Scattered light noise characterisation at the Virgo interferometer with tvf-EMD adaptive algorithm

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Abstract

A methodology of adaptive time series analysis, based on Empirical Mode Decomposition (EMD), and on its time varying version tvf-EMD has been applied to strain data from the gravitational wave interferometer (IFO) Virgo in order to characterise scattered light noise affecting the sensitivity of the IFO in the detection frequency band. Data taken both during hardware injections, when a part of the IFO is put in oscillation for detector characterisation purposes, and during periods of science mode, when the IFO is fully locked and data are used for the detection of gravitational waves, were analysed. The adaptive nature of the EMD and tvf-EMD algorithms allows them to deal with nonlinear non-stationary data and hence they are particularly suited to characterise scattered light noise which is an intrinsically non-linear and non-stationary noise. Obtained results show that tvf-EMD algorithm allows to obtain more precise results compared to the EMD algorithm, yielding higher cross-correlation values with the auxiliary channels that are the culprits of scattered light noise.
1 Introduction

Virgo is an interferometer (IFO) located near Cascina, Pisa (Italy) and together with the laser interferometer gravitational-wave observatory (LIGO), which is comprised of two more IFO located respectively in Hanford and Livingston (United States), it forms a network of three detectors which goal is to detect gravitational waves generated by events such as the inspiral and merging of two black holes [1, 2, 3]. A schematic of the Virgo IFO in its advanced configuration can be seen in Figure 1, where the injection benches (IB), the west end bench (SWEB) and north end bench (SNEB) are visible. In this paper, a methodology of adaptive time series analysis, based on the one described in [4], is tested on the Virgo strain data in order to characterise sources of scattered light noise, which is a noise that can affect the sensitivity of the Virgo IFO in the gravitational wave detection frequency band, ranging from approximately 10 Hz to a few kHz [5]. Adaptive methodologies are widely used in many fields of science, for example in seismology [6, 7, 8], in speech pattern classification [9, 10, 11] and also in radionuclide time series analysis [12, 13, 14, 15, 16, 17, 18]. As described in [4], besides known features in the sensitivity curve, such as peaks due to mechanical resonances or main power harmonics, non-stationary noise can affect the sensitivity of gravitational wave interferometers, scattered light noise being an example. Scattered light noise is a phase noise due to interactions between the instrument and the environment and it consists of light exiting the main laser beam, being scattered by moving objects, and then recombining with the main beam [19, 20]. After reflecting once from the scattering surface, the scattered light phase angle is given by [4, 19]

$$\phi_{\text{scattering}}(t) = \frac{2\pi}{\lambda} (x_0 + \delta x_{\text{surface}}(t))$$

(1)

where $x_0$ is the static optical path measured with respect to some reference system and $\delta x_{\text{surface}}(t)$ is the displacement of the moving surface along the main direction of the beam, also referred to as $z$, while $\lambda = 1.064 \mu m$ is the Virgo laser wavelength. As described in [19], the noise introduced by scattered light can be written as

$$h_{sc}(t) \propto \sin(\phi_{\text{scattering}}(t))$$

(2)

Distinctive features of scattered light noise are arch-shaped figures appearing in the spectrograms in the detection frequency band, also referred to as fringes. The fringes frequency can be computed from Equation 1 taking the time derivative [4, 19]

$$f_{\text{fringe}}(t) = \frac{1}{2\pi} \phi'_{\text{scattering}}(t) = \frac{2}{\lambda} |v_{\text{surface}}(t)|$$

(3)
where $v_{\text{surface}}$ is the velocity at which the scatterer is moving and the prime symbol stands for time derivative. Equation 3 is also referred to as predictor, since it gives an insight on the features of scattered light noise appearing in spectrograms of the differential arm motion (DARM) or also of the power recycling cavity length (PRCL) degree of freedom. If the light is scattered $N$ times before recombining with the main beam, the fringes will appear at higher frequency, given by

$$f_{\text{fringe}N}(t) = N f_{\text{fringe}}(t)$$

The methodology adopted in this paper follows the approach described in [4], where the instantaneous amplitude of modes extracted by the adaptive algorithm Empirical Mode Decomposition (EMD) is cross-correlated with predictors computed from many auxiliary channels. Results obtained from EMD [21, 22, 23] and from its recently developed time varying version, tvf-EMD [24], are compared in this paper. It is found that the tvf-EMD algorithm gives higher values of cross-correlation in all tested cases. The paper is organised as follows: In Section 2 the adopted methodology is briefly described; in Section 3 the results of the analysis are presented and discussed while conclusions are reported in Section 4.

2 Methodology

Time series of strain data from the Virgo detector have been analysed in order to identify possible sources of scattered light noise. This has been done making use of adaptive methodologies, such as EMD and tvf-EMD, which are hereafter described.

2.1 Empirical Mode Decomposition

EMD is an adaptive algorithm first introduced by Huang [21, 22, 23] that allows to deal with nonlinear and non-stationary time series and to extract oscillatory modes, referred to as Intrinsic Mode Functions (IMFs), embedded in the data. To be an IMF, such oscillatory functions must respect the following two conditions:

- The number of extrema and zero crossings must be equal or differ at most by one.
- The mean of the upper and lower envelope must be zero.
Figure 1: Schematics of the Virgo IFO in its advanced configuration, showing the injection bench (IB), the west end bench (SWEB) and the north end bench (SNEB). Figure adapted from [25].

The procedure to obtain IMFs is the following: Upper and lower extrema contained in the data are fitted with cubic splines and the mean of the upper and lower envelopes is subtracted from the time series data. This procedure is iterated until the two aforementioned conditions are met. This process is referred to as *sifting*. Having obtained the first IMF, it is subtracted from the data and the process is repeated on the remainder of the time series until a slowly varying function $T(t)$ is obtained, which represents either the trend, if present, or the baseline wandering of the data. This way, a given time series $X(t)$, can be represented by the following expansion (21)

$$X(t) = \sum_{j=1}^{K} c_j(t) + T(t)$$

where $c_j$ is the $j$th IMF, and $t = 1 \ldots L$, with $L$ being the length of the time series, and $K$ is the number of IMFs that have been extracted by the EMD algorithm. IMFs are mono-component or narrow band oscillatory modes and Hilbert spectral analysis provides physically meaningful estimation of their Instantaneous Amplitude (IA) and Frequency (IF) [26, 27, 28, 29]. The IF
and IA of a signal $x(t)$ are defined in terms of its analytic signal

$$z(t) = x(t) + iHT[x(t)] = a(t)e^{i\phi(t)}$$

where $HT[\cdot]$ is the Hilbert transform of $x(t)$ and is defined by

$$HT[x(t)] = y(t) = \frac{1}{\pi} PV \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau,$$

where PV stands for principal value integral. The Hilbert transform is the convolution product of $x(t)$ and $1/\pi t$. IA and IF are obtained by means of the following expressions

$$a(t) = \sqrt{x(t)^2 + y(t)^2}; \quad f_i = \frac{1}{2\pi} \phi'(t)$$

The combination of EMD and HSA is referred to as Hilbert-Huang spectral analysis (HHSA) and it provides a time frequency ($t$-$f$) representation of the data, known as Hilbert-Huang Transform (HHT), which has higher resolution compared to Fourier based methods. EMD is a fully data-driven technique, making no a priori assumption on the basis functions for the expansion \[30\]. It is also complete, i.e. the sum of the IMFs and the trend term equals the input data, as can be seen from Equation 5.

### 2.2 Time varying filter EMD

A known drawback of EMD application to a noisy dataset is mode mixing, namely an IMF containing oscillations of widely different scales or different IMFs having very similar ones \[21\]. To deal with mode mixing and intermittency related problems and to improve its frequency resolution, a recent modification of the EMD algorithm was introduced, the time-varying filter EMD (tvf-EMD) \[24\]. The concept of IMF is replaced by the one of local narrow-band oscillatory modes. To extract local narrow-band signals, B-splines \[31\] are employed as a filter with time-varying frequency cut off and the sifting process is stopped based on a parameter, the bandwidth threshold ratio $\xi$, which is proportional to the Loughlin instantaneous bandwidth (IB) \[26, 32\]. For a two-component signal, the Loughlin IB is given by

$$IB_{Loughlin}(t) = \sqrt{\frac{a_1^2(t) + a_2^2(t)}{a_1^2(t) + a_2^2(t)}} + \frac{a_1^2(t)a_2^2(t)(\phi'_1(t) - \phi'_2(t))^2}{(a_1^2(t) + a_2^2(t))^2}$$

in term of instantaneous amplitude and frequency. The main steps of the sifting procedure, based on the tvf-EMD algorithm, can be found in \[24\],
Algorithm 3. In the remaining of this paper the term IMFs refers both to the modes extracted by EMD and to the narrow band signals extracted by the tvf-EMD algorithm. An application of the EMD and tvf-EMD algorithms to Virgo seismometer data can be found in [33].

2.3 Adopted methodology

The adopted methodology is based on [4]. Data from the DARM and PRCL degrees of freedom of the IFO, both during period of hardware injections, i.e. when one part of the detector is put in oscillation for detector characterisation purposes, and during science mode, i.e. when the IFO is fully locked and the data so acquired are suitable for the search of gravitational waves, were analysed with EMD and tvf-EMD. Results were correlated with predictors computed for many auxiliary channels, making use of Equation 3. The data of auxiliary channels used for the analysis have been selected from the Virgo Interferometer Channel database, where the channels having units of $\mu m$ or $\mu rad$ and having sampling frequencies of $f_{sampl} = 500 \text{ Hz}$, $f_{sampl} = 200 \text{ Hz}$ and $f_{sampl} = 100 \text{ Hz}$ have been chosen. The steps of the adopted methodology are the following:

- Before starting the analysis, data were downsampled to $f_{sampl} = 100 \text{ Hz}$;
- A lowpass filter with either $f_{cutoff} = 30 \text{ Hz}$, $f_{cutoff} = 15 \text{ Hz}$ or $f_{cutoff} = 10 \text{ Hz}$ was applied to either DARM or PRCL time series;
- DARM or PRCL data were decomposed both with EMD and tvf-EMD, obtaining a set of IMFs;
- These IMFs were normalised to zero mean and unit variance;
- The IAs of the IMFs were obtained from the magnitude of their analytic signal;
- Predictors were computed taking the time derivative of the data monitoring $x_{surface}(t)$, i.e. the position of the potential scattering surface, with respect to a given reference system. Since a comparison in between predictors and the IFs of the obtained modes was not carried out, only the case $N = 1$ scattering has been considered.
- Predictors data were smoothed using a moving average, employing windows of 50 samples;
Figure 2: Hardware injections. Lines were injected on the superattenuator of the injection bench (Sa IB) (top left panel), on the suspended North end bench (SNEB) (top right and bottom left panels), and on the West end bench (SWEB) (bottom right panel). Sampling frequency is $f_s = 500$ Hz.

- The IA of DARM or PRCL IMFs was cross-correlated with the predictors from various auxiliary channels. The most correlated channel is considered to be the culprit of scattered light.

The relevant parameters of tvf-EMD used during the analysis are the bandwidth threshold ratio $\xi = 0.1$, the B-spline order $n = 26$, and the maximum number of IMFs to be extracted $K = \log_2 L$, rounded upward, where $L$ is the data length. From a visual inspection of the Hilbert-Huang Transform of the data it has been established that in most cases the first IMF was the one responsible for scattered light noise in the lowpass filtered data. Therefore the first IMF has been chosen to compute cross-correlation with the predictors, unless stated otherwise.

### 3 Results and discussion

In this Section, results of the analysis are summarised. Data sampled during Hardware Injections (HI), during periods in which the detector was in science mode affected by a known source of scattered light, and during a period in which the cause of scattered light affecting PRCL degree of freedom was
unknown were analysed. Results are presented in Section 3.1 and Section 3.2, where a comparison between the most correlated predictor and the IA of the relevant IMF of DARM and PRCL is shown. For a clearer visual comparison, the IAs have been also smoothed using a moving average with a span of 50 points.

3.1 Test of the algorithm during Hardware Injections

The algorithm was initially tested during a period of controlled hardware injections (HI), where lines of known amplitude and frequency are injected in the IFO for detector characterisation purposes. Hence, during HI’s it is known what part of the detector is causing scattered light. Four HI’s were considered and lines were injected on:

- The superattenuator (Sa) of the injection bench, auxiliary channel: Sa IB F0 X. Injection time 22 August 2019 h 12:12:00+180s (UTC).
- The suspended North end bench (SNEB), auxiliary channel: SNEB LC Z. Injection time 3 October 2019 h 19:55:00+180s (UTC).
- The suspended North end bench (SNEB), auxiliary channel: SNEB LC Z. Injection time 3 October 2019 h 20:04:00+120s (UTC).
- The suspended West end bench (SWEB), auxiliary channel: SWEB LC Z. Injection time 3 October 2019 h 20:26:30+120s (UTC).

The Sa is the chain of seismic filters that isolate the Virgo’s relevant mirrors such as the test masses, and the term suspended bench refers to the isolation system which isolates the Virgo optical benches from the seismic noise. The description of such HI’s can be found in entry #47091 (https://logbook.virgo-gw.eu/virgo/?r=47091) and #46744 (https://logbook.virgo-gw.eu/virgo/?r=46744) of the Virgo logbook. In Figure 2 the four different HI’s having amplitude up to 20 $\mu$m and frequency of $f_{HI} = 0.1$ Hz are reported. The top left panel shows the HI on the first seismic filter of the superattenuator of the injection bench (Sa IB F0), the top right and the bottom left panels show the HI on the suspended North end bench (SNEB), while the bottom right panel shows the HI on the suspended West end bench (SWEB). In Figure 3 the results obtained applying the adopted methodology to strain data sampled during the HI’s are reported. In blue is the IA of DARM’s first IMF (only results obtained with tvf-EMD are shown, due to the fact that tvf-EMD gave higher values of correlation in all cases analysed, see Table 1) obtained after the normalisation of the IMF to zero mean and unit variance. In red is the predictor for the most correlated...
channel as obtained by Equation 3. In all four cases the algorithm is able to flag the right culprit (the channel of the HI) among all the 395 analysed channels, as can be seen in Figure 3. Table 1, top panel, lists the Pearson cross-correlation coefficients, $\rho_{tvf-EMD}$ and $\rho_{EMD}$, obtained when decomposing DARM or PRCL data with tvf-EMD and with EMD, respectively. It can be seen that tvf-EMD algorithm yields higher cross-correlation values.

### 3.2 Scattered light noise during science mode

In this Section, the results obtained from data sampled with the detector in science mode are reported. The data are affected by scattered light noise that is known to be due mainly to the suspended West end bench (SWEB). The following periods were analysed:

- 15/11/2019 h 14:00:00 + 60s (UTC)
- 26/11/2019 h 22:00:00 + 120s (UTC)
- 27/11/2019 h 04:01:00 + 120s (UTC)
- 09/10/2019 h 22:09:40 + 64s (UTC)
Figure 3: Results obtained during controlled hardware injections. The culprit is correctly traced to be the superattenuator of the injection bench (Sa IB), the suspended North end bench (SNEB), and the West end bench (SWEB), respectively. Data have been downsampled to $f_s = 100 \text{ Hz}$. For clarity the plots are zoomed in regions of interest

- 02/12/2019 h 18:00:00 + 64s (UTC)
- 04/12/2019 h 06:00:00 + 64s (UTC)
- 12/12/2019 h 02:09:30 + 64s (UTC)

Figure 4 shows the results of the analysis. The IA, of IMFs normalised to zero mean and unit variance, is shown in blue. IMFs were obtained decomposing DARM or PRCL time series with tvf-EMD. The predictor for the most correlated channel, i.e. the culprit of scattered light, is instead shown in red and is obtained by Equation 3. The culprit is correctly found to be a channel related to SWEB, located at the end of the West arm of the IFO, namely "SBE SWEB diff bench MIR z". This channel is obtained from the subtraction between the linear variable differential transformer (LVDT) of
the bench local controls and the optical lever of the West end test mass. For
the case of 09/10/2019, scattered light noise was found, in the PRCL degree
of freedom, to be due to the external injection bench (EIB), channel "SBE
EIB LVDT X 200 Hz". For the case of 02/12/2019 the sum of the IA’s of
the second and third IMFs has been employed to obtain the correlation value
of the tvf-EMD case, since they both showed the highest correlation with
the same predictor. For the case of 04/12/2019 and 12/12/2019 instead, the
highest value of correlation was obtained summing the IAs of the first and
second IMF. Results for the analysed periods are reported in Table 1 bottom
panel. It should be noted that due to the fact that the cause of scattered
light is known, and due to the high coherence with the relevant photodiode,
the contribution of scattered light from SWEB could be removed during the
procedure of online noise subtraction and did not affect the sensitivity.
Figure 4: Results obtained during periods of high scattered light noise mainly due to the suspended Westend bench (SWEB). The culprit is correctly traced back to channels related to the SWEB hosted in the Virgo West End Building. In one case the culprit was found to be due to the external injection bench (EIB). For clarity the plots are zoomed in regions of interest.
Figure 5: Top: Omegagram of PRCL time series. The predictor for the most correlated auxiliary channel ("SBE EIB LVDT X 200 Hz") is represented in red. Middle and bottom: same as before but for channel "SBE SWEB diff bench MIR z". The predictors match well the arch shaped fringes appearing in the omegagrams. It should be noted that the scale is different among PRCL and DARM data.
In Table 1, bottom panel, the cross-correlation coefficients obtained for the data taken during science mode are listed. It can be seen that in all cases decomposition performed with tvf-EMD yields better results, i.e. higher cross-correlations. To validate the obtained results the Omega algorithm was also employed [34]. Figure 5 shows a comparison between a $t$-$f$ representation obtained with the Omega algorithm, also referred to as Omegagram, and the predictor for the most correlated channel, which is "SBE EIB LVDT X 200 Hz" for the top panel and "SBE SWEB diff bench MIR z" for the other cases.

4 Conclusions

In this paper, data from the Virgo IFO have been analysed and characterised using adaptive algorithms. Different periods affected by scattered light noise were considered: periods of controlled HIs, periods of science mode but where the origin of the noise was known and its effect was subtracted offline from the gravitational wave strain signal, and finally a period of scattered light of unknown origin affecting the PRCL degree of freedom of the IFO. Strain data were decomposed both with EMD and tvf-EMD and the IAs obtained from the IMFs were cross-correlated with predictors computed from many auxiliary channels. After low-passing, the first IMF was found to be the one relevant for scattered light noise in most cases. The most correlated channel is considered to be the culprit of scattered light. Adaptive algorithms were suitable for this analysis since they allow characterisation of data which are both nonlinear and non-stationary, as is the case for scattered light noise. Adaptive algorithms do not make any a priori assumption about the expansion basis, which is instead obtained from the data and is given in term of amplitude and frequency modulated IMFs. The recently developed tvf-EMD is an extension of EMD, improving its frequency resolution while mitigating end effects, mode mixing, and intermittency. tvf-EMD yielded higher values of correlation for all the analysed cases compared to standard EMD. Future developments of the adopted methodology should involve testing of the algorithm during more periods in which the auxiliary channel that is generating scattered light is not known as the ultimate goal of this approach is to allow a fast identification of the culprit of scattered light noise among the many auxiliary channels the methodology is tested on. Future developments regard the automation of the adopted methodology to identify, on a daily basis, segments of data affected by scattered light.
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