Quantifying Intermittent Disturbances

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Abstract

Diagnostic techniques related to process control loop performance is not uncommon. In fact there are many different ways to identify process control issues. This paper will introduce a new method for identifying intermittent non oscillatory wave forms. The result of this disturbance identification method is fast, yet accurate, and can help quickly identify intermittent issues in 100's of controllers at a time.

Introduction

This paper has roots to the paper industry. Several years ago a problem related to intermittent issues was solved. However, that solution was focused on cross direction profile applications. This paper will focus on how this solution was rotated 90 degrees so that it can be applied to time based signals. The following figure shows the difference between cross direction and machine direction data series.

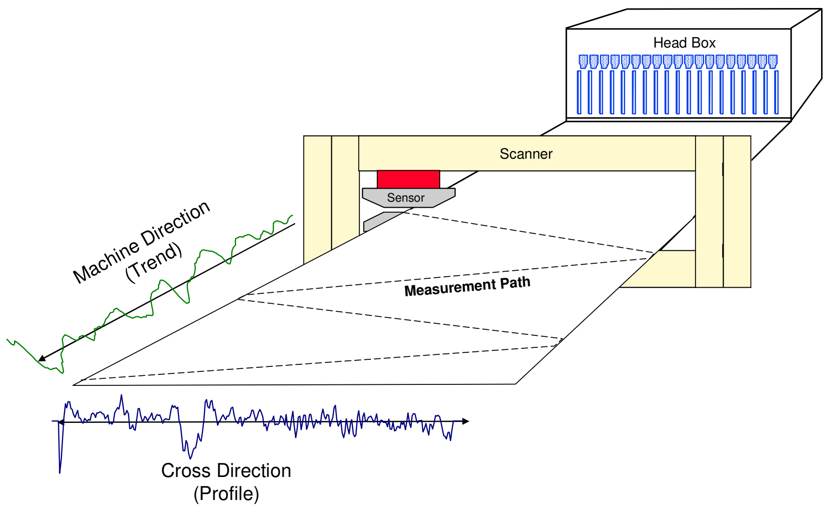


Figure 1: Measurement System

As the sensor head moves from one edge of the sheet to the next, sensor data is converted into profiles that align in the cross direction and trends that align with the machine direction. Machine direction trends are time based measurements that can be thought of as measurements that are typically found in industrial transmitters such as flow, pressure, temperature, consistency, etc.

This paper will first review the solution as it applies to cross direction applications and then build on this solution to solve the problem related to intermittent time based measurements.

Cross Direction Intermittent Disturbance Identification

A common measure of profile variability is the 2 sigma (2σ) as defined in (1).

$$2\sigma = 2\left(\sum_{i=1}^{n}(p(i)-\overline{p})^2/n\right)^{\frac{1}{2}} \qquad (1)$$

Where $p(i) \quad 1 \le i \le n$ is a profile, $\overline{p}$ is profile average and n is the size of the profile

The 2σ is a global index that measures the variability across the entire sheet. A profile is bound by the first and last measurement in scan. In other words, there is no data before or after the last measurements. Typically the units of measure in a cross direction profile are spacial in nature rather than time. The calculation of the 2 sigma is a very effective measure of the variability of the entire profile. However, it is rather ineffective for indication of localized variability. Figure 1 shows two profiles with identical 2σ, but having significantly different localized uniformity. If only the 2σ of the profile is used to evaluate profile performance, then the localized variability of the second profile will never be detected.

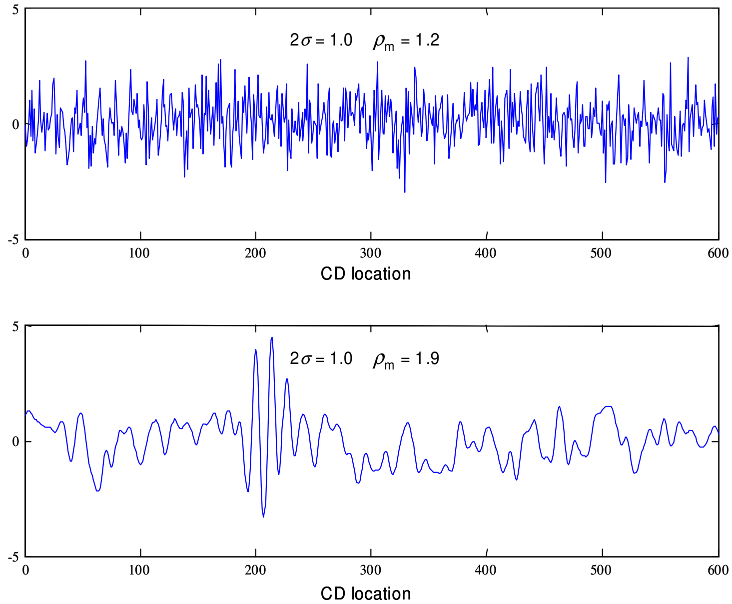


Figure 1 - Profiles with identical 2σ but different localized uniformity

There are several issues that can cause local issues in a profiles and those are defined in the paper referenced at the end of this paper. This paper is not concerned with the source of the problem, but the detection of the problem. Figure 2 is easy to pick out the area of local problem with the human eye, but it is difficult to mathematically find where or when this wave form is presented. The mathematical identification solution for finding this local variability problem is shown as follows.

Based on the definition in (1), the global measure of profile variability, 2σ, is calculated for the entire width of a profile. In other words, the 2 sigma is a function of the first and last measurement in the profile. The localized measure of profile uniformity can be defined for a localized window of a profile as indicated in Figure 2.

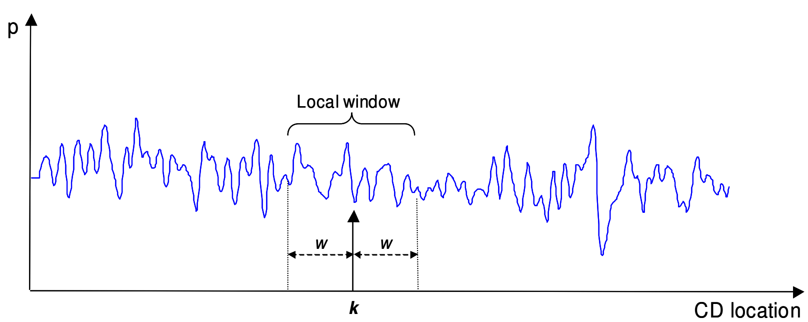


Figure 2 – Definition of Local Variability Index $\rho(k, w)$

The local measure at the location k is a normalized variability over a localized window width, $2w+1$. This measure is called the "Local Variability Index" and is denoted as "$\rho(k,w)$". The Local Variability Index $\rho(k,w)$ is defined as

$$\rho(k,w) = \left(\sum_{i=k-w}^{k+w} (p(i) - \bar{p}_k)^2 / (2w+1) \right)^{\frac{1}{2}} / \sigma \tag{2}$$

where w is the window size as indicated in Figure 2 and $\bar{p}_k$ is the local profile average over the specified window.

Basically, the standard deviation of the local window is compared with the standard deviation of the entire profile. If the ratio is 1, then the local window and global window have similar variations. Theoretically, the local variability index $\rho(k,w)$ is a function of its location k and the selected window parameter w. In practice, a fixed window can be used for all locations so that the derived local variability indices at difference CD locations can be compared with each other. The maximum ρ_m, as defined in (3), among all locations can be used as a single index of the localized variability of the entire profile. The severity of local variability of a profile is quantifiable with a single value, ρ_m. The maximum local variability index ρ_m, together with 2σ, gives users very good measures of both local and global variability for any profile.

$$\rho_m = \max_k (\rho(k,w)) \tag{3}$$

Figure 3 gives an example of using both 2σ and ρ_m to quantify profile global and local variability respectively. The 2σ's of all profiles in this example are at a normal level even in the presence of several severe local picket fences appearing in some of the profiles. The occurrence of the picket fence pattern is well correlated to the change in the ρ_m value. This indicates that ρ_m is a good measure of localized uniformity.

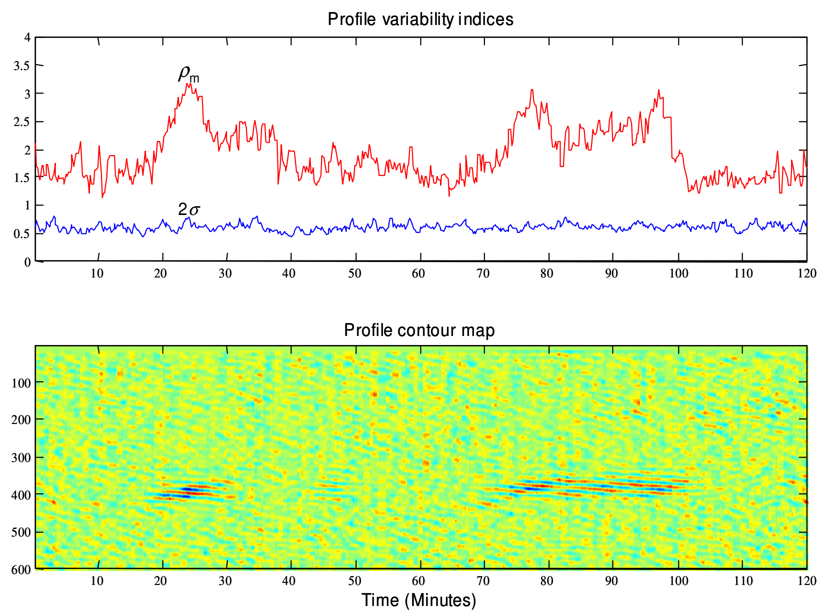


Figure 3 – Example of using 2σ and ρ_m to quantify performance

The index ρ_m is useful for quantifying the effect of non oscillatory disturbances in the measured profiles.

Machine Direction Intermittent disturbance identification

Machine direction signals are time based signals. These signals have characteristics that match common PID controlled measured values. There are several functions available for solving different persistent based wave forms. However, intermittent issues related to, pumps starting or stopping, cleaning cycles, power and grounding failures, surges, etc. often pass through persistent based disturbance identification methods. The LVI (Local Variability Index) described in the CD Profiles section above can be used to identify those signals with intermittent disturbance in the time domain. The following figure illustrates the definitions of the necessary windows.

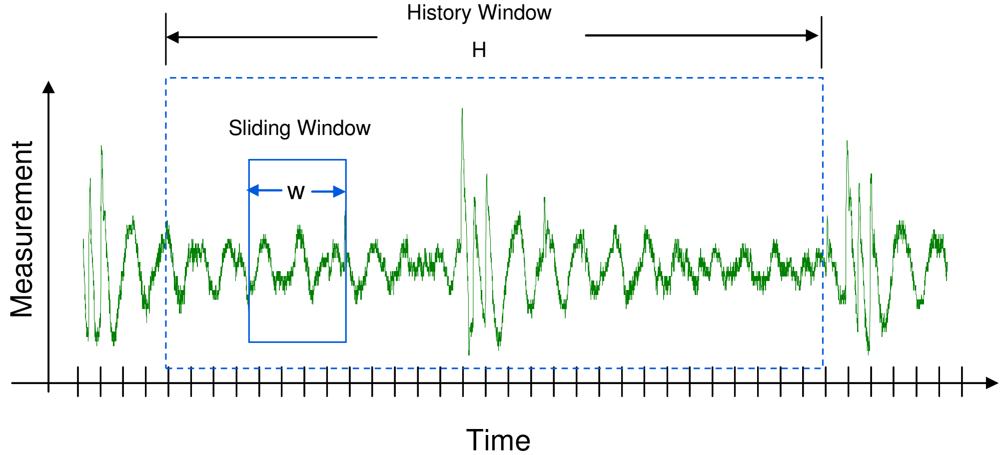


Figure 4: Time Measurement Signals

In the time domain, the data is not bound to the edge of the sheet. In other words there is data before and after the start of the history window. Therefore a bound has to be defined. In this case the history can be identified by the user, but it is often set to cover the span associated with 12 hours of information. Typical sample rates are 5 to 10 seconds. Once a collection or history buffer has been defined, the global sigma will be derived from the history buffer. The local variable will be defined by a sliding window of width w. W is typically defined by the user but values associated with 5 to 10 minutes of data are sufficient. Once the history and sliding window sizes have been set, the LVI equation used in the CD discussion is exactly the same. In this case the local variability of the sliding window at a point in time ($\rho(k,w)$)is defined as:

$$\rho(k,w) = \left(\sum_{i=k-w}^{k+w} (p(i) - \overline{p}_k)^2 \, / (2w+1) \right)^{\frac{1}{2}} / \, \sigma$$

where w is the sliding window size and $\overline{p}_k$ is the local signal average over the specified window (from index i-w to index i+w) and σ is the variability (standard deviation) of the entire history window (H) of the signal time series data.

For continuous monitoring, the term step size is introduced. Step size defines when the next history or batch of data should be analyzed. Step size can be defined in number of samples, amount of time, or in percent of the window size. If percent is used and the step size is 100%, then the first sample of the next history will start after the last sample of the previous history. In the following example, the step size percent is shown greater than 100 percent.

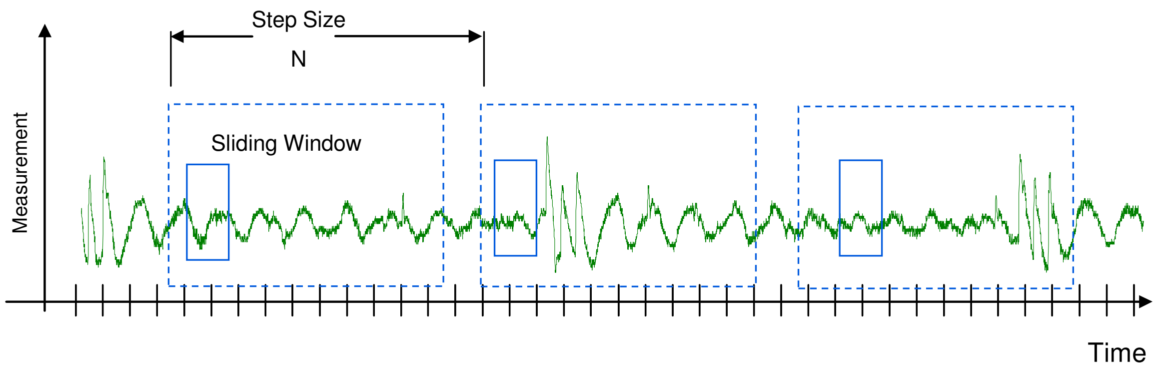


Figure 5: Step size

The conversion of the LVI calculation into a trend helps users visually see where local variability is present. A trend of LV is simply the time results of the ratio of the sliding window variability to the history variability. The following example shows the raw data associated with a single history buffer and the associated LVI trend.

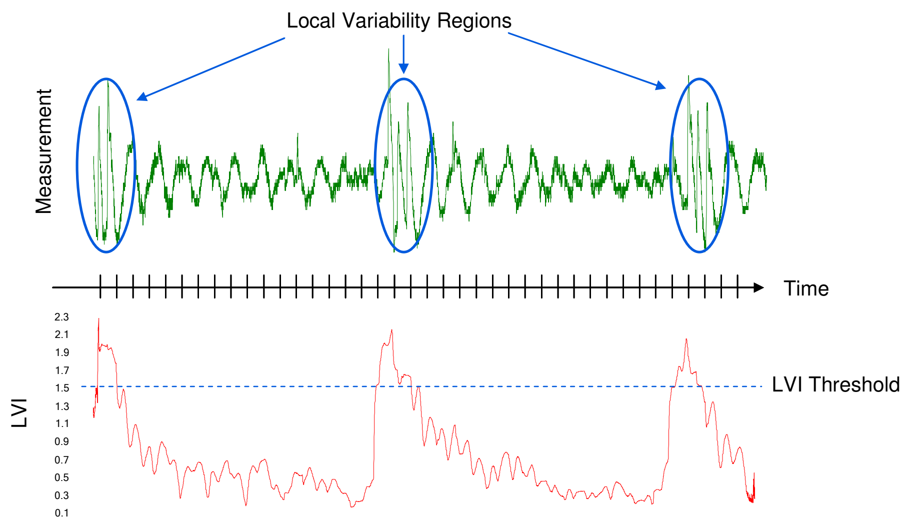
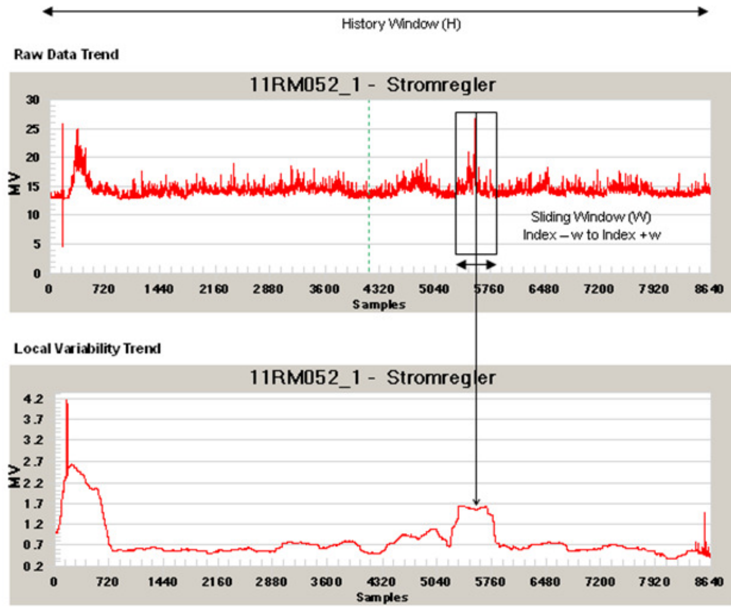


Figure 6: LVI Trend with Threshold

Trending the LV for a history allows a user to easily identify where regions of local variability are located. Since intermittent (local) disturbances affect the variability of the sliding window more than the variability of the entire history, the LVI for points near intermittent disturbances will be greater than 1.0. The ratio of the sliding window and history window variability will grow with the intensity of the intermittent disturbance. Comparing the ratio to a threshold allows for automatic detection of signals being impacted by local variability. Typical threshold values are 1.4 to 1.6. A value of 1.5 means the variability of the sliding window is 50% higher than the global variability. Those signals which have runs of consecutive LVI values that exceed the LVI threshold are considered to have intermittent disturbances.

There are several statistics that can be applied to the LVI trend. Four common ones are shown in the following figure.



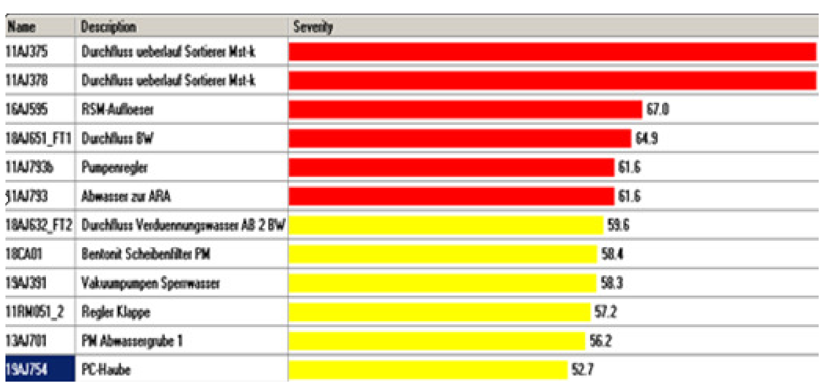
LVI Max	3.653	LVI Mean	0.7236
LVI Max Run	509	LVI Severity	48.51

Figure 7 – Example of a PID MV signal with intermittent disturbances and LVI statistics

Where:

- LVI Max is the maximum LVI value for the entire history window.
- LVI Max Run is the maximum number of consecutive LVI values in excess of the LVI threshold (1.5).
- LVI Mean is the mean value of the LVI values.
- The LVI Severity is based upon the number of runs of LVI values greater than the LVI threshold and by how much the LVI values in those runs exceed the LVI threshold.

The LVI Severity can then be used for ranking the signals identified as having intermittent disturbances. This is especially useful when evaluating 100's of control loops. The following sorted table allows the user to quickly identify those signals that are being impacted most severely by intermittent disturbances.



Name	Description	Severity
11AJ375	Durchfluss ueberlauf Sortierer Mst-k	
11AJ378	Durchfluss ueberlauf Sortierer Mst-k	
16AJ595	RSM-Aufloeser	67.0
18AJ651_FT1	Durchfluss BW	64.9
11AJ793b	Pumpenregler	61.6
1AJ793	Abwasser zur ARA	61.6
18AJ632_FT2	Durchfluss Verduennungswasser AB 2 BW	59.6
18CA01	Bentonit Scheibenfilter PM	58.4
19AJ391	Vakuumpumpen Sperrwasser	58.3
11RM051_2	Regler Klappe	57.2
13AJ701	PM Abwassergrube 1	56.2
19AJ754	PC-Haube	52.7

Figure 10 – Intermittent disturbances ranked by severity.

All the examples in this paper are from actual industrial processes. The following example helped identify problems with cleaning cycles in the stock approach system of a paper machine. In this case the process fluid was dirty and a cleaning cycle was installed to purge the build up. The application would force the actuator to 100 percent at intervals of every hour. This would allow the build up to pass through this part of the process. The problem was that this cleaning cycle actually resulted in a disturbance to a down stream process. The analysis of the intermittent disturbances quickly identified the down stream variables that were being upset by this cleaning cycle.

The top plot shows the output being forced to 100 percent every one hour. The bottom plot shows the down stream impact this cleaning cycle was having. Notice how the control tried to fix the problem. However just as the control was making its correction, the disturbance was over. The result was an unnecessary change in controller output. This caused a subsequent upset in the measured value that actually also impacted the original signal.

Using the LVI identification allows for this problem to be quickly identified. The solution was to clamp the output of the down stream controller during the purge cycle. This stopped the unnecessary controller actions of the down stream controller and helped stabilize the process.

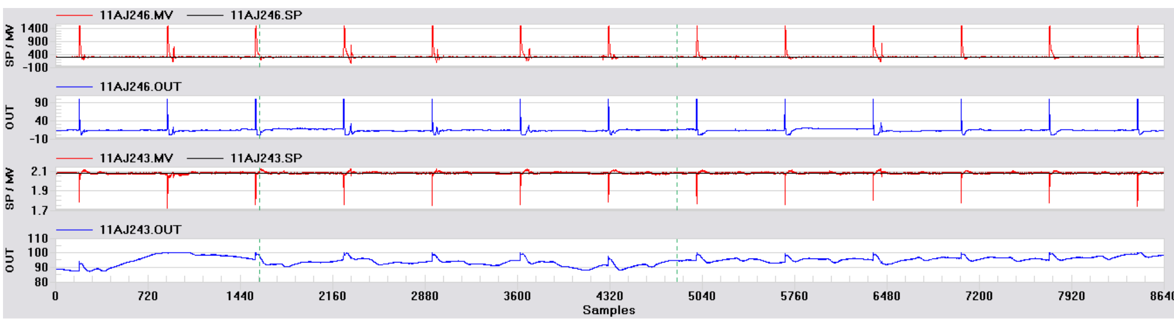


Figure 8: Cleaning Cycle induces downstream problem

References

1. Tim Mast, Kevin Starr, Pete Tran, and Shih-Chin Chen, “New Optimization of CD Control for Global and Localized Profile Performance”, Tappi Press, 2003 Paper 2648.

2. Chen, S-C., “Actuation cell response and mapping determinations of web forming machines”, Canadian Patent 2 036 833, 1991, US Patent 5 122 963, 1992.