EMF Signal Processing Scheme of Step Excitation Based on Data Fusion

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Abstract. When using electromagnetic flowmeter (EMF) to measure slurry flow, the flow signal will fluctuate randomly due to slurry noise interference. In order to reduce the influence of slurry noise, this paper proposes a signal processing scheme based on data fusion. Firstly, through different amplitude demodulation methods, multiple sets of velocity data are obtained simultaneously. Then, a single set of flow data is pre-processed based on support degree. Finally, adaptive weighted fusion is performed on multiple sets of data. The paper conducted a comparison experiment between the data fusion scheme and the moving average median filtering scheme. Experiments show that the steady-state volatility of data fusion scheme is generally smaller. The signal fusion scheme based on data fusion can effectively overcome influence of slurry noise on flow signal of step excitation EMF.

Keywords: step excitation electromagnetic flowmeter, data fusion, support degree, adaptive weighting.

1. Introduction
Data fusion is a commonly used information processing method, which can be used in signal processing, image analysis, automatic target recognition and other fields [1]. Multi-sensor data fusion can overcome the limitations of a single sensor by combining and complementing multiple sensor signals [2] to obtain more robust measurement data [3]. According to reference [4], the data fusion processing scheme has been applied to EMF flow signal processing precedentely. Reference [5] proposes an EMF signal processing scheme based on data fusion. Based on this literature, in order to give full play to the redundancy advantages of step excitation data, this paper proposes a step excitation signal processing scheme based on data fusion.

2. Principle of obtaining redundant measurement data of step excitation
In Fig. 1, signal 2 is excitation current $I_s$, signal 1 is flow signal voltage $E$. A complete excitation cycle includes positive excitation 1, positive excitation 2, positive zero excitation, negative excitation 1, negative excitation 2 and negative zero excitation. For the flow signal, $T_d$ is settling time of the flow signal and $T_s$ is the stable period time of flow signal. The sampling window $T_{st}$ should be selected within $T_s$. $N_{x1}, N_{x2}, N_{y1}, N_{y2}$ are the integration results of sampling windows of positive excitation 1, positive excitation 2, negative excitation 1 and negative excitation 2 in one cycle. The following five sets of flow data can be obtained by different amplitude demodulation methods.
Figure 1. Screenshot of oscillograph for exciting current and flow signal voltage of step excitation.

\[
\text{Speed}_1 = \frac{(N_{x2} - N_{y2}) - (N_{x1} - N_{y1})}{96000 + 0.02}, \quad \text{Speed}_2 = \frac{N_{x2} - N_{y2}}{96000 + 0.02}, \quad \text{Speed}_3 = \frac{N_{x1} - N_{y1}}{96000 + 0.02}
\]

\[
\text{Speed}_4 = \frac{N_{x2} - N_{x1}}{96000 + 0.02}, \quad \text{Speed}_5 = \frac{N_{y1} - N_{y2}}{96000 + 0.02}
\]

Fig. 2 is the block diagram of the overall structure of the signal processing scheme.

3. Introduction of signal processing algorithm theory

3.1. Single group signal sequence preprocessing based on support degree

Suppose that the measurement system can obtain m sets of data at the same time, each group of data contains n values, which are respectively \(x_1, x_2, ..., x_n\). For two observations \(x_i\) and \(x_j\) (i,j=1,2,...,n) of the same group of data, the support degree \(r_{ij}\) is:

\[
\tau_{ij} = e^{-|x_i - x_j|}
\]

If the difference between \(x_i\) and \(x_j\) is large, \(r_{ij}\) will decrease. Then, the support degree matrix \(R\) can be obtained. \(R\) is \(n \times n\) policy, matrix elements are \(r_{ij}\), i, j are row and column numbers [6].
The comprehensive support degree $a(i)$ can be used to express the comprehensive support degree [7] for the $i$-th flow data, which can be defined as: $a(i) = \sum_{j=1}^{n} r_{ij}$. The weighting factor $w_{1k}(i)$ of the $i$-th flow data of the $k$-th group of data can be calculated as Eq. 2:

$$w_{1k}(i) = \frac{a(i)}{\sum_{i=1}^{n} a(i)}$$ (2)

$0 \leq w_{1k}(i) \leq 1$, $\sum_{i=1}^{n} w_{1k}(i) = 1$. The weighted fusion estimate of the $n$ measurement data $x_1, x_2, ..., x_n$ of the $k$-th group of data is can be calculated as $\hat{x} = \sum_{i=1}^{n} w_{1k}(i) x_i$, and the fusion estimation values of other $m-1$ groups of data can be obtained in the same way.

3.2. Adaptive weighted fusion of multiple sets of signal sequences
Signal fusion has multiple fusion structures [8]. This paper adopts widely used distributed fusion without feedback. Adaptive weighted fusion is to find the optimal weighting factor in an adaptive way by estimating the variance of each sequence to minimize the total mean variance [9]. Assume that the data of $m$ groups are $x_k$, variance is $\sigma_k^2$, and weighting factor is $w_{2k}(k = 1, ..., m)$, $x_1, ..., x_m$ are unbiased estimates of the true value $X$. Then fusion value $\hat{X}$ is:

$$\hat{X} = \sum_{k=1}^{m} w_{2k} \tilde{x}_k \quad (\sum_{k=1}^{m} w_{2k} = 1)$$ (3)

The total mean square error $\sigma^2$ after fusion of multiple sets of signal data is:

$$\sigma^2 = E[(X - \hat{X})^2] = E[\sum_{k=1}^{m} w_{2k}^2 (X - \tilde{x}_k)^2 + 2 \sum_{i,j=1, j \neq i}^{m} w_{2i} w_{2j} (X - \tilde{x}_i)(X - \tilde{x}_j)]$$ (4)

Since $x_1, ..., x_m$ are independent of each other, so $E[(X - \tilde{x}_i)(X - \tilde{x}_j)] = 0$, then:

$$\sigma^2 = E[\sum_{k=1}^{m} w_{2k}^2 (X - \tilde{x}_k)^2] = \sum_{k=1}^{m} w_{2k}^2 E[(X - \sum_{i=1}^{n} w_{1k}(i) x_i)^2]$$ (5)

After further derivation, Eq. 6 can be obtained:

$$E[(X - \sum_{i=1}^{n} w_{1k}(i) x_i)^2] = \sum_{i=1}^{n} w_{1k}^2(i) E[(X - x_i)^2] = \sum_{i=1}^{n} w_{1k}^2(i) \sigma_i^2$$ (6)

So $\sigma^2$ can be expressed as the following equation:

$$\sigma^2 = \sum_{k=1}^{m} w_{2k}^2 \sigma_k^2 (\sum_{i=1}^{n} w_{1k}^2(i))$$ (7)

By Eq. 7, total mean square error $\sigma^2$ is a multivariate quadratic function about the variance of each group of data, and there must be conditional extremum. By using the Lagrange multiplier method, the weighting factor corresponding to minimum total mean square error can be obtained [10].

$$w_{2k}^* = \frac{1}{(\sigma_k^2 \sum_{i=1}^{m} \frac{1}{\sigma_i^2})} \quad k = 1, 2, ..., m$$ (8)

In Eq. 8, $\sigma_k^2 = \sigma_k^2 (\sum_{i=1}^{n} w_{1k}^2(i))$, the variance $\sigma_i^2$ can be estimated by various methods.

The signal processing algorithm execution process is as follows:
1. Calculate the comprehensive support degree $a(i)$, weighting factor $w_{1k}(i)$ and fusion estimate $\tilde{x}_k$ of the $n$ historical data of $m$ groups of flow signal respectively.
2. Calculate optimal weighting factor $w_{2k}^*$ of $k$-th group data according to Eq. 8.
3. Calculate fusion values of $5$ groups of data according to Eq. 3.

4. Processing of actual step excitation EMF flow signal
4.1. Calculation of correction coefficient $k$ for each signal sequence
Different amplitude demodulation schemes select different signal level intervals for calculation, and the amplitudes need to be unified. In Fig. 1, when the flow signal voltage $E$ changes from zero to the first order and from the first order to the second order, the amplitude is $x$ and $kx$. The amplitude of signal level change selected in the scheme of speed1-speed5 amplitude demodulation is $2kx, 2(k + 1)x, 2(2k + 1)x, ..., 2(m - 1)x, 2mx$. Therefore, according to the above order characteristics, the correction coefficient $k$ is determined as follows:

$$k = \frac{2m - 1}{2m}$$ (9)

The correction coefficient $k$ is used to correct the amplitude of the signal level change, which is determined by the range of the signal level change in each group of data.

4.2. Calculation of composite support coefficient $a(i)$ for each signal sequence
In the demodulation scheme, the comprehensive support degree $a(i)$ can be calculated as $a(i) = \sum_{j=1}^{n} r_{ij}$. The weighting factor $w_{1k}(i)$ of the $i$-th flow data of the $k$-th group of data can be calculated as Eq. 2:

$$w_{1k}(i) = \frac{a(i)}{\sum_{i=1}^{n} a(i)}$$ (2)

$0 \leq w_{1k}(i) \leq 1$, $\sum_{i=1}^{n} w_{1k}(i) = 1$. The weighted fusion estimate of the $n$ measurement data $x_1, x_2, ..., x_n$ of the $k$-th group of data is can be calculated as $\hat{x}_k = \sum_{i=1}^{n} w_{1k}(i) x_i$, and the fusion estimation values of other $m-1$ groups of data can be obtained in the same way.
1) 𝑥, 2𝑥, 𝑘𝑥, 𝑘𝑥. After measuring 𝑘 is about 0.76, the amplitude demodulation scheme of Speed1 is
taken as standard, multiplication coefficients of speed1~speed5 are 1, 0.432, 0.761, 2, 2.

4.2. Single group of signals for preprocessing based on support degree

Figure 3. Fusion results of a single set of signal sequences based on support degree.

As shown in Fig. 3, a single group of signal preprocessing based on the support degree is performed
for Speed1~Speed5 respectively, and the signal value Speed1_new~Speed5_new is obtained. It can be
seen that the fluctuation rate of the EMF flow signal has decreased significantly.

![Figure 3](image)

4.3. Adaptive weighted fusion of multiple sets of signal sequences

Fig. 4 (b) and (c) are the signal sequence variance curve and weighting factor curve of Speed1_new
~Speed5_new respectively. The larger the variance of flow sequence, the smaller the corresponding
weighting factor, so that signal estimation with the minimum total variance can be obtained.

The calculated standard deviations of Speed1_new~Speed5_new are 0.0452, 0.0303, 0.0321,
0.0588 and 0.0401. The overall standard deviation of the fused flow signal is 0.0194, which shows that
the overall standard deviation of fused signal is the smallest. Fig. 5 shows the comparison between
final flow signal after adaptive weighted fusion and unfiltered flow signal speed1. It can be seen that
the signal gradually flattens after signal processing, and the volatility decreases significantly.

![Figure 4](image)
4.4. Summary and analysis of experimental results

In this paper, the flow measurement experimental device is used to collect data. The sand water mass ratio of mortar is 1/125 and 8/125, the grain size of quartz sand is 20-120 mesh. The experiment is performed when the flow rate fluctuates at equal amplitudes of about 1m/s, 2m/s, 3m/s. According to reference [11], the steady-state volatility Var is used to measure processing effect of the software algorithm. Calculation equation is \( \text{Var} = \frac{\text{Max} - \text{Min}}{\text{Mean}} / 2 \times 100\% \), where Max, Min, Mean are the maximum, minimum and average of flow velocity. Experimental data are shown in Table 1.

| Sand water ratio | Frequency (Hz) | Flow rate (m/s) | Data fusion signal processing scheme | Moving average median filtering |
|-----------------|----------------|-----------------|-------------------------------------|--------------------------------|
|                 |                | Max(m/s) | Min(m/s) | Var(%) | Max(m/s) | Min(m/s) | Var(%) |
| 1/125           | 6.25           | 1.001    | 0.999    | 0.109  | 1.003    | 0.996    | 0.385  |
|                 |                | 2.002    | 1.997    | 0.123  | 2.008    | 1.990    | 0.447  |
|                 |                | 3.011    | 2.973    | 0.639  | 3.130    | 2.900    | 1.837  |
| 25              | 1.001          | 0.998    | 0.105    |        | 1.002    | 0.995    | 0.368  |
|                 |                | 2.002    | 1.995    | 0.139  | 2.007    | 1.992    | 0.384  |
|                 |                | 3.010    | 2.987    | 0.380  | 3.083    | 2.980    | 1.150  |
| 81.25           | 1.000          | 1.000    | 0.037    |        | 1.005    | 0.993    | 0.390  |
|                 |                | 2.002    | 1.999    | 0.083  | 2.012    | 1.992    | 0.523  |
|                 |                | 3.003    | 2.997    | 0.100  | 3.119    | 2.986    | 1.544  |
| 8/125           | 6.25           | 1.002    | 0.999    | 0.130  | 1.003    | 0.996    | 0.385  |
|                 |                | 2.003    | 1.993    | 0.237  | 2.008    | 1.990    | 0.447  |
|                 |                | 3.036    | 2.969    | 1.122  | 3.130    | 2.900    | 3.837  |
| 25              | 1.001          | 0.999    | 0.072    |        | 1.002    | 0.995    | 0.368  |
|                 |                | 2.002    | 1.997    | 0.126  | 2.007    | 1.992    | 0.384  |
|                 |                | 3.010    | 2.993    | 0.284  | 3.013    | 2.980    | 0.550  |
| 81.25           | 1.000          | 1.000    | 0.036    |        | 1.002    | 0.997    | 0.226  |
|                 |                | 2.001    | 1.997    | 0.098  | 2.012    | 1.992    | 0.523  |
|                 |                | 3.001    | 2.998    | 0.058  | 3.019    | 2.986    | 0.544  |

When sand water mass ratio is 1/125 and data queue length is 128, the fluctuation rate of data fusion algorithm is less than 0.109%, 0.139%, 0.639% at the flow velocity of about 1m/s, 2m/s and 3m/s, and the fluctuation rate of moving average median filter algorithm is less than 0.390%, 0.523%, 1.837%. The overall volatility of the data fusion algorithm is less than moving average median filtering. The results are similar when the sand-water quality ratio is 8/125. Experiments show that the step-excitation EMF signal processing scheme based on data fusion can effectively suppress slurry noise and improve EMF’s ability of overcoming slurry noise.
5. Conclusions
In this paper, a signal processing scheme based on data fusion is proposed. The scheme first obtains five sets of flow signals by different amplitude demodulation methods, then preprocesses a single group of flow signals by support degree method, and finally obtains the final flow signals by adaptive weighted fusion. The paper conducts a comparison experiment between data fusion algorithm and moving average median filtering algorithm method. Experimental results show that the steady-state volatility of the data fusion algorithm is generally smaller than the moving average median filter. This shows that the data fusion-based signal processing scheme can effectively suppress the slurry noise and improve the ability of the step excitation EMF to overcome the slurry noise.

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