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Uncertainty-based combination of signal processing techniques for the identification of rotor imbalance

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ABSTRACT

This paper describes a method for the uncertainty-based combination of signal processing techniques for the identification of rotor imbalance. The main idea of the proposed method is to compute the imbalance with different algorithms and to average the different algorithms' results. The method is based on the data fusion at feature level and uses the measurement uncertainty of the imbalance as a figure of merit for the weight computation. A static, a dynamic, and a hybrid implementation are presented. In the static one, the weights are computed in a dedicated training phase, in which four algorithms (Fourier transform and quasi-harmonic fitting of signal denoised with Hilbert-Huang Transform, Hilbert Vibration decomposition, and Wavelet Packet decomposition) have been used to estimate the known imbalance of car wheels. In the dynamic one, the weights are computed at runtime by estimating the difference between each predictor and the actual signal. The hybrid approach is the combination of the two algorithms. Results of simulations and experiments evidenced the validity of the data fusion, with uncertainty reductions between 10 and 40%, with larger benefits in presence of non-stationary disturbances.

1. Introduction

In many cases there are different signal processing techniques that can be used to extract specific features from a signal. The different information can be combined with the information fusion technique, which can be implemented at data-level, at feature-level and at decision-level [1]. The combination of different sensors or features always allows reaching a better accuracy than that achievable using a single information [2–6]. Consequently, several literature studies focused on the combination of different techniques for the identification of parameters related with mechanical systems. Niu et al. [7] proposed a faults diagnosis mechanism using the wavelet analysis and decision-level fusion technique for motors fault diagnosis. In another study [8], Niu et al. proposed a decision fusion system for fault diagnosis integrating data sources from different sensors and decisions of multiple classifiers; the use of multi-agent classifiers as the core of the fault diagnosis system allowed increasing the accuracy of the fault detection. Bhattacharyya et al. [9] suggested the combination of signal processing techniques for real-time estimation of tool wear in face milling using cutting force signals. In their work, authors combined three signal-processing methods with a statistical model. Khazaee et al. designed and implemented an intelligent system for detecting and classifying faults of internal combustion engine [10]. Classifiers extracted from vibration signals were used as inputs of an artificial neural network; results showed that the combination of separate classifiers increased the classification accuracy with respect to the single methods adopted. Yang et al. [11] proposed a noise suppression method for the extraction of features from vibration signals. In their work authors implemented a multi-point data fusion for reducing the effect of noise in the analysis of wind turbine vibration signals; also in this case, results evidenced that the data fusion allows extracting early weak faults.

At the current state of the art, the data fusion has never been adopted to increase the accuracy of rotors' balancing, the procedure in which the mass distribution of a rotor is measured and, if necessary, adjusted to ensure given tolerances. The imbalance of a rigid rotor is usually measured at constant rotation speed using the influence coefficient method [12,13] and corrected on two arbitrary planes [14] starting from the vibrations V_1 and V_2 measured at two planes of motion. The term vibration refers either to the displacement of two compliant constraints or to the reaction forces of rigid constraints [15]. The advantages provided by data fusion in a simple and traditionally successful application such as the balancing may appear limited, since the influence coefficient method already provides for satisfying results when the signal to noise ratio is favourable and when the rotor speed is constant. In presence of measurement noise and mechanical disturbances, however, the influence coefficient method requires many

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averages to obtain reliable results (typically a stable imbalance phase). Since a reduced balancing time is a key factor in the commercial success of a balancing machine, we have investigated the possibility of obtaining a more reliable imbalance estimation using data fusion techniques. With this approach, the measurement accuracy can be improved with the same measurement hardware: in a recent study, performances of four different algorithms for the identification of car wheel imbalance were compared [16]. The imbalance amplitude and phase were derived from transient signals using four different numerical methods: the computed order tracking and Fourier Transform (FT-COT) and the quasi-harmonic regression on the signal denoised using the Hilbert Vibration Decomposition (HVD), the Hilbert Huang Transform (HHT) and the Wavelet Packet Decomposition (WPD). As explained in Ref. [16], COT-FT is the method traditionally used for the identification of the wheel imbalance when the signal is asynchronously sampled; the Fourier transform is computed in the angle domain on the signal resampled using the measurements of a rotational encoder. Given the limited computational capabilities of the hardware of many machines, the COT is typically computed supposing a constant or linear velocity trend and results are therefore biased in presence of nonlinear variations of the angular velocity. HVD has been used thanks to its efficiency in decomposing the signal into quasi-harmonic components; the algorithm has been implemented according to the Feldman approach [17,18] and the first component detected by HVD is the one with the largest amplitude, which in the case of imbalance is the 1X revolution component. The imbalance amplitude and phase were estimated fitting the 1X with a harmonic equation in a least square sense, where the actual rotation speed is the one measured by the encoder without any interpolation. The HHT is very similar to the HVD, but the signal decomposition is based on the so-called intrinsic mode function, in which the decomposition is performed using the upper and lower envelope of the signal. Also in this case, the imbalance amplitude and phase were obtained by fitting the 1X revolution component with a harmonic equation. The WPD is a decomposition method based on the Wavelet transform. The decomposition was based on the Daubechies 6 family and the procedure was iterated to extract the single frequency components from the lowest level of the WPD tree. For current purposes, we have extracted the lowest frequency component from a 7-level WPD and then extracted the imbalance components using the least square fitting as in the previous cases.

The main idea behind the use of HVD, HHT and WPD is that, since their errors are uncorrelated with those of the FT, the combination of different algorithms provides for a better accuracy with respect to the use of a single method in presence of disturbances. In ref. [16], performances of the four algorithms were analysed using the Design of Experiments and results allowed evidencing the accuracy of each method. Performances of the HHT were penalized by the simplistic method used for the 1X identification, while performances of HVD, WPD and FT were comparable; the choice of the best method was not straightforward.

In this paper, we propose different approaches that can be adopted to merge the indications of different algorithms using the measurement uncertainty (evaluated in accordance with the ISO GUM [19]) as a figure of merit for the identification of the algorithms' weights. The approaches are similar to the variance-based weighting for data fusion [20], but weights are computed by with different expressions derived from the measurement uncertainty. The proposed method is described in Section 2. Section 3 describes the specific case of the rotor imbalance problem. Experimental results are presented in Section 4 and discussed in Section 5. The paper is eventually concluded in Section 6.

2. Method

If a measure Y (a parameter that can be extracted by a signal X(t), in this paper the rotor imbalance) can be obtained using M different approaches, it is possible to compute Y by averaging the different estimates Y_i (being i an index that varies between 1 and M). The arithmetic average is, in general, a non-optimal choice, given that the same relevance is given to all the Y_i independently on their performances [20]. Let us consider the estimation of Y with two quantities Y_1 and Y_2, each one characterized by a measurement uncertainty U_1 and U_2. Y can be obtained as a linear combination of Y_1 and Y_2 using two weights α and β.

$$\begin{cases} Y = \alpha Y_1 + \beta Y_2 \\ \alpha + \beta = 1 \end{cases} \tag{1}$$

For instance, in the case of rotor balancing performed at a variable rotation speed, the amplitude of the vibration component synchronous with the rotation (1X) can be estimated from the signal spectrum using COT-FT (Y_1) or in the time domain (Y_2, best quasi-harmonic signal fitting the de-noised experimental data in a least square sense). The amplitude can be computed with one of the two methods (α or $\beta = 0$) or as the average between Y_1 and Y_2 ($\alpha = \beta = 0.5$). The best estimation is the one in which α and β minimize the uncertainty of Y, U_Y. Under the hypothesis of non-correlated uncertainties, U_Y can be computed according to the ISO GUM [19] as:

$$U_Y = \sqrt{\left(\frac{\partial Y}{\partial Y_1} U_{Y_1}\right)^2 + \left(\frac{\partial Y}{\partial Y_2} U_{Y_2}\right)^2} \tag{2}$$

Given that the sum of coefficient is 1, Eq. (2) becomes

$$U_Y = \sqrt{(\alpha U_{Y_1})^2 + ((1-\alpha) U_{Y_2})^2} \tag{3}$$

U_Y can be minimized setting $\mathrm{d}U_Y/\mathrm{d}\alpha = 0$, obtaining

$$2\alpha U_{Y_1}^2 + 2\alpha U_{Y_2}^2 - 2U_{Y_2}^2 = 0 \tag{4}$$

The coefficient α minimizing the measurement uncertainty is

$$\alpha = \frac{U_{Y_2}^2}{U_{Y_1}^2 + U_{Y_2}^2} \tag{5}$$

The above expression is equivalent to the variance averaging proposed by Taniguchi and Tresp [20] if the uncertainty is computed with the ISO GUM type A approach; in this case, the weights are proportional to the inverse of the variance, exactly as in the variance approach. More generally, a measurement Y can be expressed as the combination between n estimations:

$$\begin{cases} Y = \alpha_1 Y_1 + \alpha_2 Y_2 + \ldots + \alpha_n Y_n \\ \displaystyle\sum_{i=1}^{n} \alpha_i = 1 \end{cases} \tag{6}$$

An alternative to the use of the variance-based weighting, is given by the normalization criterion with the weights α_i computed as follows:

$$\alpha_i = \frac{\left(\sum_{j=1}^{n} U_{Yj}^2\right) - U_{Yi}^2}{(n-1)\sum_{j=1}^{n} U_{Yj}^2} \tag{7}$$

Eq. (7) states that, if Y has n uncorrelated estimators Y_j, each estimator has a weight that is proportional to the "residual variance", i.e. the variance introduced from the other estimators. This approach, as later explained, is more robust versus mismatches between the training phase and the actual usage.

2.1. Computation of weighting coefficients

Weighting coefficients α_i can be computed with different approaches, depending on the evaluation of the measurement uncertainty.

(1) If the parameter Y is estimated by a single model, uncertainty can be estimated at runtime using the measurements repeatability and the difference between the model prediction and the experimental data.