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Combined Preprocessing Methods for Leak Locating Systems

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Abstract –Real leak signals, acquired in industrial pipeline systems may manifest two typical non stationary signatures: abrupt amplitude random changes on one side and a time varying mean on the other side. This paper proposes a pre-processing algorithm for extracting stationary information from the received signals, in order to improve the leak location on the pipe. This method combines the wavelet de-noising technique with a segmentation algorithm. Comparative results show that, in addition, by using a pre-whitening filter and closing the pipeline's end, improved estimates can be obtained.

Keywords: leak location, time delay estimation, stationarity index,.

I. INTRODUCTION

In a pipeline transport system early detecting and locating leaks is a problem of great economical significance. One of the most known methods for leak locating is based on the analysis of the acoustic noise generated by the fluid passing through the leak. The leak locating principle consists of estimating the time delay at which the leak signal reaches at two separate locations on the pipe [8],[9],[10]. The linear mathematical model usually used for this problem is described by:

$$\begin{cases} r_1(t) = s(t) + n_1(t), \\ r_2(t) = s(t-D) + n_2(t) \end{cases} \quad (1)$$

where $r_1(t)$, $r_2(t)$ are the received signals, $n_1(t)$, $n_2(t)$ are the additive noises at the sensors' locations, s(t) is the primary source leak signal and D is the time delay which has to be estimated. The leak position is then derived from the noise propagation velocity and the distance between the measuring points. For estimating the time delay, a typical method is to compute the acquired signals' cross-correlation function and to find the argument at which its maximum occurs [1],[4]. This technique works well for signals with ideal features i.e. stationary, white, Gaussian, uncorrelated with the disturbing noises. In practice, the leak signals prove to perform certain random mean and amplitude variations due to the disturbing noises that act in the pipeline system [7]. Fig.1 presents three typical real leak signals that have been captured in a real pipeline installation. The top signal performs a number of abrupt amplitude variations with a random occurrence, the middle one is characterized by a random varying mean while the bottom signal has both amplitude and mean changes with time.

This paper studies the possibility of bringing the imperfect acquired signals to a form that tends to reach the ideal features enumerated above, by proposing a pre-processing signals' treatment. Briefly, this procedure combines the wavelet de-noising technique for cancelling the low-pass noise component, with a stationarity index based segmentation algorithm for avoiding the amplitude bursts, and the innovations representations, for signals' whitening [2],[3],[5],[6]. This procedure is described in section 2. On the other hand, results emerged from an experimental study in which the "hardware" operation of closing the pipeline's end was allowed, proved to bring considerable improvements especially regarding the signal-to-noise ratio and stabilizing the signals' amplitudes.

A comparative study on real leak signals, acquired in both pipeline operating modes (without and with pipeline's end obstructed), is presented in section 3.

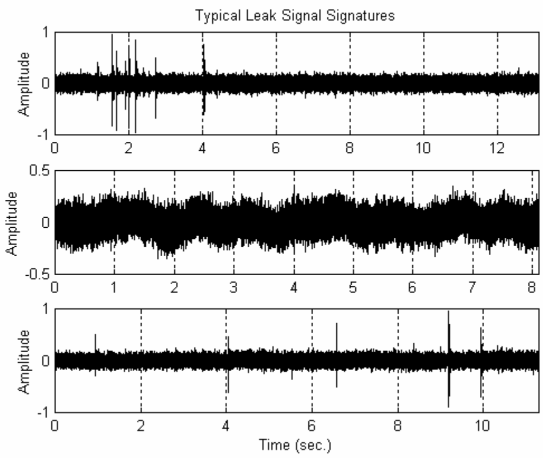

Fig.1 Typical leak signals

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II. THE COMBINED METHOD

The block diagram for the proposed technique is presented in fig.2, while fig.3 shows some comparative cross-power spectral densities (*CPSD*'s) for the leak (R_{12}) and noise (N_{12}) signals before and after applying the algorithm, respectively.

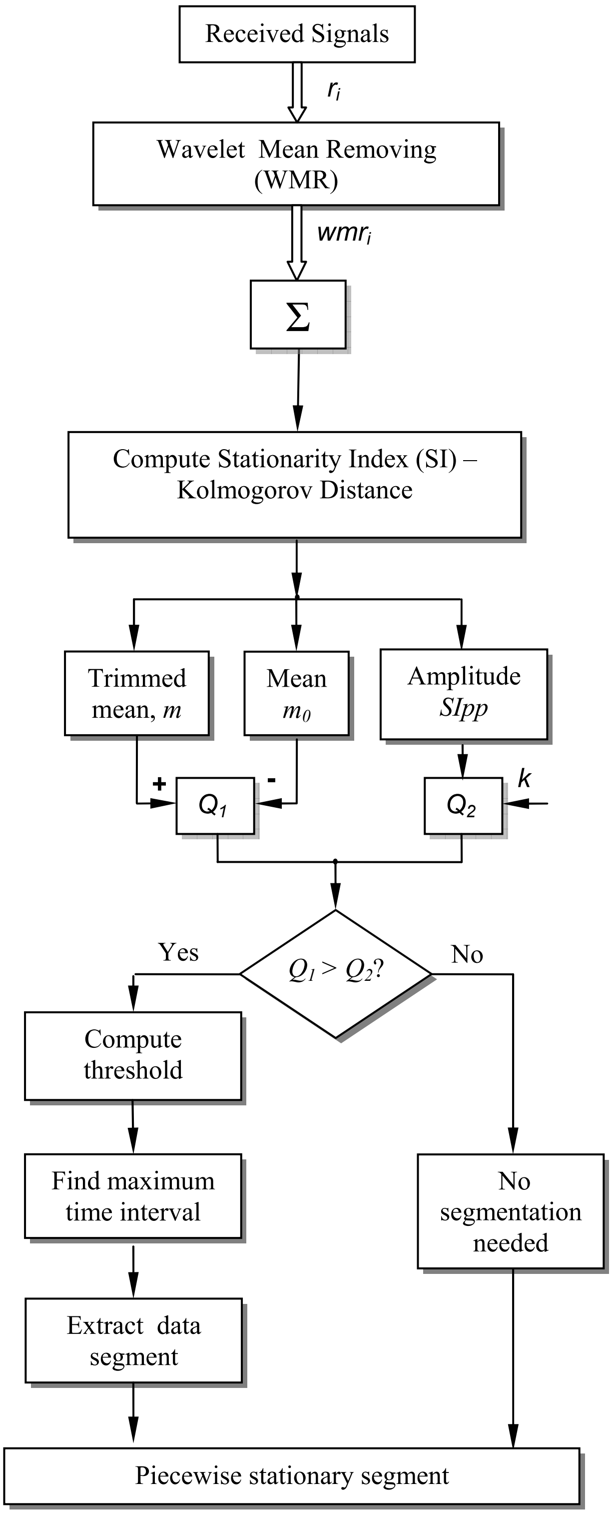

Fig. 2. Algorithm block diagram.

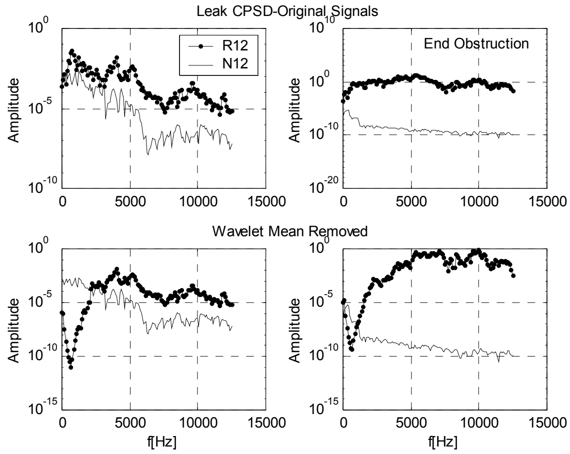

Fig.3 Typical cross-power spectral densities for leak (R_{12}) and disturbing noise (N_{12}) signals.

Use As shown in fig.2, the pre-processing algorithm consists of two major parts. Firstly, the low-pass component is removed from the received signals using the wavelet de-noising technique [11],[12], according to:

$$wmr_i = r_i - rd_i \tag{2}$$

Here, *rd* denote the signals obtained by wavelet de-noising, *wmr* denote the signals resulted by removing the "mean" or low-pass part, and i=1,2. The reason for doing this was based on the observation that both the leak signals and the disturbing noises spectra practically overlap in the low frequency domain and become distinct otherwise, as shown in fig.3, top left-hand corner. By applying (2) a certain part of the disturbing noise is removed from the signal and only the remaining spectral components that distinguish the leak from the background noise is further processed (e.g. fig.3, bottom left-hand corner). In this case the background noise is practically given by the pipeline's main stream. On the other hand, by closing the pipe's end the background noise is considerably reduced, and the leak signal is enhanced, as shown in the right part of fig.3.

The second step of the algorithm consists of extracting piecewise stationary segments of maximum length from the resulted signals, by avoiding their non-stationary amplitude parts. This method is based on computing the stationarity index (SI) [3],[6] of the signals' sum, according to the following relationship (Kolmogorov distance):

$$SI(t) = \int_{\tau=0}^{p} \int \left\| TFR(t-p+\tau, f) \right| - \left| TFR(t+\tau, f) \right\| df d\tau \tag{3}$$

where TFR is the time-frequency representation of two sub-images around the time instant t; p is the sub-image's width and τ is a time variable, $\tau \in [0, p]$.

In the upper part of fig.4 is presented the SI function computed by (3), for the first signal in fig.1. It can be observed that this function performs sharp peaks corresponding to the signals' amplitude abrupt changes, and is nearly constant otherwise. Fig. 5 shows the same function computed for a signal of the second type (fig.1, middle). In this case, there are no rapid changes in the signal, and the function is nearly constant in the entire time domain. In the first case the SI function's mean, m and its trimmed mean, m_0, (i.e. the mean after excluding a certain percent of the extreme values) differ more than in the second case. Based on this observation, the algorithm computes two quantities, Q_1 and Q_2, as in:

$$\begin{aligned} Q_1 &= \left|m_0 - m\right|, \\ Q_2 &= SI_{pp}/k, \end{aligned} \tag{4}$$

where SI_{pp} is the SI function's peak to peak amplitude and k is a constant factor. Next, the "Q" quantities are compared and if $Q_1>Q_2$, the algorithm decides that the signal pair needs segmentation. Otherwise, the entire data acquisition is considered piecewise stationary and is used for further processing.

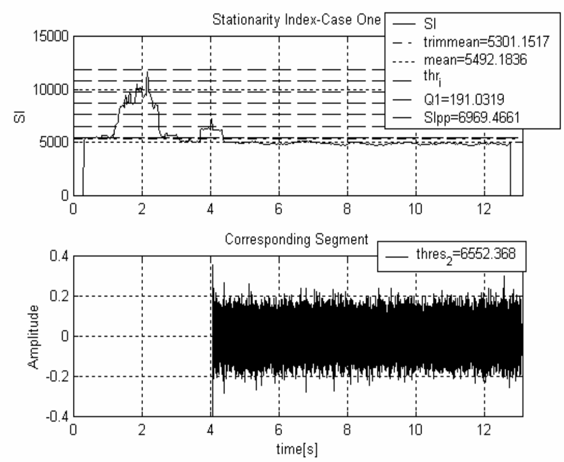

Fig.4 Extracting a piecewise stationary segment pair

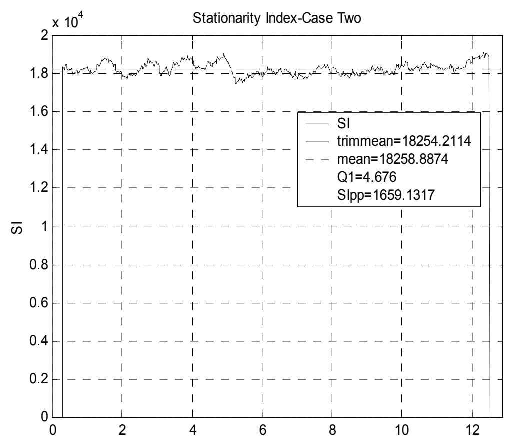

Fig.5 Case two- no need for segmentation

In the first case, a threshold level is next chosen based on establishing a tradeoff between the burst degree contained in the data and the segments' maximum time interval length. In the example from fig.4 the distance between the SI maximum and the trimmed mean, dSI, was divided in six equal intervals defining seven segmentation thresholds according to:

$$\begin{cases} thr_i = (i-1)\cdot \dfrac{dSI}{nlev-1} + m_0; i \in \{1,\dots,nlev\}, \\ dSI = \max(SI) - m, \end{cases} \tag{5}$$

where $nlev$ is the total number of thresholds and thr_i is the "i-th" threshold. It also can be noted that the last threshold is equivalent to the case of no segmentation. Finally, in the bottom part of fig.4 is shown a piecewise stationary data pair segment extracted through this procedure.

III. COMPARATIVE RESULTS

In order to evaluate the algorithm's performance, an experiment was initiated on a bended metal pipeline installation for water transportation of 12.82 meters length and 2.54 centimeters diameter.

In this experiment, the leaks were simulated by faucets for flow rate adjustments. The measuring points were equally distributed along the pipe at intervals of 0.3 meters.

Two working modalities were involved in this study, relatively to the pipeline's end: first without and then with the pipeline's end closed.

The acquisition system was composed of a pair of vibration sensors KD Radebeul, two amplifiers M60T with adjustable gain between 40 and 60 dB, anti-aliasing low pass filters and a dSPACE DS1102 board connected to a PC.

The processing algorithms were implemented using the MATLAB® environment. The time delay was estimated using the maximum likelihood processor [1], [4], directly (ML) or after pre-whitening the received signals (WML). The propagation velocity of the acoustic signals on the pipe was estimated beforehand. In the study that followed, one sensor was kept fixed while the other sensor was moved gradually from one measuring point to the next. The reason for doing this was to compare the estimation results based on two criterions: the deviation from the expected delay, (obtained from the prior estimated propagation velocity), shown in fig.6 (top) and the deviation from the proportionality on the pipe, knowing that the measuring points were equally distributed, (as in fig.6, bottom).

The two graphs on the left hand of fig.6 present the error power vs. the segmentation level. Here, the wavelet de-noising level was kept fixed and the pipeline's end was not closed. (In this situation, most of the acquired signals proved to need segmentation).

The curves obtained in the left part of Fig. 6 show that by processing the acquired signals with a combined WMR and WML algorithm, improved estimation results can be obtained, especially between the threshold segmentation levels three to six.

On the other hand, the remaining two curves on the right of fig.6 present the error power for the second working mode, with the pipeline's end obstructed.

In this situation, most of the acquired signals proved to need no segmentation, but in exchange they performed an accentuated mean variation relative to the entire signal, especially in case of small leaks (e.g. fig.1, middle). Here, the wavelet de-noising level was varied. The results obtained in this study show that the lowest estimation error was given by level four when using also a combined WMR and WML technique. Finally, fig.7 shows a comparison between the estimated delays for the most favorable results of no-end obstructing mode (WMR-WML) and the worst favorable results of the end obstructing mode (OWMR-WML). The conclusion is that the end obstructing mode gives the best estimation results.

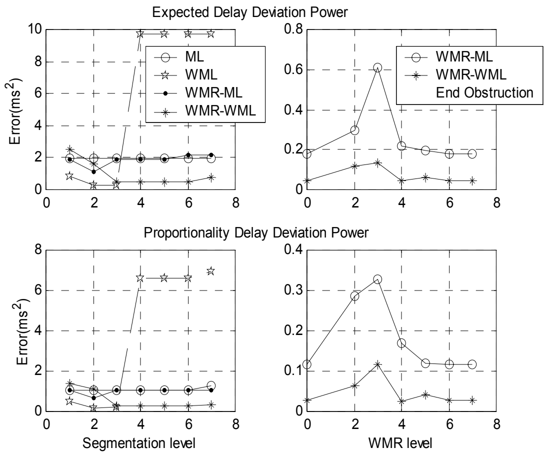

Fig.6 Comparative error power results

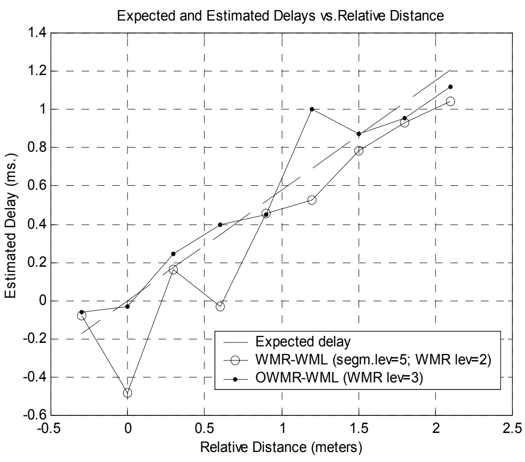

Fig.7 Results for the best (WMR-WML) and worst (OWMR-WML) cases obtained without and with end obstruction, respectively.

IV. CONCLUSIONS

Real leak signals prove to have a non-stationary behavior from both mean and variance aspects. These features represent a considerable obstacle in locating leaks. This paper proposes a pre-processing treatment in order to bring the acquired signals to a form that makes the classical algorithms easier to apply. The proposed method combines the wavelet de-noising, segmentation and whitening techniques. The best estimation results were obtained yet by closing the pipeline's end. Through this procedure, the rapid amplitude changes are avoided in majority of the cases and also the WMR method could be applied only for small leak signals.

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