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Review

Review of Different Methods for Identification of Transients in Pressure Measurements by Permanent Downhole Gauges Installed in Wells

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Abstract: Permanent downhole gauges (PDG) are massively installed in injection and production wells operated in different industries such as oil and gas, geological CO_2 storage, and the geothermal industry. These gauges provide a vast amount of real-time pressure measurements. The pressure measurements may be divided into periods with a predominantly monotonic change of pressure in response to a sudden change of rate, called transients. These transients are caused by well operations, such as variation of injection or production rate and well shut-ins. Transient identification is one of the important steps in processing and interpreting the PDG data. Traditional transient identification is performed by processing and analyzing with human involvement, which is a step in post-operation well analysis. In modern well surveillance technology, permanent and reliable data transmission from the wellbore to the surface provide the possibility to analyze well performance in real time or proactively. So automated transient identification is a practical demand, but a challenge at the same time. This article starts with the definition of a transient, then reviews and compares seven methods for transient identification proposed by previous works available in the literature. A comparative analysis of these methods is carried out accounting for the detection algorithm and procedure, results of testing, and general positive and negative sides of performance and application of these methods. The results of this review facilitate further developments of field data interpretation techniques by the R&D community and academia and may help in the selection of a proper method for further application in well surveillance workflows developed in the industry.

Keywords: permanent downhole gauge; pressure transient; break point; transient identification; well surveillance

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1. Introduction

Permanent downhole gauges (PDG) are reliable well data sources in modern well surveillance systems, which are installed in wellbores near the reservoir sand-face, where the wells are connected to the reservoir via open-hole or perforation intervals, Figure 1 shows a possible position of the gauges in the wellbores. PDG provides a long-term continuous record of data, such as pressure and temperature, which can be recorded for a well's life during production or injection, reflecting all changes in the well rate and well shut-ins. The PDG data may be used for many applications, such as detection of changes in reservoir properties [1,2], evaluation of production or injection capacity [3], effect of the well interventions [4], monitoring of well interference [5,6], and monitoring of changes in production capacity [7,8]. So, PDGs become a significant source of downhole data for pressure transient analysis in oil and gas production [9] and geological CO_2 storage [10]. Athichanagorn suggested a multi-step workflow for processing and interpretation of the

PDG data, which includes: (i) outlier removal, (ii) denoising, (iii) transient identification, (iv) data reduction, (v) flow-history reconstruction, (vi) behavioral filtering, and (vii) moving window analysis [11]. His workflow is a clear example to illustrate the procedure of performing reservoir analysis by using PDG.

PDG data are used to address some challenges in reservoir development. First, PDG provides nearly real-time data directly from the well site to reservoir and production engineer. Real-time data interpretation is a valuable resource for decision making on well operations and reservoir management. However, these vast volumes of data containing outliers and noise usually take much human effort to process, making extraction of the reservoir information difficult or provide the information with a delay. Second, to utilize the PDG dataset, it is essential to divide the huge volume of long-term PDG data into individual transients, such as flowing transients or shut-in transients; then, the data interpretation can be carried out for the identified transients. Automation of transient identification should help to facilitate analysis of big well surveillance data sets available in the industry, giving also a chance for on-the-fly analysis.

Reservoir studies, such as pressure transient analysis (PTA), were mainly carried out based on a shut-in data due to low quality and frequency of rate measurements during flowing periods. Installation of PDGs in combination with frequent and accurate flow-metering provided basis for inclusion of flowing periods in PTA applications [1]. It is a challenge to identify the desired transients from the original PDG data because (1) the volume of PDG data is huge, (2) the measurements usually contain outliers and noise, and (3) the rate data from the surface are not synchronized with downhole pressure data. The accuracy of transient identification may affect interpretation of reservoir properties. For example, inaccurate identification may lead to biased estimates of well and reservoir properties like well skin and reservoir permeability, due to inaccurate pressure drop and early time response of the transient in focus. In application of the deconvolution method, inaccurate transient identification may also mislead the interpretation of the reservoir behavior [12,13]. A few works have been published proposing solutions for transient identification issue.

In this article, we review seven methods for transients identification from the literature, discuss, and compare their performance. These methods use the pressure data from the PDG as the only data to identify transients because the flow rate is not always measured in line with pressure or may have a much lower sampling rate. Even though there are some data analysis and machine learning applications based on PDG data published, for example in [14–17], these studies were usually not concentrated on transient identification problem itself. For a clear understanding of the characteristics of each reviewed method, the terminology is first summarized using previous statements found in the literature and the terms of a 'transient' and a 'break point' are introduced. Then seven methods are categorized into four types, which are (1) wavelet decomposition methods, (2) pressure data trend methods, (3) pattern recognition methods, and (4) a segmentation method. A comparison of these methods is given to demonstrate the features of each method, considering the detection theory and procedure, results from the literature, and general positive and negative sides of the performance and application of these methods.

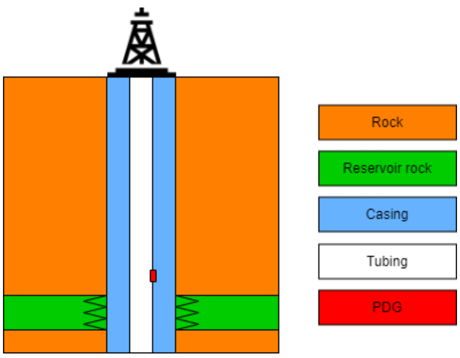

Figure 1. A common location of Permanent downhole gauge(PDG) in the wellbore.

Three main objectives of reviewing these methods may be specified as:

- Define the common terms used in processing pressure measurements from permanent downhole gauges (PDG);
- Provide strategies to identify transients from PDG datasets for well surveillance or similar transient datasets;
- Facilitate further developments of field data interpretation techniques by the R&D community and academia via helping in the selection of a proper method for further application in well surveillance workflows applied in industry.

This review is organized as below:

1. Introduce the terminology for transient identification;
2. Introduce the reviewed transient identification methods;
3. Compare the methods;
4. Discussions;
5. Conclusions.

Terminology

The term transient has a specific meaning when used in different fields. In terms of PDG data processing and interpretation, transients can be defined as pressure measurements' responses to flow rate changes. An abrupt change of measured pressure usually occurs due to a sudden change of flow rate; then, distinct flow periods may be separated by detection of these abrupt changes. In this context, definitions of a 'transient', a 'break point', and transient identification as a general task proposed by different researchers are reviewed and summarized hereafter. Regarding the description of break point, Khong [18] regarded break points as sudden pressure changes in pressure signals caused by the flow rate change. Rai [19] described a break point as a high or low point in a detailed signal. Nomura [12] referred to break point as the starting point of each transient. Liu [20] described a break point as a point where a flow rate change event happened, and it usually indicates the end of the previous transient and the beginning of the next transient. Regarding the description of transients, Thomas [21] regarded transients as distinct flow periods when the pressure changes occur with flow rate changes and break points marked as the start and end of a single transient. Regarding the description of transient identification, Athichanagorn [22] referred to transient identification as a procedure to detect changes in pressure signal when the flow rate alters. Li [23] treated transient identification as a methodology aiming at automatically identifying the time at which the pressure trend changes because of a rate change. The critical issue in transient identification according to his study is to select the proper break point of every flow period. Liu [20] mentioned that transient identification requires break-point detection. Tian [24] referred to the process of detecting the points to separate multiple transients as break-point identification. We, therefore, tried to define these common terms by summarizing the concepts from the above statements in this literature review and putting the methods for transient identification into the same context. As a result, the following formulations for these terms are suggested:

- A pressure transient is a predominantly monotonic change of pressure in response to a sudden change of rate;
- A break point is a point in time separating two transients;
- Transient identification is a process of dividing pressure time series into sequential transients based on the objectives of the data interpretation.

The first and second definitions above are in line with those suggested in the literature reviewed but slightly modified to account for different transients, usually observed in real data, namely flowing and shut-in periods. The definition of transient identification task includes an extension compared to common definitions found in the literature highlighting the fact that the same sequence of multiple rate transients may be considered as different transients or as a single transient following objective of the study. As an example, step rate testing generates sequences of transients, where each transient in the sequence may be separately interpreted [25], while the transient response to all the sequence of rate steps may also be considered as a single transient.

2. Methods for Transient Identification

The seven reviewed methods for transient identification are:

- Wavelet modulus maxima method;
- Data grouping method;
- Pressure-data slope method;
- Pressure derivative method;
- Filter convolution method;
- Image pattern method;
- Segmentation method.

The detection of breakpoints is a crucial task in identifying transients. The number of breakpoints determines the number of transients present, and their location determines the duration of each transient. As flow rate data is not always available, the methods discussed in this article for identifying transients rely solely on pressure data from PDG. These methods are categorized into four types: wavelet decomposition, pressure data trend analysis, pattern recognition, and segmentation. Pre-processing and thresholding are common techniques used across all methods, but they require human intervention for optimal results. However, pre-processing PDG data under the assumption that noise and outliers are solely caused by noise and do not reflect the behavior of the reservoir may result in the loss of valuable information. Additionally, thresholding is often used to decide the number of transients, which can lead to over- or under-detection.

2.1. Wavelet Decomposition Methods

Wavelet transformation has been widely studied and applied in signal processing, with many researchers proposing and improving wavelet decomposition methods for PDG signal processing [18,22,26–29]. The wavelet transform is particularly useful for PDG data pre-processing and the decomposed detail signals can be used for subsequent detection of transients. Wavelet-based methods can be understood as the original data being processed through a low-pass filter and a high-pass filter. After filtering, the original data is decomposed into two signals—the approximated data from the low-pass filter and the detailed data from the high-pass filter. Breakpoints are detected by setting a criterion over a certain threshold in the detailed data, as shown in Figure 2. The number of identified transients depends on the threshold selection. Khong [18] has used Fourier analysis to filter out false breakpoints based on wavelet transform. Ouyang [28] further studied the mechanism behind transient detection by considering reservoir parameters.

2.1.1. Wavelet Modulus Maxima Method

a. Detection theory

   Athichanagorn processed the original data by using spline wavelet decomposition, which decomposes the data into approximation signal data by using the scaling function and detail signal data by using the spline wavelet function [22]. Depending on the resolution level, the scaling function provides an approximation of the original data, while the wavelet function provides the differences between the approximation data and the original data. Breakpoints are detected by finding the modulus maxima over a certain pressure slope threshold, denoted as τ, in the detailed signal at an intermediate decomposition level L.

b. Detection procedure

   The detection procedure can be defined as follows:

   - Pre-process data for outlier removal and denoising;
   - Determine the level of spline wavelet decomposition L, according to desired data resolution;

- Try proper slope or pressure thresholds to detect the break points by wavelet modulus maxima higher than threshold τ;
- Confirm the position of break points by checking slope changes.

Figure 2. Detection of break points in details data by wavelet decomposition.

c. Experiment result
The author conducted three experiments using this method, and Figure 3 shows the detection results based on the denoised data. The vertical lines indicate the positions of the detected breakpoints. The level of spline wavelet decomposition used was intermediate, and the pressure slope threshold, τ, was set at 10 psi/h.

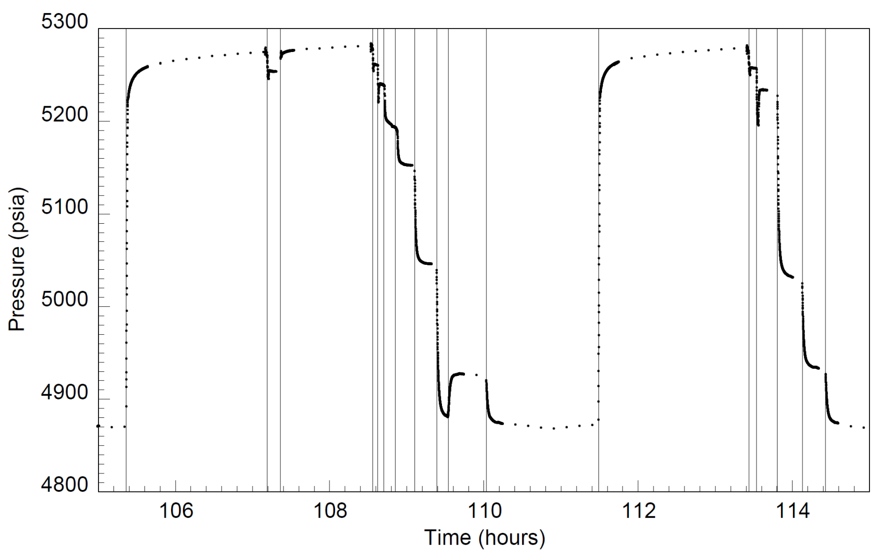

Figure 3. Detection result using Wavelet Modulus Maxima from Athichanagorn [22].

d. Advantages and Disadvantages

This method can effectively detect obvious breakpoints, but it may fail to detect breakpoints with small magnitudes. The final detection quantity of breakpoints is determined by the threshold selection. Pre-processing, including outlier removal and denoising, is necessary to avoid false breakpoint detection. The detection result is highly affected by the wavelet decomposition level and the threshold, which requires human intervention to achieve the desired result. Additionally, the final position of a breakpoint needs to be confirmed in the original data.

2.1.2. Data Grouping Method

a. Detection theory

Li [23] presented that decomposition by Haar wavelet transforms, a discrete wavelet transform, can detect more accurate breakpoint positions compared to spline wavelet transform (used in the wavelet modulus maxima method). Based on Haar wavelet decomposition, Li proposed a method to detect breakpoints by grouping data in the detailed signal. The threshold τ is decided by statistical grouping with the assistance of the mean μ and standard deviation δ calculated from the detailed signal.

b. Detection procedure

The detection procedure can be detailed as follows:

- Pre-process includes removing overlap data, outliers, and denoising;
- Apply wavelet decomposition and use the detail signal in Level 1 as default data resolution for subsequent processing;
- Identify the break points by grouping the data by setting proper threshold τ and regarding the break points located in the data group in which the data values are bigger than the threshold;
- Refine break points position.

c. Experiment result

The author conducted five experiments using this method [23], and the significant transients were detected, but with over-detection on transients with small magnitudes. The periods with different color represent different flow periods, and the period with green color represents the final flow period (Figure 4).

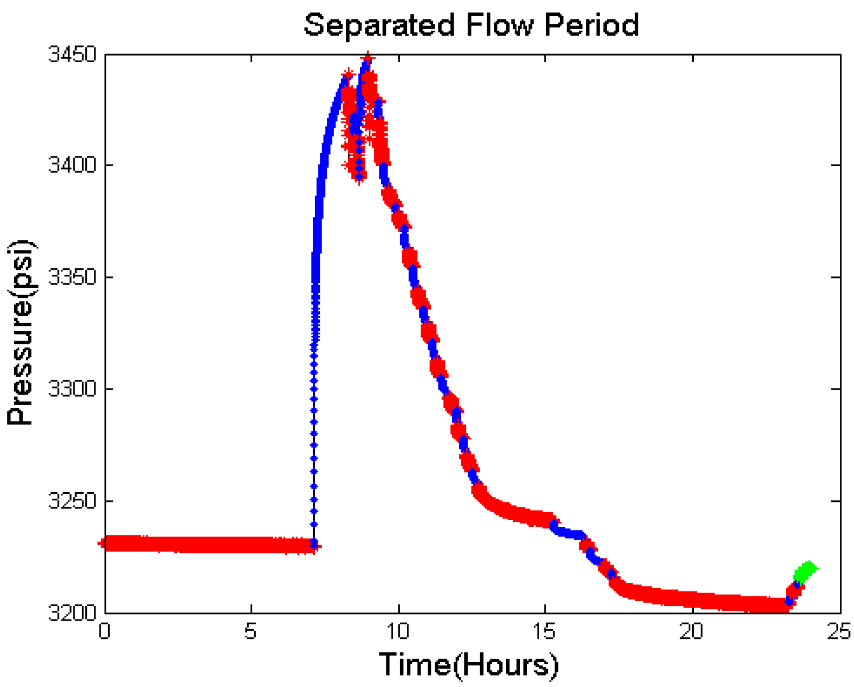

Figure 4. Detection result using the data grouping method from Li [23].

d. Advantages and Disadvantages
Li improved detection of the break points with a more precise position in the original data by using the Haar wavelet transform and detecting more break points with smaller magnitudes by determining the threshold in statistic consideration. However, pre-processing including outlier removal and denoising is necessary, and the threshold selection by a statistic method results in over-detection with redundant transients.

2.2. Pressure Data Trend Methods

Compared to wavelet decomposition methods that use detailed signal data to detect breakpoints, pressure data trend methods use the detailed data as the source to detect breakpoints by calculating the pressure slope [30,31] or pressure derivative [19] over a certain threshold, as shown in Figure 5. These methods are straightforward to implement and can detect significant breakpoints when the original PDG data are properly pre-processed. However, the desired threshold is selected through trial and error and the detected position still needs to be confirmed in the original data.

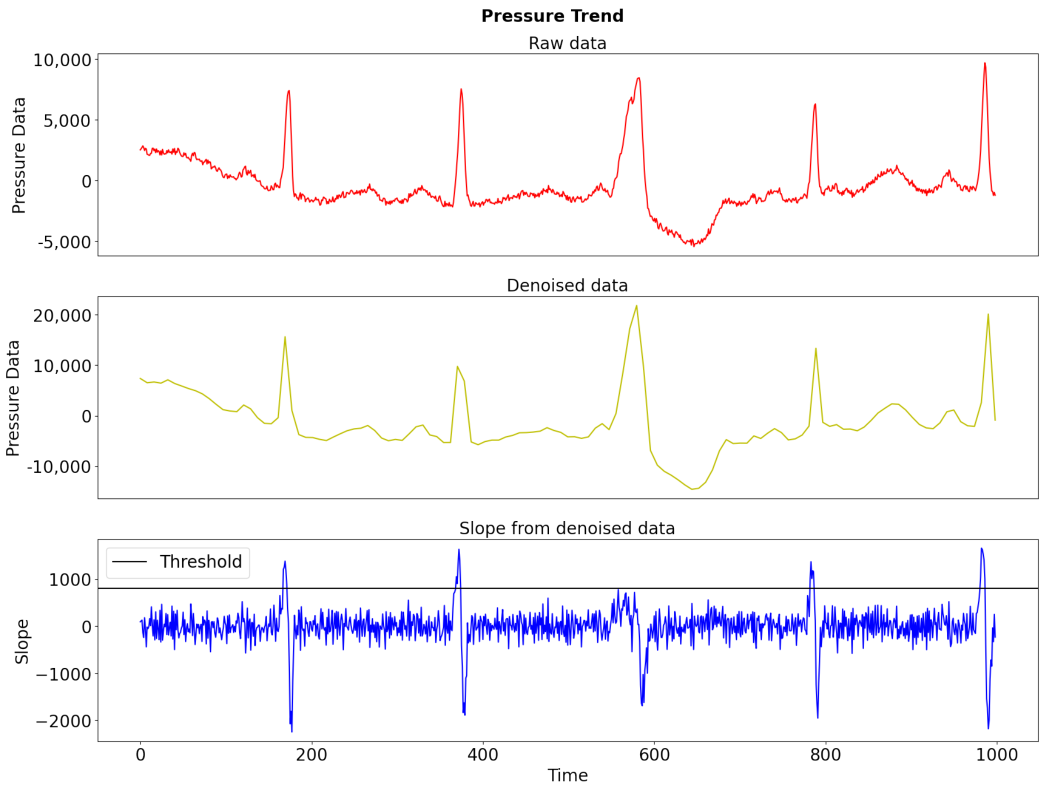

Figure 5. Detection of break points in detail data by the pressure trend method.

2.2.1. Pressure–Data Slope Method

a. Detection theory
Viberti proposed a method that uses the slope of pressure data as the criterion to identify transients [30]. The original PDG data are first pre-processed by wavelet algorithms for outlier removal and denoising. Then, the detection process starts by setting the number of points k for calculating the slope in the pre-processed data. Finally, the calculated slope values greater or less than the thresholds τ_1, τ_2 will be detected as breakpoints.

b. Detection procedure
The detection procedure can be detailed as follows:

- Pre-processing includes removing outliers and denoising;
- Decide the number of points k and calculate the slope from the pre-processed data;
- Set slope thresholds τ_1, τ_2 for flowing and shut-in break points.

c. Experiment result
The author made two experiments using this method, and Figure 6 shows the detection results based on the denoised data. The vertical line indicates the detected position of break points.

d. Advantages and Disadvantages
The pressure-slope-based method is a simple method for detecting large magnitude break points in data. It relies on pre-processing the data and selecting an appropriate threshold. The effectiveness of the approach can be affected by the quality of pre-processing and threshold selection. Human involvement is necessary in these steps.

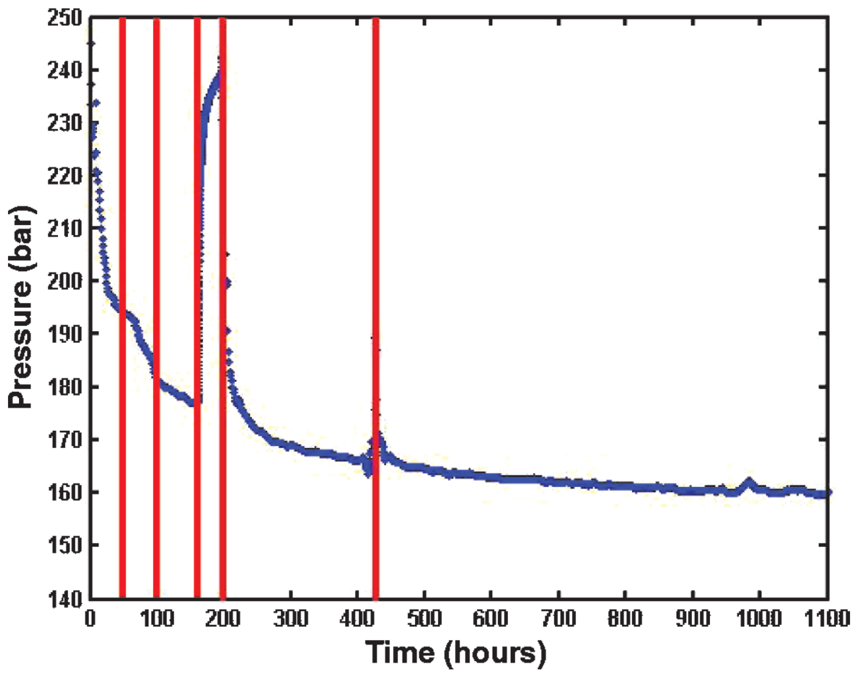

Figure 6. Detection result using the pressure slope from Viberti [30].

2.2.2. Pressure Derivative Method

a. Detection theory
Rai proposed using the derivative of pressure as a criterion to detect breakpoints in a pressure curve [19]. The Savitzky-Golay filter is used to smooth and transform the discrete pressure data into a continuous curve. The derivative of this curve is then calculated and used as the source data for breakpoint detection. The derivative of pressure exhibits peaks when there are significant changes in the gradient of the data. These peaks in the first and higher derivatives indicate the vicinity of the breakpoints location.

b. Detection procedure
The detection procedure can be detailed as follows:

- Smoothen the original pressure data using the Savitzky–Golay filter by adjusting the size of the filtering window S and the order of the polynomial θ_1;
- Calculate the pressure derivative and select the proper order of derivative θ_2;
- Detect break points by derivative values bigger than the threshold τ_1 or smaller than the threshold τ_2;
- Adjust break points position by checking slope changes.

c. Experiment result
The author conducted one experiment using this method, and Figure 7 shows the detection results based on the denoised data. The red dot indicates the detected position of break points.

d. Advantages and Disadvantages
The method can effectively detect significant breakpoints. However, it requires many parameters to be set and involves many human interactions. Additionally, the method may fail to detect a few breakpoints with small magnitudes, as seen in the author's experiments.

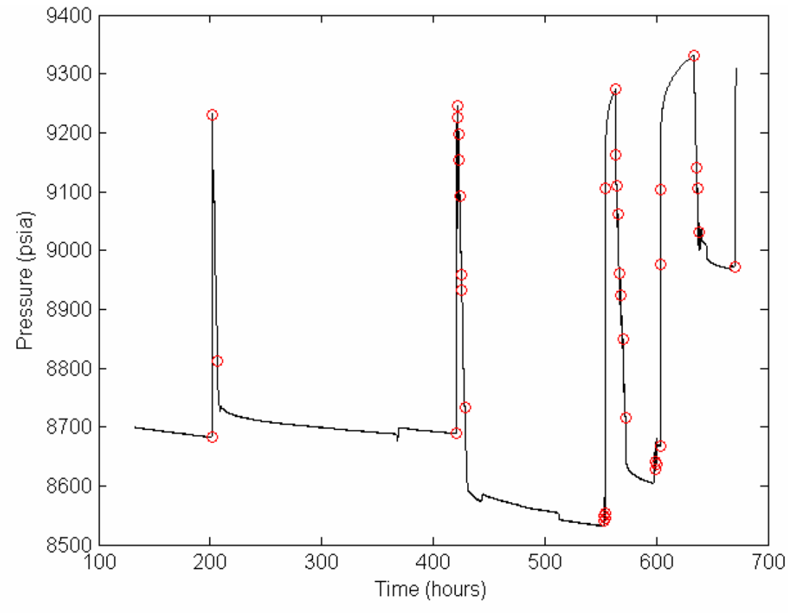

Figure 7. Detection result using the pressure derivative from Rai [19].

2.3. Pattern Recognition Methods

The pattern recognition method is a widely used concept for detecting changes and identifying pressure transients in PDG data [32]. There are two specific methods that have been developed for this purpose. Both methods involve pre-defining two patterns for detection. Suzuki [33] uses the responses of the pressure derivative as patterns to detect breakpoints, while Olsen [34] represents the time window containing breakpoints as images. One of the benefits of using pattern recognition methods is that they require minimal human intervention once the patterns have been properly set. They can also be used for real-time detection. However, these methods can be difficult to generalize to different PDG datasets, and pre-processing must be done carefully to avoid over-smoothing, which can negatively impact detection performance.

2.3.1. Filter Convolution Method

a. Detection theory
Suzuki's method is a break-point detection method that uses filter convolution to detect specific patterns in the pressure derivative rather than just changes in frequency. This method can also be combined with noise-removal filters to improve its tolerance to noise, as described in the reference [33].

b. Detection procedure
The detection procedure can be detailed as follows:

- Pre-process data for outlier removal and denoising;
- Calculate the pressure derivative;
- Determine the criterion for patterns by deciding the size of time window S in the filter function according to the minimum buildup interval desired to detect;
- Detect the break points by locating the maxima of the filter function bigger than threshold τ.

c. Experiment result
The author conducted one experiment with oil well PDG data and two experiments with gas well PDG data by using this method. The author mentioned that the detection result was better with the oil well PDG data than with gas wells. Figure 8 shows the detection results based on the denoised data with oil well PDG data. The vertical line indicates the detected position of break points.

d. Advantages and Disadvantages
The Suzuki method is designed to be tolerant to noise to some extent through the use of a filter function. However, the results of the experiment indicate that it is difficult to pre-define universal patterns for different datasets. The threshold criteria selection requires human interaction and is a trial-and-error process.

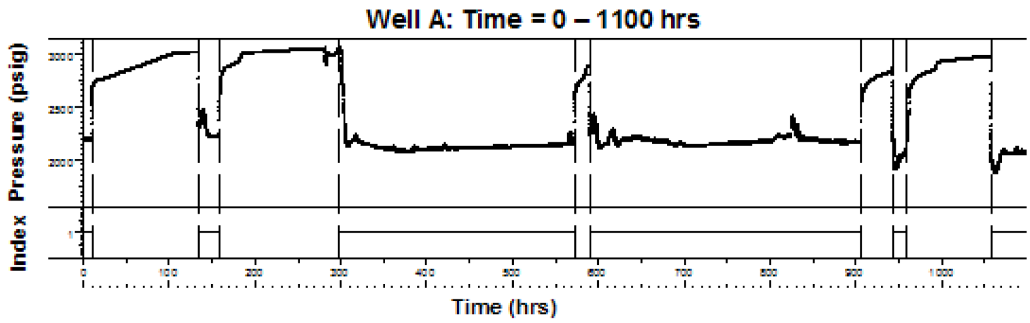

Figure 8. Detection result using the filter convolution method from Suzuki [33].

2.3.2. Image Pattern Method

a. Detection theory
In the article [35], Olsen proposed a pattern recognition method for transient identification, which is further elaborated on in his Ph.D. thesis [34]. The method pre-defines two patterns for break points, one for build-up, as shown in Figure 9, and one for draw-down, and represents the break points as binary images (0 or 1). The break points will be detected when the shape made by the points belongs to the pre-defined transient pattern. To remove the smallest transient patterns, the author proposed a complementary measure that uses statistical validation criteria. This may cause some of the smallest transients to be missed, but it also decreases the number of faulty detected transients.

	Pattern													
Pressure Interview	0	0	0	0	0	0	1	1	1	1	1	1	1	1
	0	0	0	0	0	0	1	1	1	1	1	1	1	1
	0	0	0	0	0	0	1	1	1	1	1	1	1	1
	0	0	0	0	0	0	1	1	1	1	1	1	1	0
	0	0	0	0	0	0	1	1	1	1	1	1	0	0
	0	0	0	0	0	0	1	1	1	1	1	1	0	0
	0	0	0	0	0	0	1	1	1	1	1	0	0	0
	0	0	0	0	0	0	1	1	1	0	0	0	0	0
	0	0	0	0	0	1	1	0	0	0	0	0	0	0
	1	0	0	0	0	1	1	0	0	0	0	0	0	0
	1	1	1	0	0	1	1	0	0	0	0	0	0	0
	1	1	1	1	1	1	0	0	0	0	0	0	0	0
	1	1	1	1	1	1	0	0	0	0	0	0	0	0
	1	1	1	1	1	1	0	0	0	0	0	0	0	0

Figure 9. Pre-define pattern for build-up break points.

b. Detection procedure
The detection procedure can be detailed as follows:

- Pre-process data for outlier removal and denoising;
- Pre-define patterns considering various reservoir models and the influence of noise;
- Choose the number of measurements N that represent the image for pattern recognition; decide the pressure interval ΔP in each window;
- Keep the detected break points by discarding the ones below a certain signal standard deviation value τ.

c. Experiment result
The author conducted an experiment with synthetic data and two experiments with real data using this method. The detection rate was 86% for the synthetic data and 80% for the real data. The missed detections were mainly due to small pressure changes. The results of the experiment with real data are shown in Figure 10, where the red vertical line indicates the position of the detected break points. The results are based on denoised data.

d. Advantages and Disadvantages
The Olsen's method uses pre-defined patterns for break-point detection and can be used for real-time automatic detection once the patterns are properly defined, requiring less user interaction during the detection stage. The method can detect most break points, but may miss some with small magnitude, as seen in the author's experiments. Data pre-processing is necessary before detection, but care must be taken to avoid oversmoothing the data.

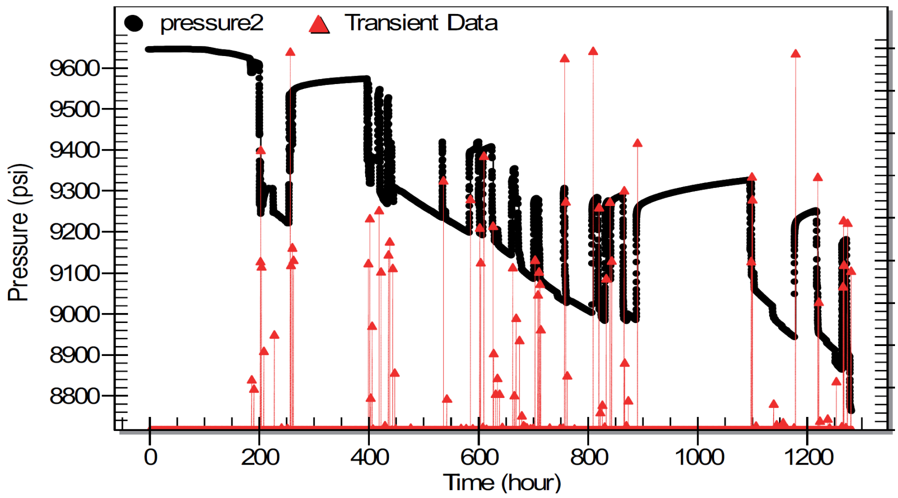

Figure 10. Detection result using the image pattern method from Olsen [34].

2.4. Segmentation Method

a. Detection theory
Rai proposed a segmentation method for break-point detection in [19] which requires only one user input parameter for identifying the break points. The method is based on time series segmentation from Wallace [36] and involves solving a sequence of maximum orthogonal (Euclidean) distance problems at strategic points, as illustrated in Figure 11. The author also attempted to improve the performance by incorporating flow rate data into the segmentation method as a variant.

b. Detection procedure
The detection procedure can be detailed as follows:

- Label the first and the last points in the dataset as two strategic points;
- Find the third point with the maximum orthogonal distance from the line segment joining the two strategic points. Put the third point in the list of strategic points;

- Perform this iterative calculation until the greatest orthogonal distance is smaller than a prescribed threshold τ.

c. Experiment result
The author conducted the experiment using this method with the same data using the pressure derivative method mentioned in the pressure data trend type with the derivative method. Figure 12 shows the detection results. The red dots indicate the detected position of break points.

d. Advantages and Disadvantages
The Rai's method can detect significant break points without pre-processing or denoising, which is an advantage over other methods. Additionally, it requires less human intervention, as only one threshold is needed to decide the number of break points. However, it may fail to detect some break points with small magnitude, and there are no similar methods found to process PDG data without denoising, so more tests are needed to prove the method's feasibility. Additionally, the author improved the method's performance by incorporating flow rate data, but this may not always be available.

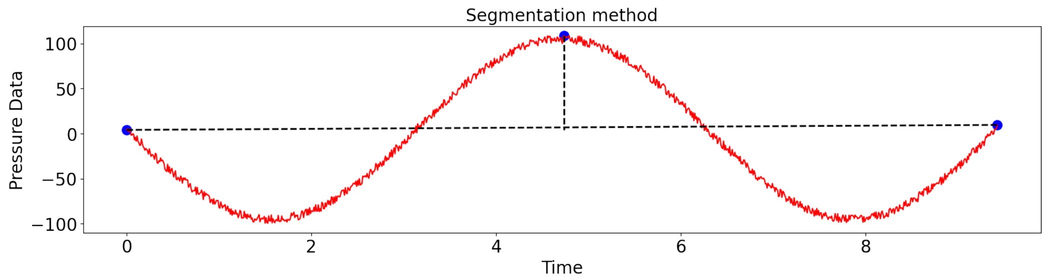

Figure 11. Points with maximum orthogonal distance.

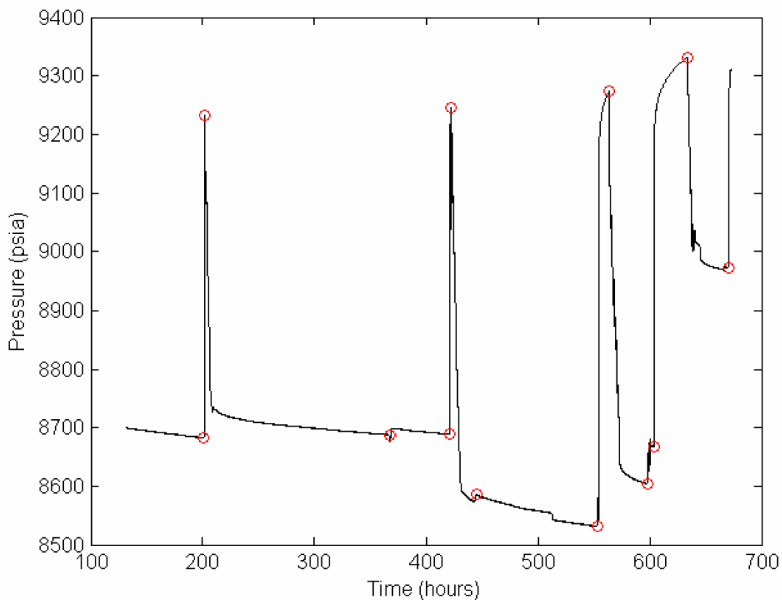

Figure 12. Detection result using the segmentation method from Rai [19].

3. Comparison of the Methods

Seven methods for transient identification have been reviewed and grouped into four types. Figure 13 shows the workflow of wavelet decomposition methods and pressure trend methods. For these two types of methods, the detection procedure is similar, and the difference is mainly related to the step of break-point detection.

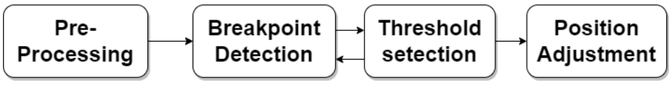

Figure 13. Workflow1: Wavelet decomposition and pressure trend.

Figure 14 shows the workflow of pattern recognition methods. Compared with Workflow 1 (Figure 13), the workflow of pattern recognition has the same four steps, but the difference is that the pre-defined patterns' function should be defined and work as a threshold. The pattern recognition workflow may be used for real-time break-point detection.

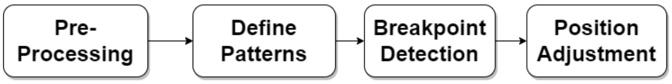

Figure 14. Workflow2: Pattern recognition.

Figure 15 shows the workflow of the segmentation method. Compared with Workflow1 (Figure 13) and Workflow2 (Figure 14), the threshold is still the crucial influencer for the detection, and the difference is in avoiding pre-processing and position adjustment, which is an advantage for automation.

Figure 15. Workflow3: Segmentation method.

By comparison, the most common thing among the three workflows reviewed is the need for data pre-processing and threshold selection, which requires human interaction in all of the seven methods. The wavelet decomposition methods, pressure derivative methods, and segmentation method need to adjust the threshold in the detection stage, whereas the pattern recognition methods set the conditions in the pre-defined patterns acting similarly to the threshold. If the threshold is set too high, then only break points with high-pressure change amplitude are detected, which may ignore many lower-amplitude transients damaging subsequent analysis. If the threshold is set too low, more break points with small amplitude are detected, which may disturb the subsequent analysis with redundant transients identified. Pattern recognition methods pre-define the patterns, so it is more efficient and suited for real-time detection compared to the rest of the methods since human interaction is needed only before the analysis. All seven methods discussed above are compared with their main ideas, aspects of positive and negative sides, and key user inputs in Table 1.

Table 1. Comparison among different methods for identification

	Main Idea	**Advantages**	**Disadvantages**	**Key Input**
Wavelet modulus maxima	Detect break points by detailed signal higher than threshold after wavelet decomposition.	Significant break points can be detected.	Pre-processing is needed. Some false break points are detected. Human intervention to adjust threshold.	Decomposition level L, Threshold τ
Data grouping	Detect break points by statistical analysis in the detailed signal after wavelet decomposition.	Both big and small break points can be detected. The detected position is more precise.	Pre-processing is needed. Some false break points are detected. Human intervention to adjust threshold.	Decomposition level L, Threshold τ
Pressure slope	Detect break points by slope value higher than threshold.	Easy to implement. Significant break points can be detected.	Pre-processing is needed. Some false break points are detected. Human intervention to adjust threshold. Some break points missed.	Number of points N, Threshold τ
Pressure derivative	Detect break points by derivative value higher than threshold.	Significant break points can be detected. Filtering is part of pre-processing.	Pre-processing is needed. Many parameters to choose. Human interaction to adjust threshold. Some break points missed	Window size S, Polynomial order θ_1, Derivative order θ_2, Threshold τ
Filter convonlution	Detect break points by processed signal higher than threshold.	Significant break points can be detected. Tolerant to low level noise. Less human interaction.	Pre-processing is needed. Sensitive to high noise level. Human interaction to adjust threshold.	Patterns criterion C Window size S, Threshold τ
Pattern recognition	Detect break points by the shape belongs to pre-defined patterns	Significant break points can be detected. Require less human interaction.	Pre-processing is needed. Failed to detect break points with small magnitude. Caution to avoid oversmoothing.	Patterns criterion C, Number of points N, Pressure difference ΔP
Segmentation	Detect break points by calculating data distance smaller than threshold.	Significant break points can be detected. Denoising may not be required. Less human interaction.	Outliers affect result. Some break points missed. Human interaction to adjust threshold. Need to confirm the detected position	Threshold τ

4. Discussions

- Pre-processing is considered a necessary step by most methods for transient identification. However, pre-processing should be cautiously used because the processed data may lose the signal of the original data. There is no clear answer to decide on the level of processing.
- Selection of a threshold is crucial for transient identification in many methods reviewed. How to minimize its effect is still an unsolved challenge.
- Transient identification includes considerations of shut-in and flowing transients. From the reviewed literature, both types of identification use the same methods.

However, a combined identification methods, which mean identification shut-in transients and multi-rate transients by using different methods may help in improving the identification results.
- The methods reviewed in this article need to be further tested on different datasets. The capabilities of the methods tested on gas or oil wells needs to be studied and further tested on different cases of wells producing or injecting different fluids (like liquid and gases).
- Integrating the methods reviewed with machine learning (ML, including hybrid ML guided by physical models) and other relevant methods is worth to be tested in order to evaluate their suitability for automated transient identification.

5. Conclusions

The modern well surveillance systems now focus on stable and reliable transient identification methods capable of processing large volumes of PDG data and requiring minimum human interaction with low processing time for on-the-fly well monitoring and control. In this context, the literature review provided analysis and guidance on the most promising methods. The following results and conclusions may be reported based on the review and analysis of the transient identification methods available in the literature:

1. The common terms used for processing pressure measurements from permanent downhole gauges (PDG) are defined based on a critical review of the concepts and the terms available in the literature.
    - A pressure transient is a predominantly monotonic change of pressure in response to a sudden change of rate.
    - A break point is a point in time separating two transients.
    - Transient identification is a process of dividing pressure time series into sequential transients based on the objectives of the data interpretation.
2. Seven methods for transient identification have been reviewed and grouped into four types.
    - Wavelet decomposition methods can effectively detect significant transients, but it needs human interaction for better performance.
    - Pressure data trend methods can be easily implemented and understood but require high-quality data pre-processing.
    - Pattern recognition methods can be used for real-time transient identification without human interaction during the identification. Human interaction is however needed before the identification of pre-defined patterns.
    - The segmentation method can detect transients without pre-processing, but threshold selection is needed for better performance as for the wavelet decomposition above.
3. The segmentation and pattern recognition methods may be suggested as the best candidates in the context of automated workflow development. The segmentation method may be considered the best choice taking the simplicity of its application and reduced workload for pre-processing. The main advantage of the pattern recognition method is the ability to use it without human interaction, although based on human pre-defined patterns.

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