Adaptive filtration of gyroscopic sensor data with neural network

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Abstract

This paper explores the study of combined measuring instruments that utilize gyroscopic devices. It provides a comprehensive analysis of the characteristics of both the measurement and computational components involved in these instruments. The focus is on a non-orthogonal configuration of the combined measuring instrument, which is built around the MEMS gyroscope MPU-6050. This specific gyroscope is known for its precision and compactness, making it an ideal choice for modern applications. The mounting structure is designed in the shape of a pyramid, which contributes to the overall stability and performance of the instrument, allowing for enhanced measurement accuracy. Additionally, the paper details the algorithm used for processing the measured data. This algorithm integrates a moving average technique, which helps smooth out fluctuations in the data, thereby providing more reliable readings. Furthermore, it incorporates a time delay neural network, a sophisticated method that allows for the analysis of temporal patterns in the data, enhancing the instrument's ability to interpret complex motion dynamics. Overall, the research presented in this paper aims to advance the understanding and functionality of combined measuring instruments, highlighting the innovative integration of gyroscopic technology and advanced data processing algorithms.

Keywords

measuring information, combined measuring instrument, moving average algorithm, time delay neural network, prediction, smoothing

1. Introduction

Nowadays Unmanned aerial vehicles (UAV) are integrated into different sides of human activity. Based on UAV design and main functions it could be equipped with different avionics. The main equipment list of UAV is still constant for different types. Electric engines, autopilot module, sensors, and actuators require a precise electrical distribution network on-board [1]. Also, a specific requirement is set to provide payload normal operation. Digital data link with ground control station is provided with specific trucking antenna system on both sides UAV and ground station. Different channels could be used for UAV control and video streaming. Also, many UAVs are capable of tracking functions that allow UAV to follow a predefined object in a dynamically changed environment [2, 3]. Performance of automatic tracking function depends on the quality of on-board camera stabilization. Level of video data stabilization is also important for a visual navigation system and has an impact on the accuracy of positioning [4, 5].

To ensure the high quality of transmission of video signals, it is necessary to use stabilization. The most efficient approach to stabilization is based on using triaxial mechanical gimbals and control signals [6, 7]. These signals are formed on information about the location of the UAV. Such data is entered from gyroscopic devices [8, 9]. Therefore, the accuracy of stabilization depends on the accuracy of information measured by gyroscopic devices [10, 11].

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The paper studies data processing of multiple gyroscopic devices to improve performance of provided data. Modern gyroscopic instruments (MEMS rate gyroscopes are usually used in the UAV's stabilization and motion control) use digital outputs. Measuring transducers are integrated with computing elements of information processing. The computing part of modern measuring instruments can carry out the following functions:

1. Transformation of analog signals into a discrete form.
2. Processing multi-dimensional information in a discrete form.
3. Exchange of multi-dimensional information in a discrete form between different channels of information processing.
4. Storage of multi-dimensional information.
5. Forming output information by requests.
6. Reverse digit-analog transformation of signals for carrying out functions of indication, control, and registration.

Therefore, developing appropriate algorithms for redundant information processing in inertial navigation system is very important. The algorithm of data processing is represented in Figure 1. The physical value which includes useful information can be directly measured in some physical form. Usually, it represents some component of another physical value, which can be measured directly. The connection between these two values can be defined as the primary conversion. Usually, this conversion is implemented by some known law. Otherwise, it will be impossible to restore the necessary information. The primary converter forms the output signal, which includes useful measuring information and noise of the primary information.

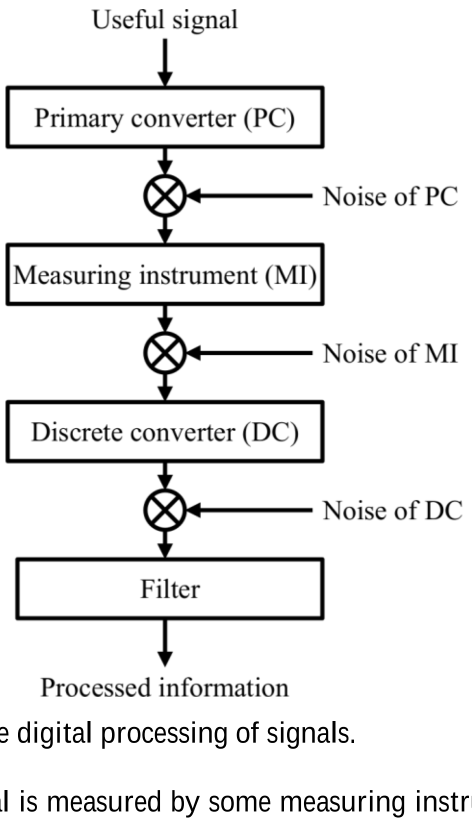


Figure 1: Block diagram of the digital processing of signals.

Further, the obtained signal is measured by some measuring instrument. In this case, distortion of the measured information due to measuring noise is added. To implement digital processing, the measured value must be converted into a discrete form using a special device containing an extrapolator and an analog-digital converter. The first transducer produces the fixed current measured value at discrete points in definite time intervals. The second transducer converts values into a digital form, allowing us to process information in digital computers. During this conversion, the noise of discretization arises. To obtain the desired information based on the discrete signals, it is necessary to calculate and create a device or computer program, which will minimize the above-mentioned distortions.

In general, filter design is an important problem that can be concretized only based on preexisting knowledge about the characteristics of measured values. Finally, the designed filter must eliminate as much as possible all the above-mentioned distortions of useful information.

During the usage of the moving average algorithm, it is possible to exclude trend and random noise [12, 13]. All the known approaches have essential disadvantages, which lead to a decrease in the quality of the obtained measuring information. The technique proposed in this paper eliminates the disadvantages of classical approaches. Therefore, the developed combined algorithm matters both in applied and theoretical aspects. Also, most algorithms of moving average algorithm represent low-frequency filters from the point of view of digital filtering.

The most widespread algorithms of the studied type are moving average, weighting moving average, and exponential moving average [14, 15].

Rapid development of artificial intelligence technologies has led to the arising of a large number of neural networks with various structures that have different ranges of computational burden and wide applicability [16, 17]. The impossibility of solving a definite problem or the possibility of obtaining results that are less accurate when using a traditional mathematical apparatus can indicate an incorrect selection of the network type. The neural network technique applied to solving some problems can noticeably shorten the computing process itself, as it allows us to avoid intricate computing conversions connected with the search for regularities of input and output data [18, 19].

The stability of the solution provided by a neural network in the presence of a noise component in the source data makes neural networks a fairly effective tool for solving complex technical problems [20].

Modern algorithms of filtering, smoothing, and prediction are widely used for increasing the accuracy and reliability of measuring information [21–23]. A new approach based on a combination of a moving average algorithm and a time delay neural network is proposed in this paper. Finally, we can obtain estimates taking into consideration both smoothing and prediction.

2. Features of redundant measuring instruments

Redundant data could improve characteristics of measuring instruments such as accuracy, reliability, durability, ability to check, resistance to faults, and survivability. Redundant measuring information could be obtained at different levels: structural, functional, code, and algorithmic. The structural redundancy foresees scheme-technical decisions, which ensure increase number of hardware used. Algorithmic redundancy is implemented at the information level. It is characterized as functional redundancy of information. Algorithmic redundancy is grounded on forming an array of redundant information. Some instruments could measure vector parameters (for example vectors of angular rate, accelerations, and strength of the magnetic field) [24, 25].

Functional redundancy can be achieved in two ways. The first one combines vectors of measuring instruments (triaxial MEMS gyroscope) in a non-orthogonal configuration. The main feature of non-orthogonal configuration is that the axes of sensitivity of the measuring instrument do not coincide with the axes of the basic reference frame, which is connected with a moving object. The second way uses a combined integration, where a set of vector measuring instruments oriented by orthogonal or non-orthogonal configurations ensures the measurement of vector parameters based on the principle of multi-dimensional measurements [26, 27].

Three-rate gyroscopes with non-collinear and non-coplanar axes of sensitivity form a combined non-orthogonal configuration. Any measuring system with redundant information based on principles of reservation, integration, and combination, in the general case, represents a multidimensional multiply-connected system [28]. In any case, a measuring system with redundant information includes both measuring and computing constituents [29, 30].

The combined measuring instrument based on MEMS rate gyroscope and non-orthogonal configuration is shown in Figure 2.

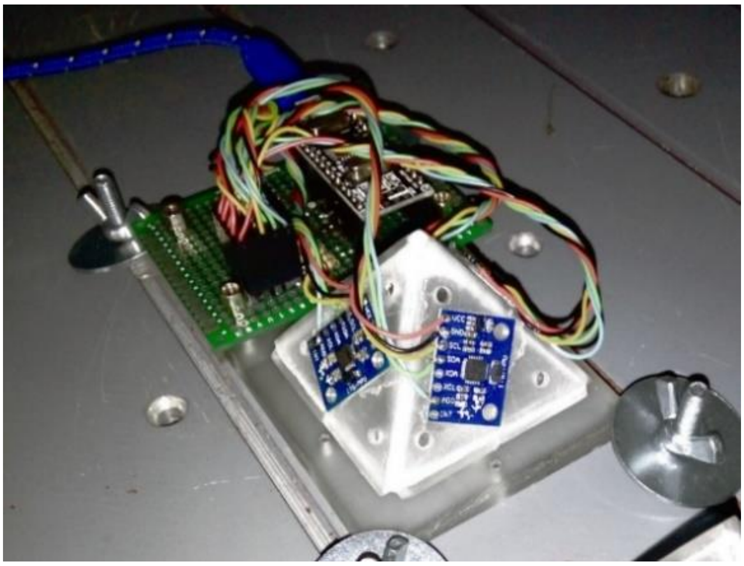


Figure 2: The combined measuring instrument based on rate gyroscopes.

Non-orthogonality of the measuring instrument is implemented by using the tetragonal pyramid as mounting blocks. Rate gyroscopes are located on the faces of the above-mentioned pyramid. The triaxial sensor MPU-6050 (Figure 3) has been chosen as a rate gyroscope for the considered configuration.

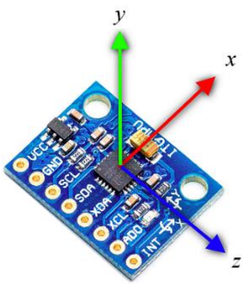


Figure 3: The triaxial M45EMS gyroscope MPU-6050.

Hence, the measuring part of the considered instrument is implemented by the rate gyroscope MPU-6050. The computing part is implemented by the microcontroller ATMEGA168. The structural diagram of the computing part is represented in Figure 4.

The application of combination in redundant measuring instruments has the following advantages:

1. Increasing the reliability of the measuring instrument in $1-(1-e^{-\lambda t})^{m-1}$, where λ is the intensity of failures; m is the multiplicity of reservation.
2. Decreasing the probability of a sudden failure.
3. Increasing the reliability of the measuring instrument.

The schematic location of the sensitivity axes of the combined measuring instrument is represented in Figure 5.

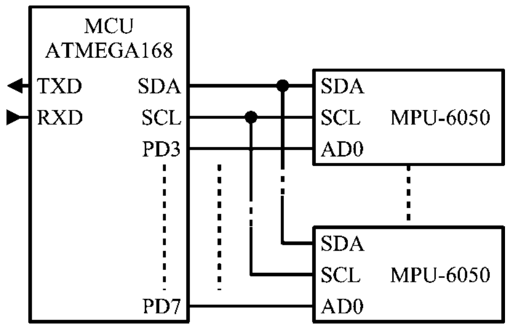


Figure 4: The structural diagram of the measuring instrument.

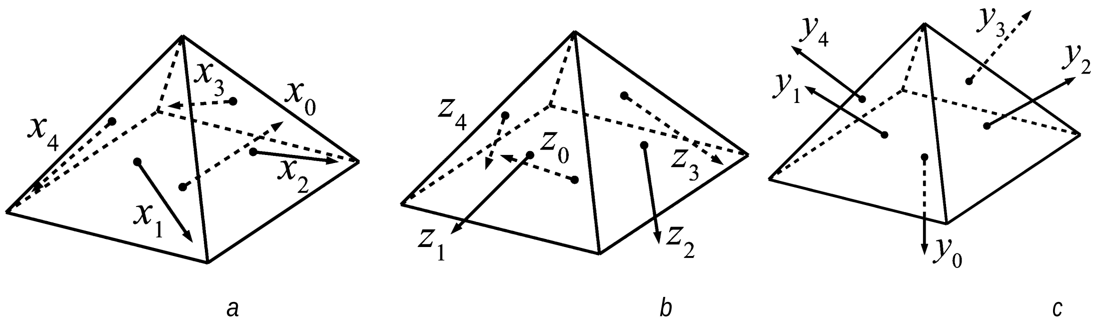


Figure 5: The location of sensitivity axes in the combined measuring instrument.

Checking of properties of the combined bench has been carried out using the triaxial tested bench. Triaxial tested bench helps to study the dynamic characteristics of the combined measuring instrument.

3. Developing of neural network for adaptation filtration

A Finite Impulse Response (FIR) filter is a kind of discrete filter that is commonly used in signal processing to manipulate or extract features from a signal. It operates by convolving the input signal with a set of filter coefficients, which are typically time-domain impulse response samples.

When designing an FIR filter using a neural network, the goal is to train the network to learn the optimal set of filter coefficients that can effectively process the input signal. The neural network is trained based on a set of input-output data pairs, where the input is the original signal, and the output is the filtered version of that signal.

The architecture of the neural network for FIR filter design can vary depending on the specific requirements and complexity of the filtering task. Typically, it consists of one or more layers of neurons, with each neuron representing a filter coefficient. The input to the network is the reference signal, and the output is the filtered signal.

During the training process, the network learns to adjust the weights (filter coefficients) of each neuron to minimize the difference between the filtered output and the desired output.

This is achieved through an optimization algorithm, such as gradient descent, which iteratively updates the weights based on the error defined as a difference between the predicted output and the desired output.

The training dataset for the neural network can be generated by applying known filter coefficients to a set of input signals, resulting in the corresponding filtered output signals. The network learns to approximate the correlation between the output and input signals, ultimately finding the optimal filter coefficients that produce the desired filtering effect.

Once the neural network is trained, it can be used to filter new input signals by applying the learned filter coefficients to the signal. This allows for real-time filtering or processing of signals using the optimized FIR filter.

Using a neural network for FIR filter design offers advantages such as flexibility in choosing the filter characteristics, adaptability to different filtering tasks, and the ability to learn complex connections between the output and input signals.

One of the widely used methods in digital signal processing is the implementation of Finite Impulse Response (FIR) filters. These filters apply a cumulative window function to a fragment of data, allowing for various processing operations such as smoothing, noise reduction, and signal prediction.

There are three types of FIR filters: causal, non-causal, and anti-causal. Causal filters only process previous samples of the input data stream and are suitable for real-time systems. For example, a causal FIR filter can be used to remove unwanted noise from an audio signal, preserving the integrity of the original sound.

Non-causal and anti-causal filters, on the other hand, utilize future samples and are considered physically unrealizable systems. They are commonly used in post-processing applications, such as analyzing recorded data or predicting future trends based on historical data. For instance, an anti-causal FIR filter can be employed to predict stock market trends based on historical price data.

Neural networks can be implemented as FIR filters to perform functions such as prediction and data smoothing. By training the network with appropriate weight coefficients, it can learn to make accurate predictions based on input data patterns. For example, a neural network-based FIR filter can be trained to predict future temperature fluctuations based on historical weather data, enabling more accurate weather forecasting.

Time delay neural networks allow us to learn the behavior of the dynamic systems. The structure of the time delay neural network is represented in Figure 6.

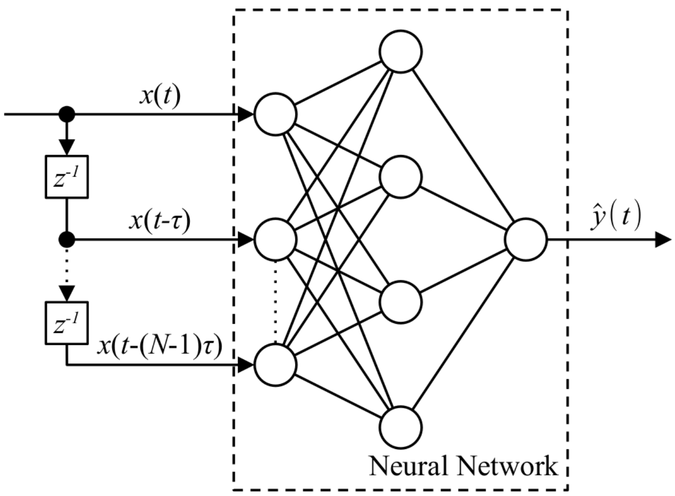


Figure 6: The structure of the time delay neural network.

The input of the considered neural network is a time series. For obtaining control signals, signals about projections of the angular rate in time $x(t),\ x(t-\tau),\ \ldots,\ x(t-(N-1)\tau)$ are used. Here N is the quantity of previous results of measurements. The output signal $y(t)$ represents the vector of angular rates of a moving object. The inputs of the time delay neural network enter the output through the delay unit forming feedbacks [31]. In such a way, the non-linear autoregressive prediction model is formed. In this case, the new vector of angular rate is predicted based on the input.

The time delay neural network allows us to create any finite time dependence as follows:

$$y(t) = F(x(t),\ x(t-1), \ldots,\ x(t-k)]. \qquad (1)$$

As recurrent connections in such a representation of a neural network are absent, the above-mentioned neural network can use the algorithm of backward propagation of an error as a learning algorithm.

The use of neural networks requires some preparatory stages, one of which is data preprocessing and filtering. To perform filtering, it is possible to use neural networks of various types: linear neural filters, networks with backpropagation of errors, dynamic networks, and networks based on radial basis functions. One of the neural networks used for filtering and noise suppression is a generalized adaptive neural filter, which is a set of neurons built based on functions that implement the Wiener filter. Also, a hybrid system consisting of a filter that uses a statistical approach for noise filtering, and a Hopfield network, is commonly used to eliminate the negative consequences of the filter [32, 33]. Different data processing technologies complement each other. Also, a filtering system could be presented in a set of sub-modules each of which is a separate neural network with backpropagation of errors.

At the stage of analysis and data processing. At this stage, the main solution to the problem is performed, the definition of a model that describes the observed processes. Accordingly, depending on the task at hand, it is possible to use a certain neural network structure. The most universal network architectures are multilayer networks with backpropagation of errors. The proposed configuration of the time delay neural network is represented in Figure 7.

Neural networks can be implemented as FIR filters to perform functions such as prediction and data smoothing. By training the network with appropriate weight coefficients, it can learn to make accurate predictions based on input data patterns. For example, a neural network-based FIR filter can be trained to predict future temperature fluctuations based on historical weather data, enabling more accurate weather forecasting.

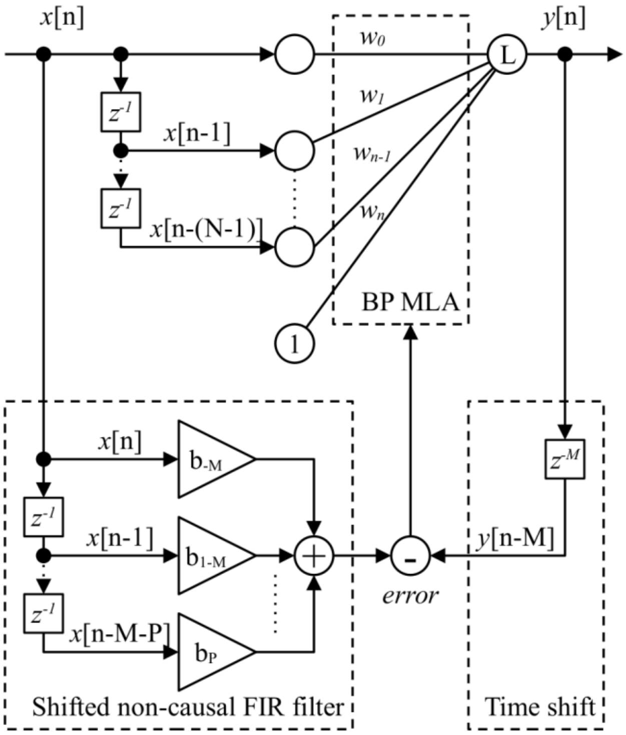


Figure 7: Configuration of the new time-delay neural network.

To evaluate the quality of prediction and smoothing, a non-causal FIR filter can be used as a reference. This reference filter is implemented by shifting the sample values in time, making it physically realizable. The response of the neural network is then compared to the response of the reference filter. If there are significant differences, an error signal is generated, which is used to update the network's weights through a modified backpropagation algorithm. This iterative training process allows the neural network to improve its predictive and smoothing capabilities over time.

Whether it is for noise reduction, signal prediction, or smoothing, these filters offer versatile solutions for a wide range of applications across various industries. An example of a non-causal filter is the Savitzky-Golay filter.

This filter is commonly used for smoothing and noise reduction in signal processing applications. It operates by fitting a polynomial function to a sliding window of data points and using the coefficients of the polynomial to perform the filtering operation.

Unlike causal filters that only use past samples, the Savitzky-Golay filter incorporates future samples in its calculations, making it a non-causal filter. This allows it to have a better smoothing performance by considering the overall trend and shape of the signal.

For example, let us say we have a noisy signal that represents temperature readings over time. We want to smooth out the noise and obtain a cleaner representation of the underlying temperature trend. We can apply a non-causal Savitzky-Golay filter to achieve this goal. By choosing an appropriate window size and polynomial order, we can adjust the level of smoothing and preserve important features of the signal. The filter will consider future samples to estimate the smoothed value at each point, resulting in a more accurate representation of the temperature trend. It's important to note that non-causal filters like the Savitzky-Golay filter are typically used when working with recorded data or analyzing time series, where future information is available. In real-time applications, causal filters are usually preferred due to their ability to process only past samples and provide immediate results. The simulation results are represented in Figures 8-9.

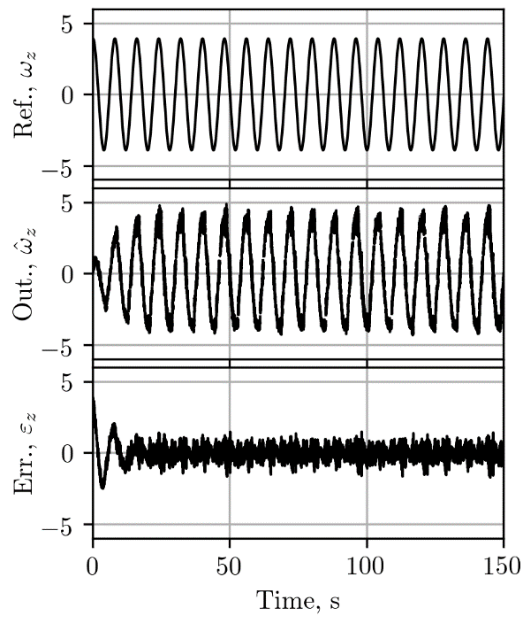
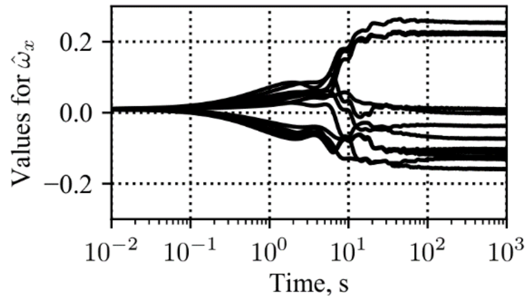
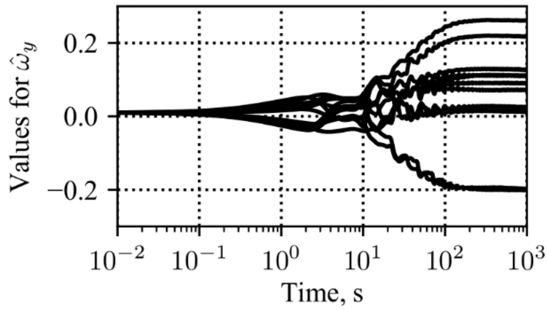


Figure 8: The illustration of learning the developed neural network.

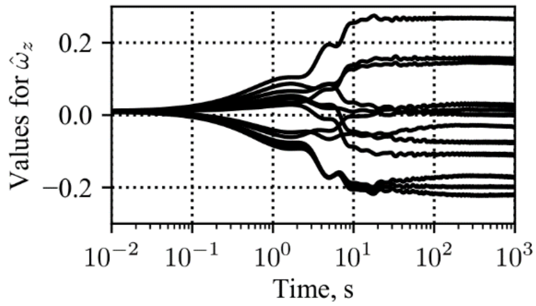
The backward difference filter is commonly used in signal processing and numerical analysis to estimate the derivative of a signal or to perform edge detection. It calculates the difference between a sample and its previous sample to approximate the rate of change or gradient at that point. Unlike causal filters that only use past samples, the backward difference filter incorporates future samples in its calculations, making it an anti-causal filter. This means that it predicts the value at a given point based on future samples. For example, we have a discrete signal representing the position of an object over time. We want to estimate the velocity of the object at each time point. We can use an anti-causal backward difference filter to achieve this.



a)



b)



c)

Figure 9: Determination of projections of the angle rate onto axes of the navigation coordinate system *x* (a), *y* (b), *z* (c).

Figure 8 characterizes the process of learning the developed neural network. In Figure 8, the following meanings are given: Ref denotes an initial signal at the neural circuit output; Out denotes the output signal changing during the learning; Err is a loss of the output signal. The results of processing information about the angular rate of the moving object obtained using the developed angular rate are shown in Figure 9.

By taking the difference between the current sample and its future sample, we can approximate the rate of change of the position, which gives us an estimate of the velocity.

This filter uses future samples to predict the value at each point, allowing us to estimate the velocity even before we have collected all the data. It's important to note that anti-causal filters like the backward difference filter are typically used in scenarios where future information is available or when analyzing recorded data. In real-time applications, causal filters are usually preferred as they only rely on past samples and provide immediate results.

4. Conclusions

The features of the combined instrument assigned for the measurement of angle rate are described. The characteristics of measuring and computing parts of the combined measuring instrument are characterized. The procedure of data processing based on a moving average algorithm and time delay neural network has been developed. Such an algorithm combines the advantages of smoothing and prediction estimates. In practice, the choice of the reference filter can vary depending on the application. For example, using a centered moving average filter with symmetrically distributed weights as a reference allows compensating for the phase shifts typically associated with classical causal moving average filters. This can be beneficial in applications such as audio processing, where maintaining the phase coherence of the signal is crucial. However, it is significantly to mark that since the filter implemented by the neural network operates on past samples and is only an approximation of a symmetric non-causal filter, there may still be some residual phase distortions. These distortions, however, are typically less pronounced compared to those observed in classical causal filters. In conclusion, the use of FIR filters, particularly implemented through neural networks, provides powerful tools for processing and analyzing data.

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