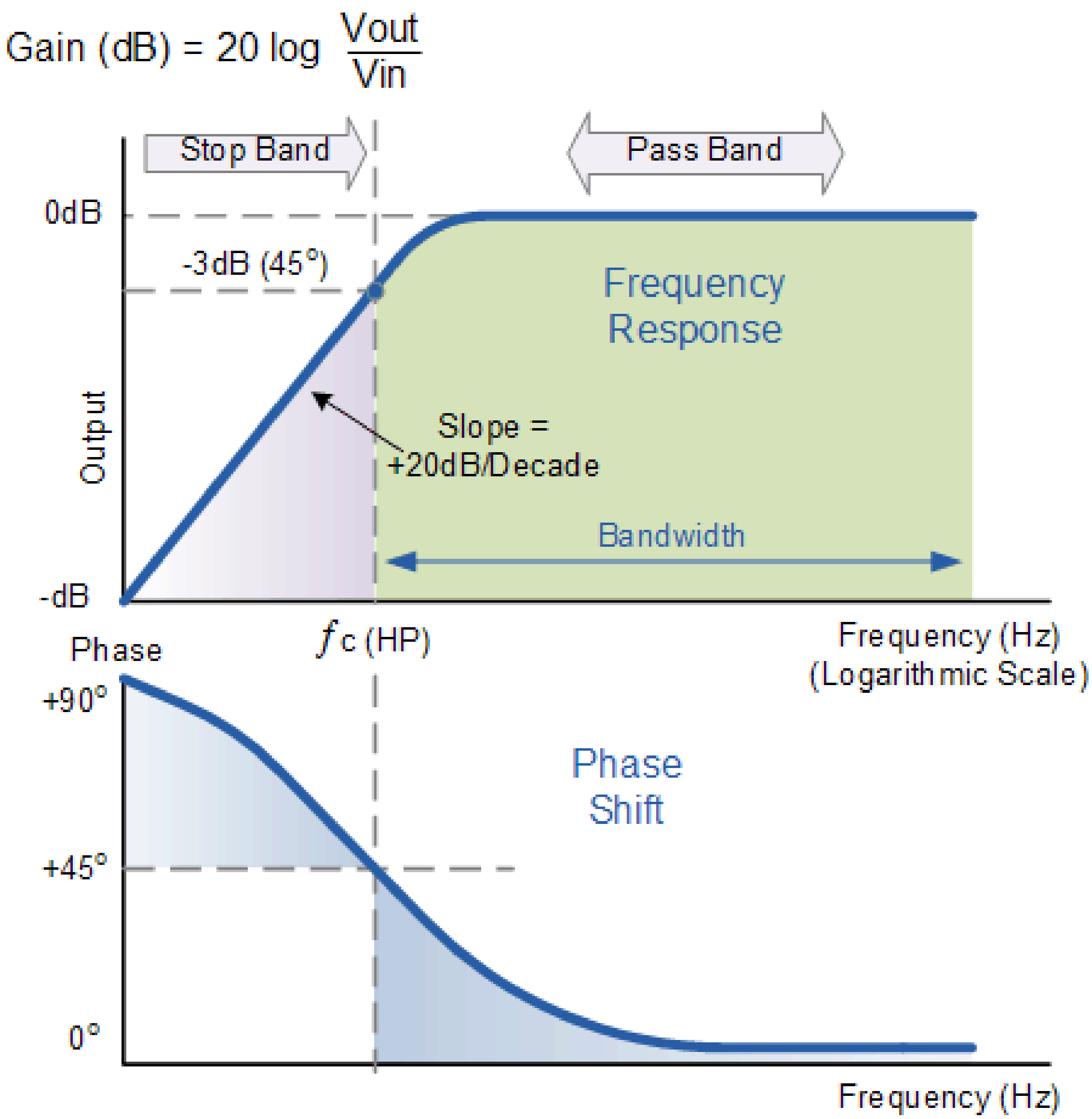


Figure 2.4 High-pass CR filter (differentiator): (a) basic circuit; (b) step input; (c) single (square) pulse ($RC = T$); (d) single pulse ($RC \gg T$); (e) single pulse ($RC \ll T$); (f) pulse train.

1.3 A CR differentiator is a High Pass Filter (HPF)

In [20]:
```
Image(filename='Images/fil13.png')
```

Out[20]:




```
In [22]: Image(filename='Images/fil37.png')
```

Out[22]:

$$fc = \frac{1}{2\pi RC}$$

$$Phase\ Shift\ \phi = arctan\frac{1}{2\pi fRC}$$

A HPF of this type is the simplest case of the most general Butterworth filter. The LPF implemented by the FEE can also be described in terms of a BWF. The Scipy library includes utilities to define HPF and LPF BF.

```
In [23]: from Filter import *
```

```
In [24]: import FEParam as FP
         from Util import *
         from scipy import signal
         import SPE as SP



         ##########################################################


         def FilterCutoffFrequency(R=4700, C=8e-9):
                 """
                 Takes R (in Ohms) and C (in Farad) and returns frequency in Htz
                 """

                 return 1./(2*pi*R*C)

         class Filter:

                  def __init__(self,type='high',fc=5E3,fs= 1e+9):
                         """
                         Defines a Butterworth HPF (high pass frequency) or LPF (low pass frequencey) f
                         the default sampling frequencey is 1 GHz (inverse of 1 ns time)
                         type may be equal to hig or low
                         """
                         self.fc = fc
                         self.fs = fs
                         self.W = 2*self.fc/self.fs
                         self.type = type
                         self.b, self.a = signal.butter(1, self.W, btype=self.type, analog=False, outpu
                         self.ba, self.aa = signal.butter(1, 2*self.fc, btype=self.type, analog=True, o

                 def FilterCoef(self):
                         """
```

```
        Returns the filter coefficients
        """
         return self.b,self.a

   def FilterAnalogCoef(self):
        """
        Returns the filter coefficients
        """
         return self.ba,self.aa

 def FilterPulse(self,pulse):
        """
        Filters a pulse
        """
         return signal.lfilter(self.b,self.a, pulse)

   def FilterResponse(self):
         """
         Gives the response of the filter y frequency-amplitude
         """

         self.w, self.h = signal.freqs(self.ba, self.aa)
         return self.w, self.h


 def __str__(self):

        s= """
        Filter:
        fc = %7.2f Hz, fs = %7.2f, W = %7.2f Hz type = %s
        """%(self.fc, self.fs, self.W, self.type)
        return s
```

1.4 The effect of filters in signals

```
In [25]: def FilterScan(spe,C):
                spe_pulse_t, spe_pulse = spe.SpePulse(100*ns)
              print "Capacitance of filter (nF) = %7.2f"%(C/nF)

              Ra = np.logspace(0., 3.0, num=3)

                for R in Ra:
                        print "Resistance of filter (O) = %7.2f"%(R)

                        freq_HPF = FilterCutoffFrequency(R=R*ohm, C=C)
                        print "cutoff frequence (kHz) = %7.2f"%(freq_HPF/1e+3)
                        hpf = Filter(type='high',fc=freq_HPF,fs=f_sample)
                        w,h = hpf.FilterResponse()
                        plt.subplot(3,1,1)
                      plt.xscale('log')
                      plt.title('HPF  frequency response')
                      SetPlotLabels(xlabel='Frequency [radians / second]', ylabel='Amplitude [dB]')
```

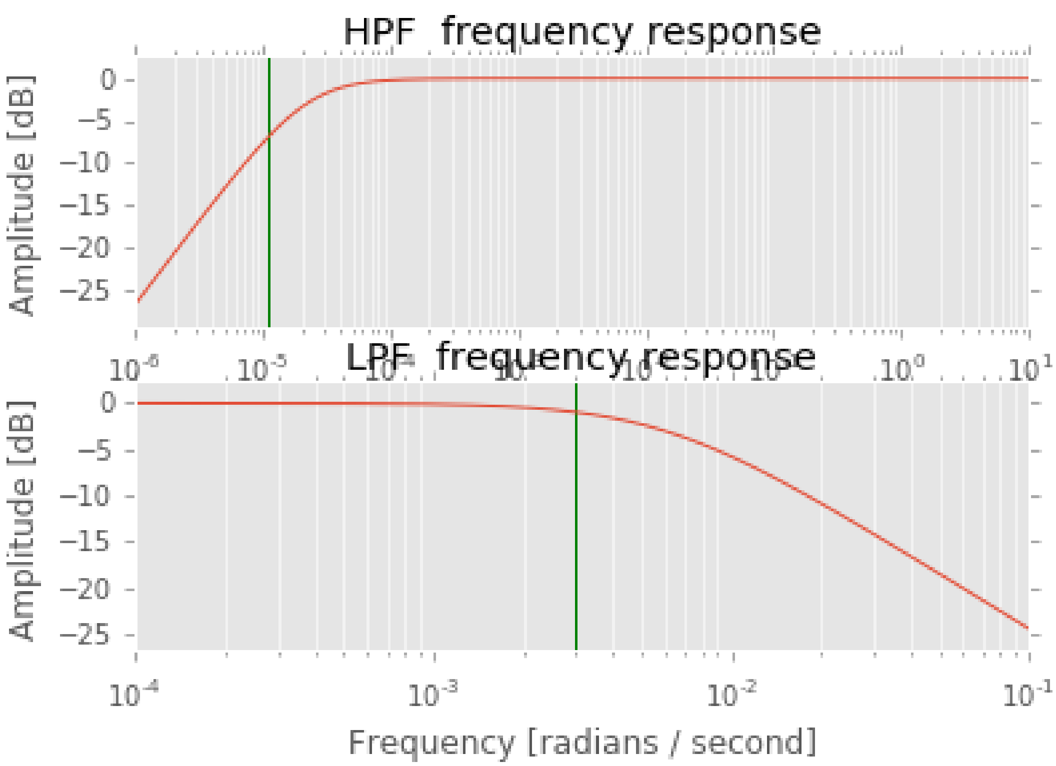
```
            plt.margins(0, 0.1)
            plt.axvline(freq_HPF, color='green') # cutoff frequency
            plt.plot(w, 20 * np.log10(abs(h)))

            spe_hp_pulse = hpf.FilterPulse(spe_pulse)

            ax1 = plt.subplot(3,1,2)
            ax1.set_xlim([0, 200])
            SetPlotLabels(xlabel='t (ns)', ylabel='I (muA)')
              plt.title('SPE pulse')
            plt.plot(spe_pulse_t/ns, spe_pulse/microampere)

            ax2 = plt.subplot(3,1,3)
            ax2.set_xlim([0, 200])
            SetPlotLabels(xlabel='t (ns)', ylabel='I (muA)')
              plt.title('SPE pulse after HPF')
            plt.plot(spe_pulse_t, spe_hp_pulse/microampere)

            plt.show()
```

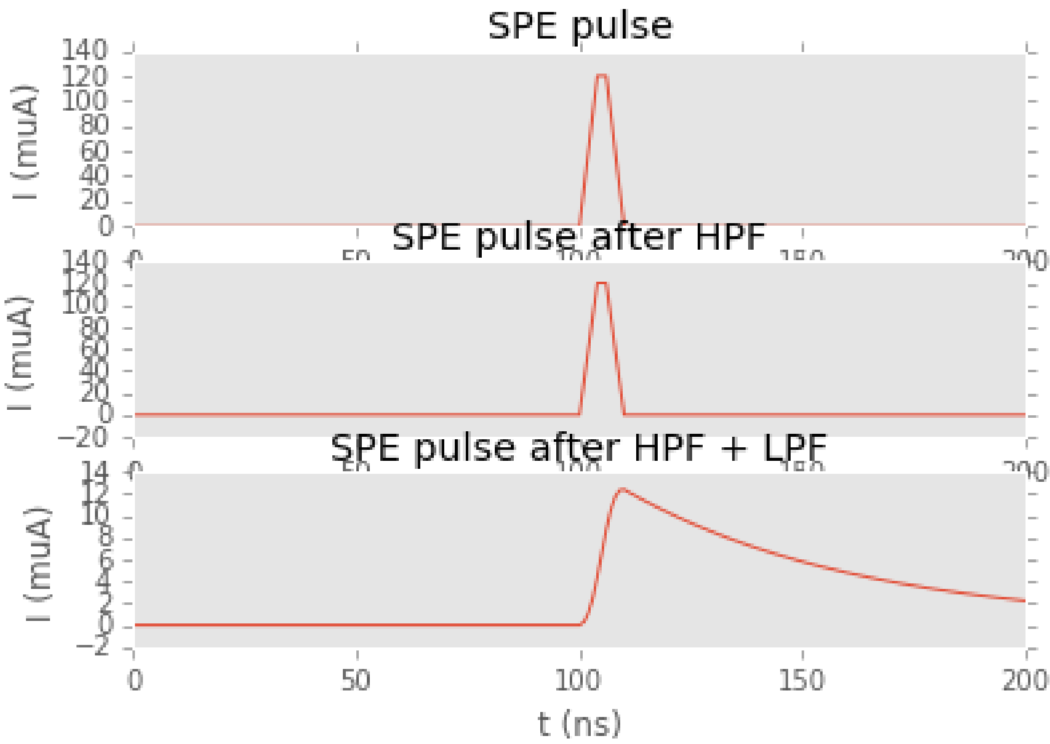
```
In [30]: def FilterCharacterization(spe):
        spe_pulse_t, spe_pulse = spe.SpePulse(100*ns)

          hpf = Filter(type='high',fc=FP.freq_HPF,fs=FP.f_sample)
          lpf = Filter(type='low',fc=FP.freq_LPF,fs=FP.f_sample)

          w,h = hpf.FilterResponse()

          plt.subplot(2,1,1)
        plt.xscale('log')
        plt.title('HPF  frequency response')
        SetPlotLabels(xlabel='Frequency [radians / second]', ylabel='Amplitude [dB]')

        plt.margins(0, 0.1)
        plt.axvline(FP.freq_HPF, color='green') # cutoff frequency
        plt.plot(w, 20 * np.log10(abs(h)))


        w,h = lpf.FilterResponse()
        plt.subplot(2,1,2)


        plt.xscale('log')
        plt.title('LPF  frequency response')
        SetPlotLabels(xlabel='Frequency [radians / second]', ylabel='Amplitude [dB]')

        plt.margins(0, 0.1)
        plt.axvline(FP.freq_LPF, color='green') # cutoff frequency
        plt.plot(w, 20 * np.log10(abs(h)))

        plt.show()

          spe_hp_pulse = hpf.FilterPulse(spe_pulse)
```

```
  spe_hp_lp_pulse = lpf.FilterPulse(spe_hp_pulse)

  ax1 = plt.subplot(3,1,1)
ax1.set_xlim([0, 200])
SetPlotLabels(xlabel='t (ns)', ylabel='I (muA)')
  plt.title('SPE pulse')
plt.plot(spe_pulse_t/ns, spe_pulse/microampere)

ax2 = plt.subplot(3,1,2)
ax2.set_xlim([0, 200])
SetPlotLabels(xlabel='t (ns)', ylabel='I (muA)')
  plt.title('SPE pulse after HPF')
plt.plot(spe_pulse_t, spe_hp_pulse/microampere)

ax3 = plt.subplot(3,1,3)
ax3.set_xlim([0, 200])
SetPlotLabels(xlabel='t (ns)', ylabel='I (muA)')
  plt.title('SPE pulse after HPF + LPF')
plt.plot(spe_pulse_t, spe_hp_lp_pulse/microampere)

plt.show()
```

1.4.1 Effect in a SPE

In [61]:
```
spe = SP.SPE(pmt_gain=FP.PMT_GAIN,x_slope = 5*ns,x_flat = 1*ns)
FilterCharacterization(spe)
```






```
In [39]: def FilterTrain(spe,ti=100*ns,tf=200*ns, tm=50*ns):
             spe_pulse_t, spe_pulse = spe.SpePulseTrain(ti,tf)

             print "pulse train: ti = %7.2f ns, tf = %7.2f ns, area = %7.2g muA"%(ti,tf,spe_pulse.su

               hpf = Filter(type='high',fc=FP.freq_HPF,fs=FP.f_sample)
               lpf = Filter(type='low',fc=FP.freq_LPF,fs=FP.f_sample)

               w,h = hpf.FilterResponse()

               plt.subplot(2,1,1)
             plt.xscale('log')
             plt.title('HPF  frequency response')
             SetPlotLabels(xlabel='Frequency [radians / second]', ylabel='Amplitude [dB]')

             plt.margins(0, 0.1)
             plt.axvline(FP.freq_HPF, color='green') # cutoff frequency
             plt.plot(w, 20 * np.log10(abs(h)))


             w,h = lpf.FilterResponse()
             plt.subplot(2,1,2)


             plt.xscale('log')
             plt.title('LPF  frequency response')
```

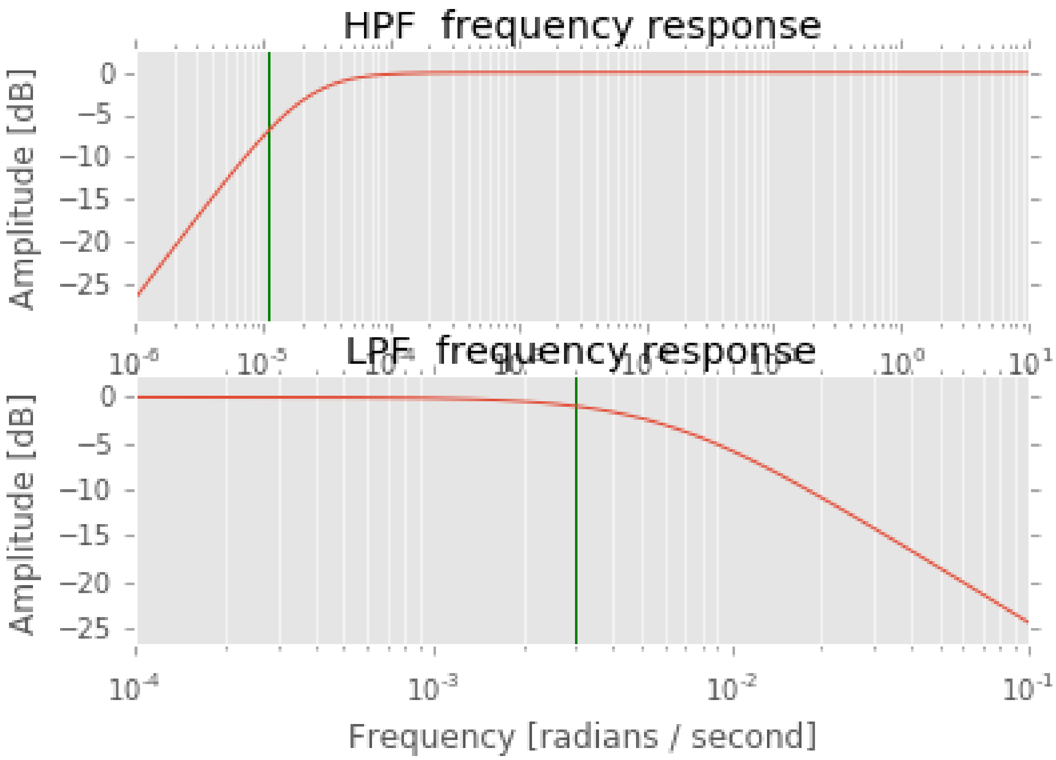
```
SetPlotLabels(xlabel='Frequency [radians / second]', ylabel='Amplitude [dB]')

plt.margins(0, 0.1)
plt.axvline(FP.freq_LPF, color='green') # cutoff frequency
plt.plot(w, 20 * np.log10(abs(h)))

plt.show()

  spe_hp_pulse = hpf.FilterPulse(spe_pulse)
  spe_hp_lp_pulse = lpf.FilterPulse(spe_hp_pulse)
  area_hp = np.sum(spe_hp_pulse[np.where(spe_hp_pulse>0)])
  area_hp_lp = np.sum(spe_hp_lp_pulse[np.where(spe_hp_lp_pulse>0)])


  print "pulse area after HPF = %7.2g muA, pulse area after HPF + LPF  = %7.2g muA"%(
          area_hp,area_hp_lp)

  ax1 = plt.subplot(3,1,1)
ax1.set_xlim([0, tf+tm])
SetPlotLabels(xlabel='t (ns)', ylabel='I (muA)')
  plt.title('SPE pulse')
plt.plot(spe_pulse_t/ns, spe_pulse/microampere)

ax2 = plt.subplot(3,1,2)
ax2.set_xlim([0, tf+tm])
SetPlotLabels(xlabel='t (ns)', ylabel='I (muA)')
  plt.title('SPE pulse after HPF')
plt.plot(spe_pulse_t, spe_hp_pulse/microampere)

ax3 = plt.subplot(3,1,3)
ax3.set_xlim([0, tf+tm])
SetPlotLabels(xlabel='t (ns)', ylabel='I (muA)')
  plt.title('SPE pulse after HPF + LPF')
plt.plot(spe_pulse_t, spe_hp_lp_pulse/microampere)

plt.show()
```

1.4.2 Effect in square pulses of different lengths

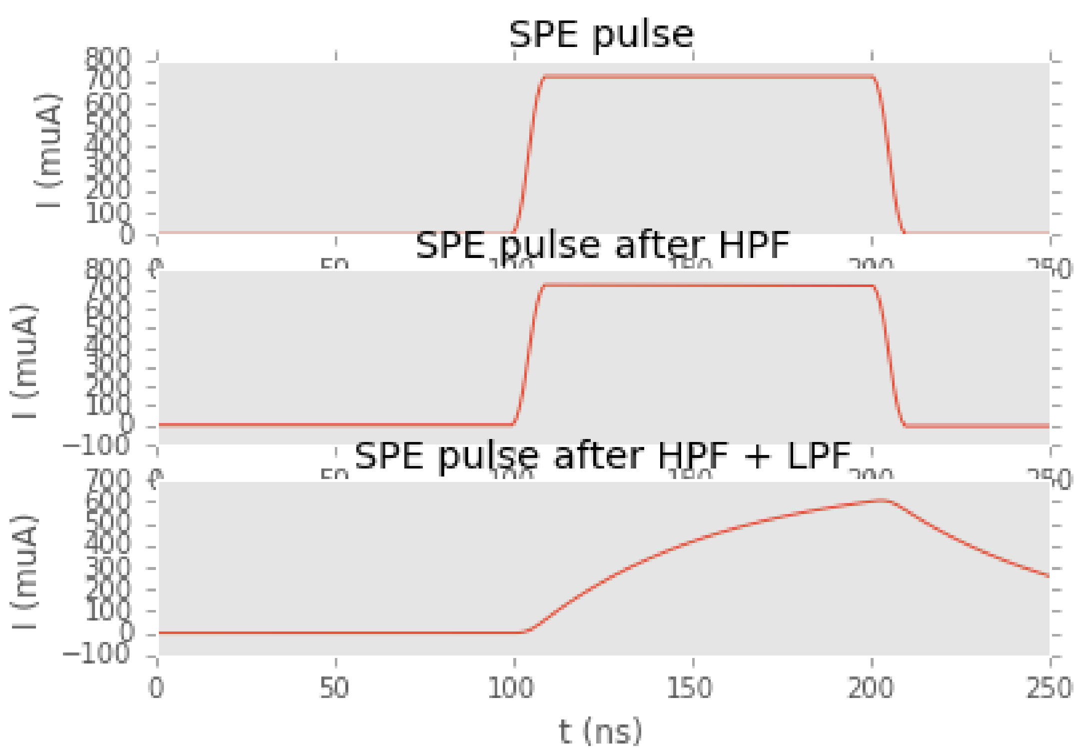
Short

```
In [40]: FilterTrain(spe,ti=100*ns,tf=200*ns, tm=50*ns)
```

```
pulse train: ti =  100.00 ns, tf =  200.00 ns, area = 4.5e+08 muA
```



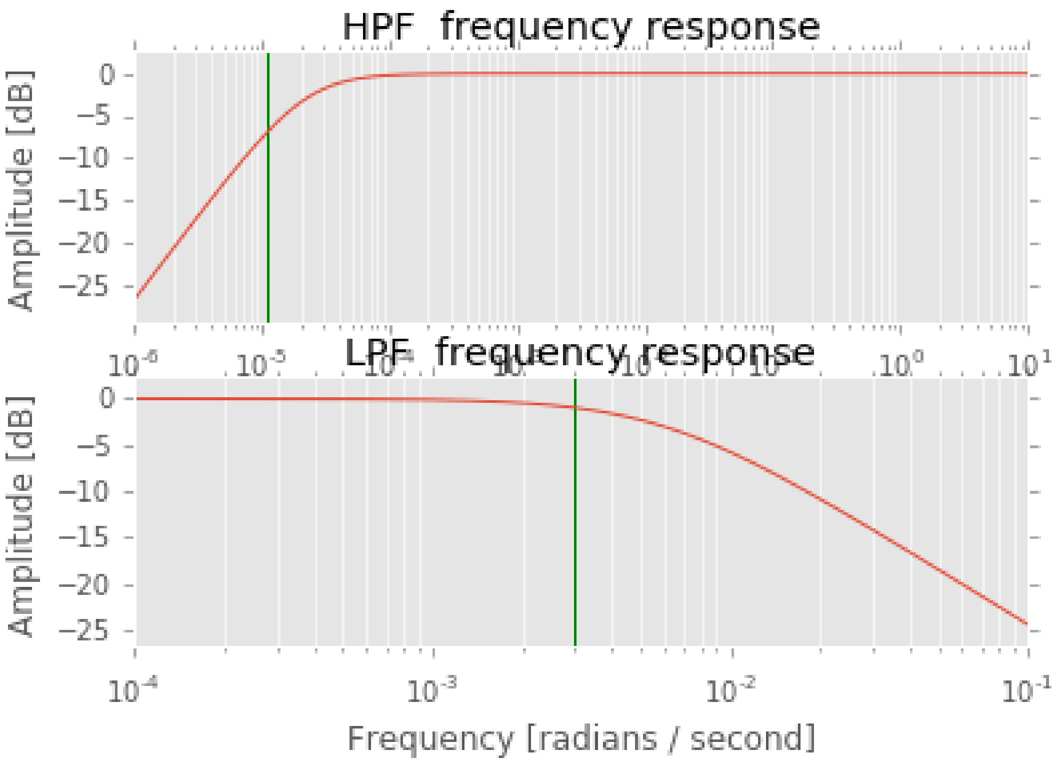

```
pulse area after HPF = 4.5e+08 muA, pulse area after HPF + LPF  = 4.5e+08 muA
```



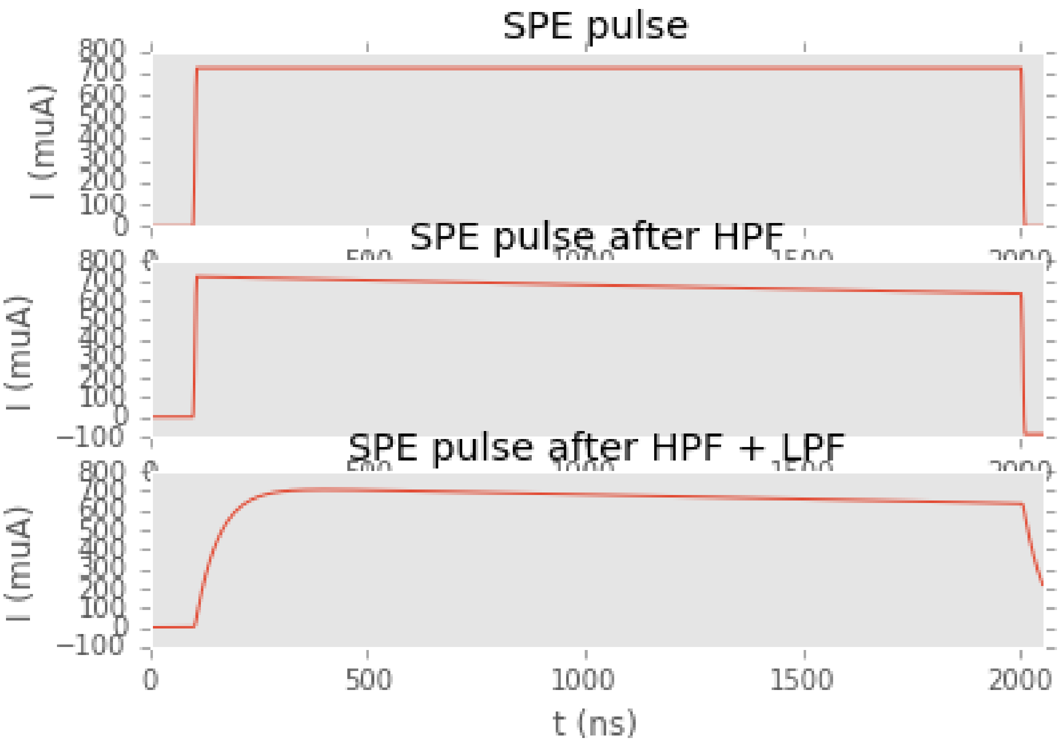
Medium

```
In [41]: FilterTrain(spe,ti=100*ns,tf=2000*ns)
```

```
pulse train: ti =  100.00 ns, tf = 2000.00 ns, area = 8.6e+09 muA
```



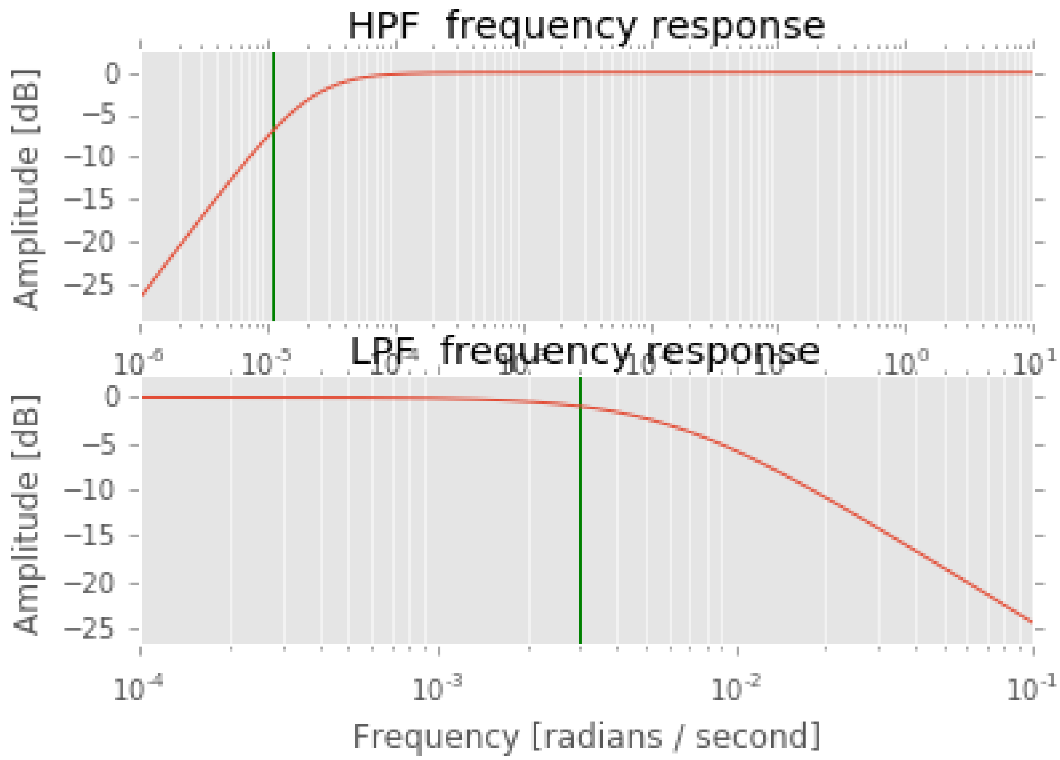

```
pulse area after HPF =   8e+09 muA, pulse area after HPF + LPF  =   8e+09 muA
```



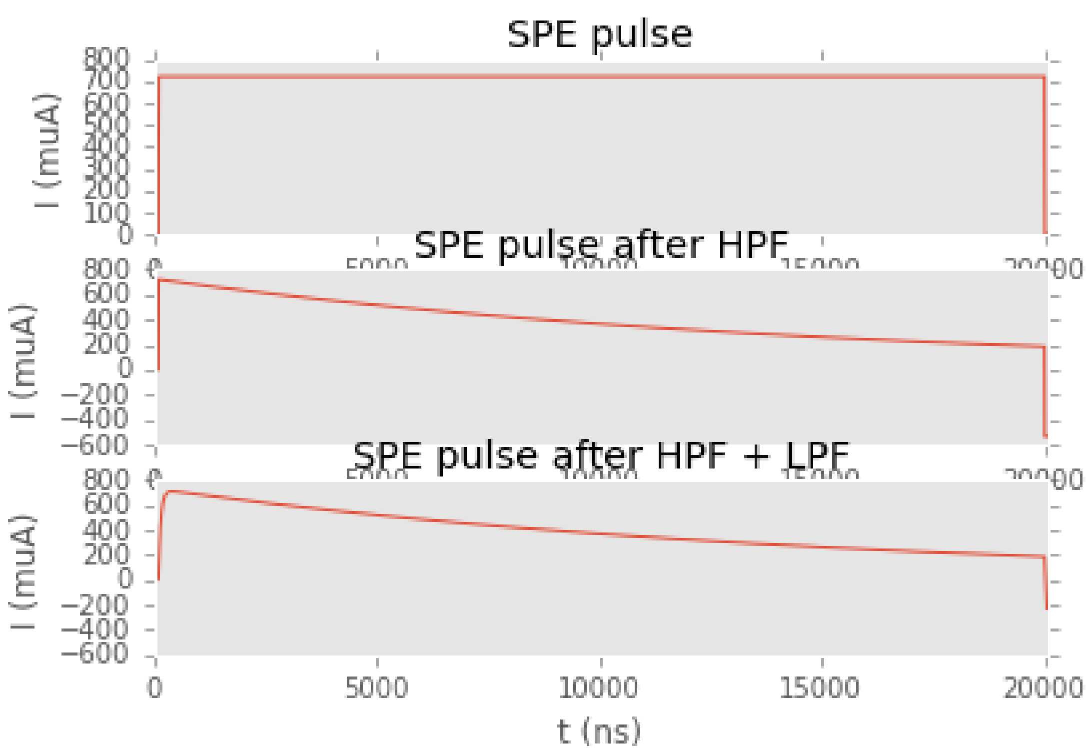
Long

```
In [42]: FilterTrain(spe,ti=100*ns,tf=20000*ns)
```

```
pulse train: ti =  100.00 ns, tf = 20000.00 ns, area =   9e+10 muA
```



pulse area after HPF = 4.9e+10 muA, pulse area after HPF + LPF = 4.9e+10 muA



1.5 First step for deconvolution: simulate the signal

1.5.1 PMT response

1. To simulate the response of the PMTs, one needs to start with an input signal, which can be, for example a square pulse (used for calibration), or a simulation of the physical signal that the PMT receives. In any case the "waveform" describing the input pulse must be densely binned to simulate a continous signal. Given that the DAQ will sample each 25 ns, a reasonable bin for the input waveform is 1 ns.

2. The input waveform is then described as a continous (1 ns) train of photoelectrons. The PMT response to each photoelectron is simulated following the experimental input as a trapezoidal pulse.

1.5.2 FEE response

1. The output of the PMT is then passed by a HPF defined by the RC constant and an additional LPF filter used for shaping. The resulting signal shows the diferentiation introduced by the filter.

2. Finally the signal is decimated by the DAQ producing waveforms (in bins of 25 ns and in adc counts).

3. It follows that for MC data, the initial waveforms of the PMTs (in photoelectrons per 1 ns bin, called MCRD) is transformed in a signal (adc counts per 25 ns bins) which reflects the effect of the PMT and electronics (RWF).

1.6 Simulation of EneRgy PlanE (SIERPE)

```
In [10]: from SPE import *
         from FEE2 import *
```

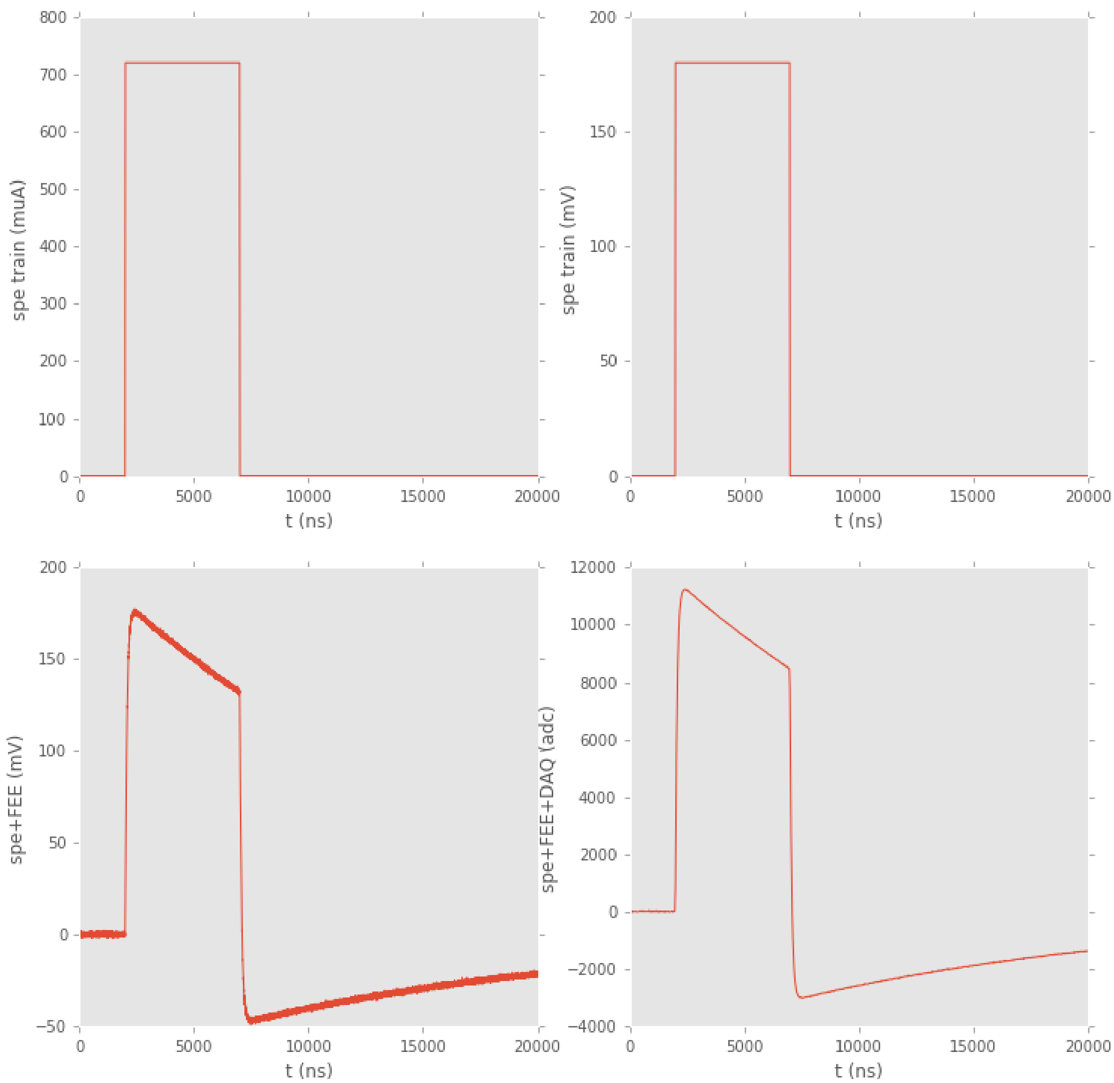
1.7 Example: simulate a square pulse

```
In [11]: def pulse_train(signal_start=2000*ns, signal_length=5000*ns, daq_window = 20*microsecond, nois
             signal_end = signal_start + signal_length
             spe = SP.SPE()
             fee = FEE()
             # PMT response to a photon train
             signal_t, signal_PE = spe.SpePulseTrain(signal_start,signal_end,daq_window)
             # spe in voltage (without FEE)
             signal_PE_v = fee.VSignal(signal_PE)
             #effect of FEE
             signal_fee = fee.FEESignal(signal_PE, noise_rms=noise)
             #effect of DAQ
             signal_t_daq, signal_daq = fee.DAQSignal(signal_t, signal_fee, noise_rms=0)
             signal_daq *=FP.time_DAQ #re-scale by decimation factor
             plt.figure(figsize=(12,12))

             ax1 = plt.subplot(2,2,1)
             ax1.set_xlim([0, len(signal_t)])
             SetPlotLabels(xlabel='t (ns)', ylabel='spe train (muA)')
             plt.plot(signal_t, signal_PE/muA)

             ax2 = plt.subplot(2,2,2)
             ax2.set_xlim([0, len(signal_t)])
```

```
            SetPlotLabels(xlabel='t (ns)', ylabel='spe train (mV)')
            plt.plot(signal_t, signal_PE_v/mV)

            ax3 = plt.subplot(2,2,3)
            ax3.set_xlim([0, len(signal_t)])
            SetPlotLabels(xlabel='t (ns)', ylabel='spe+FEE (mV)')
            plt.plot(signal_t, signal_fee/mV)

            ax4 = plt.subplot(2,2,4)
            ax4.set_xlim([0, len(signal_t)])
            SetPlotLabels(xlabel='t (ns)', ylabel='spe+FEE+DAQ (adc)')
            plt.plot(signal_t_daq, signal_daq)

            area = np.sum(signal_daq)
            print("adc counts per spe = {}".format(area))

            plt.show()
            return signal_t, signal_fee
```

```
In [12]: signal_t, signal_fee = pulse_train()
```

```
adc counts per spe = 877672.482144
```



1.8 Second step: perform DBLR

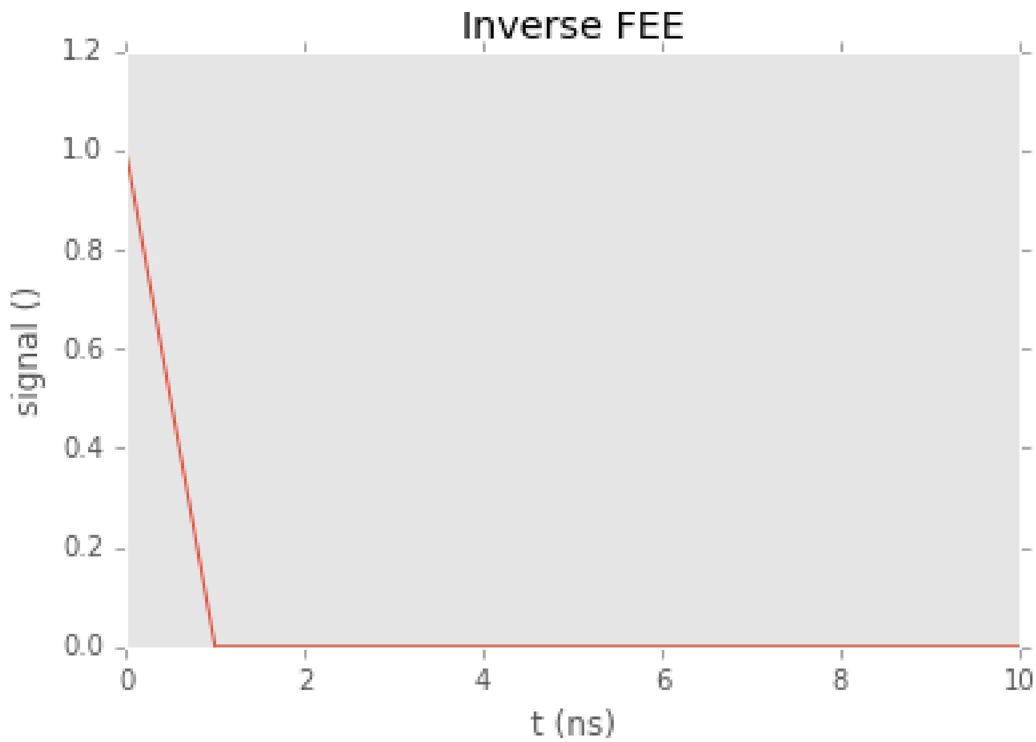
1. DBLR profits from the fact that the inverse of the HPF is a constant!

```
In [15]: fee = FEE()
         print fee
```

```
NEW FEE
                  PMT gain = 4.5e+06
                  decoupling capacitor =    6.75 nF
                  decoupling resistor = 2350.00 ohm
                  resitor gain =  250.00 ohm
                  HPF frequency =   1e+04 Hz  W_HPF =   2e-05
                  LPF frequency =   2e+06 Hz  W_LPF =   0.004
                  LPF frequency noise =   2e+05 Hz
```

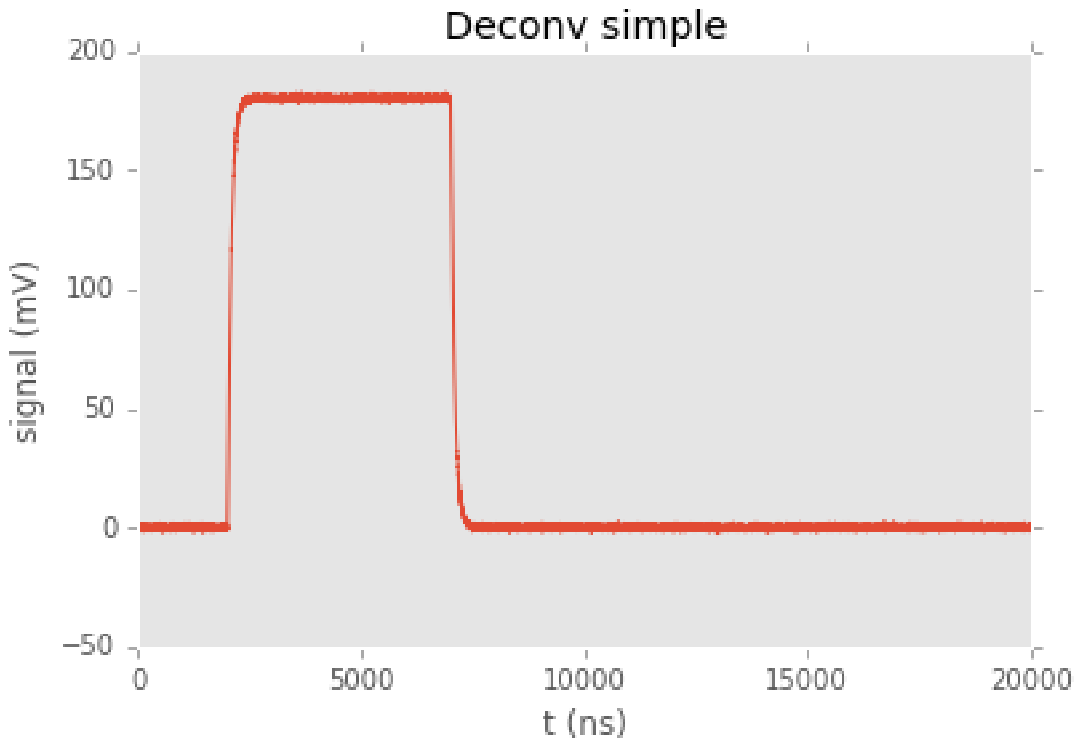
```
In [16]: signal_fee_inv = fee.InverseSignal(signal_t)
         plot_signal(signal_t/ns,signal_fee_inv,
```

```
            title = 'Inverse FEE',
            signal_start=0*ns, signal_end=10*ns,
            units='')
```




```
In [17]: def DeconvSimple(signal,signal_inv):
             """
             Deconvolution of the fine-grained fee signal (no DAQ)
             no noise
             using true start and end of signals
             """

             coef = signal_inv[100]

             print "coef = %7.4g"%coef

             acum = np.zeros(len(signal))

             acum[0]=coef*signal[0]
             for n in xrange(1,len(signal)):
                     acum[n] = acum[n-1] + signal[n]

             signal_r = signal + coef*acum

             return signal_r

In [18]: signal_r = DeconvSimple(signal_fee,signal_fee_inv)

coef = 6.304e-05
```

```
In [19]: plot_signal(signal_t/ns,signal_r/mV,
                                title = 'Deconv simple',
                                signal_start=0, signal_end=len(signal_t),
                                units='mV')
```



1.9 Deconvolution of physical signals

1. NEW/NEXT physical signals vary in length from few mus to some 100 mus. The effect of the HPF is different for each type of signal, but the deconvolution procedure is the same.
2. As an example we can examine Kripton signals

```
In [43]: ls '/Users/jjgomezcadenas/Documents/Development/NEXT/data/Waveforms/25ns/WF_Na_test_RWF.h5'
```

```
/Users/jjgomezcadenas/Documents/Development/NEXT/data/Waveforms/25ns/WF_Na_test_RWF.h5
```

```
In [45]: import matplotlib.pyplot as plt
         import pandas as pd
         import tables
         import numpy as np
```

```
In [46]: h5f =tables.open_file('/Users/jjgomezcadenas/Documents/Development/NEXT/data/Waveforms/25ns/WF_
```

```
In [47]: h5f
```

```
Out[47]: File(filename=/Users/jjgomezcadenas/Documents/Development/NEXT/data/Waveforms/25ns/WF_Na_test_R
         / (RootGroup) ''
         /BLR (Group) ''
```

```
/BLR/acum (EArray(10, 24000), shuffle, blosc(9)) ''
  atom := Float64Atom(shape=(), dflt=0.0)
  maindim := 0
  flavor := 'numpy'
  byteorder := 'little'
  chunkshape := (1, 8192)
/BLR/mau (EArray(10, 24000), shuffle, blosc(9)) ''
  atom := Float64Atom(shape=(), dflt=0.0)
  maindim := 0
  flavor := 'numpy'
  byteorder := 'little'
  chunkshape := (1, 8192)
/BLR/pulse_on (EArray(10, 24000), shuffle, blosc(9)) ''
  atom := Int32Atom(shape=(), dflt=0)
  maindim := 0
  flavor := 'numpy'
  byteorder := 'little'
  chunkshape := (1, 16384)
/BLR/wait_over (EArray(10, 24000), shuffle, blosc(9)) ''
  atom := Int32Atom(shape=(), dflt=0)
  maindim := 0
  flavor := 'numpy'
  byteorder := 'little'
  chunkshape := (1, 16384)
/Detector (Group) ''
/Detector/DetectorGeometry (Table(1,)) ''
  description := {
  "x_det": Float64Col(shape=(2,), dflt=0.0, pos=0),
  "y_det": Float64Col(shape=(2,), dflt=0.0, pos=1),
  "z_det": Float64Col(shape=(2,), dflt=0.0, pos=2),
  "r_det": Float64Col(shape=(), dflt=0.0, pos=3)}
  byteorder := 'little'
  chunkshape := (1170,)
/MC (Group) ''
/MC/FEE (Table(1,)) 'EP-FEE parameters'
  description := {
  "offset": Int16Col(shape=(), dflt=0, pos=0),
  "pmt_gain": Float32Col(shape=(), dflt=0.0, pos=1),
  "V_gain": Float32Col(shape=(), dflt=0.0, pos=2),
  "R": Float32Col(shape=(), dflt=0.0, pos=3),
  "C12": Float32Col(shape=(12,), dflt=0.0, pos=4),
  "CO12": Float32Col(shape=(12,), dflt=0.0, pos=5),
  "time_step": Float32Col(shape=(), dflt=0.0, pos=6),
  "time_daq": Float32Col(shape=(), dflt=0.0, pos=7),
  "freq_LPF": Float32Col(shape=(), dflt=0.0, pos=8),
  "freq_HPF": Float32Col(shape=(), dflt=0.0, pos=9),
  "LSB": Float32Col(shape=(), dflt=0.0, pos=10),
  "volts_to_adc": Float32Col(shape=(), dflt=0.0, pos=11),
  "noise_fee_rms": Float32Col(shape=(), dflt=0.0, pos=12),
  "noise_adc": Float32Col(shape=(), dflt=0.0, pos=13)}
  byteorder := 'little'
  chunkshape := (461,)
/MC/MCTracks (Table(26606,)) ''
  description := {
```

```
  "event_indx": Int32Col(shape=(), dflt=0, pos=0),
  "mctrk_indx": Int32Col(shape=(), dflt=0, pos=1),
  "particle_name": StringCol(itemsize=10, shape=(), dflt='', pos=2),
  "pdg_code": Int32Col(shape=(), dflt=0, pos=3),
  "initial_vertex": Float64Col(shape=(3,), dflt=0.0, pos=4),
  "final_vertex": Float64Col(shape=(3,), dflt=0.0, pos=5),
  "momentum": Float64Col(shape=(3,), dflt=0.0, pos=6),
  "energy": Float64Col(shape=(), dflt=0.0, pos=7),
  "nof_hits": Int32Col(shape=(), dflt=0, pos=8),
  "hit_indx": Int32Col(shape=(), dflt=0, pos=9),
  "hit_position": Float64Col(shape=(3,), dflt=0.0, pos=10),
  "hit_time": Float64Col(shape=(), dflt=0.0, pos=11),
  "hit_energy": Float64Col(shape=(), dflt=0.0, pos=12)}
  byteorder := 'little'
  chunkshape := (1,)
/RD (Group) ''
/RD/epmt (EArray(10, 12), shuffle, blosc(9)) ''
  atom := Int32Atom(shape=(), dflt=0)
  maindim := 0
  flavor := 'numpy'
  byteorder := 'little'
  chunkshape := (1365, 12)
/RD/esipm (EArray(10, 1792), shuffle, blosc(9)) ''
  atom := Int32Atom(shape=(), dflt=0)
  maindim := 0
  flavor := 'numpy'
  byteorder := 'little'
  chunkshape := (9, 1792)
/RD/pmtcwf (EArray(10, 12, 24000), shuffle, blosc(9)) ''
  atom := Float64Atom(shape=(), dflt=0.0)
  maindim := 0
  flavor := 'numpy'
  byteorder := 'little'
  chunkshape := (1, 1, 16384)
/RD/pmtrwf (EArray(10, 12, 24000), shuffle, blosc(9)) ''
  atom := Int32Atom(shape=(), dflt=0)
  maindim := 0
  flavor := 'numpy'
  byteorder := 'little'
  chunkshape := (1, 5, 24000)
/RD/pmttwf (EArray(10, 12, 24000), shuffle, blosc(9)) ''
  atom := Int32Atom(shape=(), dflt=0)
  maindim := 0
  flavor := 'numpy'
  byteorder := 'little'
  chunkshape := (1, 5, 24000)
/RD/sipmrwf (EArray(10, 1792, 600), shuffle, blosc(9)) ''
  atom := Int32Atom(shape=(), dflt=0)
  maindim := 0
  flavor := 'numpy'
  byteorder := 'little'
  chunkshape := (1, 218, 600)
/Sensors (Group) ''
/Sensors/DataPMT (Table(12,)) ''
```

```
  description := {
  "channel": Int32Col(shape=(), dflt=0, pos=0),
  "active": Int32Col(shape=(), dflt=0, pos=1),
  "position": Float64Col(shape=(3,), dflt=0.0, pos=2),
  "gain": Float64Col(shape=(), dflt=0.0, pos=3),
  "adc_to_pes": Float64Col(shape=(), dflt=0.0, pos=4)}
  byteorder := 'little'
  chunkshape := (1365,)
/Sensors/DataSiPM (Table(1792,)) ''
  description := {
  "channel": Int32Col(shape=(), dflt=0, pos=0),
  "active": Int32Col(shape=(), dflt=0, pos=1),
  "position": Float64Col(shape=(3,), dflt=0.0, pos=2),
  "gain": Float64Col(shape=(), dflt=0.0, pos=3),
  "adc_to_pes": Float64Col(shape=(), dflt=0.0, pos=4)}
  byteorder := 'little'
  chunkshape := (1365,)
```

1.9.1 True Waveform

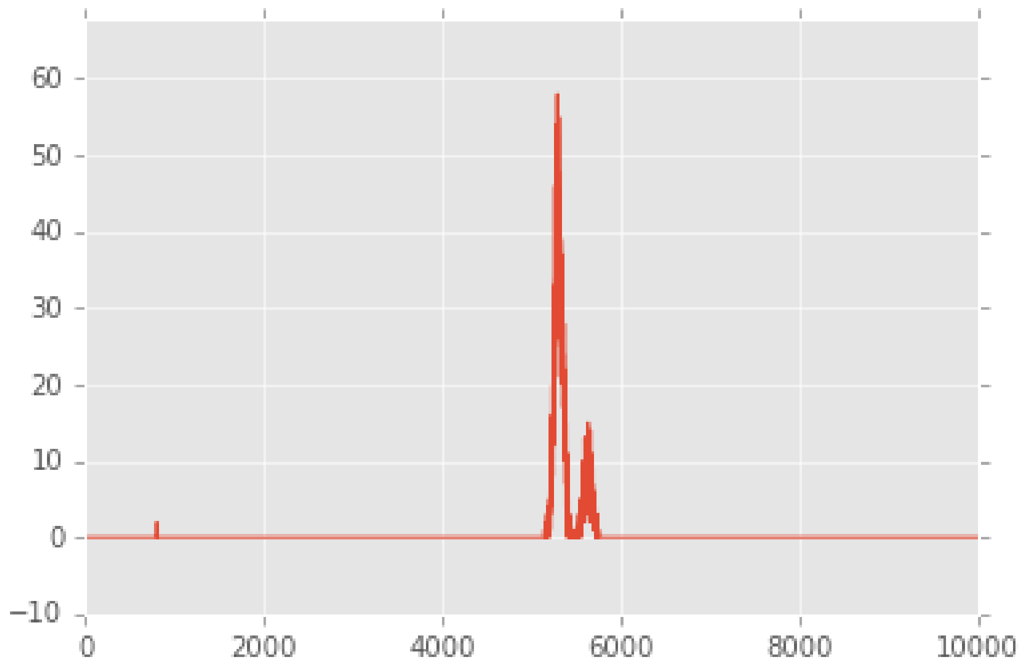
```
In [55]: pmttwf = h5f.root.RD.pmttwf
         pmt0 = pmttwf[0,0]
```

```
In [49]: pmttwf
```

```
Out[49]: /RD/pmttwf (EArray(10, 12, 24000), shuffle, blosc(9)) ''
           atom := Int32Atom(shape=(), dflt=0)
           maindim := 0
           flavor := 'numpy'
           byteorder := 'little'
           chunkshape := (1, 5, 24000)
```

```
In [50]: def plts(signal, signal_start=0, signal_end=1e+4, offset=5):

             ax1 = plt.subplot(1,1,1)
             ymin =np.amin(signal[signal_start:signal_end]) - offset
             ymax =np.amax(signal[signal_start:signal_end]) + offset
             ax1.set_xlim([signal_start, signal_end])
             ax1.set_ylim([ymin, ymax])
             plt.plot(signal)
```

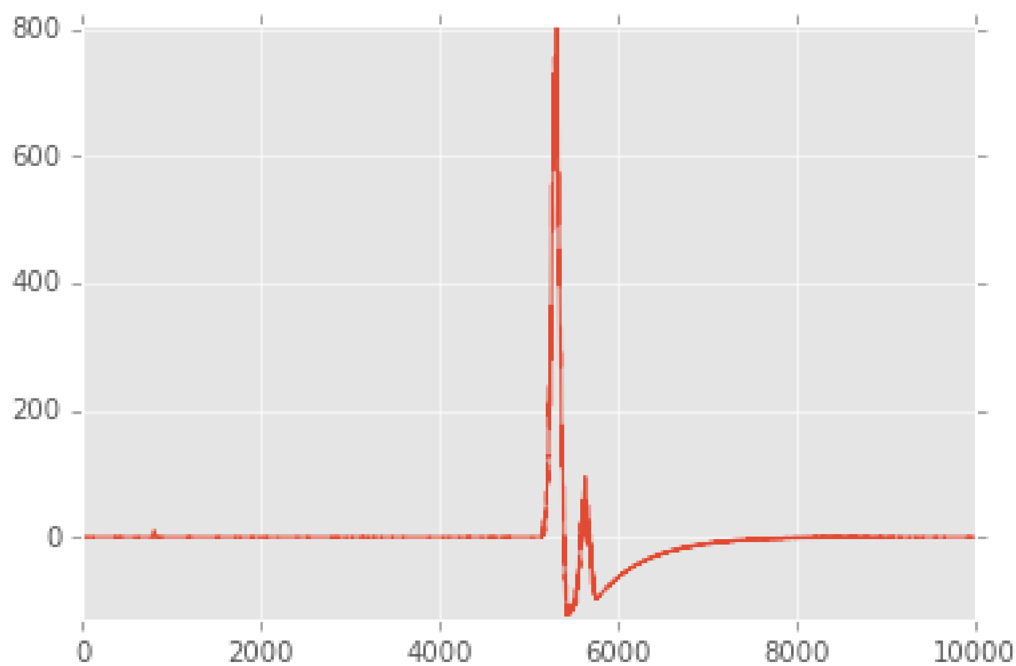
```
In [52]: plts(pmt0,0,10000,5)
```



1.9.2 Raw Waveform

```
In [56]: pmtrwf = h5f.root.RD.pmtrwf
         pmtr0 = pmtrwf[0,0]
```

```
In [57]: plts(pmtr0,0,10000,5)
```



1.10 DBLR algorithm

1. The DBLR algorithm for NEW/NEXT (credits: Super-Raul, Super-Vicente, JJ's old student) is quite sophisticated. The core of the algorithm is the simple accumulator described above, but considerable gimnastics is implemented to make sure that the signal is properly recovered.
2. The algorithm was initally written in MATLAB, then translated to python.

In [ ]:
```
def BLR(signal_daq, coef, mau_len=250, thr1 = 3*FP.NOISE_ADC, thr2 = 0,
        thr3 = FP.NOISE_ADC, log='INFO'):

    """
    Deconvolution offline of the DAQ signal using a MAU
    moving window-average filter of a vector data. See notebook
    y(n) = (1/WindowSize)(x(n) + x(n-1) + ... + x(n-windowSize))
    in a filter operation filter(b,a,x):
    b = (1/WindowSize)*ones(WindowSize) = (1/WS)*[1,1,1,...]: numerator
    a = 1 : denominator
    y = filter(b,a,x)
    y[0] = b[0]*x[0] = (1/WS) * x[0]
    y[1] = (1/WS) * (x[0] + x[1])
    y[WS-1] = mean(x[0:WS])
    y[WS] = mean(x[1:WS+1])
    and so on
    """

    lg = 'logging.'+log
    logger.setLevel(eval(lg))
    len_signal_daq = len(signal_daq)
    sblr = SBLR(len_signal_daq)

    signal_i = np.copy(signal_daq) #uses to update MAU while procesing signal
    nm = mau_len
    B_MAU = (1./nm)*np.ones(nm)

#   MAU averages the signal in the initial tranch
#    allows to compute the baseline of the signal

    sblr.MAU[0:nm] = SGN.lfilter(B_MAU,1, signal_daq[0:nm])
    sblr.acum[nm] =  sblr.MAU[nm]
    sblr.BASELINE = sblr.MAU[nm-1]

    logging.debug("""-->BLR:
                  MAU_LEN={}
                  thr1 = {}, thr2 = {}, thr3 = {} =""".format(
                  mau_len, thr1, thr2, thr3))
    logging.debug("n = {}, acum[n] = {} BASELINE ={}".format(nm, sblr.acum[nm],sblr.BASELINE))

#----------

# While MAU inits BLR is switched off, thus signal_r = signal_daq
```

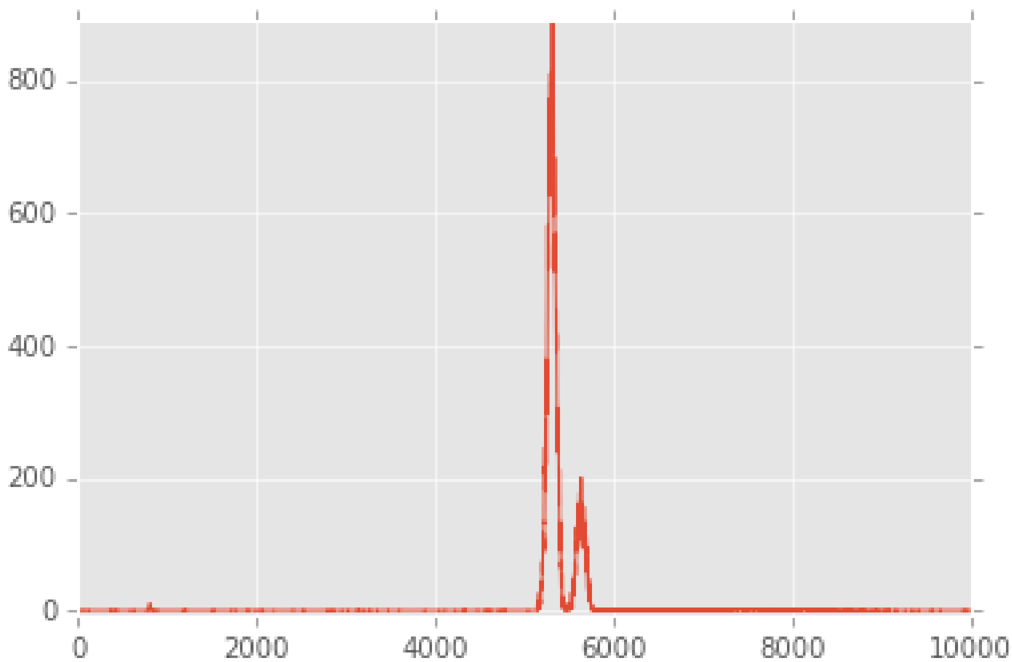
```python
sblr.signal_r[0:nm] = signal_daq[0:nm]
pulse_on=0
wait_over=0
offset = 0

# MAU has computed the offset using nm samples
# now loop until the end of DAQ window

logging.debug("nm = {}".format(nm))

for k in range(nm,len_signal_daq):

    trigger_line = sblr.MAU[k-1] + thr1
    sblr.pulse_on[k] = pulse_on
    sblr.wait_over[k] = wait_over
    sblr.offset[k] = offset

    # condition: raw signal raises above trigger line and
    # we are not in the tail
    # (wait_over == 0)
    if signal_daq[k] > trigger_line and wait_over == 0:

        # if the pulse just started pulse_on = 0.
        # In this case compute the offset as value
        #of the MAU before pulse starts (at k-1)

        if pulse_on == 0: # pulse just started
            #offset computed as the value of MAU before pulse starts
            offset = sblr.MAU[k-1]
            pulse_on = 1

        #Pulse is on: Freeze the MAU
        sblr.MAU[k] = sblr.MAU[k-1]
        signal_i[k] = sblr.MAU[k-1]  #signal_i follows the MAU

        #update recovered signal, correcting by offset
        sblr.acum[k] = sblr.acum[k-1] + signal_daq[k] - offset;
        sblr.signal_r[k] = signal_daq[k] + coef*sblr.acum[k]


    else:  #no signal or raw signal has dropped below threshold

    # but raw signal can be negative for a while and still contribute to the
    # reconstructed signal.

        if pulse_on == 1: #reconstructed signal still on
            # switch the pulse off only when recovered signal
            #drops below threshold
            #slide the MAU, still frozen.
            # keep recovering signal

            sblr.MAU[k] = sblr.MAU[k-1]
            signal_i[k] = sblr.MAU[k-1]
            sblr.acum[k] = sblr.acum[k-1] + signal_daq[k] - offset;
```

```
            sblr.signal_r[k] = signal_daq[k] + coef*sblr.acum[k]

            #if the recovered signal drops before trigger line
            #rec pulse is over!
            if sblr.signal_r[k] < trigger_line + thr2:
                wait_over = 1  #start tail compensation
                pulse_on = 0   #recovered pulse is over


        else:  #recovered signal has droped below trigger line
        #need to compensate the tail to avoid drifting due to erros in
        #baseline calculatoin

            if wait_over == 1: #compensating pulse
                # recovered signal and raw signal
                #must be equal within a threshold
                # otherwise keep compensating pluse

                if signal_daq[k-1] < sblr.signal_r[k-1] - thr3:
                    # raw signal still below recovered signal
                    # keep compensating pulse
                    # is the recovered signal near offset?
                    upper = offset + (thr3 + thr2)
                    lower = offset - (thr3 + thr2)

                    if sblr.signal_r[k-1] > lower and sblr.signal_r[k-1] < upper:
                        # we are near offset, activate MAU.

                        signal_i[k] = sblr.signal_r[k-1]
                        sblr.MAU[k] = np.sum(signal_i[k-nm:k])*1./nm

                    else:
                        # rec signal not near offset MAU frozen
                        sblr.MAU[k] = sblr.MAU[k-1]
                        signal_i[k] = sblr.MAU[k-1]

                    # keep adding recovered signal
                    sblr.acum[k] = sblr.acum[k-1] + signal_daq[k] - sblr.MAU[k]
                    sblr.signal_r[k] = signal_daq[k] + coef*sblr.acum[k]

                else:  # raw signal above recovered signal: we are done

                    wait_over = 0
                    sblr.acum[k] = sblr.MAU[k-1]
                    sblr.signal_r[k] = signal_daq[k]
                    signal_i[k] = sblr.signal_r[k]
                    sblr.MAU[k] = np.sum(signal_i[k-nm:k])*1./nm


            else: #signal still not found

                #update MAU and signals
                sblr.MAU[k] = np.sum(signal_i[k-nm:k]*1.)/nm
                sblr.acum[k] = sblr.MAU[k-1]
```

```
                    sblr.signal_r[k] = signal_daq[k]
                    signal_i[k] = sblr.signal_r[k]

    #energy = np.dot(pulse_f,(signal_r-BASELINE))

    #return  signal_r-BASELINE, energy
    return  sblr
```

1.10.1 Performance of BLR

In [60]:
```
pmtcwf = h5f.root.RD.pmtcwf
pmtc0 = pmtcwf[0,0]
plts(pmtc0,0,10000,5)
```



1.11 Summary

1. DBLR algorithm performs well, but parameters must be carefully tuned.
2. The effect on the energy resolution appears to be small, but needs to be fully quantified.
3. Conditions 1. and 2. imply that during initial operation of NEW, the deconvolution must be performed offline, not in the FPGA (in fact the FPGA will also perfrom deconvolution of 4 channels for trigger).
4. It also implies that Monte Carlo production must start from MCRD, then the effect of the FEE electronics simulated, then the deconvolution simulated, then the energy of the waveforms measured (with all corrections) and the effect on resolution assesed. This must be done for calibration samples as well as for signal and background samples.
5. The software to handle the full chaing (from MCRD to CWF) has been developed this summer. Its core is the scipy signal library (to implement the HPF and LPT filters). It is fully written in python.
6. Currently ART does not include neither the simulation of the FEE nor the deconvolution.

1.12 How to proceed?

1. For MC
2. For Data

1.12.1 For Monte Carlo

1. hdf5 module already operative in art chain (JMB).
2. It allows to write MCRD files using HDF5 and ZLIB compression (250 kB per event to be compared with 10 MB per event in the case of GATE DST).
3. HDF5 MCRD code is the input for the simulation of the FEE plane (SIERPE) which produces Raw Waveforms (RWF), writting a new HDF5 file. The DBLR algorithm then produces Corrected Waveforms (CWF).
4. A new module (to be written by JMB) can simply read the resulting file containing the CWF and pass them along to the next ART module.

1.12.2 For Data

1. Write RWF in hdf5 format (module already avaialble).
2. Pass DBLR algorithm and produce CWF.
3. Read back to art.