A noise reduction method for force measurements in water entry experiments based on the Ensemble Empirical Mode Decomposition

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Abstract

In this paper a denoising strategy based on the EEMD (Ensemble Empirical Mode Decomposition) is used to reduce the background noise in non-stationary signals, which represent the forces measured in scaled model testing of the emergency water landing of aircraft, generally referred to as ditching. Ditching tests are performed at a constant horizontal speed of 12 m/s with a controlled vertical motion, resulting in a vertical velocity at the beginning of the impact of 0.45 m/s. The measured data are affected by a large amplitude broadband noise, which has both mechanical and electronic origin. Noise sources cannot be easily avoided or removed, since they are associated with the vibrations of the structure of the towing carriage and to the interaction between the measurement chain and the electromagnetic fields. The EEMD noise reduction method is based on the decomposition of the signal into modes and on its partial reconstruction using the residue, the signal-dominant modes and some further modes treated with a thresholding technique, which helps to retain some of the sharp features of the signal. The strategy is developed and tested first on a synthetic signal with a superimposed and known background noise. The method is then verified on the measurement of the inertial force acting on the fuselage when it is moving in air, as in this case the added mass is negligible and the denoised force should equal the product of the mass by the acceleration, both of them being known. Finally, the procedure is applied to denoise the forces measured during the actual ditching experiment. The results are superior to those obtained by other classical filtering methods, such as a moving average filter and a low-pass FIR filter, particularly due to the enhanced capabilities of the EEMD-denoising strategy here developed to preserve the sharp features of the signals and to reduce the residual low-frequency oscillations of spurious origin.

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1. Introduction

There are cases in which the experimental setup introduces large noise components that make it difficult even to identify the trends of the physical signals. This is the case of some laboratory tests performed at CNR-INM (Institute of Marine Engineering) to investigate the aircraft emergency landing on water, generally referred to as ditching. The ditching experiments are performed by towing a scaled fuselage model via a moving carriage and, once a constant horizontal speed of the carriage is reached, by imposing a computer-controlled guided motion in the vertical plane that assigns both
the position and the pitch angle. During the ditching experiments, the loads acting on the fuselage are measured. The nature of the ditching test is, of course, intrinsically non-stationary and transient, and the induced loads are characterised by sharp variations within the observation time window. The measured loads are composed of different contributions, as discussed below. In order to accelerate and to tow the model together with the actuator systems at the desired horizontal speeds, a quite heavy carriage of large dimensions is used. Inherently, this introduces large vibrations that, in turn, are transferred to the fuselage model, the actuators and the measuring systems. Furthermore, the presence of high power electric motors, together with several electronic devices for the control of the carriage and of the linear actuators, create an intense electromagnetic field, which interferes with the acquisition setup. Consequently, despite the efforts to keep the noise level as low as possible during the tests, the recorded signals are highly contaminated with noise of different nature.

The relevant part of the signal is commonly referred to as just signal, and in the present work it refers to the inertial and the hydrodynamic loads acting of the fuselage model during the water entry. The recorded time series contain both the signal and the background noise, or simply the noise, which, just like the signal, is also non-stationary. In order to enable a correct interpretation of the experimental measurements, a strategy allowing to distinguish between the signal and the noise components is essential. It is worth specifying that, due to the peculiarities of the experimental setup and of the specific test conditions, the noise cannot be completely removed from the physical data. As such, in the following the expression "denoise" has to be interpreted as a noise reduction rather than a noise suppression.

Classical filtering techniques, such as the moving average or low-pass or band-stop filters, are based on the Fourier decomposition of the recorded signal and to the attenuation either of the highest frequency components or those in a predetermined frequency band. However, in water entry problems the force is generally characterized by steep rises and short-duration peaks (impulsive loads) [1, 2, 3, 4]. Being the signal broad-banded in frequency, the sharp variations might be removed or significantly smoothed out by the application of a frequency-based approach. This is particularly evident when the noise is induced by structural vibrations, since it is generally characterized by a low frequency content and the use of a low-pass or a frequency band filter would strongly affect the frequency content of the signal.

In order to develop a proper denoising strategy for such non-stationary signals (with non-stationary noise), one option is to recur to time-frequency approaches, such as the Discrete Wavelet Transform [5, 6] or the Empirical Mode Decomposition, introduced by Huang et. al [7, 8, 9]. Both these methods yield a so-called multi-resolution analysis, through which the raw signal is decomposed into a series of components or non-monochromatic modes, either orthogonal or quasi-orthogonal, with a limited frequency band, therefore suitable for a successive time-frequency analysis using the Hilbert transform [10]. The EMD, often used in combination with the Hilbert transform, is applied in different engineering contexts. It is worth mentioning its application in naval engineering for the detection of slamming events [11] and in machine health monitoring and fault detection [12, 13, 14]. The greatest advantage of the Empirical Mode Decomposition, compared to other time-frequency methods, lies in its capability to conform to the signal itself. Therefore, the EMD does not require a predefined basis of functions, as it happens for the wavelet transform [15] or for the classical Fourier transform. The basis of the EMD is a sifting process, in which the envelopes of maxima and minima are computed and their average is used to retrieve the different modes, which are referred to as Intrinsic Mode Functions (IMFs).

EMD and related methods are also employed to achieve a noise reduction of non-stationary signals. In fact, by distinguishing the signal-dominant modes from the noise-dominant ones, it is possible to perform a partial reconstruction accounting for the relevant modes only, possibly using a mode thresholding to improve the results. A review of the first EMD-denoising techniques, applied to synthetic signals corrupted with white Gaussian noise or fractional Gaussian noise can be found in [16, 17, 18]. Noise reduction in signals with a variable mean value is sometimes referred to as "de-trending", and the main approaches to achieve it through the EMD are outlined in [19]. An early application of EMD denoising to biomedical signals (ECG - electrocardiogram) is presented in Weng et al. [20]. Therein a time-windowing of the EMD modes is implemented to preserve the
typical waveforms of the ECG signal. An application of EMD-denoising to voice speech signals is presented in Khaldi et al. [21]. Kopsinis and MacLaughlin [22, 23] developed an enhanced strategy for signal denoising using EMD, inspired by the wavelet thresholding method. The hard and soft thresholding techniques were revisited and a new thresholding method was proposed, the so-called interval thresholding, to improve the effectiveness of the denoising. A basic and an advanced iterative method of denoising using interval thresholding were proposed and tested on synthetic test signals. Komaty and Boudraa [24] developed a strategy of EMD denoising in which the IMFs relevant for the reconstruction are selected based on the similarity of the probability density function of each mode to that of the original signal. The effectiveness of the method is proven through the denoising of artificial and real signals, to which both white and coloured noise is added. Klioskiy et al. [25] developed a new approach for the application of EMD denoising to signals with heteroscedatic noise, i.e. noise in which the variance is not constant in time. Tsolis et al.[26] developed a hybrid signal denoising technique based on Empirical Mode Decomposition and Higher Order Statistics, to reduce fractional Gaussian noise in synthetic signals and in RADAR signals. Kabir and Shahnaz [27] continued the development of the EMD-denoising method developed by Weng et al [20] for ECG signals, by combining an EMD with a DWT (Discrete Wavelet Transform) thresholding. Yang et al. [28] applied interval thresholding, with some proper modifications, to perform EMD denoising. The relevant modes are selected based on the similarity between the PDF of the original signal and the PDFs of the modes.

Although the classical EMD is rather suitable for the analysis of non-linear and non-stationary signals, it has some drawbacks. In particular, it exhibits an excessive sensitivity to small perturbations, meaning that a small change in the data can lead to rather different mode shapes. Moreover, the decomposition is prone to mode mixing, i.e. the undesired condition for which a single mode may contain widely separate scales (in the frequency domain), and to mode splitting, i.e the presence of similar time scales in different modes [29, 30, 31, 32]. Among the different approaches that can be adopted to reduce these issues, such as Iterative Filtering [33, 34] and Variational Mode Decomposition [35], the EEMD, introduced in [36], is employed in this work, being quite straightforward and particularly indicated for the present signals, which display some intermittency. The EEMD also displays a lower sensitivity to perturbations, which is also essential for the present applications, as specified in the following.

In literature only a few applications of noise reduction using EEMD can be found. Su et al. [37] developed and applied a noise reduction method based on EEMD to prototypical observations on dam safety. Wang et al. [38] developed denoising methods similar to that developed by Kopsinis et al. [23] by using EEMD, instead of a pure EMD. A modified interval thresholding method was also implemented, to suit the characteristics of the EEMD modes. These methods provide a better performance than the EMD-based ones, especially for data with low signal-to-noise ratio. Wang et al. [39] developed a novel method to identify the frequency components of the pressure pulsation that causes damage in the off-design operation of a Francis turbine; a targeted EEMD-based denoising strategy is devised, which includes an autocorrelation analysis and a wavelet thresholding. Zhang et al. [40] proposed an improved filtering method by performing an EEMD decomposition, followed by a wavelet thresholding applied to flow-induced vibration signals, recorded for the structural health monitoring of a hydraulic structure. Bao [41] used EEMD to retrieve the amplitude-modulated components, related to the cavitation noise from ship-radiated sound, containing a significant amount of background noise.

The existing literature on denoising using the EMD or the EEMD indicates that it is very difficult to design a strategy that is valid in all contexts. Instead, ad-hoc solutions must be developed and tuned for the specific signals under examination and for the type of background noise superimposed to the signal. Most of the works cited above are focused on non-stationary signals with a more or less constant trend. On the other hand, as mentioned above, the signals of our interest display trends with large signal variations, sometimes also rather sharp. In the existing literature, transient signals are addressed only rarely to our knowledge. Furthermore, most works focus on reducing a white Gaussian noise or noise coming from one single source, whereas the type of background noise in the signals considered in the present paper is associated with multiple sources, therefore it is broadband and non-stationary. The development and the application of an EMD/EEMD denoising strategy to signals recorded during ditching experiments offers an opportunity to address such kind of noise sources in a
more systematic way than in the previous works.

In particular, in this paper an Ensemble Empirical Mode Decomposition (EEMD) denoising strategy is developed and applied to the analysis of the force measured during the controlled water entry with horizontal speed of fuselage models. The denoising method exploits a proper interval thresholding, to improve the quality of the denoised data. The method is tested and validated first on a synthetic signal and on a dry test, in which only the inertial force acts, which can be easily derived based on the mass of the body and the imposed acceleration. Hence, the method is applied to the real force measurements.

2. Experimental Setup and Data

In order to properly understand the hydrodynamic phenomena occurring during aircraft ditching, experimental tests on scaled fuselage models entering water with a horizontal speed and a controlled vertical trajectory have been performed at the CNR-INM Towing Tank. The objective of these experiments is to measure the forces acting on the fuselage during a guided water landing, thus allowing to retrieve essential information on the aircraft dynamics in this critical phase. An accurate reproduction of the hydrodynamic phenomena and of the fluid-structure interaction aspects occurring in the ditching phase necessarily requires full scale tests on sample specimens [42] [3] [43], whereas the investigation of the aircraft dynamics at ditching needs small-scale free-flight tests [45] [46][47]. Unfortunately, in the latter kind of tests it is quite difficult to achieve a precise control of the attitude at the impact and, due to the strong non-linearity of the impact loads, the resulting dynamics of the aircraft is not repeatable. This makes the data not fully exploitable for the purpose of validation of the computational models. Generally, computational models are able to integrate accurately the equations governing the dynamic of the body motion, as long as the forces acting on the body are estimated correctly. Based on the above considerations, an alternative to the free flight tests is represented by guided tests on scaled models, mimicking a ditching with an imposed pitch motion. In this way, it is possible to measure the loads during the ditching with precise information on the aircraft attitude, thus making the data useful for the validation of the loads provided by the simulation tools.

The experiments are performed on fuselage models, the shapes of which are defined analytically. The one used for the tests considered here has a circular cross section with a diameter of 0.4 m and a length of 4 m. More details can be found in [48]. The tests have been performed at the CNR-INM towing tank, which is 470 m long, 13.5 m wide and 6.5 m deep. The fuselage model is towed by a carriage at the ditching speed, while the motion in the vertical plane is imposed by two linear servo-actuators, computer-controlled. The two actuators are installed on a frame, which is clamped to the structure of the towing carriage. The experimental setup and the instrumented fuselage are shown in Figure 1. The fuselage models are connected to the two actuators by two 6-axes Kistler load cells 9306A, driven by charge amplifiers ICAM 5073A. The cells enable the measurements of the loads in both the longitudinal and normal direction to the fuselage axis. The longitudinal force components are indicated with $F_{xF}$ and $F_{xR}$ whereas the normal force components are denoted as $F_{zF}$ and $F_{zR}$, subscripts $F$ and $R$ being used to distinguish the front and rear measurements, respectively. The loads are sampled at 200 kHz and acquired by a DAQ system, which includes an analogue anti-aliasing filter at 78 kHz. For the data processing, the signals are further down-sampled to 20 kHz.

Figure 2 shows a sketch of the fuselage and of the reference frames used for the data analysis as well as the force components measured by the load cells. The vertical displacement, velocity and acceleration of the fuselage are relative to the reference frame $(X,Z)$ fixed to the carriage. The forces acting on the fuselage are expressed in the reference frame $(x,z)$ fixed to the fuselage. At the beginning of the test, the fuselage is set at the given attitude with the lowest point of the shape positioned 0.20 m above the still water level. During the run, when the carriage reaches the constant speed of 12 m/s, the fuselage model starts its vertical motion. The fuselage is accelerated with an analytically defined law of motion, and moves 0.15 m vertically. At the end of the acceleration phase the velocity is 0.45 m/s, which corresponds to a vertical-to-horizontal velocity ratio of $V/U = 0.0375$. Hence, the fuselage moves at a constant vertical velocity for 0.05 m until it touches water. As soon as the fuselage touches the water, it starts decelerating with the same law used in the acceleration phase, until it stops when the first contact point is 0.15 m below the still water level. Therefore, the overall vertical
Figure 1: The instrumented fuselage model installed on the towing carriage.

Figure 2: Schematic of the reference frames used for the data analysis and of the force components measured by the load cells.
displacement of the fuselage is 0.35 m. The imposed vertical displacement \( Z(t) \), the velocity \( v(t) \) and the acceleration \( a(t) \) of the fuselage are shown in Figure 3. The acquisition is started 1 s before the fuselage motion (Fig. 3). The recorded time histories in that initial interval are used both to set the reference zero values for the different transducers, as well as to evaluate and characterize the signal noise before the fuselage descent. As the fuselage is initially set 0.2 m above the still water level, the intersection of the horizontal line at \( Z = 0.20 \) m with the fuselage position line, allows to identify the time at which the fuselage gets in touch with the water. The time of the initial contact can be also estimated analytically as \( t \approx 1.778 \) s. It is worth remarking that the exact value may vary due to the lowering of the free surface caused by the air-flow field induced by the motion of the carriage and by the presence of the residual standing wave in the tank caused by the previous runs. In total, the two effects may be responsible for a oscillation in the water level of \( \pm 5 \) mm, which implies a variation of the impact time of \( \pm 0.011 \) s.

A typical example of the force time histories recorded by the load cells is provided in Figure 4. By limiting the attention to the \( z \)-component of the loads, given the manoeuvre of the fuselage, two different contributions can be distinguished: an inertial part, which is proportional to the fuselage acceleration in the various phases, and a hydrodynamic part, which accounts for the force exerted by the water on the fuselage during the entry phase. The time histories of the measured data clearly show that the phenomena are non-stationary, with large and rather sharp variations. Several noise sources affect the measurements. The frames holding the two actuator systems are firmly clamped to the carriage structure. The rigid connection of the frames allows a precise control of the fuselage motion, however the carriage vibrations are transferred to the frame without damping. Vibrations are also associated with the control system of the two servo-actuators. In addition to the mechanical vibrations, the data are affected by the electronic noise resulting from the interaction between the electromagnetic fields generated by the carriage motors and by the two servo-actuators with the cables and the electronic circuitry of the data acquisition system. Finally, other sources of noise could be ground loops and clearance adjustments. Given the presence of noise of different nature, it is necessary to develop ad-hoc strategies capable to isolate and distinguish the noise from the physically-relevant components of the signals.
3. Algorithm development and verification based on a synthetic signal

3.1. EMD algorithm

The EMD algorithm used in the following is based on the original procedure described in \cite{8,9}, with some minor modifications needed to make it applicable to the signals considered in the present work. The basic principle of the EMD is to perform an iterative cycle, named sifting, in which a sort of moving average of the signal is computed by averaging point-wise the two cubic splines that interpolate the local maxima and minima of the signal, respectively. This sort of moving average, which represents the main trend of the signal, is subtracted from the original signal, thus yielding a temporary Intrinsic Mode Function (IMF). The temporary IMF may still be characterized by a residual trend. To remove it, the sifting is repeated within an inner sifting cycle until the number of maxima/minima of the temporary IMF is equal to the number of zero-crossing ± 1 and the mean value of the maxima and minima envelopes is zero \cite{8}. Hence, the temporary IMF is marked as an actual IMF, sometimes also referred to as mode in the following. Once the first actual IMF is identified, it is subtracted from the original signal leading to a temporary residue. The sifting procedure is applied to the temporary residue until a final residue, which is either monotone or sufficiently small, is obtained. At the end of the procedure, the original signal results decomposed into a set of IMFs and a final residue, in other words the EMD is said to be complete.

In the present work, the EMD algorithm is slightly modified compared to the one first proposed in \cite{8}. First of all, the convergence of inner sifting cycle is based on a Cauchy criterion, i.e. the loop is terminated when the sum of the differences \( SD \), defined as:

\[
SD = \frac{\int (h_{k-1}(t) - h_k(t))^2 \, dt}{\int h_{k-1}^2(t) \, dt},
\]

drops below a threshold value, i.e. \( SD \leq SD_T \), where \( h_k(t) \) is the temporary IMF at the \( k \)-th iteration. For the convergence, it is assumed \( SD_T = 0.2 \). Such a convergence criterion is proposed in \cite{7}, but the definition of \( SD \) suggested in \cite{49} is used, which makes the criterion itself more stable. Of course, the application of such a criterion is not directly related with the conditions for the attainment of an actual IMF, as specified in \cite{7}. However, it is considered rigorous enough for the EMD procedure \cite{7} and also provides the advantage of speeding up computation. The attainment of an actual IMF to terminate the inner sifting loop, in fact, typically leads to a large number of sifting iterations. As noticed in \cite{49}, a large number of sifting iterations using the cubic spline interpolation would lead to
constant-amplitude IMFs, without any amplitude modulations, and therefore not very meaningful. As a second difference, the loop is forced to terminate when the number of maxima or minima is lower than 3, and for 3 points a parabolic interpolation is used instead of cubic splines. Finally, in order to improve the accuracy in the representation of the modes at the sides, according to the suggestion by Rato et al. [50], a number of 3 maxima and minima at the two edges are mirrored, and the spline envelopes encompass the mirrored maxima and minima as well. Owing to the specific behaviour of the signals considered in the present study, the initial and final values may be quite different from each other. As such, the average of the spline envelopes may differ substantially from the trend of the signal. This generally happens in the first sifting iteration, as shown for example in Figure 5. Such a limitation may be overcome by forcing, only in the first iteration of the inner loop, the first and last values of the signal to both maxima and minima.

Figure 5: (a) Example of the issue encountered in the first sifting iteration if using edge mirroring at both ends with initial and final values significantly different and (b) improved prediction obtained by forcing the initial and final values to be both maxima and minima.

3.2. Ensemble Empirical Mode Decomposition (EEMD) algorithm

As already mentioned in Section 1, the classical empirical mode decomposition suffers from two main limitations: sensitivity to the input perturbations (and to time shifts) and mode-mixing. The sensitivity to the input perturbations is mainly introduced by the interpolation with cubic splines, and may also lead to an instability of the decomposition itself, as the spline interpolation is used repeatedly within the sifting loops [15, 33]. An immediate consequence is that the EMD of two different repeats of the same test, which contain a different background noise and approximately the same signal, but with slight time-shifts, may result in significantly different IMFs, particularly for the last modes. Mode mixing (and/or mode splitting), on the other hand, occurs when there are oscillations at significantly different frequencies within the same mode and/or when oscillations at similar frequencies occur in different modes [29, 30, 31, 32]. These phenomena are critical if the signal exhibits a certain degree of intermittency, as it happens in the present case. Reducing or avoiding mode mixing enables a more robust decomposition, leading to an easier interpretation of the physics [30].

In order to overcome, or to partially reduce at least, the above limitations, the Ensemble Empirical Mode Decomposition, or EEMD, introduced in [36] is employed in this work, being rather straightforward and very efficient in presence of signal intermittency associated to the background noise. The EEMD is based on the use of the classical EMD on a certain number of artificially perturbed signals $y_i(t)$ which are obtained from the original signal $y(t)$ as:

$$y_i(t) = y(t) + w_i(t) \quad i = 1 \ldots N_e$$

where $w_i(t)$ is an artificial white Gaussian noise realisation with amplitude $N_a \sigma$, $N_a$ being a parameter (typically from 0.1 to 0.2) and $\sigma$ the standard deviation of the original signal $y(t)$ or of a part of it. It makes sense to compute $\sigma$ over a time interval in which the signal is characterized by a constant trend, so that it can be directly related to the level of background noise. Once the EMD is repeated
on $N_e$ different signal perturbations, the IMFs are retrieved from the ensemble-averages resulting from the different EMDs. Such a procedure partially reduces the effect of random perturbations on the final decomposition. Moreover, the addition of artificial white Gaussian noise to the original signal provides a uniformly distributed reference scale to the input, which contributes to reduce the mode mixing [8], as mentioned in Section 1.

The improvements that the EEMD yields compared with the pure EMD can be seen by comparing the decompositions of different repeats of the experimental tests. Such a comparison can be established for the dry tests, i.e. the tests in which the fuselage motion is activated with the carriage at rest, starting from a position high enough so that the fuselage is always out of the water. This kind of test is highly repeatable and avoids both the uncertainty in the water level as well as the noise induced by the movement of the carriage. The decomposition is applied to the total vertical force. The EMD is performed on each of the three test repeats, and the resulting IMFs and the residue are shown in Figure 6(a). Hence, an EEMD with $N_a = 0.1$ and $N_e=1000$ is performed on the same data. The standard deviation $\sigma$ is computed over an interval during which the fuselage descends at constant speed, i.e between $t = 1.70$ and $t = 1.75$s. The resulting IMFs and the residue are shown in Figure 6(b). The IMFs obtained from the pure EMD display significant differences in the shapes of the modes extracted from the three repeats, especially for the last IMFs and for the residue. Instead, the modes provided by the EEMD for the three repeats are much closer and repeatable. Such a result clearly testifies the reduced sensitivity of the EEMD to the background noise, compared to the EMD. Furthermore, as suggested in [36], the EEMD is also less sensitive to the end effects, which are more relevant in the last modes. Based on the above experience and results the EEMD approach is used in the following.

3.3. Denoising Strategy

The principles of the denoising techniques based on the EMD and EEMD are described in [16, 17, 18, 19, 22, 23] and in [37, 39] respectively, as briefly reviewed in Section 1. The conventional EMD denoising strategy consists first in decomposing the signal into its intrinsic mode functions (IMFs) and then in distinguishing the signal-dominant from the noise-dominant modes. Typically, the noise-dominant modes are discarded, whereas the signal-dominant modes are retained. Hence, a denoised signal is obtained by partial reconstruction, i.e. by the sum of the residue and the signal-dominant IMFs only. In most cases, it is reasonable to assume that the first modes, which have a high frequency content, are noise-dominant, whereas the last modes, with a typically lower frequency content, are signal-dominant. However, for the present applications sharp variations occur and, therefore, some of the first modes, which are noise-dominant, might also contain physically relevant contributions that should be preserved. A possibility to improve the denoising strategy is to include part of the noise-dominant IMFs only. In most cases, it is reasonable to assume that the first modes, which have a high frequency content, are noise-dominant, whereas the last modes, with a typically lower frequency content, are signal-dominant. However, for the present applications sharp variations occur and, therefore, some of the first modes, which are noise-dominant, might also contain physically relevant contributions that should be preserved. A possibility to improve the denoising strategy is to include part of the noise-dominant IMFs with a thresholding. Such a technique enables a reduction of the background noise within the single modes, which can then be included in the partial reconstruction [22, 17, 23]. The most challenging aspect of such denoising methods is how to discern the noise-dominant modes from the signal-dominant ones, as well as the definition of the thresholding strategy and the choice of the threshold value. All these choices strongly depend on the type of signal to be analysed and on the background noise to be reduced, as no universal method is available in the existing literature.

In order to devise a criterion to choose the set of parameters to be used in the denoising strategy, the EEMD-based method is tested on a synthetic signal with a superimposed background noise. In this way, the effectiveness of the denoising strategy can be easily assessed by comparing reconstructed signal with the original one. The synthetic signal is constructed to be representative of a typical force time history measured in the water entry tests. The time length of the synthetic signal and the sampling rate are the same as those of the signals recorded during the actual experiments. The synthetic signal is constructed as as the sum of three components, shown in Figure 2. The three components are a ramp, a Gaussian pulse and the inertial contribution, proportional to the fuselage acceleration shown in Figure 3. The ramp starts exactly at the time at which the fuselage touches the water in the water entry tests, i.e. at $t = 1.778$ s, as described in Section 2. The pulse occurs at $t = 2$ s.

A background noise component is added to the signal, which, to be more consistent with the type of noise encountered in the experimental tests, is obtained by subtracting the denoised version of a
Figure 6: Comparison between the pure EMDs and the EEMDs of three repeats of the dry test. The EEMD is performed with $N_a = 0.1\sigma$ and $N_e = 1000$. 

(a) Pure EMD

(b) EEMD
Figure 7: Synthetic signal employed to develop the denoising strategy and its different components.

(a) Synthetic signal with superimposed background noise and only signal

(b) Different components of the signal
typical experimental signal from the raw data. This *background noise* time history is shown in Figure 8. It is observed that also the background noise displays significant non-stationary features, especially in the central part, i.e. during the vertical motion of the fuselage. In that time interval, the oscillations are larger in amplitude, and the variance of the signal is also higher. In Figure 9(a) the histogram of the background noise is provided. It is worth noting that the background noise does not deviate significantly from the Gaussian distribution that best-fits the data, except for the central part, where the sample counts lie above the Gaussian distribution. The power spectral density of the synthetic signal (signal+background noise) and of the background noise only are computed using the Welch’s periodogram method and are shown in Figure 9(b). The background noise displays a quite clear broad frequency content with peaks at 600 Hz, 1800 Hz and 6500 Hz. The power spectral density of the synthetic signal is well overlapped to that of the background noise for $f > 27$ Hz. The peaks at 27 Hz and at 16 Hz occur on both the power spectral density of the synthetic signal and of the background noise, although they are slightly lower in the latter case.

By looking at Figure 9(b), the simplest way to denoise the signals seems to be a classical low-pass FIR filter with a cut-off frequency of 20 Hz or a moving average filter spanning 1000 samples, which corresponds to a time interval of 0.05 s. The outputs of the two filters are shown in Figure 10. The use of the moving average filter reduces the background noise but smooths out significantly the Gaussian pulse at $t = 2$ s. On the other hand, the application of the FIR filter has a lower effect on the peak smoothing, but it does not eliminate the oscillating behaviour. Given the nature of the background noise, which exhibits a significant low frequency content (see Figure 9(b)), it is very difficult to suppress the spurious oscillations and at the same time to preserve the sharp features of the signal. This is the reason why non-stationary filtering techniques are deemed essential for such cases.

3.4. Determination of the EEMD Parameters

In order to perform the EEMD, the input signal is corrupted with an artificial white Gaussian noise with amplitude $N_a \sigma$, where $\sigma$ is the standard deviation of signal computed over a time interval in which the trend is constant, thus being representative of the background noise. The parameters $N_a$ and $N_e$ have to be determined based on the characteristics of the signals.

The number of modes retrieved via the EEMD method is typically higher than what would be obtained via the standard EMD. This is because the addition of artificial white noise introduces more scales in the input, which are distributed among the various IMFs and may not be eliminated completely through the ensemble averaging. As such, it is expected that if $N_a$ is higher, also the number of modes tends to be higher, and some redundant modes can also be generated [51]. Furthermore, due to the features of the signal, which is characterised by sharp variations, and to the implementation of the EMD algorithm (in particular the stopping criterion both for the inner sifting cycle and for the outer while cycle), each pure EMD does not return the same number of modes. For example, the number of IMFs obtained by performing an EEMD over 1000 realizations for different values of

![Figure 8: Time history of background noise superimposed to the synthetic signal components.](image-url)
Figure 9: (a) Histogram of the background noise and best-fitted Gaussian distribution and (b) power spectral density of the synthetic signal with background noise and of the background noise only.
Na are shown in Figure 11. In order to perform the ensemble average of the modes, it is essential that the decompositions of all perturbed signals return the same number of modes. Unfortunately, this cannot be imposed a priori. Therefore, a large number of EMDs is performed and the ensemble averaged modes are computed on the subset of the EMDs that return the most frequent number of modes, discarding the others. Figure 11 shows that the number of modes grows when increasing the amplitude of the artificial noise.

As noticed in [36], the parameters Na and Ne are not independent, because if an artificial noise realization with a higher amplitude is added to the original signal, a higher Ne is required to achieve convergence in the ensemble averaging process. An analysis of convergence is performed by assuming Na = 0.1, which is the value used in the following. The EEMD modes are computed by for a different number of ensembles Ne. Figure 12(a) shows three modes of the EEMD, namely IMF7, IMF8 and IMF9, computed as ensemble average of a different number of EEMDs from 10 to 100. It can be noticed that the modes approach a certain shape when the number of realizations of the ensemble average is increased. In Figure 12(b) it is shown that if the number of realizations is increased beyond 100, the variability of the modes is much lower. In order to introduce a more precise convergence criterion, a norm that measures the “distance” between an IMF of the EEMD computed with Ne perturbations and an IMF obtained with Ne + 1 perturbations is defined as:

\[
\text{Norm}_{i|Ne} = \frac{\int (\text{IMF}_{i}(t)|_{Ne+1} - \text{IMF}_{i}(t)|_{Ne})^2 \, dt}{\int (\text{IMF}_{i}(t)|_{Ne+1})^2 \, dt}.
\] (3)

The tested number of ensembles varies from 2 to 10000. The norms are plotted in Figure 13 as a function of Ne for all the IMFs. The norm for all the IMFs tends to decrease when Ne is increased. The last modes, in which the artificial noise in each perturbed signal introduces additional artificial low frequency components, clearly display some oscillations in the norm for low Ne. It is assumed that a satisfactory convergence is achieved when the norm drops below 10^{-5}. Based on the data shown in Figure 13, this generally happens, at least for the last modes, at about Ne = 500. To be even more conservative, in the following the EEMD is performed by using Ne=1000.

It is less straightforward to establish the optimal value of Na. In the paper that introduced the EEMD first [36] the values of 0.1 and 0.2 for Na are proposed. It is also suggested choosing Na by taking into consideration the type of signal. In Figure 14 the modes from IMF5 to IMF9, which result
Figure 11: Histograms of the number of IMFs obtained over 1000 EMDs of the synthetic signal, with different values of the artificial noise amplitude $N_a \sigma$.

(a) $N_e = 1, 10, 20, 50$ and 100.  

(b) $N_e = 100, 150, 200, 500$ and 1000.

Figure 12: IMF$_7$, IMF$_8$ and IMF$_9$ obtained by increasing the number of artificial noise realizations using the EEMD algorithm on the synthetic signal: (a) $N_e$ from 1 to 100 and (b) $N_e$ from 100 to 1000.
Figure 13: Norm indicating the “distance” between a mode obtained with a certain value of $N_e$ and $N_e + 1$, as a function of $N_e$. The EEMDs are all performed with $N_a=0.1$. 
from the EEMDs with \( N_e = 1000 \) and different values of \( N_a \), are shown. It is worth noting that in all cases the reconstruction of the original signal as the sum of all modes still holds, aside from a small difference, in this case negligible, due to the fact that, differently from the EMD, the EEMD is not a complete decomposition. It is observed that for such type of signals, if \( N_a \) is higher than 0.2, the peaks at \( t=2 \) s are smoothed out, especially in the IMF\(_5\) and IMF\(_8\). In the present case, those peaks results from the decomposition of the Gaussian pulse component of the synthetic signal, see Figure 7, hence it is necessary to preserve them. It can be anticipated that this is achieved in this paper by employing a thresholding strategy, see Section 3.5, according to which the signal values below a certain threshold are discarded, assuming that they are part of the background noise of the mode. Of course, the thresholding strategy preserves better the peaks that are more pronounced, hence choosing \( N_a < 0.2 \) provides an advantage in this sense. Furthermore, it is also observed that an increase in the amplitude of the artificial noise causes a corresponding growth of the amplitudes of all frequency components, which make all modes noisier. This is evident for instance by looking at IMF\(_5\), IMF\(_6\) and IMF\(_7\). The higher noise level makes the application of the thresholding strategy more difficult, as some non-physical peaks and valleys may appear, which cannot be distinguished from the physically

Figure 14: IMF\(_5\), IMF\(_6\), IMF\(_7\), IMF\(_8\) and IMF\(_9\) obtained from the EEMD of the synthetic signal with different artificial noise amplitudes and \( N_e = 1000 \).
relevant ones. Given these two circumstances, a value of $N_a=0.1$ is chosen. It must be stressed again that such a choice is made based on this specific type of signal and on the derived EEMD. For different type of signals, the optimal value of $N_a$ might be different.

Once the number of realizations and the artificial noise amplitude is chosen, an EEMD with $N_a = 0.1$ and $N_e = 1000$ is performed, yielding ten IMFs and a residue. The decomposition is shown in Figure 15. The first IMFs contain mostly oscillations at high frequencies, which are presumably associated with the electronic noise. As a matter of fact, most of the oscillations with increased variance in the central time interval, i.e. $1.2 \, s < t < 2.1 \, s$, are contained in those modes. That time interval is the one during which the fuselage is moving, and thus the control-system of the actuators is operating. On the other hand, the oscillations due to the mechanical vibrations of the carriage and of the actuator systems are also visible in the last IMFs, being characterized by a lower frequency content. Finally, the presence of the pulse at $t = 2 \, s$ is visible in modes from IMF$_5$ to IMF$_{10}$. The oscillation related to the pulse broadens more and more moving towards the last modes, as expected. 

![Figure 15: IMFs obtained from the EEMD of the synthetic signal with $N_e = 1000$ and $N_a = 0.1$](image-url)
3.5. Thresholding Methods

As anticipated, the modes are a combination of physical components and spurious noise. In the first modes it is expected that the noise component is dominant, but it cannot be excluded that a physical component exists as well. Based on the above considerations, it is worth introducing a technique which allows to preserve the relevant components and remove the background noise. One possibility to achieve such a goal is to perform a mode thresholding. Denoising using thresholding is commonly performed in literature following the application of the Discrete Wavelet Transform \[53, 54, 55\]. In that case, the thresholding is applied to the wavelet coefficients, hence in the wavelet domain (i.e. in the time-frequency or time-scale domain). However, it is also possible to perform a thresholding in the time domain, applying it directly to the IMF time samples, as described in \[23\].

Different types of thresholding can be performed: hard thresholding, soft thresholding and interval thresholding. Given a signal \(y(t)\), the corresponding hard thresholded signal \(y_T(t)\) is given by:

\[
y_T(t) = \begin{cases} y(t) & \text{if } |y(t)| > T \\ 0 & \text{if } |y(t)| \leq T \end{cases}
\]  

(4)

Hard thresholding helps to preserve the highest peaks and valleys in the signal, but it introduces jumps at the instants where the time series crosses the threshold. Such jumps are quite evident, especially if the threshold value is relatively high. A soft-thresholding, or shrinkage, can be achieved by using the following approach:

\[
y_T(t) = \begin{cases} y(t) - T & \text{if } |y(t)| > T \\ y(t) + T & \text{if } |y(t)| < -T \\ 0 & \text{if } |y(t)| \leq T \end{cases}
\]  

(5)

With soft thresholding the modes are shrunk, so jumps are still present in the thresholded signal, but their amplitudes are smaller. Even if there is a significant improvement compared to the hard thresholding, soft thresholding is not suitable for the present applications, in which it is required to preserve the full values of peaks of valleys in the time histories, even in presence of large background noise components.

A technique that seems more appropriate for the present applications is the hard interval thresholding, introduced in \[23\]. The input signal \(y(t)\) is initially divided into a series of time intervals in between two successive zero-crossings. Then a thresholding is performed interval-wise rather than point-wise, meaning that

\[
y_T(t_a \leq t < t_b) = \begin{cases} y(t_a \leq t < t_b) & \text{if } \max(|y(t_a \leq t < t_b)|) > T \\ 0 & \text{if } \max(|y(t_a \leq t < t_b)|) \leq T \end{cases}
\]  

(6)

where \(t_a\) and \(t_b\) correspond to two successive zero-crossing time instants. The procedure is repeated for all the time intervals in between two successive zero-crossings. As pointed out in \[23\], the application of interval thresholding has some similarities with the wavelet thresholding, where setting to zero a wavelet coefficient that is below a certain value, affects a set of contiguous time samples. A comparison between hard thresholding and interval thresholding is shown in Figure \[16\]. Interval thresholding helps to preserve the whole semi-oscillations of the original signal without introducing undesired jumps in the thresholded output. Owing to such good peculiarities of the method, the interval thresholding is used in the following.

3.6. Denoising procedure and results

Through the EMD or EEMD, the background noise is removed from the original signal by discarding some of the first modes in the reconstruction of the signal. Formally, the “denoised” signal is reconstructed by summing the last \(N - M + 1\) modes and the residue, which is:

\[
\hat{y}_M(t) = \sum_{i=M}^{N} \text{IMF}_i(t) + \text{Res}(t)
\]  

(7)
where \( M \) is the first mode considered in the reconstruction and \( N \) is the total number of modes. This approach is referred to as conventional EMD denoising, see [22, 23].

The most difficult part of the approach concerns the choice of the number of modes to be accounted for and disregarded in the reconstruction, a choice that is strongly dependent on the specific problem and on the noise characteristics. In this regard, some considerations can be made based on the synthetic signal without the background noise. It is worth noticing that this synthetic signal cannot be treated with the classical EMD, since it does not contain sufficient maxima or minima to start the sifting cycles. Nevertheless, the problem can be overcome by performing the EEMD. For the reader’s convenience, the signals without and with the background noise are shown in Figure 17(a) and (b) respectively, and the corresponding EEMDs with \( N_a=0.1 \) and \( N_e=1000 \) are shown in Figure 17(c) and (d) respectively. Unfortunately, it is not possible to find a mode to mode correspondence between the two decompositions. However, the EEMD of the signal only is useful as it provides a visual indication of the shape of the modes that would be attained without background noise. By looking at Figure 17(c), the first two IMFs of the synthetic signal just account for some residual noise that is not eliminated during the ensemble averaging; the amplitude of these modes is rather small, though. The most relevant oscillations that should be accounted for in the signal reconstruction appear from the IMF3 and beyond. The residue accounts mainly for the increasing trend of the signal, from a null value at the beginning to a positive constant value at the end. By looking at the EEMD of the signal with noise, shown in Figure 17(d), it is possible to recognize modes with shapes quite similar to those of the undisturbed signal. The background noise spreads throughout all the modes, although it looks negligible in the last three modes, i.e. IMF8, IMF9 and IMF10, and it is smaller than any prevailing mode oscillation in modes IMF5, IMF6 and IMF7. The background noise is instead dominant in the first modes, from IMF1 to IMF4, where no prevailing oscillations are visible. Therefore, the latter modes can be disregarded in the partial reconstruction for denoising.

Based on the above considerations, it is concluded that, for such specific signal types, compared to the conventional EMD or EEMD denoising, an improved noise deduction can be obtained by performing a thresholding of IMF5, IMF6 and IMF7, and then reconstructing the denoised signal, denoted with \( \hat{y}_T(t) \), as:

\[
\hat{y}_T(t) = \sum_{i=L}^{(M-1)} \text{IMF}_{T,i}(t) + \sum_{i=M}^{N} \text{IMF}_i(t) + \text{Res}(t)
\] (8)
Figure 17: Synthetic signals (a) without and (b) with background noise and related EEMDs, (c) and (d) respectively.
where IMF\(_{T,i}(t)\) indicates the \(i\)th thresholded IMF, \(L = 5\) and \(M = 8\). Given the background noise that is superimposed to the signal (see Figure 8), it makes sense to define a mode-dependent threshold as
\[
T_i = N_\sigma \sigma_i \quad i = 1 \ldots N
\]
where \(N\) is, again, the number of EEMD modes, \(\sigma_i\) is the standard deviation of each mode over the initial time interval, from \(t = 0.05\) s to \(t = 0.95\) s, and \(N_\sigma\) is a parameter to be determined. The interval over which \(\sigma_i\) is computed for the threshold definition is the one in which only the noise induced by the vibrations of the carriage and of the actuator system is present. In fact, as anticipated, such contributions to the background noise affect all modes. In the central part of the acquisition the amplitude of the background noise is higher but it is mostly associated with the electronic noise, which has a relatively high frequency content and is almost completely contained in the first modes, which are discarded in the partial reconstruction. A comparison between the original IMFs derived from the EEMD and the IMFs after the application of the interval thresholding is shown in Figure 18. The threshold for last three modes is set to 0, i.e. those modes are not thresholded, whereas it is \(T_i = N_\sigma \sigma_i\) with \(N_\sigma = 4.75\) for the other modes. These values are chosen by trial and error, in order to remove the undesired oscillations in IMF\(_5\), IMF\(_6\) and IMF\(_7\).

In Figure 19 the result of the denoising technique described above is compared with the original synthetic signal, the signal only and the result of FIR low-pass and the moving average filter. The comparison shows that the EEMD denoising, integrated with the interval thresholding, provides superior results compared to other techniques and it is able to retrieve the original signal hidden in the background noise with just a few spurious oscillations and with only a limited smoothing of the pulse. The good quality of the reconstruction can also be appreciated from the close-up views provided in Figure 20.

3.7. Guidelines for the development of a EEMD denoising strategy transient signals

The application of the denoising strategy to the present synthetic signal enables to draw some guidelines for the determination of the parameters of the EEMD denoising of a general transient signal in terms of the number of modes to be included in the partial reconstruction and the threshold values.

At first a visual method can be applied. If the technique is applied to a synthetic signal with superimposed background noise, as done before, it is possible to perform an EEMD decomposition of the synthetic signal only and of the signal plus noise. By comparing the two EEMDs, it is possible to visually establish how the background noise is distributed across the different modes, and thus to identify the modes that should be preserved in full, the ones that should be thresholded and to determine an initial threshold value. The determined parameters can be further tuned through a trial-and-error approach.

For a real measurement, the signal only is of course not available. In some cases it is possible to derive an expected behaviour of the time history of the measured quantity from theoretical considerations or from numerical simulations. Such solutions provide a clean signal that can be decomposed through the EEMD. The EEMDs of the clean and of the measured signal, similarly to the case of the synthetic signal, can help to choose the denoising parameters either visually or with a more sophisticated methods.

If, instead, a theoretical or a numerical solution is not available, it is suggested to build a synthetic clean signal that is very similar in shape to that under examination and to examine its EEMD, together with that of the noisy signal, in order to test different combination of the denoising parameters.

4. Application of the denoising method to the experimental measurements

4.1. Dry Tests

The principles of the denoising technique developed in the previous sections are used in the following to reduce the background noise of the data acquired in the experimental campaign. As anticipated in Section 3.2 before starting the actual water entry tests, preliminary dry tests were performed, i.e. tests in which the fuselage is moved vertically with the same time velocity profile of Figure 3 but
Figure 18: Comparison between the original IMFs and the thresholded IMFs of the synthetic signal using interval thresholding.
Figure 19: Comparison between the different denoising techniques: moving average filter (span 1000 samples i.e. 0.05 s), low-pass FIR Hanning window filter (cut-off frequency 20 Hz) and the EEMD denoising with interval thresholding.

(a) Close-up view about the Gaussian peak

(b) Close-up view near the ramp

Figure 20: Detailed views of the comparison shown in Figure 19
starting from a position such that it does not get in contact with the water at the end of the descent. The aim of the dry test is to isolate the inertial force contribution that has to be subtracted from the data acquired in water entry tests to retrieve the hydrodynamic loads. The total vertical force in the carriage reference frame \( F_{Z}^{\text{TOT}} \), according to the notation provided in Figure 2, can be evaluated as:

\[
F_{Z}^{\text{TOT}} = (F_{zR} + F_{zF}) \cos(\alpha) + (F_{xR} + F_{xF}) \sin(\alpha)
\]

where \( \alpha \) is the pitch angle. The inertial force is a good reference for the validation of the denoising strategy, since it can be analytically computed starting from the body mass and the time history of the acceleration (see Figure 3). The time histories of the inertial force recorded in three different repeats are shown in Figure 21. Of course, the measured force is affected by a significant background noise. It is worth observing that part of the background noise during the descent seems to be in phase in all the three repeats, hence it is likely associated with the vibrations experienced by the actuator system. As discussed in Section 3.2, the EEMD is more robust than the pure EMD approach. In the dry test the EEMD parameters are chosen as \( N_{e}=1000 \) and \( N_{a}=0.1 \). The artificial noise amplitude is \( N_{a}\sigma \), where \( \sigma \) is the standard deviation computed over the time interval \( 1.70 < t < 1.75 \) s, during which the fuselage descent with a constant velocity.

An estimate of the denoising output is the theoretical force computed from the acceleration, drawn in Figure 22(a), whereas the experimental force measured in one of the dry tests is shown in Figure 22(b). As suggested in Section 3.7, the EEMD of the theoretical and of the experimental signals can be compared in order to drive the selection of the EEMD denoising parameters. The resulting modes are provided in Figure 22(c) and (d) respectively. Both the decompositions consist of eleven IMFs and a residue. Also in this case, due to the presence of the background noise, it is not possible to establish a direct comparison between the modes resulting from the theoretical and the experimental decompositions. Nevertheless, it is possible to spot a good similarity of the last modes. The shape of these mode suggests that a partial reconstruction including the residue, the last two modes and two further thresholded modes can provide a satisfactory denoising of the experimental inertial force. In other words, the reconstruction is made by using equation (8) with \( L=8 \), \( M=10 \), and \( N=11 \). For the thresholds it is assumed \( T_{i} = 2\sigma_{i} \), where \( \sigma_{i} \) is computed between \( t=1.7 \) s and \( t=1.75 \) s in each mode.

The denoised signal, the theoretical force, together with the outputs of the classical moving average filter (with span 0.05 s), and of the low-pass FIR filter at 20 Hz are shown in Figure 23. The comparison indicates that the EEMD denoising approach performs much better than the other filtering methods, since it allows to remove the background noise while preserving quite faithfully the sharp variations of the signal. The EEMD-denoised signal also displays a good match with the theoretical estimate.
Figure 22: Time histories of (a) the theoretical and (b) measured force. The corresponding EEMDs are drawn in (c) and (d), respectively.
4.2. Water entry tests with horizontal velocity

Based on the above experience, the denoising method is applied to the time histories of the force recorded during the water entry of the fuselage set at $6^\circ$ and moving at a horizontal velocity of 12 m/s and a vertical velocity at the impact of 0.45 m/s. For the purpose of the present study, only the forces measured by the load cells acting normal to the fuselage axis (see Figure 2), i.e., $F_{zR}$ and $F_{zF}$, are considered. The raw data of the three repeats are depicted in Figure 24. Despite the large noise, the data of the three repeats display a good overlapping, thus denoting a satisfactory repeatability of the tests. Aside from the background noise, there is a small time-shift of the curves, which is caused by some differences in the position of the free surface as a consequence of the residual waves in the tank. The time histories of the $z$-component of the forces $F_{zR}$ and $F_{zF}$ display a peak, positive at the rear and negative at the forward cell, occurring about $t \approx 1.778$ s, which is about the first contact with water. After the peak, the force at the rear diminishes, attains a minimum and grows up to reach a constant value in the last part of the test. A similar behaviour, but opposite in sign, is observed for the forward cell. It is worth noticing that the two forces do not balance at the end of the test, meaning that there is a net force, which is the buoyancy (hydrostatic) component at that specific attitude. The
inertial contribution is visible between $t = 1\ s$ and $t = 1.5\ s$, particularly at the rear. In the next phase, the effect of the inertia is hidden by the action of the hydrodynamic loads. The background noise is present throughout the acquisition period, but it looks more intense starting from $t = 1\ s$, i.e. concurrent with the motion of the fuselage.

In order to reduce the background noise, the EMD and EEMD are applied to the forces measured by the forward and rear cells. The EEMD is computed by using $N_a = 0.1$ and $N_e = 1000$. In Figure 25 the pure EMD and the EEMD performed on the time histories of the three repeats of the forward force $F_x F$ are shown. Aside from the different number of modes, the advantage of the EEMD over the EMD is clearly visible by the much closer overlapping of the most significant modes, i.e. those above IMF$_7$, denoting a much lower sensitivity to the slight differences between the signal shapes in the three repeats.

In order to retrieve the denoised signal, a partial reconstruction is used, by including the residue, the last two modes (IMF$_{10}$ and IMF$_9$) in full and the previous two (IMF$_8$ and IMF$_7$) after being treated with an interval thresholding, with a mode-dependent threshold $T_i = 3\ \sigma_i$. More formally, by using Equation (8), it is assumed that $L = 7$ and $M = 9$, with $N = 10$. The standard deviation for the interval thresholding, $\sigma_i$, is computed over the time interval $t = 0.05 - 0.95\ s$. The reconstructed signal is shown in Figure 26. The results confirm that the denoising based on the EEMD is rather efficient in removing the undesired oscillations without affecting too much the sharpness of the signal. This is certainly an advantage compared to classical filters. It is difficult to establish whether the double peak occurring after the water impact has an actual physical origin or it is associated with the background noise. In order to understand its origin, numerical simulation of the water entry are ongoing. As explained in Section 3.7, such simulations should provide a reference force time history that can support the understanding of the experimental measurements and to tune the denoising method.

A similar analysis is performed for the force measured at the rear $F_x R$ and results are provided in Figure 27. In this case both the pure EMD and the EEMD yields ten modes, but again the last EEMD modes and the residue exhibit a much closer overlapping among the different repeats.

The denoised force is derived by using the same approach adopted for the forward force. The results are shown in Figure 28. As already observed, the denoising based on the EEMD is more effective than the classical filters, even though some undesired oscillations are still present. The results for $F_x R$ are somewhat cleaner than for $F_x F$.

5. Conclusions

In this paper a noise reduction strategy based on the Ensemble Empirical Mode Decomposition (EEMD) has been developed and applied to transient signals affected by a broad-band non-stationary noise. The signals are the measured loads in scaled fuselage ditching tests in a towing tank. The noise affecting the signals originates both from mechanical vibrations and from electromagnetic interferences with the data acquisition system.

The denoising strategy has been first tested and tuned on a synthetic signal resembling the time histories of the measured force, on which a consistent background noise is superimposed. The denoising strategy is based on a partial reconstruction including the residue, a few EEMD modes in full, typically the higher order ones, and a few other modes to which an interval thresholding is applied. The latter modes, in fact, account for physically meaningful components to be preserved. The proposed denoising strategy has been proved to be more efficient than classical low-pass FIR and moving average filters, since it allows to reduce the noise without smoothing excessively the sharpness of the signal. Hence, the strategy has been applied to two type of real force measurements. In the dry test case the denoising strategy has provided a signal very close to the one expected from theory. In the ditching tests, the denoising approach has been found to outperform the other filtering techniques, even though some residual oscillations still appear.

Owing to the features of the signal and of the noise, a universally valid criterion to choose the thresholds and the modes to be included in the reconstruction cannot be defined. For a synthetic signal with a known superimposed noise, it is recommended to compare the EEMD of the whole signal with the EEMD of the signal only component, and to choose the denoising parameters through a trial and
Figure 25: Comparison between the pure EMDs and the EEMDs performed on the three repeats of $F_zF$ during the water entry test.
error approach to achieve a satisfactory match between the reconstructed signal and the signal only component. In the case of real signals, the parameters of the EEMD denoising can be chosen similarly by using as a reference an expected denoised time history, which can be estimated from theory or from numerical simulations, when possible. Further improvements of the EEMD denoising techniques can be achieved, for instance, by exploiting a time-windowing approach, e.g. [20 27], or by developing a method that selects the denoising parameters in an automatic way.

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Figure 27: Comparison of the pure EMDs and the EEMDs of the $F_{zR}$ time histories for the three repeats of the water entry test.
Figure 28: Comparison between the different denoising techniques applied to the force $F_{zR}$: moving average filter (span 1000 samples i.e. 0.05 s), low-pass FIR Hanning window filter (cut-off frequency 20 Hz) and the EEMD denoising techniques with interval thresholding.

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