Anexo A

Desarrollos matemáticos

Relación ventana de hamming con ventana rectangular

La ventana de Hamming de L muestras de duración se define como:

$$h(n) = 0{,}54 - 0{,}46\cos\left(2\pi\frac{n}{L-1}\right) \tag{A.1}$$

Para que ésta presente una resolución con longitud L equivalente a una ventana rectangular de longitud $2N$-1, éstas deben presentar igual área, de forma que:

$$\begin{aligned}
\sum_{n=-N+1}^{N+1} 1 &= \sum_{n=0}^{L-1} h(n) \\
2N-1 &= \sum_{n=0}^{L-1} 0{,}54 - 0{,}46\cos\left(2\pi\frac{n}{L-1}\right) = 0{,}54L - 0{,}46\sum_{n=0}^{L-1}\cos\left(2\pi\frac{n}{L-1}\right) \\
&= 0{,}54L - 0{,}46\sum_{n=0}^{L-1}\frac{1}{2}\left(e^{j2\pi\frac{n}{L-1}} + e^{j2\pi\frac{n}{L-1}}\right) = 0{,}54L - \frac{0{,}46}{2}\left(\sum_{n=0}^{L-1} e^{j2\pi\frac{n}{L-1}} - \sum_{n=0}^{L-1} e^{-j2\pi\frac{n}{L-1}}\right) \\
&= 0{,}54L - \frac{0{,}46}{2}\left(\frac{1-e^{j2\pi\frac{L}{L-1}}}{1-e^{j2\pi\frac{1}{L-1}}} - \frac{1-e^{-j2\pi\frac{L}{L-1}}}{1-e^{-j2\pi\frac{1}{L-1}}}\right) = 0{,}54L - 0{,}46\cos(\pi)\frac{\sin\left(\pi\frac{L}{L-1}\right)}{\sin\left(\pi\frac{1}{L-1}\right)} \\
&= 0{,}54L + 0{,}46\frac{\sin\left(\pi\frac{L}{L-1}\right)}{\sin\left(\pi\frac{1}{L-1}\right)} = 0{,}54L - 0{,}46
\end{aligned} \tag{A.2}$$

Relación ventana exponencial con ventana rectangular

La ventana exponencial con factor de amortiguamiento γ se define como:

$$h(n) = e^{-\gamma|n|} \tag{A.3}$$

Para que ésta presente una resolución con factor de amortiguamiento γ equivalente a una ventana rectangular de longitud $2N$-1, éstas deben presentar igual área, de forma que:

$$\begin{aligned}
\sum_{n=-N+1}^{N+1} 1 &= \sum_{n=-K+1}^{K-1} h(n) \\
2N-1 &= \sum_{n=-K+1}^{K-1} e^{-\gamma|n|} = \sum_{n=-K+1}^{-1} e^{\gamma n} + \sum_{n=0}^{K-1} e^{-\gamma n} = -1 + 2\sum_{n=0}^{K-1} e^{-\gamma|n|} \\
&= -1 + 2\frac{1-e^{-\gamma(K-1)}}{1-e^{-\gamma}} = \frac{1+e^{-\gamma}-2e^{-\gamma(K-1)}}{1-e^{-\gamma}}
\end{aligned} \tag{A.4}$$

Obteniendo su valor asintótico:

$$2N-1 = \lim_{K\to\infty} \frac{1+e^{-\gamma}-2e^{-\gamma(K-1)}}{1-e^{-\gamma}} = \frac{1+e^{-\gamma}}{1-e^{-\gamma}} \tag{A.5}$$

Tomando el desarrollo en serie de Taylor de una exponencial:

$$e^{-\gamma} = \sum_{n=0}^{\infty} \frac{(-\gamma)^n}{n!} \approx 1 - \gamma + O(\gamma^2) \tag{A.6}$$

y sustituyendo en (**??**) obtenemos una relación aproximada para ventanas de igual resolución:

$$2N-1 \approx \frac{2-\gamma}{\gamma} = 1 + \frac{2}{\gamma} \approx \frac{2}{\gamma} \tag{A.7}$$

Anexo B

Publicacion en congreso internacional

Respiratory Frequency Estimation From Heart Rate Variability Signals in Non-Stationary Conditions Based on the Wigner-Ville Distribution

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Abstract

Respiratory sinus arrhythmia is a modulation of heart rate synchronous with respiration, which allows the estimation of respiratory frequency from the high frequency (HF) component of heart rate variability (HRV). The extraction of the respiratory frequency from the maxima of the smoothed pseudo Wigner-Ville distribution (SPWVD) is challenging, since the time-frequency smoothing used to suppress the interference terms of the WVD introduces an estimation error which can be high both in mean and standard deviation. Additionally in non-stationary conditions the error can be augmented due to the non-linear trend of the instantaneous frequency (IF).

In this study the respiratory frequency is estimated from the HF band maxima of the SPWVD of the HRV signal. The algorithm adjusts the degree of frequency filtering (time-lag window length) to the time-frequency structure of the signal, in order to reduce the estimation error of the IFs. The optimal time-lag window length, at each time instant, depends on the instantaneous amplitude estimate of the signal components as well as on the noise present in the signal. The instantaneous amplitude is estimated independently of the time-frequency smoothing by deconvolving and correcting the instantaneous power estimates. The instantaneous power of the signal components is obtained by bounded integration of the SPWVD.

The method has been evaluated on simulated HRV signals with time-varying amplitudes and non-linear frequency trends, obtaining a mean amplitude error of $0.324 \pm 2.294\,\%$ and a mean frequency error of $0.239 \pm 2.041\,\%$ (-0.008 ± 6.026 mHz) for a SNR of 20 dB. A database containing the ECG and respiratory signals simultaneously recorded for 58 subjects during the listening of different musical stimuli has been analyzed. The method estimates the respiratory frequency with a median error of $-1.525 \pm 4.557\,\%$ (1.953 ± 4.883 mHz) during musical stimuli and of $-0.919 \pm 6.542\,\%$ (11.465 ± 43.477 mHz) during transitions between stimuli, which are highly non-stationary and non-linear.

Respiratory Frequency Estimation From Heart Rate Variability Signals in Non-Stationary Conditions Based on the Wigner-Ville Distribution

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Abstract

A method to estimate the respiratory frequency from the high frequency (HF) component of heart rate variability (HRV) by means of the smoothed pseudo Wigner–Ville distribution (SPWVD) is presented. The method is based on maximum peak detection of the SPWVD and includes an adaptive time-lag window length which reduces the mean squared error (MSE) of the estimation, specially when the instantaneous frequency trends are non-linear.

Evaluation of the proposed method is performed over simulated signals with time-varying amplitude, non–linear frequency, and SNR of 20dB, obtaining a mean frequency estimation error of -0.24±2.04% (0.01±6.03 mHz). The method has been tested on a database of ECG and respiration signals simultaneously recorded during the listening of different musical stimuli, obtaining a median respiratory frequency estimation error of -1.53±4.56% (1.95±4.88 mHz) during musical stimuli and of -0.92±6.54% (11.47±43.48 mHz) during transitions between stimuli, which are highly non-stationary and non-linear.

1. Introduction

Respiratory sinus arrhythmia (RSA) is a modulation of heart rate synchronous with respiration, which allows the estimation of respiratory frequency from the high frequency (HF) component of the heart rate variability (HRV) signal. In non–stationary conditions the respirator frequency can be estimated from maximum peak detection of the smoothed pseudo Wigner–Ville distribution (SPWVD) of the HRV signal in the HF band.

The extraction of the respiratory frequency from the maxima peak location of the SPWVD is challenging, since the time-frequency (TF) smoothing used to suppress the interference terms of the Wigner–Ville distribution introduces a frequency estimation error which can be high both in mean and standard deviation [1].

A method for the estimation of the IF of a frequency modulated (FM) signal based on the SPWVD is presented in [1], which uses an adaptive time-lag window length to resolve the bias–variance tradeoff that appears, specially when the IF varies non–linearly. For each time instant the optimal window length depends on the IF trend as well as on the signal amplitude and noise variance. The assumption of constant signal amplitude made in [1] is not suitable for the estimation of the respiratory frequency from the HRV signal in situations where the RSA amplitude varies in time, such as during stress testing, tilt testing or induced emotion experiments.

In this paper an extension of the method in [1] is presented for the estimation of the respiratory frequency from the HRV signal, which accounts for time-varying amplitudes and noise variance.

2. Methods and Materials

2.1. Instantaneous frequency estimation

Assuming that the discrete analytic version of the HF component of the HRV signal can be modeled as [2]:

$$z(n) = A_{\text{HF}}(n)e^{j\phi_{\text{HF}}(n)} + v(n) \tag{1}$$

where $A_{\text{HF}}(n)$ and $\phi_{\text{HF}}(n)$ are the instantaneous amplitude and phase of the HF component, and $v(n)$ complex additive white gaussian noise.

The IF is estimated from the maxima of the SPWVD at each time instant by:

$$\hat{F}_{\text{HF}}(n) = \frac{F_s}{4M} \arg\max_m \{W_z(n,m)\}, \tag{2}$$

where F_s is the sampling frequency of $z(n)$ and $W_z(n,m)$ represents the SPWVD calculated as [2]

$$W_z(n,m) = 2\sum_{k=-K+1}^{K-1} |h(k)|^2 \left[\sum_{p=-N+1}^{N-1} g(p) r_z(n+p,k)\right] e^{-j2\pi\frac{m}{M}k}$$
$$m = -M+1, ..., M \tag{3}$$

where n and m represent time and frequency indexes, respectively, $r_z(n,k) = z(n+k)z^*(n-k)$, and $g(n)$ and

$|h(k)|^2$ are the time and frequency smoothing windows with length $2N$-1 and $2K$-1, respectively.

The asymptotic formulae for the IF estimation error variance and bias for a frequency smoothing window length of $h_s = 2K$-1, $\sigma^2_{h_s}$ and θ_{h_s}, respectively, derived in [1], are extended in this paper for time-varying amplitudes and noise variance, giving

$$\sigma^2_{h_s}(n) = \frac{3\sigma_v^2(n)}{2\pi^2 A^2_{\text{HF}}(n)}\left[1+\frac{\sigma_v^2(n)}{2A^2_{\text{HF}}(n)}\right]\frac{T_s}{h_s^3} \tag{4}$$
$$\theta_{h_s} \leq \frac{1}{80}\sup_n\left\{\left|F^{(2)}_{\text{HF}}(n)\right|\right\}h_s^2,$$

where $\sigma_v^2(n)$ is the instantaneous noise variance, $T_s = \frac{1}{F_s}$, and $F^{(2)}_{\text{HF}}(n)$ represents the second derivative of $F_{\text{HF}}(n)$. From (4) it can be seen that increasing the frequency smoothing window length h_s increases the bias and decreases the variance. The idea is to find for each time instant n the optimal h_s which resolve the bias-variance tradeoff minimizing the mean squared error (MSE).

In [1] a suboptimal approach for the estimation of the optimal h_s which does not need information about the unknown derivatives of the IF is proposed. An increasing sequence of h_s, $h_1 < h_2 < \cdots < h_J$ is considered, and for each h_s the IF estimate $\hat{F}_{\text{HF},h_s}(n)$ as well as the variance $\sigma^2_{h_s}(n)$ are computed. Assuming that h_s is small enough so that $|\theta_{h_s}| < \kappa\sigma_{h_s}(n)$, the following confidence interval is defined

$$D_{h_s}(n) = \left\{\hat{F}_{\text{HF},h_s}(n) - 2\kappa\sigma_{h_s}(n), \hat{F}_{\text{HF},h_s}(n) + 2\kappa\sigma_{h_s}(n)\right\} \tag{5}$$

The largest h_s for which segments $D_{h_{s-1}}$ and D_{h_s} have a point in common is chosen as the optimal h_s, for which the bias and standard deviation are of the same order. The IF estimate is initialized with the estimate obtained for the shortest length h_1, and then corrected with the estimate obtained for the optimal length h_s. In this work a value of $\kappa = 2$ is used [1].

2.2. Instantaneous amplitude and noise estimation

In order to estimate $\sigma^2_{h_s}(n)$, the instantaneous amplitude $A_{\text{HF}}(n)$ and noise variance $\sigma_v^2(n)$ need to be estimated.

The method proposed in this paper to estimate $A_{\text{HF}}(n)$ from the SPWVD comprises three steps: i) integration of $W_z(n,m)$ over a suited band, ii) correction with a time-varying factor depending on the frequency smoothing window, iii) deconvolution of the time smoothing window.

Let us define $\hat{P}_{\text{SP}}(n)$ as the instantaneous power obtained by the integration of $W_z(n,m)$ over a band $[m_1,\ m_2]$, where m_1 is the discrete frequency index corresponding to the minimum frequency of $\hat{F}_{\text{HF}}(n) - \frac{\Delta f}{2}$, m_2 corresponds to the maximum frequency $\hat{F}_{\text{HF}}(n) + \frac{\Delta f}{2}$, and Δf is the frequency smoothing window bandwidth estimated from $H(m) = DFT_{2M}\left\{|h(k)|^2\right\}$ as the frequency distance between the first zero cross at each side of the its maximum peak.

From [3] it is derived that the instantaneous power of the HF component $P_{\text{HF}}(n)$ can be computed from the SPWVD attenuating the time and frequency smoothing effects as

$$\hat{P}_{\text{HF}}(n) = g^{-1}(n) * \left(\hat{P}_{\text{SP}}(n) f_c(n)\right), \tag{6}$$

where $f_c(n)$ is a correcting factor computed as

$$f_c(n) = \frac{\sum_{m=-M+1}^{M} H(m)}{\sum_{m=m_1}^{m_2} H(m - m_{\text{HF}}(n))} \tag{7}$$

being $m_{\text{HF}}(n)$ the discrete frequency index corresponding to $F_{\text{HF}}(n)$, and g^{-1} is the inverse function of $g(n)$, which can be computed in terms of the inverse Wiener filter [4]. Finally, the instantaneous amplitude is computed as $\hat{A}_{\text{HF}}(n) = \hat{P}^{\frac{1}{2}}_{\text{HF}}(n)$.

The noise present in the signal is estimated subtracting from $z(n)$ the estimated HF component with amplitude $\hat{A}_{\text{HF}}(n)$ and frequency $\hat{F}_{\text{HF}}(n)$, so that the estimated noise signal $\hat{v}(n)$ accounts also for the amplitude and frequency estimation errors. Finally, the instantaneous noise variance is computed as $\hat{\sigma}_v^2(n) = \hat{v}(n)\hat{v}^*(n)$.

2.3. Materials

2.4. Simulation study

In order to evaluate the method proposed in this paper a simulation study has been designed. The analytic version of HRV signals have been simulated according to

$$z(n) = A_{\text{LF}}(n)e^{j\phi_{\text{LF}}(n)} + A_{\text{HF}}(n)e^{j\phi_{\text{HF}}(n)} + v(n) \tag{8}$$

where $A_{\text{LF}}(n)$ and $\phi_{\text{LF}}(n)$ are the instantaneous amplitude and phase of the LF component. The frequency of the LF component is considered constant and equal to 0.1 Hz. The $A_{\text{HF}}(n)$ and $F_{\text{HF}}(n)$ vary as shown in Figure 1 and $A_{\text{LF}}(n)$ is defined to have a constant sympathovagal balance $B_{sv} = A^2_{\text{LF}}(n)/A^2_{\text{HF}}(n)$ of 0.5. Note the degree of variations of $A_{\text{HF}}(n)$ and $F_{\text{HF}}(n)$ and their non–linearity. The noise $v(n)$ is set to have a SNR of 20 dB at the instant of maximum instantaneous power. Since the model in (1) assumes monocomponent signals the simulated signals are filtered by a 9^{th} order Butterworth filter with bandpass [0.1–0.65]Hz.

2.4.1. Database

A database consisting in the simultaneous ECG and respiratory signals of 58 subjects submitted to different musical stimuli is analyzed [5]. The database is characterized by the non-stationarity of both respiration and HRV signals, as well as by non-linear IF variations specially in the

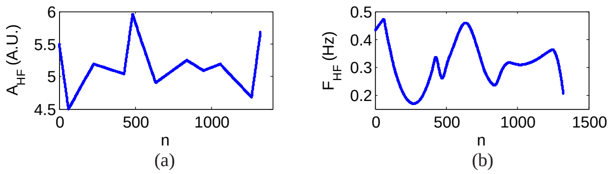

Figure 1. Simulated (a) A_{HF} and (b) F_{HF}.

transitions between different musical stimuli. The ECG and respiration signals are sampled at 1000 Hz.

The HRV signal is estimated from the ECG by an algorithm based on the integral pulse frequency modulation (IPFM) model, which accounts for the presence of ectopic beats [6]. The HRV signal is sampled to F_s=4 Hz and filtered, as in the simulation study, in the band [0.1, 0.65] Hz. Respiratory signals baseline wander is removed by means of a 3^{rd} order Butterworth filter with cut-off frequency 0.1 Hz and resampled at 4Hz. The IF estimation on the respiratory signal is used as the reference IF for the evaluation over real signals.

2.5. Evaluation

Evaluation over the simulated signals is done in terms of mean and standard deviation of the instantaneous frequency or amplitude estimation errors while over real signals it is done in terms of median and median absolute deviation (MAD) in order to minimize the effect of outlier estimates.

3. Results

3.1. Simulation study

A total of 100 realizations were generated. For the instantaneous amplitude estimation different types of windows for TF smoothing were considered. Results obtained with a Hamming window for time smoothing and an exponential window for frequency smoothing are shown in Table 1 in terms of normalized MSE for different lengths in terms of the equivalent resolution of a rectangular window.

Table 1. Squared root of the normalized MSE of $A_{HF}(n)$.

2N-1	h_s 15	31	49	63	63	127
21	3.313	3.390	3.360	3.325	3.248	3.131
51	2.383	2.317	2.332	2.360	2.423	2.535
71	2.660	2.659	2.717	2.639	2.799	2.899
101	3.375	3.348	3.365	3.390	3.460	3.593

Fig.2(a) presents the simulated amplitude $A_{HF}(n)$ (black), estimated from (6) (red), without the deconvolution (blue), estimated by simple integration over the classical HF band (magenta) and over a 0.25Hz band centered on $\hat{F}_{HF}(n)$. The method proposed in this paper estimates $A_{HF}(n)$ quite accurately, although oscilations can be appreciated due to discrete deconvolution and filter transients of the inverse function and to Gibbs phenomenon.

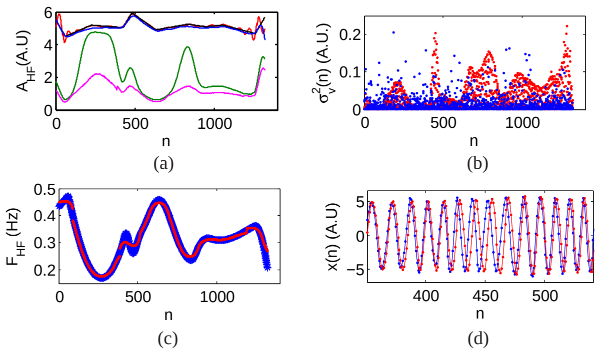

Figure 2. (a) Different $\hat{A}_{HF}(n)$ estimates, (b) $\hat{\sigma}_v(n)$, (c) $\hat{F}_{HF}(n)$ comparison and (d) HF component estimate.

Fig.2(b) shows simulated instant noise power (blue) and $\hat{\sigma}_v^2(n)$ (red), where it can be appreciated a central part with high estimation error due estimation errors in $A_{HF}(n)$ and $F_{HF}(n)$, which can be seen in Fig.2(c), that introduce a phase shift into the estimated HF component as it can be appreciated in Fig.2(d), which presents the estimated (red) and simulated (blue) HF component.

Frequency estimates were compared to those obtained with method in [1] based on constant amplitude estimation. Our method performs better in both types of segment, soft and sharp IF trends. Fig.3 shows a comparison between the simulated IF (blue), $\hat{F}_{HF}(n)$ by the method proposed in this paper (black) and $\hat{F}_{HF}(n)$ with the method in [1] (red).

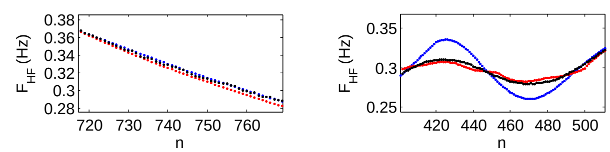

Figure 3. IF comparison on the two most significative type of segment on one simulated signal with a 51 sample Hamming window for time smoothing.

The IF estimates were also compared to those obtained with the frequency smoothing windows of constant length (see Table 2). It turns out that the adaptive algorithm does not always achieve the minimum MSE, as there is always a constant length providing lower MSE. The matter is that this optimal constant length varies depending on the type of segment and on the time smoothing window length.

3.2. Database

Results on the database support those obtained in the simulation study. Fig.4 shows the median error distribution

Table 2. Squared root of the normalized MSE of $\hat{F}_{\text{HF}}(n)$ for different time smoothing window length

Soft IF trend segments

$2N$-1	Adapt.	3	7	15	23	31	49	63	95	127
	h_s									
51	0.671	0.838	0.801	0.735	0.687	0.635	0.568	0.695	1.448	1.838
101	1.690	2.167	2.093	1.818	1.462	1.283	2.472	4.238	5.986	6.637

Sharp IF trend segments

$2N$-1	Adapt.	3	7	15	23	31	49	63	95	127
	h_s									
51	2.862	2.989	2.929	2.846	2.826	2.816	2.835	2.978	3.608	4.231
101	6.392	6.925	6.827	6.596	6.348	6.055	5.453	5.046	5.069	5.370

Whole signal

$2N$-1	Adapt.	3	7	15	23	31	49	63	95	127
	h_s									
51	2.055	2.172	2.120	2.055	2.033	2.018	2.021	2.138	2.725	3.233
101	4.623	5.076	4.995	4.784	4.553	4.325	4.201	4.650	5.557	6.051

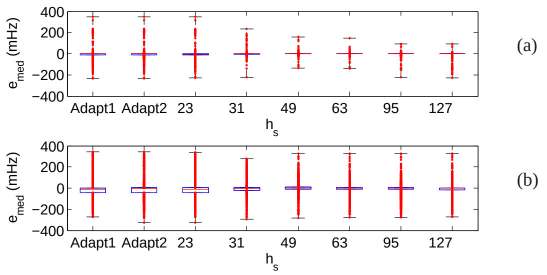

Figure 4. Median error distribution over each segment on real signals in (a) music stimuly and (b) transition between stimuly and $2N$-1 = 51

for each type of segment, where adapt1 refers to $\hat{F}_{\text{HF}}(n)$ with instantaneous amplitude estimates while adapt2 refers to method in [1]. Both methods perform in a similar way, and there always exists a constant frequency smoothing window length which provides an estimate with less median error, specially during the musical stimuli. The drawback again, is that the constant length is not the same for both type of segments. Shortest lengths used in the simulation study were discarded as they do not provide sufficient smoothing.

The adaptive algorithm proposed in this paper allows to estimate the respiratory frequency from the HF component of HRV with a median error of -1.53$\pm$4.56% (1.95$\pm$4.88 mHz) during musical stimuli and of -0.92$\pm$6.54% (11.47$\pm$43.48 mHz) during transitions between stimuli.

4. Discussion and conclusions

In this paper a method for the estimation of the respiratory frequency from the HF component of HRV signal in non–stationary conditions has been presented. The method is based on maximum peak detection of the SPWVD and includes adaptive frequency smoothing window length to reduce the MSE of the estimation, specially when the IF variations are non-linear making the bias high. It is based on the method proposed in [1] but includes instantaneous amplitude and noise variance estimates, reducing the MSE of the frequency estimation errors, specially for large or non–linear variations of the IF.

Evaluation over simulated signals with time-varying amplitude, non–linear frequency, and SNR of 20dB, yielded a mean frequency estimation error of -0.24$\pm$2.04% (0.01$\pm$6.03 mHz). Over the database the method obtained a median respiratory frequency estimation error of-1.53$\pm$4.56% (1.95$\pm$4.88 mHz) during musical stimuli and of -0.92$\pm$6.54% (11.47$\pm$43.48 mHz) between stimuli.

One of the problems associated to the instantaneous amplitude estimation presented in this paper is the appearance of oscillations due to the deconvolution process. In practice, the deconvolution can be skipped since it has been shown that is the proper definition of the integration band as well as the correction of the influence of the frequency smoothing make estimates based on integration of the SP-WVD be closer to real values.

In the simulation study the IF estimation algorithm presented in this paper showed a slightly better performance than that in [1] even though the simulated signals used in this paper presented sharper IF trends. However, results on the database showed no significant difference between them. On the other hand [1] shows that the adaptive algorithm improves the IF estimation from the ones obtained when using a fixed window length for frequency smoothing. In this paper we have demonstrated that there always exists a fixed length which performs better, but it depends on the IF trend and the time smoothing window length.

Acknowledgements

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