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Morphological filtering assisted field-pipeline small leakage detection

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***Abstract*—Field-pipelines leakage detection based on the negative pressure wave theory is mainly aiming to effectively process pressure sample signal in time domain. Previous methods often perform well for detecting large leakage but poorly for small leakage. In this paper, an alternative way using a particular morphological filter constructed by basic morphological operators is considered. The particular filter employed can remove noise and disturbance while retaining the basic geometry shape of pressure sample signal. This feature allows the filter facilitating signal small and slow change detection. The effect of the structuring element length selection is also analyzed on simulated data to acquire empirical rules for practical applications. An experiment is studied to validate the performance of the employed morphological filter.**

***Keywords*—petroleum field-pipeline, small leakage detection, morphological filtering**

I. INTRODUCTION

Field-pipelines, unlike the civilian purpose underground pipelines, are temporarily built on the ground surface or in the jungles during wartime. They are commonly jointed with fast connectors and pump tracks to achieve high mobility. This feature makes field-pipelines directly expose to natural surroundings with complex force condition, thus pipelines rupture, erosion, mechanical damage become the major threats to safety operation, even the process of the war. All those failures mentioned above result in pipelines leakage which are detected widely using Negative Pressure Wave (NPW) theory [1] combined respectively with fast difference algorithm, kalman filer, wavelet transform, or correlation analysis and etc. These methods are capable of locating the leak point more accurately when applied to large leakage amount situation. However, confronted with small leakage (leak flow rate weighs less than 2% of nominal flow rate) together with more intensive disturbance and noise in the open air than under the ground, they are often no longer available. This paper considers a possible alternative, the application of purely time-domain analysis leakage detection procedure based on morphological signal-processing concepts.

Mathematical morphology (MM) is firstly proposed by *Matheron G* and *Jean Serra* on the fundamental of integral geometry [2].From then on varied Morphological filters (MF) as nonlinear filters are widely used in signal processing area based on MM theory. *PETROS et al.* [3][4] and *Jean Serra et al.*[5] gave an detailed analysis of MF in mathematical representation, its properties and relations to linear filters. The main idea of MF can be expressed in the following way: it views signal in terms of sets, and according to signal geometry feature, selects another sets called structuring elements to modify signal geometric shape in order to remove noise and extract useful information. This technique is firstly used to analyze binary image data and grey-level images. MF technique has grown very rapidly since its launching [2][6][7]. It both retains image details (e.g. image edge) and filters noise which linear tool like Fourier analysis fails to accomplish. However, MF applications on one-dimensional (1-D) time series are relatively limited, mainly retrained particularly to EEG (electroencephalogram) signal [8]， acoustic signal [9] and vibration signal [10].

In this paper, we focus on 1-D discrete time series morphological filtering. It is employed to preprocess pipeline pressure sample signal which contains leakage relevant information. The aim is to modify the geometrical features of the sample signal in time domain to extract a kind of envelope which exhibits signal time-varying evolution and accentuates information under relative low signal-to-noise ratio (SNR) condition. Then, traditional leakage detection methods can be applied to analyze the envelope to detect and locate the leakage. In the next section, basic concepts and operations of mathematical morphology is firstly introduced in order to make this paper self-contained, then a particular morphological filter employed for small leakage detection is presented and analyzed. Section 3 uses simulated signals to illustrate effects of the employed morphological filter in different noise magnitude situations. Section 4 is a case study demonstrating the filter's performance. Section 5 gives the summary.

II. MORPHOLOGICAL FILTER CONSTRUCTED BY BASIC MORPHOLOGICAL OPERATORS

A. Basic concepts of morphological processing

The basic concept of morphological signal processing is to modify the shape of a signal, equivalently considered as a set, by transforming it through its interaction with another object, called the structuring element. In practice, the structuring element can be viewed as compact and of a simpler shape than the original signal. The key notion in morphological processing is based on set theory, so signals should be represented by sets in the first place. Limited in 1-D time series, signals are commonly represented by functions, we firstly introduce two concepts: function cross sections and function umbra. They are two different but equivalent representation of a function.

The cross section of a function f at level t is defined as:

$$X_t(f) = \{x \in D : f(x) \geq t\}, t \in V \quad (1)$$

where $f(x)$ is the function, D is the domain of f over the set Z of integers or the set R of real numbers, V is the range space of $f(x)$, t is a selected threshold. An illustration of function cross section is indicated in Fig.1. f can be associated with a family of sets by providing all different levels t. The number of elements of sets $X_t(f)$ decreases as t increases when D is a subset of Z. Generally, the functions we deal with are classified as the upper semi-continuous functions (U.S.C.) [3]. For any real-valued U.S.C. function f, the umbra $U(f)$, also presented in Fig.1, satisfies the followings:

$$(x,t) \in U \Leftrightarrow t \leq f \Leftrightarrow x \in X_t(f)$$

$$(x,t) \in U \Rightarrow (x,a) \in U, \forall a < t$$

Then the function $f(x)$ can be also represented as:

$$f(x) = \sup\{t \in R : (x,t) \in U(f)\} \quad (2)$$

With the definitions of function cross section and function umbra both representing a function by sets, the four basic morphological operations of set dilation, erosion, opening and closing can be easily defined by Minkowski set operation and are used to construct morphological filters. The four basic morphological operations are defined as follows respectively:

$$dil(f,g) = \sup_{y \in D}\{f(y) + g(y-x)\} \quad (3)$$

$$er(f,g) = \inf_{y \in D}\{f(y) - g(y-x)\} \quad (4)$$

$$op(f,g) = dil(er(f,g),g) \quad (5)$$

$$cl(f,g) = er(dil(f,g),g) \quad (6)$$

where set D is the region of support of the function $f(x)$, $g(x)$ is defined in a compact subset of D.

In the practical applications, signal f commonly consists of sample data, i.e. 1-D discrete time series and g is chosen as an even function. Let $f(n)$ be 1-D discrete function, called input signal, defined on set $F=\{1,\ldots,N\}$, $g(m)$ is the structure element defined on set $G=\{-M,-M+1,\ldots,-1,0,1,\ldots M-1,M\}$, $N \geq 2M+1 \geq 0$. Thus (3)-(6) can be simplified as:

$$dil(n) = \max_{m \in G}\{f(n+m) + g(m)\} \quad (7)$$

$$er(n) = \min_{m \in G}\{f(n+m) - g(m)\} \quad (8)$$

$$op(n) = dil(er(n)) \quad (9)$$

$$cl(n) = er(dil(n)) \quad (10)$$

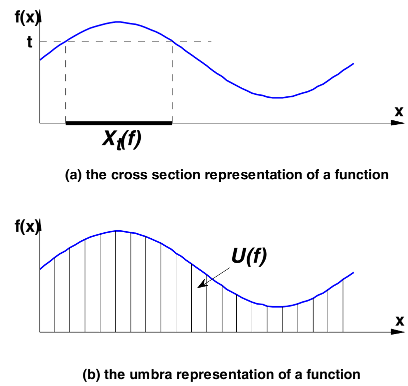


Fig.1. Equivalent function set representation: the function cross section $X_t(f)$ and the function umbra $U(f)$

The geometry explanation of morphology signal processing can be further interpreted: consider observed signal being generally represented as useful signal adding noise and disturbance. So the shape of the observed signal is showing high positive peaks and low negative peaks. The dilation operation widens the width of the positive peaks and reduces the width of the negative peaks, while the erosion operation widens the width of negative peaks and reduces the width of the positive peaks. The opening operation cuts off positive peaks and retains the negative peaks, and the closing operation only cuts off negative peaks.

In morphological filtering, each signal geometrical feature is modified by morphologically convolving the signal with a structuring element. Different information from the signal can be extracted by varying the structuring element in terms of its shape (set elements) and length (set elements number). Compared to the linear convolution operation, in morphological non-linear convolution, the summation or subtraction corresponds to multiplication, while max or min operation's counterpart is the summation or integration. Thus the morphological filter can be viewed as a set mapping. It must satisfy: 1) translation-invariant, 2) scale-invariant, 3) depend only on local knowledge of the signal, 4) U.S.C. [3].

B. A particular morphological filter using open-closing and close-opening operators

PETROS et al. [3] have defined 1-D time series morphological open-closing (11) and close-opening (12) operators. The former is opening operation followed by closing operation using the same structuring element, and the latter can be symmetrized accordingly. For open-closing operation, it firstly cuts off original signal's positive peaks and at the same time, extracts the envelope of negative peaks, then the following closing operation just cuts off negative peaks of the envelope signal, leaving the result signal still retains negative peaks in comparison with original signal. It is easily inferred that closing-open operation also cannot effectively remove all the positive peaks. In order to overcome this difficulty, *ZHAO* [11] and ZHANG [12] have proposed a combination filter based on opening and closing operators shown in (13), denoted as Extended Morphological Filter (EMF).

$$OC(f,g) = cl(op(f,g),g) \tag{11}$$

$$CO(f,g) = op(cl(f,g),g) \tag{12}$$

$$EMF(f,g) = [OC(f,g) + CO(f,g)]/2 \tag{13}$$

where f , g have the same definitions with those in (7)-(10).

The EMF can not only restrain additive white noise, positive and negative impulse disturbance, but also retain drastic and slow change in original signal, recovering signal geometry structure relatively precisely.

III. The Study of the Structuring Element Length Selection on Simulated Signal

In section III, a discrete time series is created to evaluate the effect of EMF. Assume original time signal $s(x)$ (x =1, 2…15000) be expressed into four successive segments with changing time 7000, 10000 and 13000. Each segment is a group of sample values corresponding to a function. The four functions are increasing linear function, decreasing linear function, sinusoidal function and steady function in turn, reflecting five regular morphologies: increasing, step, decreasing, transient and steady. Four functions are defined as (14). $f(x)$ (x =1, 2…15000) in (15) is EMF input signal and $n(x)$ (x =1, 2…15000) denotes white noise added to $s(x)$ (x =1, 2…15000). Structuring element $g(x)$ ($x = -M, -M+1, ...0...M-1, M$) is an even function and chosen as a flat (zero) structuring element shown in (16).

$$s(x) = \begin{cases} \dfrac{2x+5000}{10000} & x = 1,2...,7000 \\ \dfrac{-0.5x+5000.5}{10000} & x = 7001,702...,10000 \\ \dfrac{5\text{-}5000\sin(\pi\frac{x-10001}{1500})}{10000} & x = 10001,10002...,13000 \\ 0.0015 & x = 13001,1302...,15000 \end{cases} \tag{14}$$

$$f(x) = s(x) + n(x) \quad x = 1,2...15000 \tag{15}$$

$$g(x) = 0 \quad x = -M, -M+1, ...0...M-1, M \tag{16}$$

According to (13)-(15), M is the only parameter to be tuned for carrying out morphological filtering. Fig.2 (a) shows $f(x)$ (x =1, 2…15000) given signal-to-noise ration (SNR) is 15 and Fig.2 (b) is original signal s and EMF result (dotted) with structuring element g with M =20. To study the optimal M under different SNR conditions, three typical SNR value is selected, i.e. SNR=2, 10 and 40. The l_1 norm between EMF (f , g) and original signal $s(x)$ (x =1, 2…15000) is defined as ED, to numerically compare EMF approximation ability under different M , shown in (17), where N is the length of $f(x)$ and $y(x) = EMF(f(x), g(x))$.

$$ED = \sum_{x=1}^{N} | y(x) - s(x) | \tag{17}$$

Fig.3 depicts tuning M ranging from 1 to 2% of N , i.e. 300, results in different ED under three SNR conditions respectively. It indicates under high noise condition (SNR=2), in order to minimize ED , M is selected 0.1% to 0.7% of N to be the effective length to get an optimal EMF approximation to $s(x)$. The other two cases are 0.33% to 1% of N with moderate noise magnitude (SNR=10) and 0.07% to 0.1% with low noise magnitude (SNR=40) for M value selection. These empirical rules provide the criterion for effective extracting useful information under different noise magnitude circumstances.

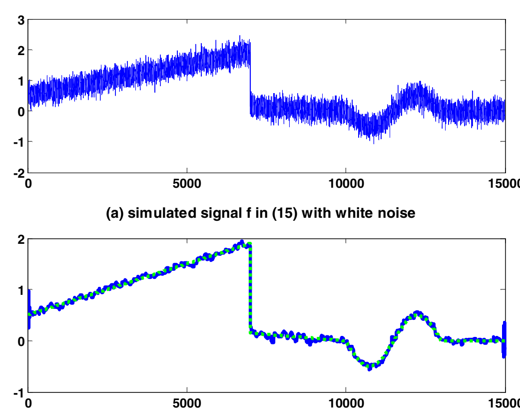
IV. Application on Field-Pipeline Small Leakage Detection

Field-pipeline leakage detection and location is of great importance as generalized in section I. *Henrique et al.* [13] gives a review of all the proposed methods, NPW theory is among the most prevalent ones because of its lower hardware demand compared with the others [14].In this section, an brief introduction of NPW theory is firstly presented, then a small leakage experiment is conducted to validate the effect of EMF.

A. NPW theory leakage detection method

When a leakage occurs anywhere along the pipelines, the fluid density in the vicinity of the leak point would diminish because of fluid loss. This change leads to pressure lessening in the vicinity, exerting on running fluid medium to decrease pressure value every point along the pipes. This phenomenon is recognized as an impulse, called NPW, spreading both to the upstream and downstream pumps on pipelines. Two pressure sensors installing in each pump can detect and record pressure sample value decrease. According to the sample signals' start-dropping time difference between two sensors, combining with the given distance between two pumps and propagation speed of NPW, leakage judgment and location can be determined.

Fig.4 is schematic of leakage location based on NPW theory leakage detection method. The start-dropping time difference T_w between two neighboring pumps is calculated:



(a) simulated signal f in (15) with white noise

(b) original signal s in (14)(dotted) and its result filtered by EMF with g

Fig.2 An example of a simulated signal and its EMF result given M =20

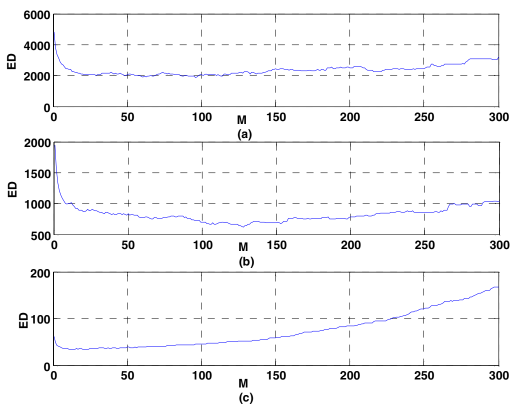


Fig.3 Different ED value obtained by M ranging from 1 to 300 under different noise conditions: (a) SNR=2 (b) SNR=10 and (c) SNR=40 respectively

$$T_w = X/(v-v_0) - (L-X)/(v+v_0) \tag{18}$$

$$X = \frac{1}{2v}[L(v-v_0)+(v^2-v_0^2)T_w] \tag{19}$$

Where X — Distance between the leak point and upstream pump, L — Distance between upstream and downstream pumps, v —Propagation speed of NPW, v_0 —Liquid velocity, which is estimated by nominal flow rate and pipelines cross-section area. In general situation, v_0 <<1m/s, so in (19), v_0 can be ignored. Eqn. (19) can be simplified as (20):

$$X = \frac{1}{2}(L+vT_w) \tag{20}$$

Eqn. (20) is defined as leakage location formula.

B. *Applying EMF to pressure sample signal prefilter*

Firstly, EMF applied to pressure sample signal greatly removes the disturbance impulses and results in trend which recovers the useful information in the sample signal. Then fast difference algorithm is used to produce difference signal of trend data, reflecting trend time-varying characteristic. Each difference value is compared with a preset threshold to determine at which moment pressure sample value starts to drop to an unacceptable extent.

A field-pipeline small leakage experiment is performed in the following way: we select a point along the pipeline in advance and deliberately conduct a leakage right at this point. With initial conditions, EMF is employed here to preprocess observed sample pressure data to gain its general geometry shape. The initial conditions are the followings: distance between upstream and downstream pumps L =1213.85m, propagation speed of NPW v =1125m/s, data sample period Δt =0.01s, nominal flow rate Q_0 =47.78m^3/s, actual distance between upstream pump and leak point X_0 =755.7m.

The flow rate of leakage we conducted is approximate 0.7 m^3/s, which is 1.47% of the nominal flow rate. Fig. 5(a) shows the pressure sample signal (dotted) detected by upstream pump pressure sensor, which is known as upstream pressure signal.

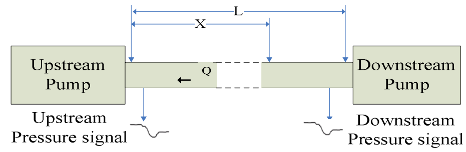


Fig.4. leakage location principle diagram of NPW detection theory

N is the length of upstream pressure signal, it is 10000 in this experiment. The leakage experiment conducted is under moderate noise condition, so select M =33, 0.33% times of N, according to the empirical rule observed in section III. Then upstream pressure trend can be obtained by EMF, also showed in Fig. 5(a). Fig. 5(b) shows corresponding downstream counterpart: downstream pressure signal and its EMF-extracted trend.

C. *Leak point location*

Let $T_u(k)$ and $T_d(k)$ (k =1, 2…10000) denote upstream and downstream trend acquired by EMF in Fig.5 respectively. In order to enhance leakage location real-time performance, we separate $T_u(k)$ and $T_d(k)$ (k =1, 2…10000) into 10 segments in order to shorten data analysis length for the following fast difference algorithm, each segment has a length of 1000 data. Eqns. (21)-(22) indicate the separation.

$$T_u = [T_{u1}, T_{u2} \ldots T_{u10}] \tag{21}$$

$$T_{ui}(k) = [T_u(1000(i-1)+1) \ldots T_u(1000i)] \; i = 1,2\ldots10$$

$$T_d = [T_{d1}, T_{d2} \ldots T_{d10}] \tag{22}$$

$$T_{di}(k) = [T_d(1000(i-1)+1) \ldots T_d(1000i)] \; i = 1,2\ldots10$$

For each trend segment, fast difference algorithm detects the start-dropping moment when sample value falls to an unacceptable extent. Assume t_{ui} be the upstream start-dropping moment detected in segment T_{ui} (i =1, 2….10) correspondingly and t_{di} for downstream trend ($t_{ui}, t_{di} \in [1,1000]$).

Taking $T_{u1}(k)$ (k =1, 2…1000) as an example, the difference algorithm is described as:

$$T_{u1}'(k) = T_{u1}(k+2) - T_{u1}(k) \tag{23}$$

$$T_{u1}''(k) = \frac{T_{u1}'(k)}{0.5H} \tag{24}$$

where $H = |T_{u1}'(k)|$ .If $T_{u1}''(k) < Th$ (a preset negative value due to detecting start-dropping moment) at moment $k = k_0$, then the trend data fluctuation is reaching a relatively high level. However, this fluctuation may not be leakage-causing drop because of noise disturbance or measurement artifacts. In order to exclude those kinds of false alarms, two average values of $T_{u1}(k)$ over WL length before and after moment k_0 are calculated and denoted as:

$$T_{u1}^{k_0-WL:k_0-1} = \sum_{i=k_0-WL}^{k_0-1} T_{u1}(i) \Big/ WL \qquad (25)$$

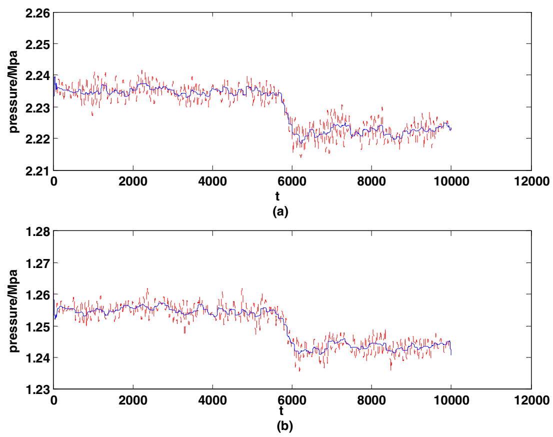


Fig.5 (a) Upstream pressure signal and its EMF result (solid); (b) Downstream pressure signal and its EMF result(solid)

and

$$T_{u1}^{k_0+1:k_0+WL} = \sum_{i=k_0+1}^{k_0+WL} T_{u1}(i) \Big/ WL \qquad (26)$$

If

$$T_{u1}^{k_0+1:k_0+WL} < T_{u1}^{k_0-WL:k_0-1} \times (1-\alpha) \qquad (27)$$

where α is defined as acceptable fluctuation range and reasonably set to be pressure sensor accuracy, then moment k_0 is considered as start-dropping moment and $t_{u1} = k_0$, else the moment k_0 will be neglected as a normal fluctuation moment. If no such k_0 is detected in current segment T_{u1}, then t_{u1}=-1. For the other upstream pressure segments T_{ui} (i=2~10) and downstream trend segments T_{di} (i=1~10), t_{ui} (i=2~10) and t_{di} (i=1~10) can be detected in the same way.

Predefine Th =-1.5, WL =200, α =0.9957, then results show only the fifth segments, i.e. T_{u5} and T_{d5}, find start-dropping moments satisfying the fast difference algorithm detection conditions: t_{u5}=802, t_{d5}=773. The time difference in (20) can be calculated: $T_w = (t_{u5} - t_{d5})\Delta t$ =0.29s and the leak point X =[1213.85m+1125m/s × 0.29s]/2=770.05m, the location relative error η is: $\eta = (X - X_0)/L$ =1.18%.

Further experiment finds out if the fast difference algorithm is directly performed on original pressure sample signals rather than their trend reconstructed by EMF, leakage flow rate smaller than 1.43 m^3/s, namely approximately 3% of nominal flow rate, cannot be detected. *Reinaldo et al* [1] also shows traditional leakage detection methods using NPW theory normally detect leakage ranging from 5% to 50% of the nominal flow rate, which indicates morphology filtering technique assists enhancing ability to detect smaller leakage. The experiment illustrates EMF is capable of tracing basic signal online evolution with small or slow variation, showing a promising prospect in data monitoring and decision.

V. Conclusion

This paper employs morphological signal processing technique to assist field-pipeline small leakage detection. Extended Morphological Filter (EMF) is constructed by basic opening and closing morphological operators to not only filter noise and disturbance but also retain signal general geometry. It is capable of effectively recovering the trend of signal with small and slow change. This trend can offer a better visual inspection of pressure sample signal time-varying feature, containing sufficient qualitative information about locating small leakage, while traditional leakage detection methods fails to extract correct information directly from original pressure sample signal without EMF prefilter.

The length of structuring element is examined under different SNR conditions. The empirical rule for the length selection is less than 1% of the total length of analyzed signal. Under different noise magnitude condition, the length selection will vary slightly. In the further experiment, we also found when large amount leakage occurs (more than 10% of the nominal flow rate), which indicates the observed pressure sample signal has a very sudden and clear falling edge, the structuring element length M of EMF should be tuned smaller compared with that in small leakage detection, because the signal time-varying characteristic is much less influenced by disturbance and noise. Then the further study can be focused on adaptive structuring element length EMF in different data monitoring applications.

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