EE512 – Applied Biomedical Signal Processing

Lab session – Instantaneous Frequency

Experiment 1: the importance of pre-filtering for instantaneous frequency estimation

1.1. Bandpass filter design

```
>> [Nb,wn] = buttord([0.16 0.32], [0.12 0.36],0.5,20);
>> [b,a] = butter(Nb,wn);
```

A1.1. Figure 1 shows the amplitude response of the filter with the passband frequencies of 4Hz and 8Hz (the filter gain is unitary in the frequency range of [4-8] Hz and zero otherwise).

```
>> [h,w]=freqz(b,a,1000);
>> plot(Fs.*linspace(0,0.5,1000),abs(h))
%Fs = 50Hz (The analyzed signals are sampled at 50Hz)
```

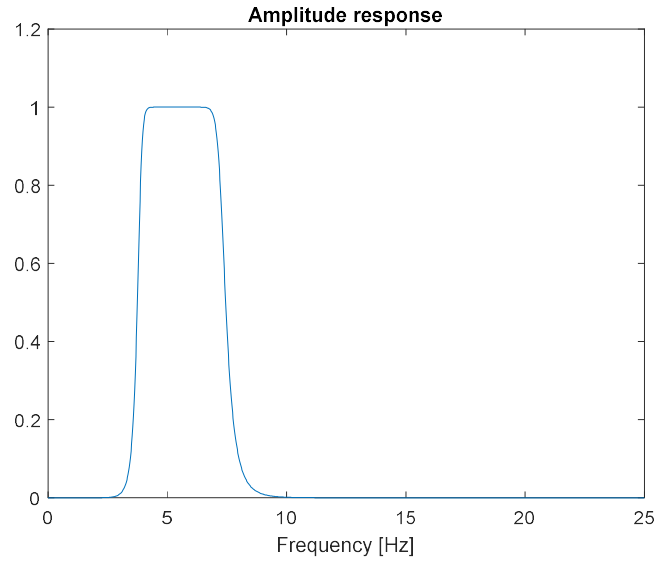

Figure 1. Bandpass filter.

The signals recorded from the ECG lead V3 and V4 are bandpass filtered:

```
>> V3_filt = filtfilt(b,a,V3);
>> V4_filt = filtfilt(b,a,V4);
```

Figure 2 shows the raw atrial ECG signals on lead V3 and V4, and the corresponding power spectral densities. The atrial ECG signals represent the original ECG after the cancellation of the ventricular activity. The cancellation process may lead to residual ventricular activity still present in the atrial signals. One notes the negative spikes in the signals, but also the spectral components at low frequencies (that cannot be attributed to the fibrillatory frequency during atrial fibrillation).

Looking at the filter output (Figure 3), one notes indeed that the amplitude modulation of the two atrial activities (lead V3 and V4) are quite similar, which would be difficult to assess on the raw signals.

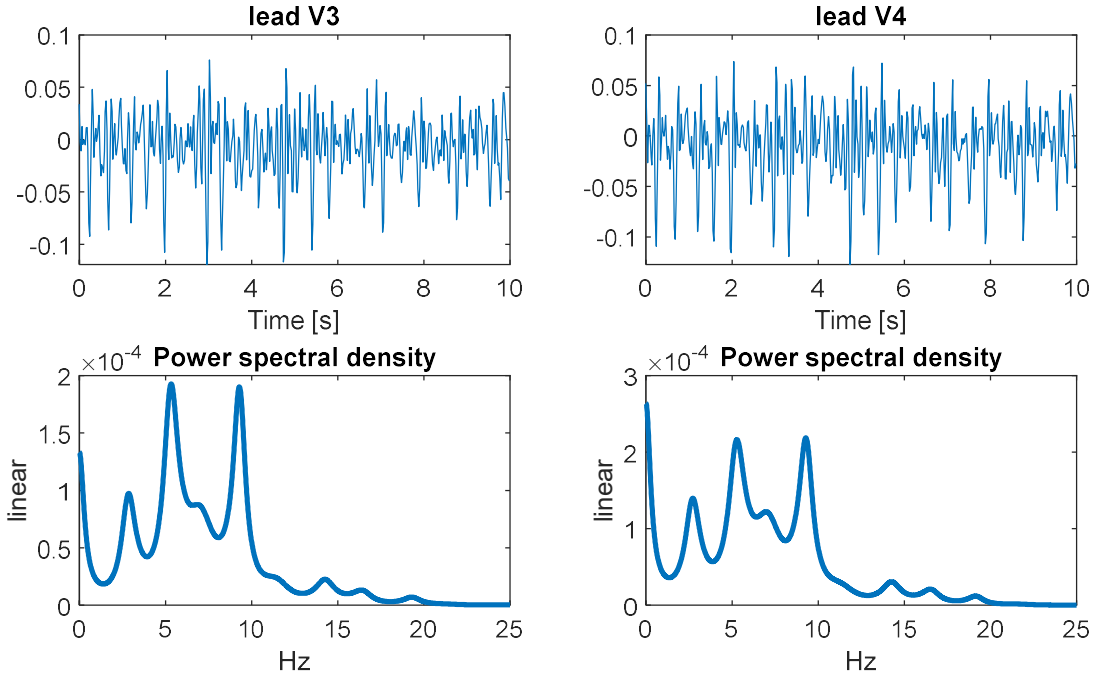

Figure 2. Lead V3 (left) and lead V4 (right) before bandpass filtering.

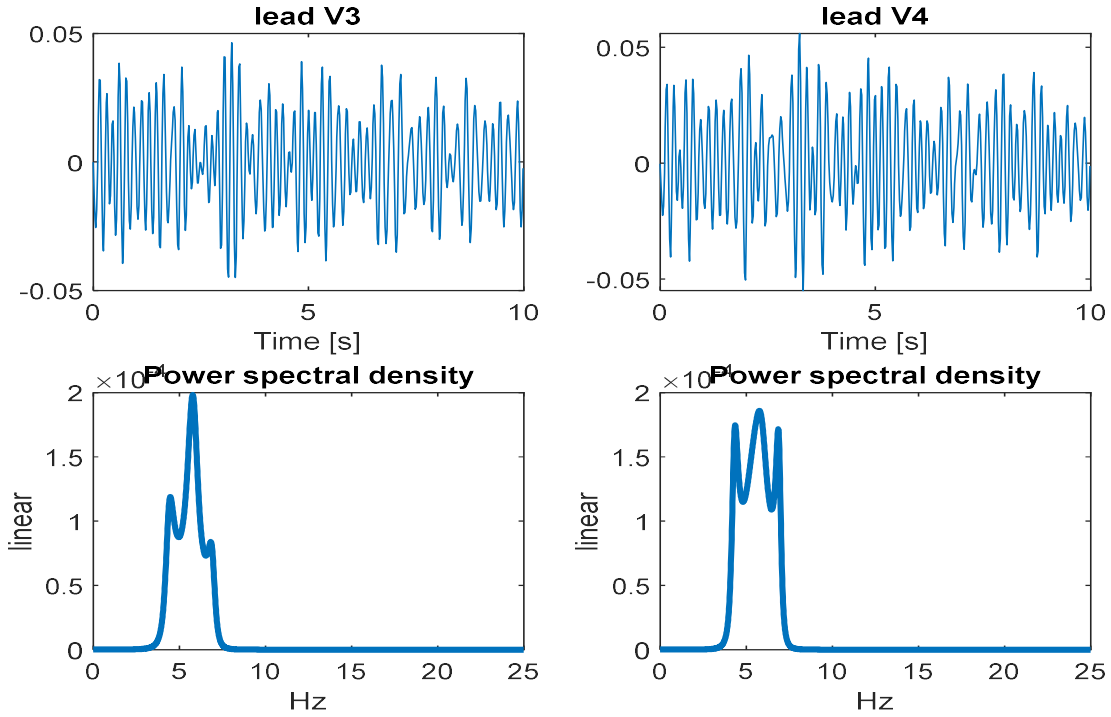

Figure 3. Lead V3 (left) and lead V4 (right) after bandpass filtering.

A1.2. The signals are sampled at 50Hz, thus the highest signal frequency is half the sampling frequency.

1.2. Estimating the instantaneous frequency (IF) on the raw V3 signal yields the estimates in Figure 4.

```
>> IF_Hilbert = IFhilbert(V3,50);
>> [IF_Teager, env] = teager(V3,50);
```

```
>> IF = STFT(V3,31,50);
>> [IF_Adapt_1,y] = AdaptBP(V3,5,0.85,0.9,50,0);
>> [IF_Adapt_2,y] = AdaptBP(V3,5,0.98,0.9,50,0);
```

A1.3. The IF estimates negative (Hilbert), too high (influence of harmonics) and the STFT estimate presents problems due to a large constant (zero frequency) component sometime present in the raw V3 signal. The adaptive IF estimate for β = 0.98 is smoother and lower than the IF estimates for β = 0.85. The parameter β controls for the bandwidth of the adaptive bandpass filter which makes that for narrow bandwidth (high β values) the frequency tracking is more accurate.

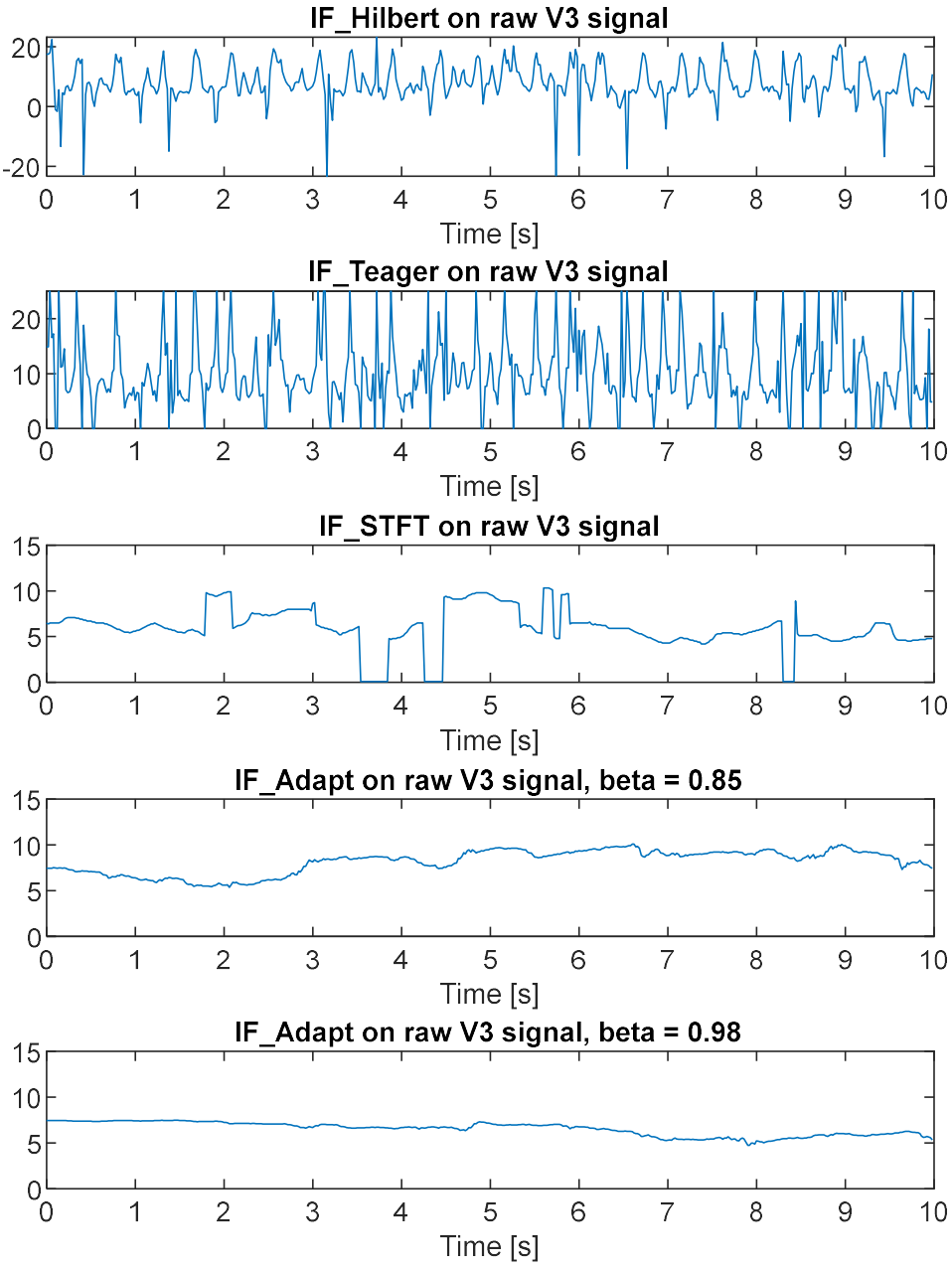

Figure 4. Instantaneous frequency estimated on the raw V3 signal

Estimation of the instantaneous frequency (IF) on the bandpass filtered signal:

```
>> IF_Hilbert_f = IFhilbert(V3_filt,50);
>> [IF_Teager_f,env] = teager(V3_filt,50);
>> IF_STFT_f = STFT(V3_filt,31,50);
>> [IF_Adapt_1f,y] = AdaptBP(V3_filt,5,0.85,0.9,50,0);
>> [IF_Adapt_2f,y] = AdaptBP(V3_filt,5,0.98,0.9,50,0);
```

Figure 5 shows the benefits of the bandpass filtering of the raw signal: the IF estimates are centered on the right frequency value and present less distortions. Note that, the underlying assumption for IF is that the signal is locally mono-component (or at least narrow-band). This is rarely the case in practice and thus some band-pass filtering should be performed.

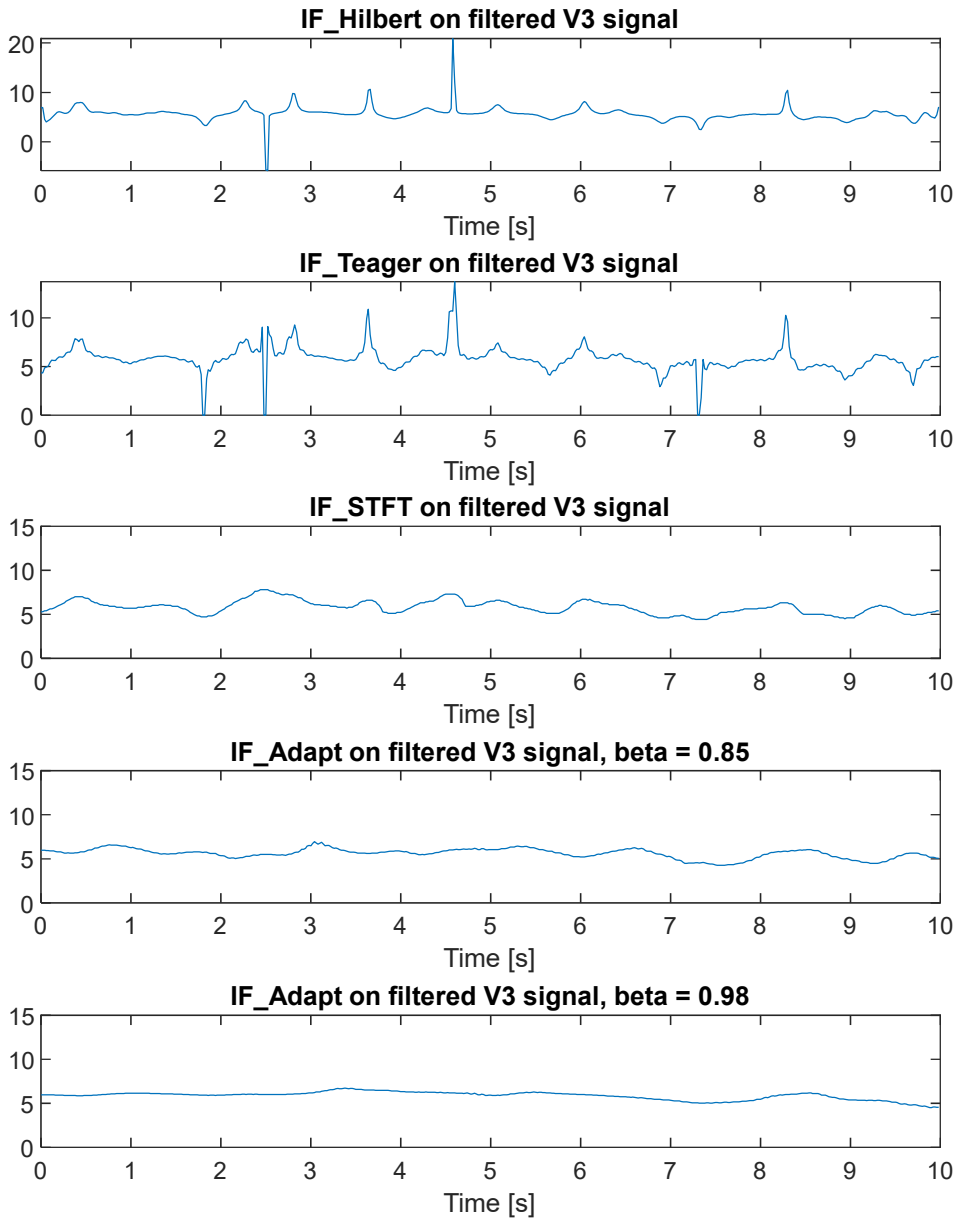

Figure 5. Instantaneous frequency estimated on the filtered V3 signal.

Experiment 2: indirect estimation of respiration frequency from respiration sinus arrhythmia (RSA) during a VO2-max test

2.1. Extract the respiration component present in the RR-intervals (!sampling frequency of 4Hz)

```
>> [Nb,Wn] = buttord(0.24/4,0.34/4,0.5,20) ;
>> [b,a] = butter(Nb,Wn, 'high') ;
>> Resp = filtfilt(b,a,RR);
```

A2.1. The extracted signal shows clear oscillatory components corresponding to the respiration.

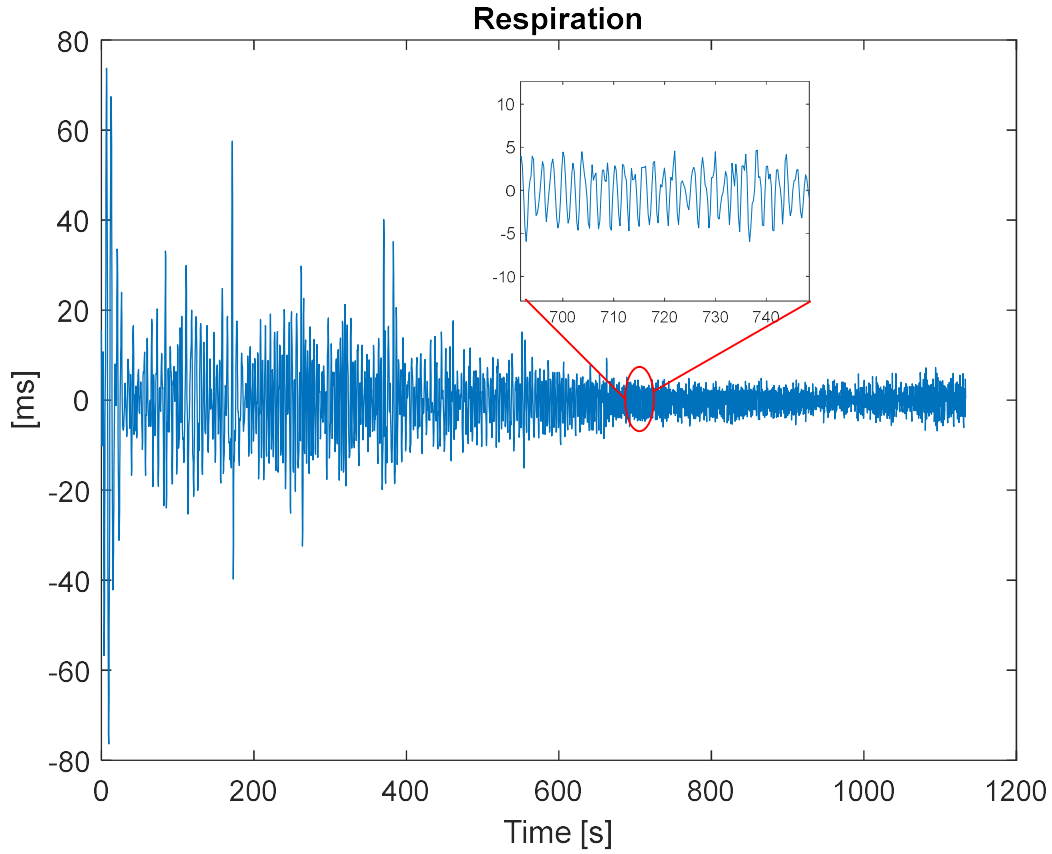

Figure 6. Respiration component extracted from the RR-intervals time-series

2.2 Instantaneous frequency (IF) estimation using the Hilbert transform (Figure 7), Teager transform (Figure 8), STFT (Figure 9) and the adaptive bandpass filter (Figure 10).

IF estimation using Hilbert transform:

```
>>IF = IFhilbert(Resp,4);
>>a=0.05;
>>IFf = filtfilt(a,[1 a-1],IF);
>>plot(tr,RF,t,IFf,'r','LineWidth',2)
```

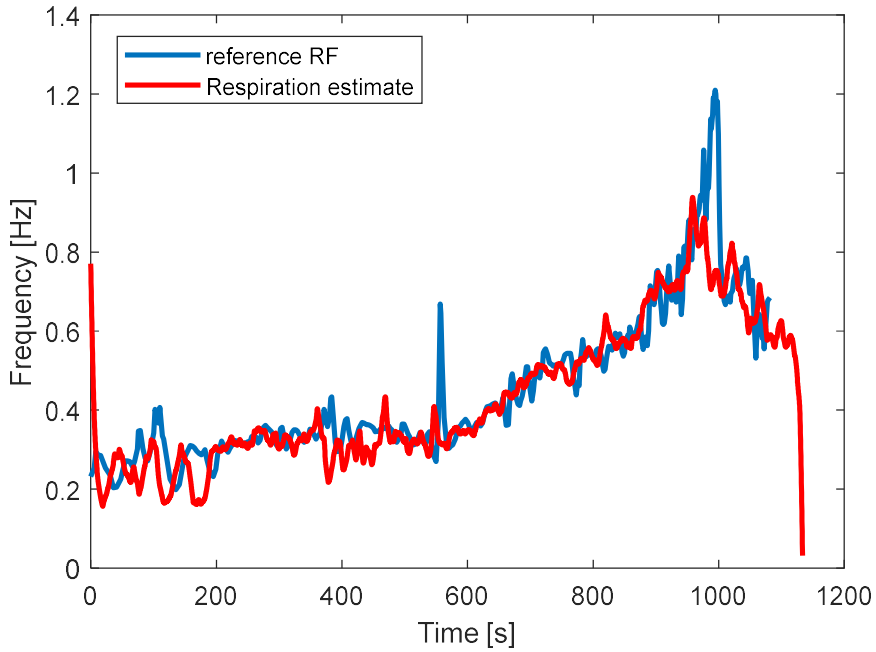

Figure 7. Instantaneous frequency estimation using the Hilbert transform.

IF estimation using Teager transform:

```
>>IF = teager(Resp,4);
>>a=0.05;
>>IFf = filtfilt(a,[1 a-1],IF);
>>plot(tr,RF,t,IFf,'r','LineWidth',2)
```

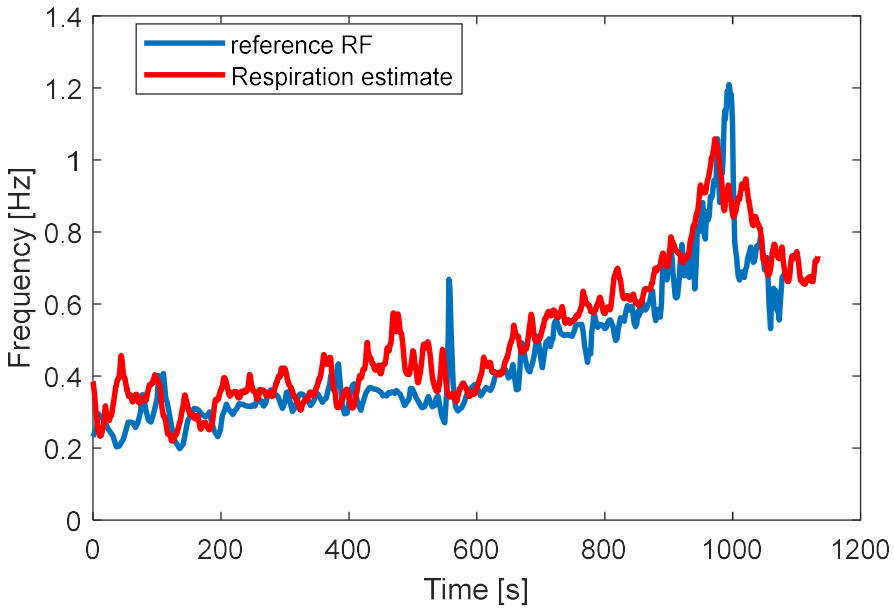

Figure 8. Instantaneous frequency estimation using the Teager transform.

IF estimation using Short-Term Fourier transform:

```
>>IF = STFT(Resp, 31, 4); %window length of 31 samples
>>a=0.05;
>>IFf = filtfilt(a,[1 a-1],IF);
>>plot(tr,RF,t,IFf,'r','LineWidth',2)
```

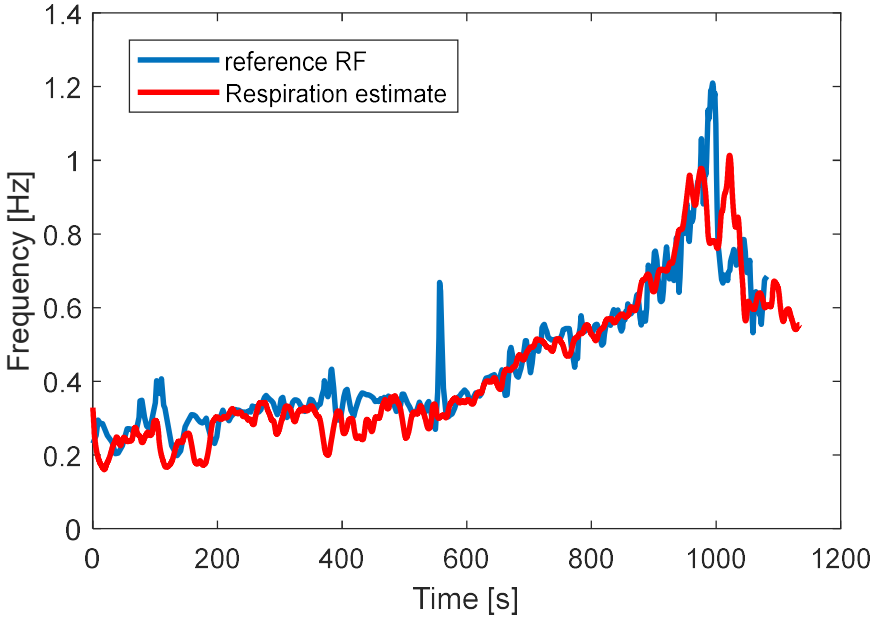

Figure 9. Instantaneous frequency estimation using STFT.

IF estimation using adaptive bandpass filter:

```
>>[IF, y] = AdaptBP(Resp,0.25,0.925,0.925,4,0);
>>plot(tr,RF,t,IF,'r','LineWidth',2)
```

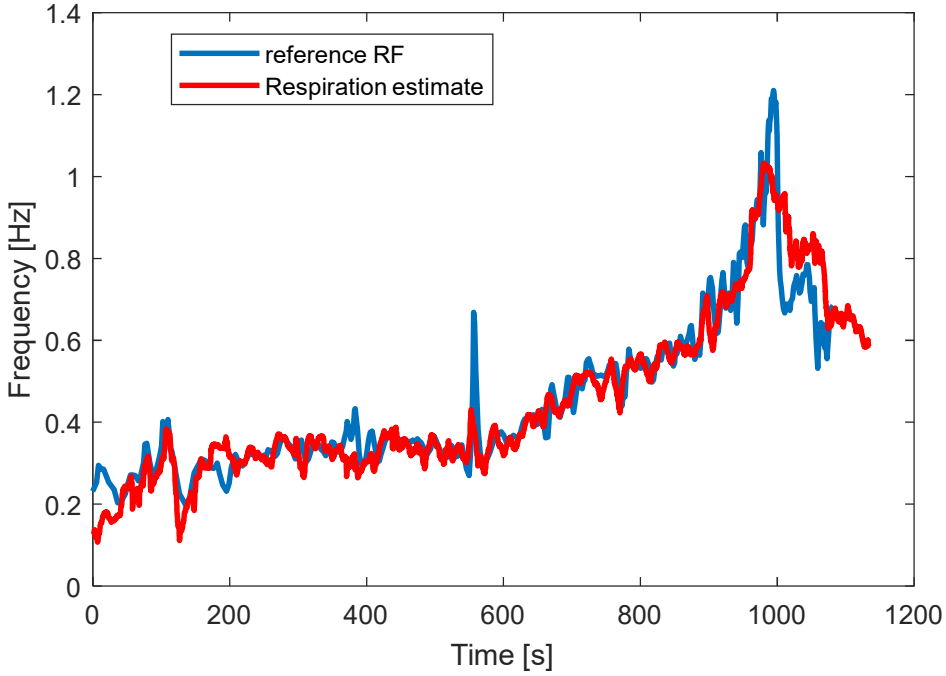

Figure 10. Instantaneous frequency estimation using adaptive bandpass filter

A2.2. The best estimate seems to be obtained with the adaptive bandpass filter (note that no lowpass filtering of the estimate is needed).

Experiment 3: extraction of a common oscillation and estimation of its instantaneous frequency using bandpass adaptive filtering

Remove the mean values and resample the signals at 1 Hz:

```
>> X=heart_3; %load the data
>> X=X-ones(length(X),1)*mean(X); %remove the mean value
>> X=resample(X,1,4); %resampling at 1Hz

>> RR = X(:,1);    %RR-intervals
>> BP = X(:,2);    %Blood pressure signal
>> Resp = X(:,3); %Respiration signal
```

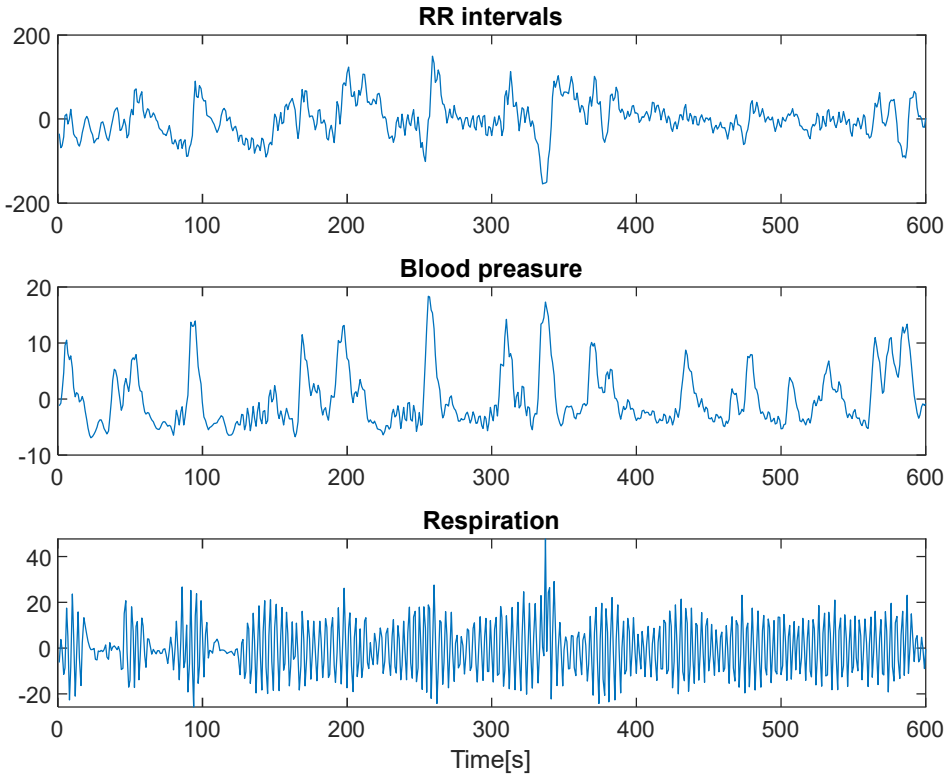

Figure 11. Cardiovascular recordings: RR intervals (upper), Blood pressure (middle) and Respiration (lower).

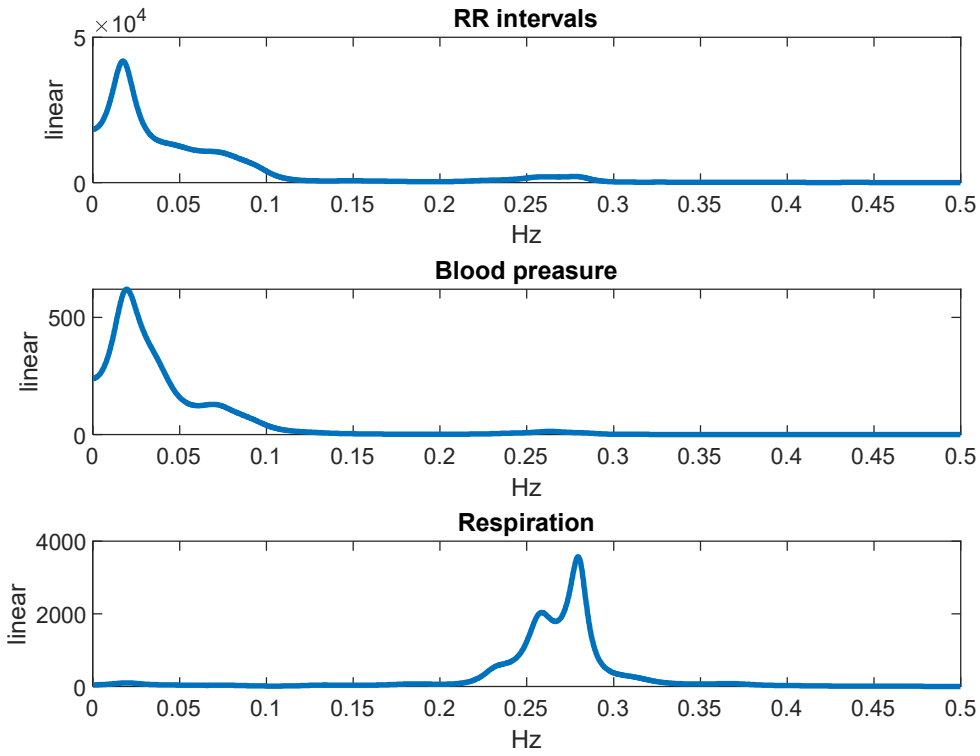

Figure 12. Power spectral density of the RR intervals (upper), Blood pressure (middle) and Respiration (lower).

A3.1. Power spectral density of the Blood pressure signal shows a frequency component around 0.07Hz (corresponding to the baroreflex effect). For the respiration signal, the main frequency component is around 0.25Hz. It makes senses to down-sample the signals from 4Hz to 1Hz to enhance these low frequency components.

3.1. Using adaptive bandpass filter, one extracts the common oscillation between RR intervals and respiration:

```
>> [IF,Y,weights] = AdaptBP_weight([RR Resp],0.2,0.9,0.95,0.95,1);
```

A3.2. Figure 13 shows the outputs of the common filter for these two signals. The common oscillation of the two signals is of course the respiration itself (the respiration modulates the RR signal, the so-called respiratory sinus arrhythmia). Apart from the transient, Figure 13 shows that there is a good correspondence between the amplitude of respiration component extracted from the RR -intervals (upper panel) and the amplitude of component extracted from the respiration signal (middle panel). The respiration frequency (lower panel) varies during the recording, which would make the use of a fixed bandpass filter to extract the respiration frequency inaccurate. One notes in Figure 12 (lower panel) that the power spectral density of the original respiration signals shows two main distinct frequency components (two distinct peaks).

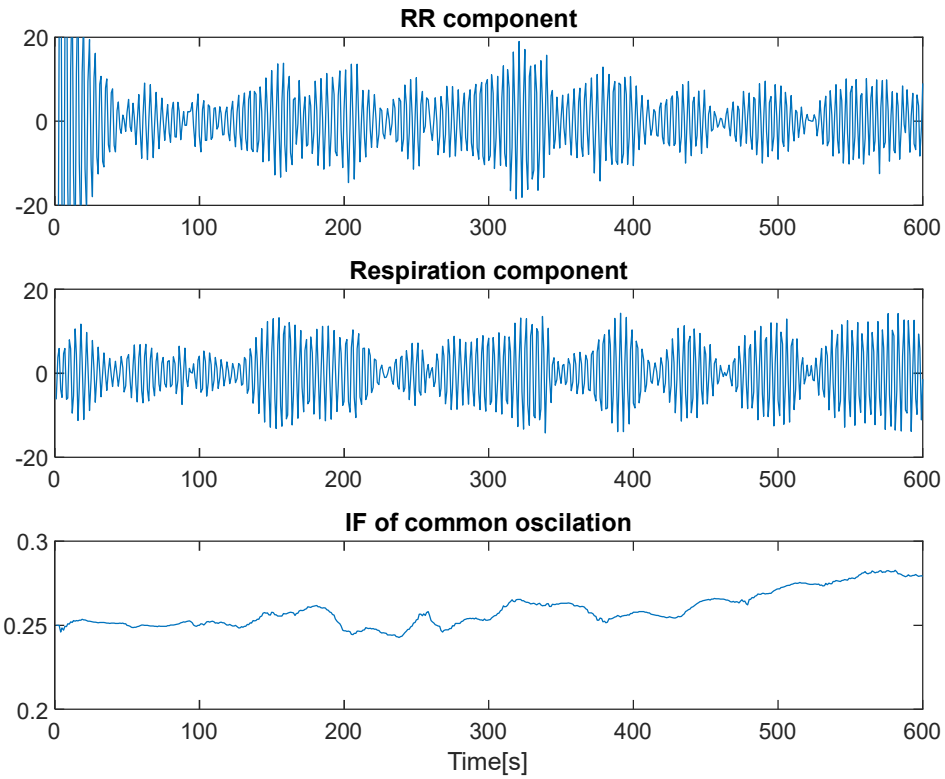

Figure 13. Respiration frequency component extracted in the RR -intervals (upper) and in the respiration signal (middle). The IF estimation of the common oscillation between the RR-intervals and the respiration is illustrated on the lower graph.

3.2. Using adaptive bandpass filter, one extracts the common oscillation between RR intervals and blood pressure:

```
>> [IF,Y,weights] = AdaptBP_weight([RR BP],0.06,0.9,0.95,0.95,1);
```

A3.3. The common oscillation with the largest amplitude is the baroreflex. Figure 14 shows the outputs of the common filter for the RR intervals (upper) and blood pressure signal (lower). There is some correlation between the amplitudes of the RR intervals and blood pressure components, especially in the large amplitude regions. The baroreflex frequency is assumed constant in most studies (being estimated through power spectral density estimation of the RR-intervals), but one clearly notes that the baroreflex is characterized by a time-varying frequency (the frequency of the baroreflex lies between 0.05 Hz and 0.09 Hz; Figure 14, lower panel).

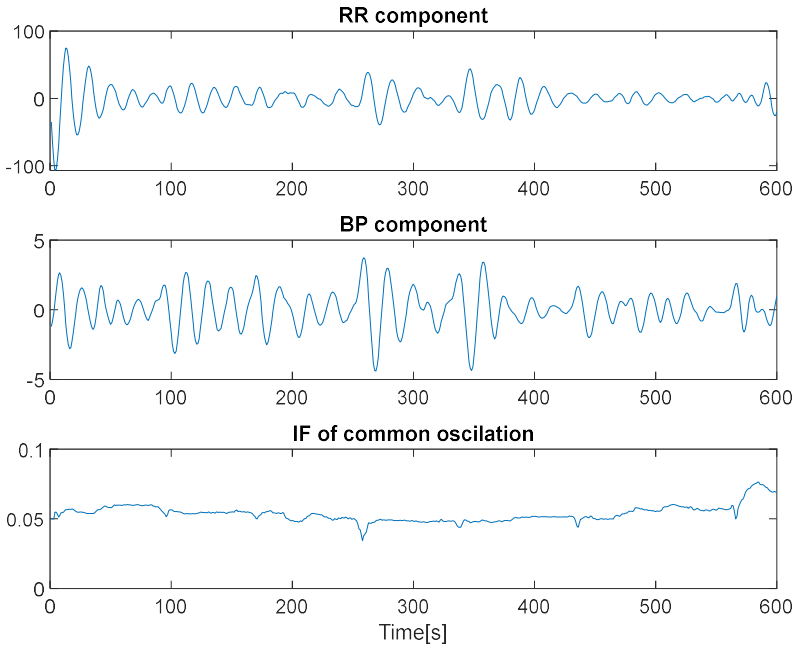

Figure 14. Baroreflex frequency component extracted in the RR-intervals (upper) and in the blood pressure signal (middle). The IF estimation of the common oscillation (baroreflex) between the RR-intervals and the blood pressure signal is illustrated in the lower graph.