

Towards Hardware Implementation of Homogeneous Multi-Sensor Self-X System through Simulation-Based Virtual Sensor Modeling

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Summary:

Modern sensor systems are expected to provide reliable and consistent measurement quality even under non-ideal mechanical, environmental, or operational conditions. In many applications, achieving sustained high measurement quality with a single sensor depends on a high-quality sensing element, precise mechanical integration, and application-specific calibration or compensation, which increases system cost and design complexity.

This work investigates a Self-X sensor system in which several low-cost and imperfect homogeneous sensors are used instead of relying on a single high-quality and precisely mounted sensor. The main objective is to improve and stabilize the estimation of the target measurand through algorithmic fusion of redundant measurement channels. While previous work mainly focused on testing this hypothesis using simulation-based models, the present study represents a first step toward hardware realization. For this purpose, measurements from one real tunnel magnetoresistance (TMR) sensor were acquired at three different positions around a rotating magnet and used to emulate a homogeneous multi-sensor configuration. After alignment and resampling, the resulting channels were combined using dimensionality reduction to generate a virtual sensor representation.

Compared with the best individual sensor, the virtual sensor reduced mean absolute error (MAE) from 2.214° to 0.953° and root mean square error (RMSE) from 2.854° to 1.288° . This corresponds to improvements of approximately 57% and 55%, respectively. The results indicate that multi-sensor fusion can compensate for position-dependent distortions and provide a useful basis for further hardware development of the Self-X sensor concept.

Future work will focus on moving towards a simultaneous multi-channel hardware configuration, including configurations with more than three sensors and extended measurement campaigns under various operating conditions.

Keywords: Self-X System, TMR Sensor Array, Virtual Sensor, Dimensionality Reduction, Multi-Sensor Integration, Real-Measurement-Based Emulation.

Introduction

In modern Industry 4.0 environments, sensor systems are expected to operate autonomously, reliably, and with minimal human intervention [1, 2]. A homogeneous multi-sensor architecture can support these requirements by allowing several identical sensors to measure the same physical variable simultaneously. In contrast to a solution based on a single high-quality and carefully mounted sensor, such architecture can exploit redundancy among several low-cost and imperfect sensing units. However, redundancy alone does not ensure reliable operation, since individual channels may be affected by drift, misalignment, installation tolerances, amplitude scaling, phase shifts, and other sensor-specific distortions [3–5].

As a result, the potential benefits of multiple sensors cannot be fully exploited by conventional aggregation methods alone.

This limitation creates the need for more intelligent methods capable of evaluating sensor behavior, identifying inconsistencies, and adapting the measurement process accordingly. In this context, the Self-X approach provides a suitable framework for next-generation intelligent sensing solutions. Self-X properties, such as self-monitoring, self-calibration, and self-healing, allow sensor systems to detect internal deviations, compensate for partial failures, and maintain functionality under changing operating conditions. Within such architecture, a virtual sensor can provide a global estimate by combining information from multiple physical channels while accounting for their current condition and mutual consistency.

The present study is a logical continuation of previous work, where the Self-X-based fusion concept for homogeneous sensor systems was investigated mainly using simulation-based models [6]. In contrast, this work introduces real

measurement data as a first hardware-oriented step toward the realization of such a system. TMR sensors are used as a representative use case for angle estimation. The measured TMR signal is sensitive to the sensor placement relative to the magnetic source [7]. Even small deviations between the sensor and the magnet can introduce amplitude and phase distortions, thereby reducing angle estimation accuracy. Therefore, this use case is suitable for studying the compensation of position-dependent channel imperfections. However, the general Self-X concept is not restricted to this sensor type. Instead of implementing a complete multi-sensor hardware prototype with several concurrently operating sensors at this stage, a simplified proof-of-principle setup is used. A single real TMR sensor is measured at several different spatial positions around a rotating magnet, and the resulting signals are treated as individual channels of an emulated homogeneous multi-sensor configuration. The choice of three positions serves the current experimental design and does not represent a fundamental limitation of the concept. The individual channels are then combined into a virtual sensor using dimensionality-reduction methods, with Principal Component Analysis (PCA) used as an illustrative example. The combined latent representation is subsequently used to estimate the angle and is quantitatively compared with the individual sensor channels.

The main contributions of this work are threefold. First, a real-measurement-based proof-of-principle emulation framework is introduced as a first hardware-oriented step toward a homogeneous multi-sensor Self-X system. Second, dimensionality-reduction-based virtual sensor modeling is applied to real TMR signals obtained from multiple spatial positions. Third, the achieved improvement is quantified using standard regression error metrics applied to the angle estimation task and discussed with respect to the further development of a complete multi-sensor hardware implementation.

Concept of the Homogeneous Multi-Sensor Self-X System

The proposed concept is represented by a multi-layer architecture, as shown in Figure 1. This architecture represents the intended complete structure of a homogeneous multi-sensor Self-X system, which is planned to be realized in a full hardware implementation with several concurrently operating sensor channels. In this complete realization, sensor readings are gradually transformed from raw data into synchronized multi-sensor measurements, then into a fused virtual sensor representation, and finally into estimated values of the target parameter. Self-X

capabilities are then used to evaluate system behaviour and introduce correction or adaptation when deviations are detected.

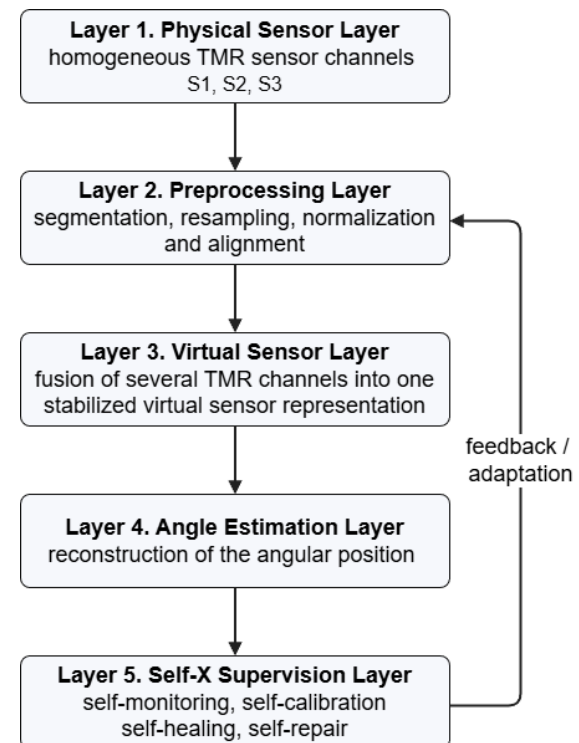


Fig. 1. General layer-based representation of the proposed homogeneous multi-sensor Self-X architecture.

The physical sensor layer represents the data collection stage of the architecture. In a complete hardware realization, this layer consists of homogeneous sensor channels that provide individual measurements of the same quantity or state of the physical system. Their purpose is to provide measured data for further processing.

The preprocessing layer converts the raw channel outputs into a form suitable for data fusion. These operations are required to ensure that the data compared across channels represent equivalent physical states or comparable measurement conditions. Depending on the measured process, these operations may include segmentation, resampling, normalization, filtering, synchronization, and alignment with a reference. The virtual sensor layer acts as the central transformation stage of the architecture. Its purpose is to generate a representative signal from the prepared multi-channel input. Instead of selecting one physical channel, this layer combines the available measurements into a system-level representation. In the present study, this layer is the main object of investigation, since it determines how several related sensor channels can be transformed into a more stable signal basis.

The estimation layer receives the virtual sensor output and converts it into the required target quantity q .

In the TMR-based use case considered in this work, this quantity corresponds to the estimated angular position θ .

The Self-X supervision layer forms the decision-making part of the architecture. It evaluates the behaviour of the preceding layers and initiates feedback, correction, or adaptation when deviations are detected. In a later hardware realization, this layer may adjust preprocessing parameters, update fusion settings, identify unstable channels, or trigger recalibration procedures. Current work focuses on a first hardware-oriented proof-of-principle step. At this stage, data from one real TMR sensor are acquired, preprocessed, and used to emulate a homogeneous multi-sensor configuration. The main focus is therefore placed on the signal-processing part of the architecture, namely virtual sensor formation from real measured data.

Experimental Setup with Multi-Sensor Emulation

The data used in this study were obtained using a previously developed setup for measuring TMR sensor outputs [4]. The experimental setup is shown in Figure 2 and consists of a rotating permanent magnet driven by an electric motor and a single TMR sensor placed near the magnet.

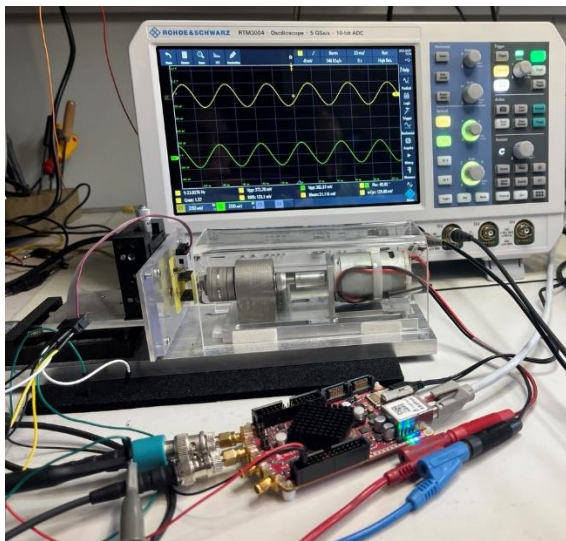


Fig. 2. Experimental setup.

During operation, the sensor records the variation of the magnetic field caused by the rotating magnet. This produces a periodic signal whose structure depends on the relative geometry between the sensor and the magnetic source. For the experiments, the motor operated at approximately 1200 rpm. Since the rotational speed was not perfectly constant, the number of recorded samples per revolution varied from 4140 to 4236, with a mean value of about 4185 samples. To ensure comparability between revolutions and

sensor positions, each revolution was segmented individually and resampled to a fixed length of 5000 samples. This preprocessing step was used only to obtain a consistent temporal representation for subsequent comparison and fusion.

To emulate a homogeneous three-channel sensor configuration, a single TMR sensor was sequentially placed at three different positions relative to the rotating magnet. Additional placement-related imperfections were introduced by tilting the sensor board during positioning, as shown in Figure 3.

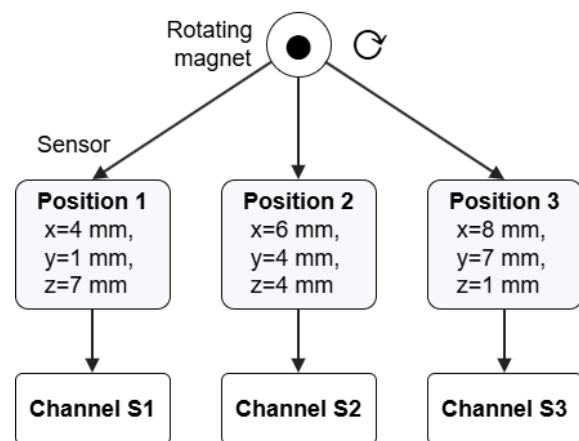


Fig. 3. Real-measurement-based emulation.

At each position, a separate measurement series was recorded and treated as one channel of an emulated homogeneous multi-sensor configuration.

The number of three channels was chosen for experimental feasibility only and is not a fundamental limitation of the proposed approach. The same fusion concept can be extended to a larger number of homogeneous sensor channels.

The present emulation has several limitations. The three channels were acquired sequentially rather than simultaneously; therefore, synchronization effects and possible sensor-to-sensor interactions were not represented. In addition, only one physical sensing element was used, so manufacturing variability between different sensors was not captured. The setup was also limited to one rotational regime and one magnetic configuration. Nevertheless, for a first hardware-oriented proof-of-principle step, the proposed emulation provides a feasible basis for assessing the benefit of virtual sensor representation using real measured data.

Virtual Sensor Modelling Methodology

Figure 4 presents the processing sequence used to derive the virtual sensor. The pipeline starts with synchronized sine-like and cosine-like outputs from the three TMR sensor positions.

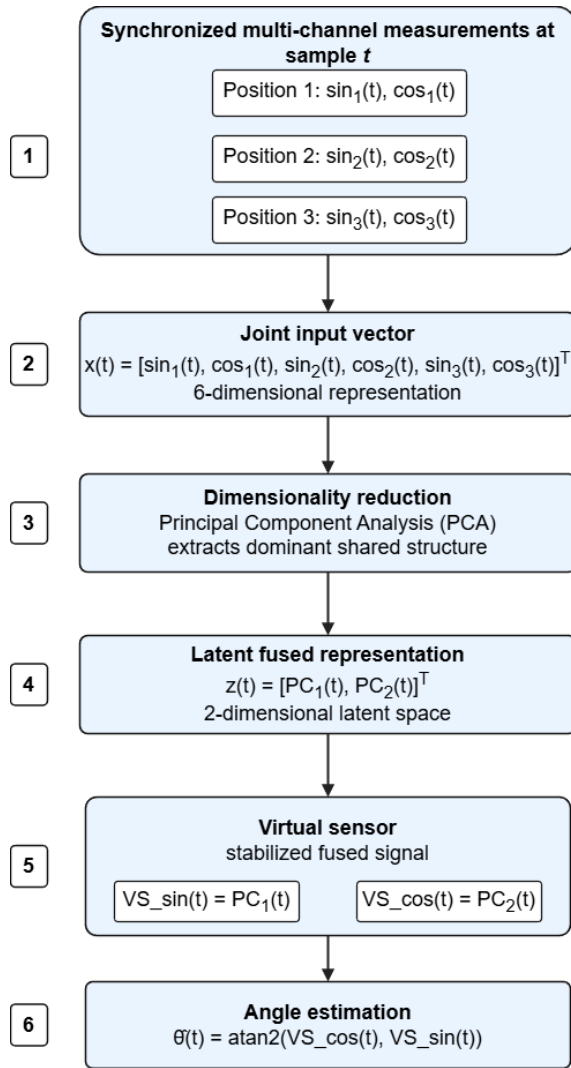


Fig. 4. Dimensionality-reduction pipeline for virtual sensor modelling.

After preprocessing, the outputs from the three sensor positions are organized into a common multi-channel representation. At each sample point, the input vector contains the sine-like and cosine-like components from all available emulated channels. Thus, the same rotational state is described by several spatially different observations rather than by one sensor position alone. The individual sensor-position signals are then processed jointly in the dimensionality-reduction stage. PCA is used in this study as a representative dimensionality-reduction method. It transforms the synchronized multi-channel data into a lower-dimensional latent representation that emphasizes the common rotational pattern shared across the channels and reduces the influence of position-specific signal distortions.

The obtained latent representation is interpreted as the virtual sensor output. Instead of selecting one physical channel or manually correcting amplitude deviations, local distortions, or residual

phase differences in each channel separately, the fusion stage extracts a system-level representation from the combined behaviour of multiple channels. In this sense, the virtual sensor provides a stabilized signal basis derived from redundant measurements.

Based on the virtual sensor representation, angle estimation is performed and compared with the estimates derived from the individual measurement channels.

Experimental Results

Figure 5 shows the comparison between the three individual TMR sensor positions and the fused virtual sensor representation obtained by dimensionality reduction. The individual channels exhibit visible differences in amplitude, phase, and signal shape, which are caused by the different spatial positions of the sensor relative to the rotating magnet. These placement-dependent differences also affect the reconstructed angle and lead to channel-specific error patterns.

The virtual sensor does not simply reproduce one of the individual channels. Instead, it represents a fused latent signal derived from the common structure of the three measured channels. Although the fused representation differs from the individual sensor outputs in its signal form and scale, it provides a more consistent basis for angle reconstruction.

The quantitative comparison is presented in Figure 6. The evaluation was performed over 100 consecutive rotations using standard regression error metrics computed between the estimated and reference angles. Sensor position 1 achieved MAE of 6.652° and RMSE of 8.689° , Sensor position 2 achieved MAE of 2.327° and RMSE of 2.933° , and Sensor position 3 achieved MAE of 2.214° and RMSE of 2.854° . In comparison, the virtual sensor achieved MAE of 0.953° and RMSE of 1.288° .

Compared with the best-performing individual channel, the virtual sensor reduced MAE by approximately 57% and RMSE by approximately 55%. These results show that dimensionality-reduction-based fusion provides a more accurate signal basis for angle estimation than any individual TMR sensor position in the considered proof-of-principle setup. The lower RMSE also indicates that the virtual sensor representation is less affected by larger deviations than the individual channels. Therefore, the results support the use of redundant imperfect measurement channels for improving the quality of the estimated target quantity within the proposed Self-X sensor concept. At the same time, the results should be interpreted in the context of the current real-measurement-based emulation, where the

channels were acquired sequentially rather than by a complete multi-sensor hardware prototype.

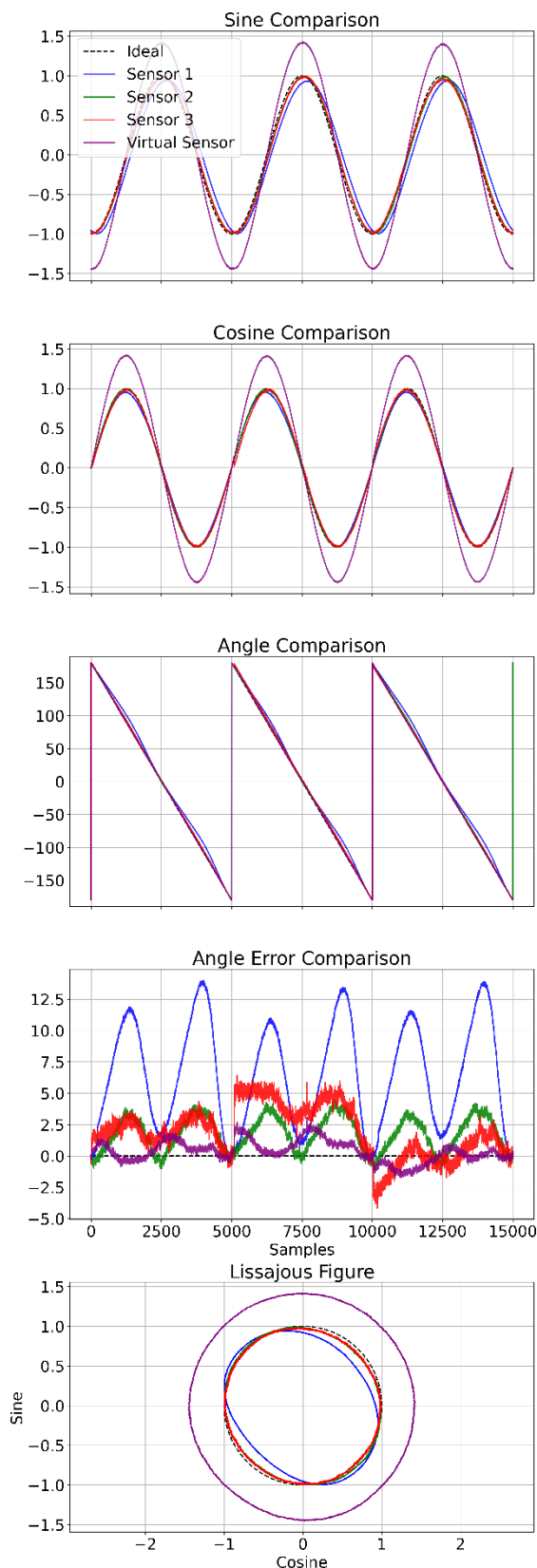


Fig. 5. Measured signals from three individual TMR sensor positions compared with the fused virtual sensor obtained via dimensionality reduction.

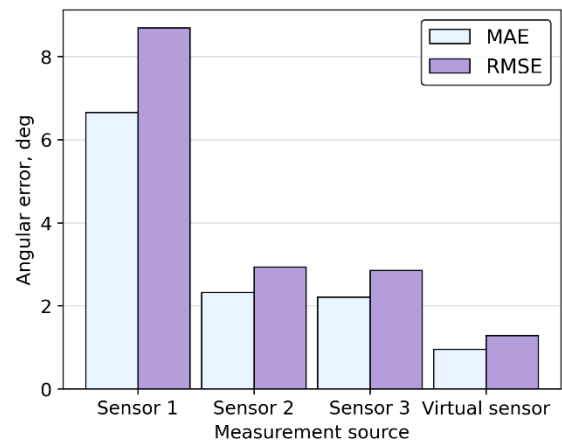


Fig. 6. Error comparison for three individual TMR sensor positions and the virtual sensor.

Conclusion

This study brings the previously developed Self-X sensor system [6] closer to practical hardware realization by introducing a real-measurement-based emulation of a homogeneous multi-sensor configuration. Instead of relying on one ideal sensor, the approach combines redundant information from imperfect homogeneous sensing channels and transforms it into a virtual sensor representation.

For the considered TMR-based angle estimation task, the virtual sensor provided a more accurate reconstruction than any individual measured channel. Compared with the best single channel, MAE decreased from 2.214° to 0.953° , and RMSE from 2.854° to 1.288° over 100 consecutive rotations, corresponding to improvements of about 57% and 55%, respectively. These results support the use of multi-channel fusion as an intermediate step toward a hardware-based Self-X sensor system.

The concept is not limited to TMR sensors or to three sensor channels. Future work should move from the present sequential emulation to a simultaneous multi-channel hardware setup with more than three physical sensor channels, different spatial arrangements, and longer measurement campaigns. Further experiments should also include varying operating conditions and more severe sensor faults, such as scale and offset errors, nonlinear distortions, clipping, drift, aging effects, and gradual loss of sensor quality.

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