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A novel virtual modelling tool for investigating time shift estimation methods in Coriolis mass flowmeters

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ABSTRACT

Coriolis mass flowmeters are crucial for measuring mass flow rates of fluids with diverse characteristics, including gas-liquid and other single-phase flow mixtures. Precision in measuring mass flow rates relies on accurately determining the time shift between the sensor signals from the flowmeters. Real-life testing of the methods for time shift measurement poses challenges, prompting the exploration of a virtual modelling tool as a cost-effective alternative. This paper introduces a pioneering virtual model designed for testing signal processing algorithms that are or to be used in Coriolis mass flowmeters. Through the simulation of various time shift determination algorithms, the paper showcases the effectiveness of this virtual tool for Coriolis mass flowmeter testing. By simulating different time shifts, the model tackles the challenges inherent in real-life testing scenarios. The study scrutinizes algorithms such as zero-crossing, cross-correlation, and the Hilbert Transform, offering insights into their performance and applicability of Coriolis mass flowmeters with the virtual model offering advantages such as cost-effectiveness and controlled environments. Through a comprehensive comparison and iterative testing, the virtual model not only aids in algorithm development but also facilitates the development of innovative flowmeters tailored for diverse industrial needs, promising enhanced applicability across a wider range of sectors.

1. Introduction

Coriolis mass flowmeters are indispensable instruments in various industrial processes, relying on the principle of Coriolis forces to measure mass flow rates accurately. These meters operate by inducing a vibration in flow tubes through which the fluid passes. The resulting Coriolis forces cause the tubes to deform, leading to a phase shift between the inlet and outlet vibrations, which is directly proportional to the mass flow rate of the fluid [1–4].

Accurate measurement of mass flow rates using Coriolis meters hinges upon the precise determination of the time shift between the two signals captured by the sensors. Time shift estimation methods, including conventional cross-correlation, zero-crossing [5], and the Hilbert Transform [6], are integral to this process. Each of these methods possesses unique characteristics, strengths, and weaknesses, which significantly impact the overall accuracy and reliability of the mass flowmeters. Conventional cross-correlation [7], for instance, is widely used for its robustness in identifying signal similarities and determining time shifts. Zero-crossing methods [5], on the other hand, offer simplicity and computational efficiency but may struggle with accuracy in the presence of noise or non-linearities in the signals. The Hilbert Transform method [6], known for its ability to extract instantaneous phase information, can be sensitive to signal variations and noise levels, impacting its performance in certain scenarios. Understanding the nuances of each method is crucial for selecting the most suitable approach based on the specific characteristics of the flow measurement application and the environmental conditions in which the Coriolis meters are deployed.

In contrast, virtual modelling tools offer a compelling alternative by providing a simulated environment where these methods can be rigorously evaluated and refined. Virtual modelling tools offer several advantages for Coriolis mass flowmeters [8]. Firstly, they provide a cost-effective means of testing various time shift estimation methods without the need for expensive physical setups. Additionally, virtual models offer a controlled environment where parameters can be precisely adjusted to simulate different flow conditions, facilitating comprehensive testing and analysis [9]. Moreover, the iterative nature of virtual modelling allows for the rapid prototyping and refinement of signal processing algorithms, leading to improved performance and accuracy.

By leveraging the advantages of virtual modelling, this paper introduces a novel virtual modelling tool that offers significant benefits over conventional methods for simple signal generation. These include repeatable idealised signals, controllable added noise, testing flexibility, cost-effectiveness, high efficiency in algorithm development. Users can customize parameters like noise levels and sensor characteristics enabling accurate replication of diverse scenarios. This adaptability allows the developers to undertake thorough testing under various conditions without the need for physical prototypes, saving time and resources. By eliminating the requirement for expensive equipment and testing facilities, the virtual tool offers a cost-effective alternative for extensive testing and optimization of flow signal processing algorithms. Additionally, the accessibility and reproducibility of the virtual tool foster seamless collaboration, peer review, and validation across different teams and organizations, driving knowledge advancement and innovation. Ultimately, this research aims to enhance the understanding

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and implementation of time shift estimation methods, leading to advancements in the design and performance of Coriolis mass flowmeters for a wide range of industrial applications including the measurement of multiphase flow. This paper evaluates the performance of various time-shift determination methods. We analyse their processing times in relation to different signal lengths. We use relative error plotted against different SNR (Signal-to-Noise Ratio) values to assess the performance of each algorithm. The rest of the paper is organized as follows: Section 2 is the review of the time shift calculation algorithms; Section 3 describes the methodology for developing the virtual modelling tool; Section 4 presents the results and discussion; and Section 5 provides the conclusion.

2. Review of time shift calculation alogrithms

Zero-crossing detection offers a simple and efficient way to estimate the time shift between two similar signals, especially those with a periodic nature like sine waves. It works by finding points where the signal crosses zero from positive to negative or vice versa. Corresponding zero-crossings in the time-shifted signals will occur at slightly different times due to the shift. By calculating the time difference between these matched zero-crossings. This concept is useful for estimating the time shift between two similar periodic signals. By identifying zero-crossing points (t_{zc2} and t_{zc1}) in both signals ($x(t)$ and $y(t)$), we can estimate the time shift (τ) as the absolute difference in their times ($|t_{zc2} - t_{zc1}|$) using the following equation:

$$\tau = |t_{zc2} - t_{zc1}|. \tag{1}$$

However, this method is limited by its sensitivity to noise. Even moderate noise can introduce errors in zero-crossing locations, leading to inaccurate time shift estimates. Additionally, it's not suitable for all signals, particularly those with complex shapes or lacking clear zero-crossings. Despite these limitations, zero-crossing detection remains a valuable tool for time shift estimation in specific scenarios due to its simplicity and computational efficiency.

Cross-correlation measures the similarity between two signals by sliding one signal over the other and computing the integral of their product at each time step. The time shift is calculated based on the peak of the cross-correlation function, which indicates the point of maximum similarity between the signals.

The mathematical equation for cross-correlation $R_{xy}(\tau)$ between two continuous signals x(t) and y(t) with a time shift τ is given by Ref. [10]:

$$R_{xy}(\tau) = \frac{1}{T}\int_0^T y(t)x(t+\tau)dt \tag{2}$$

Cross-correlation's computational efficiency is enhanced by fast algorithms like the Fast Fourier Transform (FFT), making it suitable for processing large datasets and real-time applications. Moreover, cross-correlation requires no assumptions about the signals or underlying systems, offering a data-driven approach that directly measures similarity. With its fine temporal resolution, it enables precise estimation of time shifts, making it invaluable for applications requiring accurate timing information.

The Hilbert transform is a mathematical operation that converts a real-valued signal into a complex-valued analytic signal. By calculating the phase difference between the analytic signals corresponding to two input signals, the time shift can be estimated. The Hilbert transforms of x (t) and y(t) are denoted as H(x(t)) and H(y(t)), respectively. The phase difference ($\Delta\varphi$) between the two original sinusoids can be calculated using the following equation:

$$\Delta\varphi(t) = \arctan\left(\frac{H(y(t))}{x(t)}\right) - \arctan\left(\frac{H(x(t))}{y(t)}\right) \tag{3}$$

The time shift can be determined by analysing the phase difference between the analytic signals. Additionally, its ability to preserve phase information ensures accuracy even with varying phase relationships between signals.

These methods are compared within the virtual tool to assess their accuracy and effectiveness in estimating the time shift of Coriolis mass flowmeters under different noise levels. The results aid in selecting the most suitable time shift determination algorithm for practical applications.

3. Virtual model methodology

Fig. 1 shows the flow chart and explain the steps to develop the virtual model in detail. Virtual model development is divided into three distinct steps, each being elucidated below:

Step 1: Model the Mass-Spring-Damper System

In this step, a Simulink model is constructed to represent the system with components including a mass (representing the mass of both the tube and fluid inside), a spring (emulating the damping effect), and a damper (representing Coriolis force). The model is designed to mimic the dynamics of a Coriolis flowmeter by attaching two mass-spring-damper systems to a lever, with each system representing one end and generating separate signals labelled as A and B. An external force is introduced to the lever, causing it to impact and initiate oscillations in the two systems, thereby generating distinct signals. These signals serve as the foundation for subsequent processing.

Step 2: Generate Sensor Signals

This step involves incorporating sensors into the model to measure the motion and deformation of the system. These sensors function similarly to those found in actual Coriolis flowmeters, producing signals that mirror real-world sensor outputs. These sensor signals provide essential data for further analysis and processing.

Step 3: Implement Signal Processing

In this final step, white Gaussian noise is added to the signals to simulate realistic conditions encountered in practical applications. Signal processing algorithms within Simulink are then utilized to process the sensor signals and estimate parameters such as time delay and mass flow rate. Various techniques including cross-correlation, zero-crossing, and Hilbert transform are applied for signal analysis. The results obtained from these techniques are simultaneously compared to evaluate their effectiveness in accurately estimating parameters. This comprehensive approach ensures a thorough assessment of the performance of different signal processing methods in the context of Coriolis mass flowmeter simulation.

By utilizing Simulink to simulate a mass-spring-damper system with the Coriolis effect, researchers and engineers can develop cost-effective, versatile platforms for studying and optimizing Coriolis mass flowmeters. These virtual tools expedite development cycles, enable thorough testing under diverse conditions, and ultimately advance Coriolis flowmeter technology.

4. Results and discussion

In the virtual model, signals were initially generated to emulate the behaviour of a Coriolis mass flowmeter using a mass-spring-damper system in Simulink, following step 1 from the flow chart in Fig. 1. As both mass-spring-damper systems are attached to each end of the lever, they initiate oscillations, resulting in the generation of sinusoidal signals A and B. To showcase the performance of different time-shift estimation methods, we used two sinusoidal signals (A and B) with a length of 1 second and a sampling rate of 10,000 kHz. A 500 ns time shift was

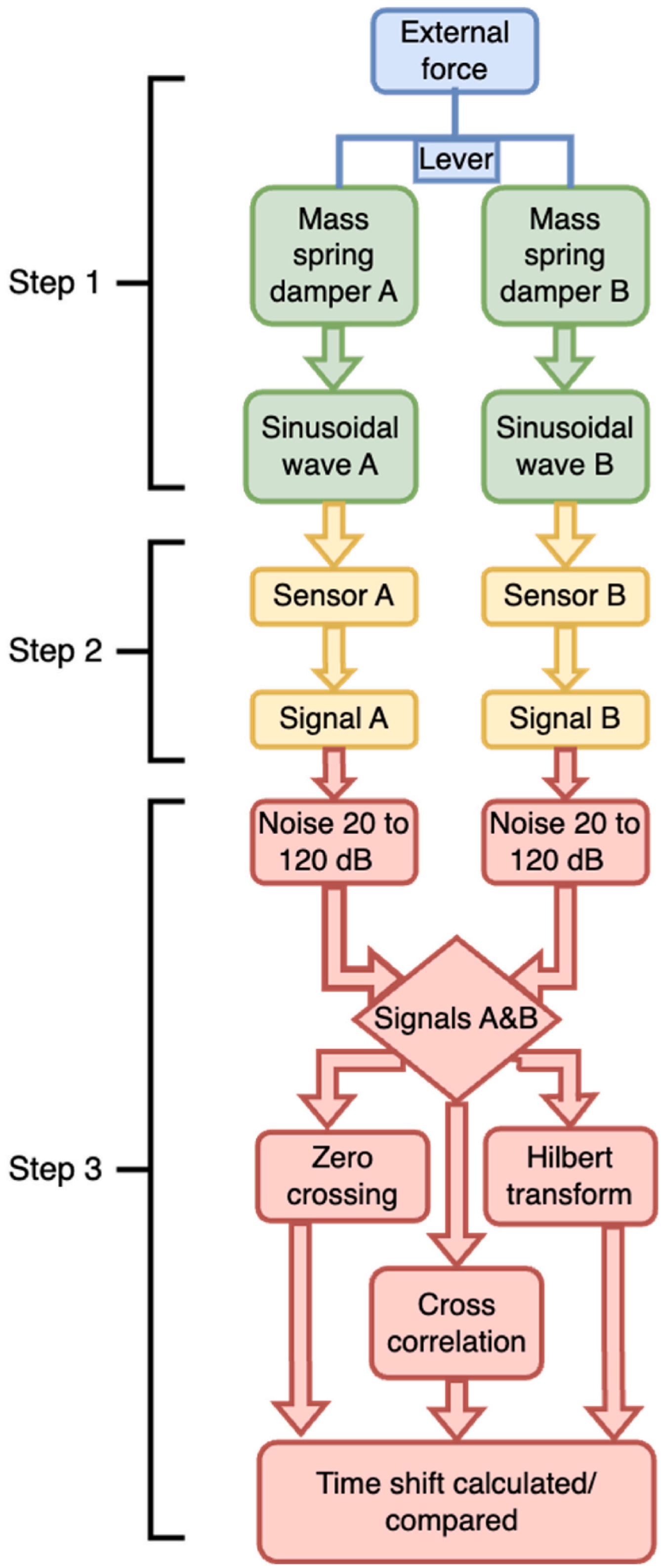

Fig. 1. Main steps in developing the virtual modelling tool.

introduced between the signals during this initial simulation. To mimic real-world conditions, we added varying levels of noise to the signals, with SNR. ranging from 20 dB to 120 dB. We then calculated the time shift using three different methods and compared their relative errors. For demonstration purposes, the resulting noisy signals A and B from 20 dB to 40 dB can be observed in the subplot of Fig. 2.

Subsequently, the time shift calculation algorithms are implemented and applied to the noisy signals to estimate the time shift between them. For the zero-crossing method, it initially identifies points where the input signals change sign (cross zero), followed by the computation of the average time shift between corresponding zero-crossings of the two signals. The cross-correlation method computes the correlation function between the two signals and determines the time shift by identifying the peak in the correlation function. Lastly, the Hilbert transform method shifts the phase of a signal by 90°, determining the phase difference between them, which aids in estimating the time shift. The reference time shift is first converted from seconds to samples, considering the sampling frequency, and then stored for future comparison. Subsequently, the relative error of the estimated time shift for each method is computed and plotted against multiple SNR values. To further analyse the processing time, the average processing time of each method is calculated for a range of signal lengths between 1 second and 4 seconds with a sampling rate of 10,000 kHz in Table 1. The analysis was conducted with MATLAB version R2023b on a Macbook Pro (M2 Pro chip and 16 GB memory). Across all algorithms, processing times for zero-crossing and cross-correlation remain constant (Table 1). In contrast, the Hilbert transform exhibits a clear increase in processing time, despite consistent performance for all algorithms with varying signal lengths.

Fig. 3 compares the performance of three time-shift estimation methods (zero-crossing, cross-correlation, and Hilbert transform) under varying SNR. This allows us to analyse their effectiveness across different noise conditions. The results are plotted for SNR values ranging from 40 dB to 120 dB. Data for zero-crossing at lower SNR (20 dB–30 dB) is omitted due to significantly higher error, making it difficult to visualize alongside the other methods.

Zero-crossing exhibits the lowest processing time but has the slowest error reduction. It reaches 0.5 % error at 90 dB and 0.05 % at 110 dB.

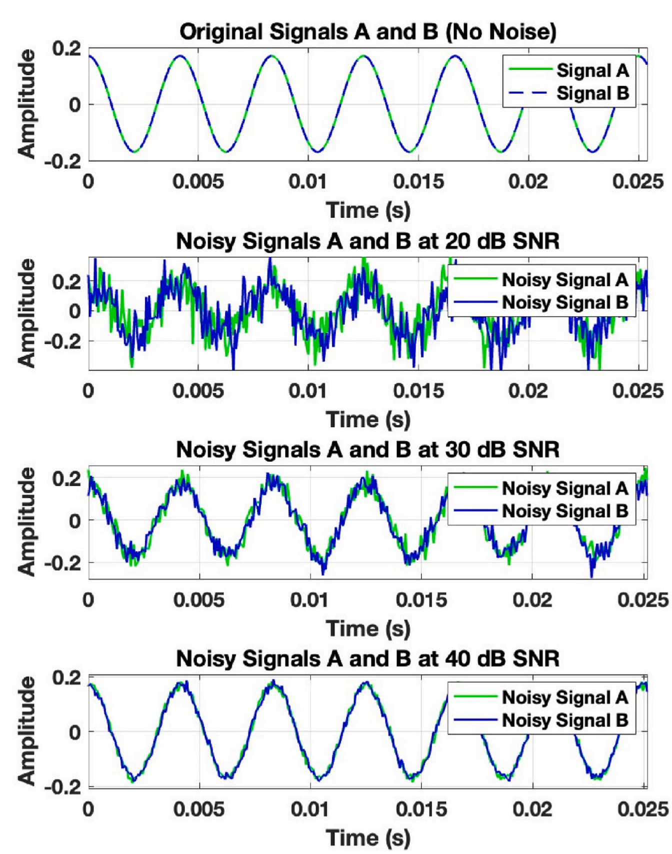

Fig. 2. Original signals A and B generated by the virtual model and noisy signals (A & B) with noise level from 20 dB to 40 dB for time shift of 500 ns.

Table 1
Average processing time (ms) of the algorithms according to the different signal's lengths from 1 second up to 4 seconds and sampling rate of 10,000 kHz.

Signal Length	Zero- Crossing	Cross-Correlation	Hilbert Transform
1 second	0.1	10	1000
2 second	0.2	10	3200
3 second	0.2	10	4500
4 second	0.2	10	6300

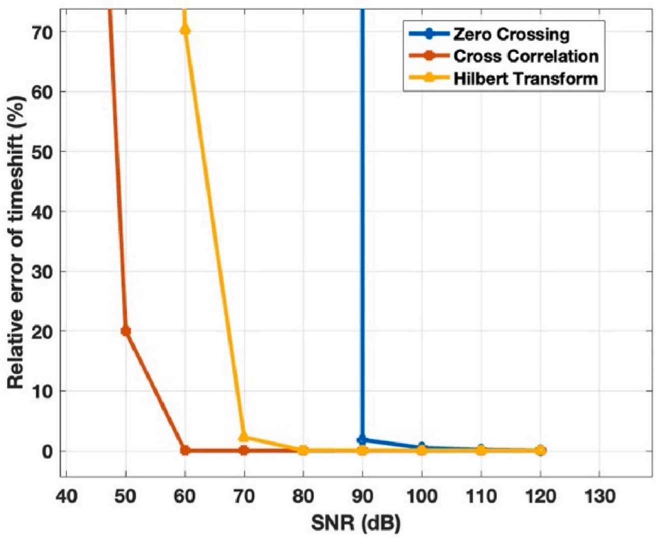

Fig. 3. Relative error of zero-crossing, cross-correlation, and Hilbert transform against SNR values from 40 dB to 120 dB for time shift of 500 ns and sampling rate of 10,000 kHz.

Cross-correlation achieves a 20 % error rate at 50 dB and practically eliminates errors by 60 dB. The Hilbert transform follows closely, reaching a 70 % error rate at 60 dB and a minimal 0.05 % error by 80 dB. While zero-crossing offers the fastest processing speed, its error reduction takes longer compared to the Hilbert transform and cross-correlation. However, cross-correlation, generally the most accurate and consistent method, comes at the cost of significantly higher processing time compared to zero-crossing (refer to Table 1 for details). In conclusion, for this scenario, cross-correlation provides the best accuracy and consistency in time-shift estimation.

5. Conclusions

In this paper, we have proposed a virtual modelling tool for testing multiple signal processing algorithms for Coriolis mass flowmeters. Using mass spring damping systems generates sinusoidal signals, we have demonstrated the generation of equivalent signals from Coriolis mass flow meters. These signals are processed in the virtual model, with noise added to enhance realism. Our approach allows testing of multiple time shift algorithms, including cross-correlation, zero-crossing, and Hilbert transform. The results presented in this paper have indicated that zero-crossing yields the lowest error at higher SNR values and the shortest processing time among the three algorithms. Hilbert transform achieves the highest accuracy at lower SNR values compared to zero-crossing and maintains its performance throughout, but at the cost of very long processing time. Cross-correlation performs best overall, achieving near zero error at lower SNR values and maintaining its performance at higher SNR values as well with an acceptable processing time. The iterative nature of the approach enables the replication of different meter designs, facilitating testing of signal processing techniques, multiple filter designs, and diagnostic methodologies. It is envisaged that, using the developed virtual tool, the best combination of algorithms tailored to specific meter designs may be identified. Overall, the virtual tool has the potential to facilitate the development of innovative flowmeters tailored to diverse industrial needs, enhancing efficiency in flowmeter design and optimization, and improving accuracy in mass flow metering.

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