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VIBROMOD – An experimental model for change detection and diagnosis problems

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Abstract – **The objective of the paper is to introduce an experimental model (VIBROMOD) designed for solving change detection and diagnosis problems in various fields of applications, mainly vibration engineering. The hardware structure contains two basic levels: one for fast computations and alarms, which processes data in a matter of hours, and, an upper level, for large-scale monitoring and statistical computation of moments, over a time span of days and months. The algorithms running on VIBROMOD are coming from a specialized toolbox, which contains classical methods, based on statistical signal processing techniques, but also some advanced methods, based on time-frequency and information transforms. The monitored interaction between VIBROTOOL and VIBROMOD is the goal of a large project called VIBROCHANGE, and allows for rapid implementations, checking and testing of various algorithms and the development of benchmarks as well, for change detection and diagnosis problems**.

I. INTRODUCTION

Change detection and diagnosis (CDD) is an important scientific and technical problem. It is present in the monitoring of some usual vibrational systems, and in many complex pieces of equipment as well. They could be associated with high risk activities, such as: energy production (thermo, hydro, nuclear), crude oil extraction, chemical plants, high power machinery and industrial equipment, etc. (see some reference papers, such as [1] to [5], with different points of view concerning system theory, signal processing, or system engineering). Many applications on this subject make use of theories based on statistics, [6] and [7], which provide the theoretical instruments for solving the problem of early detection. Such a theory is referred to as the local approach [8] and is based on the transformation of the general detection problem into a classical problem of monitoring the mean of a Gaussian vector variable. Another approach is based on the signal-processing paradigm, signals coming from the observed process, most commonly vibration signals. It is also the case of this work.

The vibrations' analysis and surveillance of the machinery's or industrial equipment's correct functioning represent important cases in the detection and diagnosis problems, e.g. [9] and [10]. There are two basic approaches in CDD, which can be shortly described as based on quantitative models (using analytical redundancy), see e.g. [11], and qualitative models. Regarding the existing challenges of the CDD domain, there is still a "gap" between the theoretical results and the applications. This is mainly caused by the requirements of some "strong" hypotheses in the existing algorithms, which are not easily verified in practice. These hypotheses are connected to the non-unique model, the nonlinear and variant properties of the process and high-level noise with unknown properties. Another challenge is the time restriction in the case of real time applications, when low computation effort is possible and reduced order models have to be used, but without reducing the performance of the detection and diagnosis system.

The success of any new method and the optimal arrangements of algorithms used in CDD require specialized functions and tools, software and hardware, for various primary and secondary tasks, i.e. experimental models dedicated to the CDD problem.

From a software point of view, there are many trials for toolboxes designed for the MATLAB environment, for education and research purposes, e.g. the signal processing group [12] which lists more than 35 domains with more than 200 links for such toolboxes. A very simple tool implements an interesting nonparametric sequential change-point detection test that uses the Intersection of Confidence Intervals rule, [14], to monitor the evolution of the data generating processes. The method introduces a two-level hierarchical change detection test, [15]. The major application field is machine-learning community. Another toolbox is CPMD, a MATLAB™ Toolbox for Change Point and Constraint Motif Discovery. The toolbox contains a set of routines for solving change point discovery problem and motif discovery problems as well as several supporting routines for evaluation, test dataset generation, etc., as described in [16] and [17] . The major application field is robotics and man-machine interaction. DETECT (DETection of

Events in Continuous Time) is a MATLAB™ toolbox for detecting event-time intervals in long, multi-channel time series, [18]. The major applications are in medicine for detecting signal artifacts found in continuous multi-channel EEG recordings and show the functionality of the tools found in the toolbox. A pair of two toolboxes is developed also by Gustafsson: (1) A Change Detection and Segmentation Toolbox, [19]; (2) Matlab Change Detection and Adaptive Filtering Toolbox, [20]. Both packages contain mainly methods belonging to the statistical signal-processing field. The toolbox features the algorithms and examples of the text book [21]. The core of the toolbox consists of adaptive filters for recursive system identification and state estimation, together with a variety of change detectors.

There are also commercial equipment, e.g. [29] or [30], but which the software for and hardware units cannot be easily updated or changed by the end users. The present work presents an experimental model for which both software and hardware blocks could be changed without major difficulties. The paper is organized as follows: Section II highlights the framework of the VIBROCHANGE project, which supports the development of the toolbox and experimental model. Section III introduces the toolbox developed for the CDD problem plus some examples based on advanced methods of data processing. Section IV presents the main structure of the experimental model, mainly from hardware and data management point of views.

II. THE VIBROCHANGE PROJECT

The project is under development but on the final stage. Alternative information is available on its web page, [13]. In Fig.1 the basic blocks are presented. The first block, VIBROGEN, emulates the process in laboratory conditions, i.e. generates vibration under imposed and controlled working regimes and parameters. The electro-mechanical process generates vibrations. The mechanical elements are open, in the sense that they accept incipient faults. The parameters of the working regimes and load conditions are under computer-based control. The range and rotation speed can be modified, under various and imposed slopes. The electrical load is able to change the mechanical working regimes of the system.

The VIBROTOOL implements various, classical and advanced change detection and diagnosis algorithm, all under the MATLAB™ modeling and simulation environment. It is set of programs for CDD activities. This toolbox is described in the next section. Some of the algorithms developed in this toolbox are implemented also in an experimental model, called VIBROMOD. The VIBROTOOL and VIBROMOD receive the same data about the vibration signals, and finally should indicate the same results.

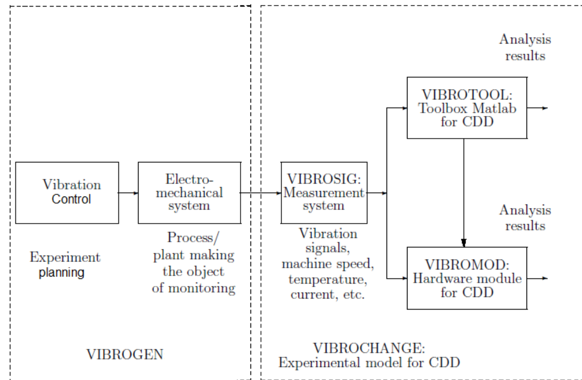

Fig. 1. The main processing blocks involved in the VIBROCHANGE project

The VIBROMOD represents the experimental model, which is a customized hardware structure arround a kernel based on PLCs (Programmable Logic Controllers). At the higher levels, JavaTM based software is used.

III. THE STRUCTURE OF THE VIBROTOOL

VIBROTOOL is a toolbox for the CDD problem, built as a set of programs that compute specific parameters and solve specialized tasks for change detection and diagnosis, and point changing estimation as well. The algorithms make use of classical techniques (pattern recognition, maximum likelihood, model-based techniques, novelty detection, and blind separation) and some of the more recent techniques (multiresolution analysis, soft computing, and information fusion).

The toolbox allows: (1) developing new theoretical and algorithmic CDD concepts and techniques for diagnosing machinery and industrial equipment; (2) developing practical and commercial products for monitoring and maintenance. The main building blocks of computing, signal processing of vibration are presented in Fig. 2. There are many ways in which the building blocks of computing can be interconnected in order to resolve some problems related to the monitoring of rotating machinery. The preprocessing of the vibration signal includes a series of three modules (blocks), as shown in the left side of Fig. 2: PRO1: calculation of statistical parameters of the signal. 11 statistics parameters (mean, median, rank, dispersion, standard deviation, rectified average, root mean square, maximum peak, crest factor, degree of inclination, kurtosis), the probability density function (histogram); PRO2: calculation of Fourier amplitude spectrum. The resulting information will be used for diagnosis (the location of a possible malfunction); PRO3: filtering the signal components in low pass, high pass, band-pass, or depending on the objectives pursued.

In the current stage, the toolbox contains the following software modules: (1) Programs for primary processing of signals (PRO): 3 modules + 1 demo; (2) Programs for the detection and segmentation of changes (CDS): 8 modules + 4 demos; (3). Programs for blind separation of sources (BSS): 2 modules + 2 demos; (4) Software for analysis of time-frequency (TFR): 15 modules + 5 demos. The four categories of program modules contribute to solving a problem of monitoring purposes CDD for rotating machines, as follows: (1) the PRO module allows for a first analysis of the phenomena's characteristics produced in the machine's operation, providing information on how they would continue investigations; (2) the CDS module allows for a first CD detection of changes in the measured vibration signals, or in the main sources of vibration, determined with programs in the BSS module, including signal segmentation analyzed in areas with similar characteristics; (3) the BSS module will allow for the separation of blind sources using instant second order statistics (SOBI) and higher-order statistics (JADE - Joint Approximate Diagonalization of Eigen-matrices) to real signals; (4) the TFR module allows viewing time-frequency representation, group delay calculation and variance of the estimators, instantaneous frequency and variance of the estimators, calculating limits and representation, energy calculation of Renyi entropy for a real signal with various class distributions.

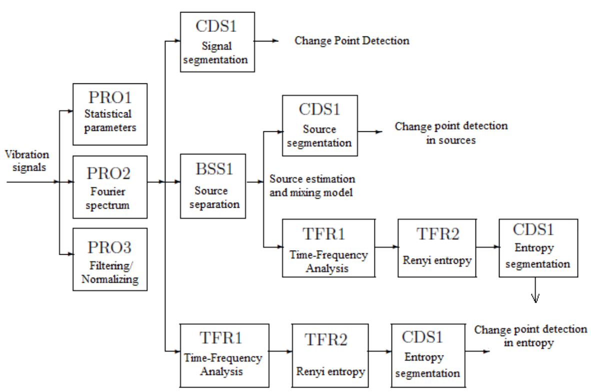

Fig. 2. The main computation block in VIBROTOOL

The toolbox is operational in the Matlab environment, version 4.0 or upper, and appeal to the toolbox MATLAB™ sites: IDENT, intended for identification, and SIGNAL systems, for signal processing, as well as to some components from public MATLAB software, see e.g. [22].

Two new methods are presented below, methods which are not considered elsewhere. These are specific to VIBROTOOL as absolute novelties. One of the methods is based on the envelope detector function implemented with the help of Hilbert Transform. The Hilbert transform is computed by using the standard Discrete Fourier Transform, following the method described in [23]. The distance between the envelope $\mathbf{S}^{+}$ of the signal having changes and the signal without changes, $\mathbf{S_0}$, is computed next. When the distance is greater than the imposed level, *k*, the decision variable is triggered. The advantage of the approach is the high accuracy in tracking the envelope of the signal, even for high derivative slopes as the transient signals have. An example is presented in Fig. 3 for a rectangular based signal.

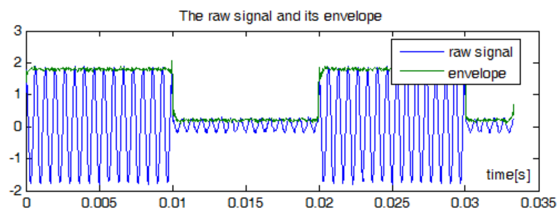

Fig. 3. Envelope detection for change detection for impulse-based signals

The second method considers the second order Renyi entropy, defined by

$$H_2(\mathbf{P}) = -\log\left(\sum_{j=1}^{N} P_j^2\right) \tag{1}$$

where $\{P(j)\}$ are the probabilities of a finite set of independent events from a discrete information source model as

$$S:\begin{pmatrix} x_1 & x_2 & \dots & x_N \\ P(x_1) & P(x_2) & \dots & P(x_N) \end{pmatrix} \tag{2}$$

with

$$\sum_{j=1}^{N} P(x\,j) = \sum_{j=1}^{N} P_j = 1 \tag{3}$$

The computation of entropy needs the availability of the exact or estimated probability density function (pdf). If we consider sets with *N* records and observation vectors of size $mx1$, $\mathbf{a}_i$, the pdf could be estimated by using a Parzen window [23] with Gaussian kernel

$$\hat{p}(\mathbf{x}/\mathbf{a}_i) = \frac{1}{N}\sum_{i=1}^{N} G(\mathbf{x}-\mathbf{a}_i, \sigma^2\cdot\mathbf{I}) \tag{4}$$

where $G(.,.)$ is the Gaussian function

$$G(\mathbf{x}-\mathbf{a}_i,\sigma^2\cdot\mathbf{I}) = \frac{1}{\sqrt{(2\pi\sigma^2)^m}}\exp\left(-(\mathbf{x}-\mathbf{a}_i)^T\cdot(\mathbf{x}-\mathbf{a}_i)/2\sigma^2\right) \tag{5}$$

σ^2 is the variance, and $\mathbf{I}\in R^{mxm}$ is the identity matrix.

The Renyi entropy estimator is, [24]:

$$\hat{H}_2(\mathbf{x}_m, \sigma) = -\log \frac{1}{N}\sum_{n=1}^{N}\left(\frac{1}{N}\sum_{k=1}^{N}\left(G(x_m(n)-x_m(k),\, 2\sigma^2\right)\right) \quad (6)$$

According to [25], a more efficient relation is

$$\hat{H}_2(\mathbf{x}_m, \sigma) = -\log \frac{1}{N}\sum_{k=1}^{N}\left(G(x_m(k)-x_m(k-1),\, 2\sigma^2\right) \quad (7)$$

The entropy estimators require the selection of the kernel size, σ. This should be small (relative to the standard deviation of the data). Values between 0.1 and 2 for unit-variance signals are good choices. Two examples are presented in Fig. 4 for a random signal with changes in variance, from 1 to 2, and for a signal with multiple components, of various frequencies from 200 to 500 Hz. By Renyi transform the changes in the input signal are mainly transformed in changes of the mean, and a CUSUM test procedure could be applied, as in [27] or [28]. At the bottom of the figure, the evolution of the change criterion based on cumulative sum test is presented. The changes in the slopes of the criterion suggest a change in the input signal.

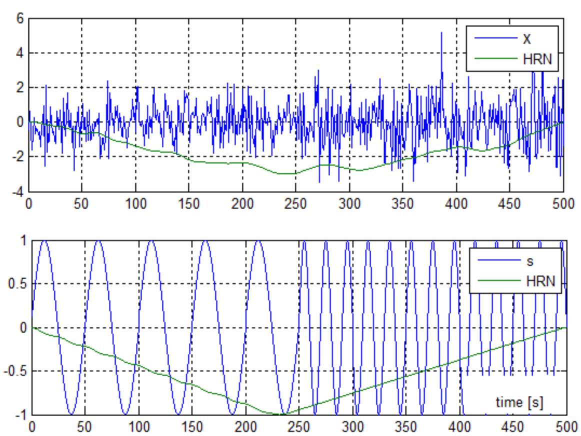

Fig. 4. Example of change detection by Renyi entropy

IV. THE STRUCTURE OF THE VIBROMOD

The basic structure of the experimental model is presented in Fig. 5. Two levels could be identified. The bottom level is for signal acquisition and pre-processing of the vibration signals, as generated by the monitored process. At this level, some indicators and statistical moments could be represented. This is made by a set of customized block based on PLCs (Programmable Logic Controllers). The time interval for the bottom level start from one min and it is going to one hour. At the end of this interval, synthetic coefficients and statistic moments are transmitted to central unit (server), to continue the processing based on various transforms and records. This is the second level of the application.

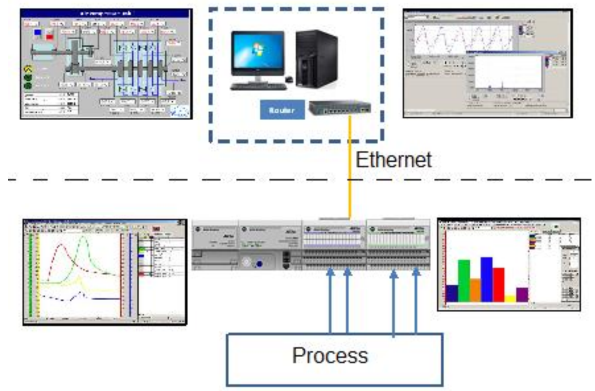

Fig. 5. Structure of experimental model

The block structure of data acquisition is presented in Fig. 6 and it is designed to provide a first image about the hardware structure of the experimental model, the from input (vibration) signals up to working memory. The module has a number of NV = 4 channels vibration with synchronous acquisition and conversion, plus a number of auxiliary NS = 4 channels for other variable of interest, e.g., temperature, current speed, etc. The maximum number of channels is $N = NV + NS = 8$. The lower part of Fig. 6 shows the vibration signals acquisition process. It is considered a band of frequency of vibrations from HPF (High Pass Frequency) = 100 Hz up to LPF (Low Pass Frequency) 5000 Hz. Both filters are of analog type (Cebisev) of order n = 2, with 1 dB ripple in bandwidth. This is followed by a voltage amplifier with gain between 10 and 100. The conversion to numerical signal is made with a sampling frequency FS = 10…20 kHz, each sample on 12-bit. For each channel of vibration, a frame of NV = 2048 … 4096 samples is stored and processed. For the NV channels, it gives an array of samples of vibration **V** of dimension to nv x nv. The data length of the observation (data frame) and the frequency resolution is variable, and might be changed and adjusted according to the required resolution of methods of detection from frequency domain. At the top of Fig.6, additional signals such as speed or different electrical currents are measured and processed. The structure is similar to the processing of vibration, but the number of stored samples (samples and thus frequency) is much smaller, due to the large time constants of these physical parameters (speed, for example). A value of ns=512 is considered to be sufficient, and will be changed if necessary. Data coming from this processing chain's output is stored in an array of data called dimension ns x NS. Fig. 7 is a description of the experimental model's data management structure. It processes data on three time levels (stairs): (1) the process level (1 min., elementary interval time (e.i.t)), the lowest level; (2) the laboratory level (1 hour, e.i.t.); (3) the enterprise level (1 day, e.i.t.), the highest level. At the lowest level, numeric data from the process, vibrations and additional sizes are processed to calculate some statistical parameters (in time domain) and sizes in frequency domain or other variables of interest (for example entropies) (not presented in the figure). These sizes are calculated and saved with a period of 1 min.

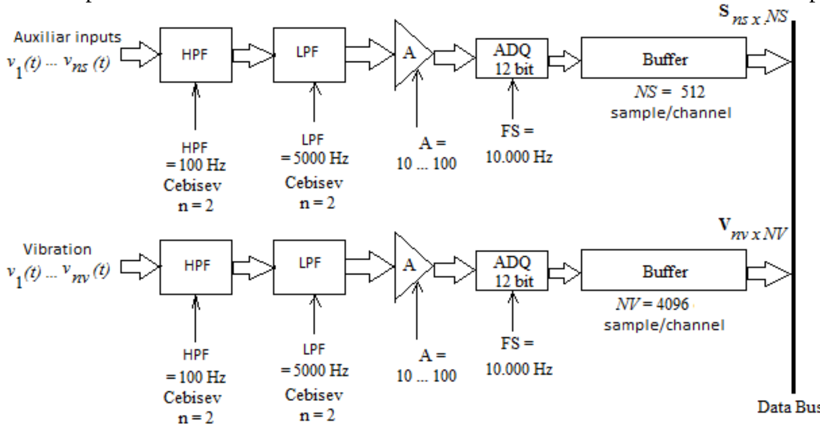

Fig. 6. *The hardware structure of the acquisition module*

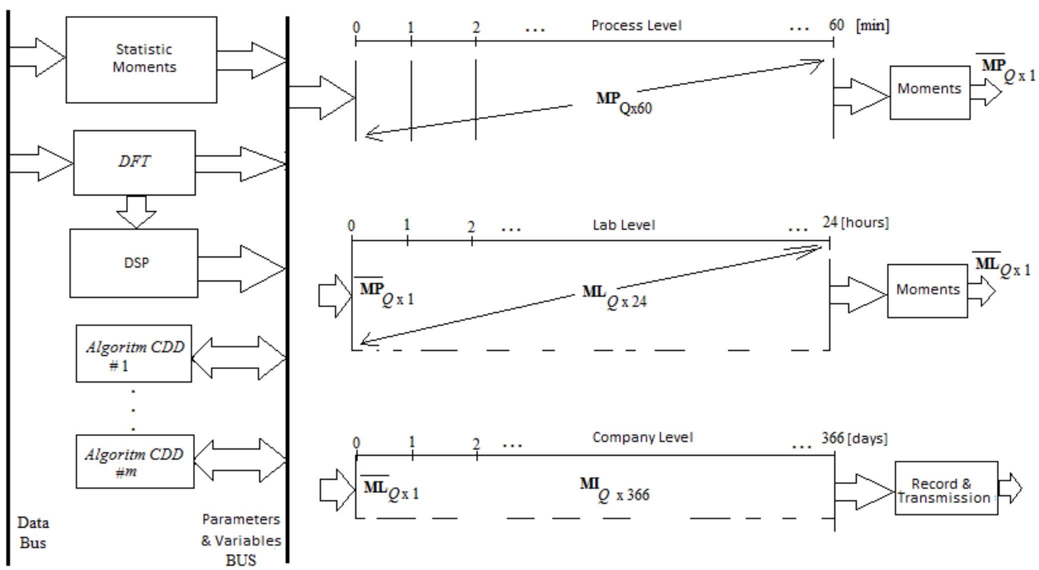

Fig. 7. *Data flow in experimental model*

The number Q of these records depends on the number of the parameters and variables used in the upper levels to implement various transforms. At the laboratory level, the data is saved at the end of each hour. At the enterprise level, the data is updated at the end of each day, so with a period of 24 hours. At each level, the data is described through two-dimensional arrays (matrices). At each level, the first input is saved in the first column of the data array. Before saving, the data is moved of the right direction, under a cyclic permutation process. When a database has been completely updated, the statistical averages made on lines will be forwarded to the next level. At the last level, the enterprise level, data processed or not is recorded on hard media (HDD or CD) and will be sent to the server for further processing. For each CDD algorithm, which is implemented in the experimental model, an entry window is presented for setting working parameters and an output window to display its results. A command input-output text window is used to describe/present the information about the state of the monitored process.

CONCLUSIONS

An experimental model designed for solving CDD problems in various field of applications, mainly vibration engineering, was presented. The hardware structure has two basic levels: one for fast computation and alarms, which processes data in a matter of hours, and, an upper level, for monitoring and statistical moment's computation, spanning a time interval of days and months. The algorithms running on VIBROMOD are coming from a specialized toolbox, which contains classical and advanced methods based on statistical signal processing techniques but also some based on time-frequency and information transforms. The basic functions and modules of VIBROTOOL were also presented together with some examples of advanced methods used in CDD, and based on Renyi entropy, for information representation and processing, and Hilbert transform, for envelope detection of rapid varying of impulse-based signals or spectra. The monitored interaction between VIBROTOOL and VIBROMOD, allows the rapid implementation and checking of various algorithms for CDD problems and the development of benchmarks for change detection and diagnosis problems. The basic CDD application will use vibration signals from electrical equipment which have rotating elements. Other dynamic processes could be considered, as those from seismic or biomedical engineering.

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