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RESEARCH ARTICLE

Improving Measurement Accuracy With a Neuro-Inspired Multi-Sensor Approach

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ABSTRACT In this paper, we present a novel approach that draws inspiration from the way the brain processes sensory information, using multiple sensors to provide redundant and complementary information that can be combined with machine learning techniques to improve accuracy and reduce noise. In particular, we train a machine learning model to estimate ground truth signals using response data obtained from multiple sensors exhibiting heterogeneity. After only one stage of training, our method can be applied under various conditions. We present simulation results demonstrating the effectiveness of our approach in reducing noise and improving accuracy in a variety of measurement scenarios. Our method achieves competitive outcomes in comparison to the Kalman filter without relying on historical data. The theoretical efficacy of our method is elucidated by establishing a connection with parallel Gaussian channels from information theory. Moreover, we provide estimation to the extent of performance improvement in relation to the increasing count of sensors. Our approach has the potential to be applied to a wide range of industries and fields.

INDEX TERMS Machine learning, multi-sensor approach, neuro-inspired, parallel Gaussian channels.

I. INTRODUCTION

Accurate measurement is a fundamental aspect of various scientific and technological endeavors, influencing fields such as robotics [1], healthcare [2], and environmental monitoring [3]. The presence of noise can distort signals and compromise accuracy. Various techniques in data acquisition, filtering, state estimation, fusion, etc. have been devised to directly attenuate noise or estimate signals while mitigating errors arising from noise [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15].

With the widely application of multiple sensors, how to improve measurement performance under the complex relation between accuracy, number of sensors and noise is becoming important for measurement system design and deployment. However, this remains relatively unexplored in previous studies. While earlier works have focused on extracting information from sensors, they still lack the exploration of the optimal number of sensors required to attain specific accuracy levels, as well as the impact of

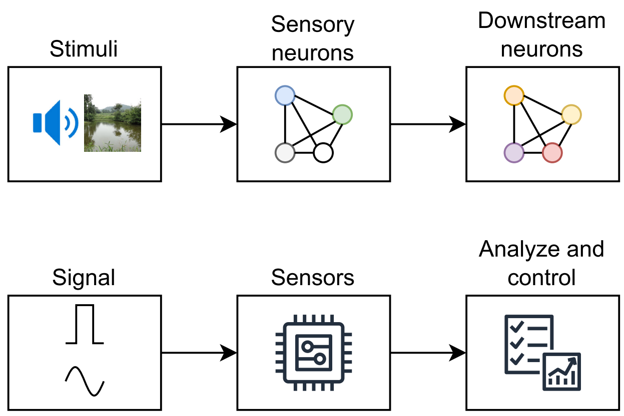

FIGURE 1. Similarities between the brain and measurement system.

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noise on measurement performance. Although improving measurement accuracy under independent noise distribution with multiple identical sensors has been suggested in [16] and [17], they are limited to homogeneous sensors, and have not considered noise covariance of sensors.

To mitigate this gap, we propose a framework to improve measurement accuracy and help to understand the interplay between accuracy, the number of sensors and noise. Enlightened by recent success of brain-inspired paradigms [18], [19], [20], we draw inspiration from how the brain might work under noise.

Here, we postulate that the high-dimensional representation formed by a large number of neurons plays an essential role to the accuracy of the brain. And we notice that the brain, which exhibits robustness and precision in the face of environmental and neuronal noise [21], [22], [23], bears similarities to measurement systems. As shown in Figure 1, in the brain, sensory neurons receive stimuli and transmit representations to downstream neurons, while in measurement systems, sensors receive signal input and convey information to data acquisition and analysis systems [24]. Throughout the progression from input to output, noise permeates the system. Linking the brain and measurement system, we devise an innovative measurement approach that integrates information from multiple sensors with machine learning techniques to augment measurement accuracy. After the training phase to acquire the ability to map multi-sensor responses to estimated signals, our approach can be effectively employed under varying noise levels and dynamic signal properties. Notably, our method demonstrates remarkable precision without relying on any assumption or prior knowledge of the signal, and including additional sensors results in continuous enhancement of measurement accuracy.

In order to elucidate the potential improvement in measurement accuracy through the addition of more sensors, we formulate a model wherein multiple sensors are represented as parallel Gaussian channels. Intriguingly, our findings reveal an increase in channel capacity proportional to the number of sensors employed, signifying that the inclusion of more sensors facilitates the acquisition of signal information, consequently leading to more precise estimations.

Our contribution has several folds:

- We propose a method that integrates multi-sensor information with machine learning techniques, which is "once trained, deploy everywhere". Additionally, we provide an estimation of the reduction in measurement error corresponding to the increase of sensor count. Rigorous evaluations establish that our approach achieves high accuracy, surpassing the performance of optimal filtering methods like the Kalman filter, while avoiding lag errors.
- Through empirical investigation, we elucidate the influential role of noise correlation when incorporating additional sensors, showcasing the benefit of negative correlation while highlighting the marginal improvement of measurement accuracy resulted from positive correlation.
- We explicate the theoretical linkage between the success of multi-sensor methods and parallel Gaussian channels in information theory.

The rest of the paper is structured as follows. Section II provides introduction of preliminaries, followed by overall description of methods in Section III. Section IV presents the static and dynamic results of our method. Finally, discussion and future work directions are stated in section V, followed by conclusions in Section VI.

II. PRELIMINARIES

In this section, we introduce the notation and terminology which is utilized throughout this work. Figure 2 illustrates the process from the ground truth signal to the estimated signal. The ground truth signal $s(t)$ represents the signal of interest, which varies over time t and is the target for estimation. The M sensors measure the ground truth signal and receive input signal

$$s_{in}(t) = s(t) + \epsilon_s(t), \tag{1}$$

where $\epsilon_s(t) \sim \mathcal{N}(0, \sigma_s^2)$ is the signal noise obeying a normal distribution. The response function of each sensor $i \in \{1, M\}$ to input x is denoted as $r_i(x)$ and can take the linear form

$$r_i(x) = w_i x + b_i, \tag{2}$$

where w_i and b_i are parameters depend on response characteristic of i. Upon receiving input, the sensors generate an ideal response $r_i(s_{in}(t))$ while the sensor noise $(\epsilon_1(t), \epsilon_2(t), \cdots, \epsilon_M(t)) \sim \mathcal{N}(0, \Sigma)$, is added to the ideal response to create the measured response $r_i'(t) = r_i(s_{in}(t)) + \epsilon_i(t)$, which is then used to estimate the ground truth signal. The estimated ground truth signal is denoted as $\hat{s}(t) = f(r_1'(t), \cdots, r_M'(t))$, where the mapping function f is learned from N pairs of the ground truth signal and the measured sensor response $\mathcal{D} = \{((r_1'(t), \cdots, r_M'(t)), s(t)) : t \in \{0, \cdots, N-1\}\}$.

III. METHODS

To effectively implement our methodology for measurement purposes, first we need to train a mapping combining information from multiple sensors to provide an accurate estimation of the ground truth signal. Once trained, our approach can be applied to various signal and noise conditions.

In order to train the mapping function that connects the sensor response to the estimated signal, a systematic procedure was followed. Initially, a ground truth signal s was generated, comprising a total of $N = 1100$ data points spanning the range from 0 to 1 with a step size of 0.1. This ensured the presence of 100 data points at each unique value. Subsequently, the signal noise was introduced to the ground truth signal, resulting in the creation of the input signal s_{in}. The sensors then produced the measured response $\mathbf{r}'$ based

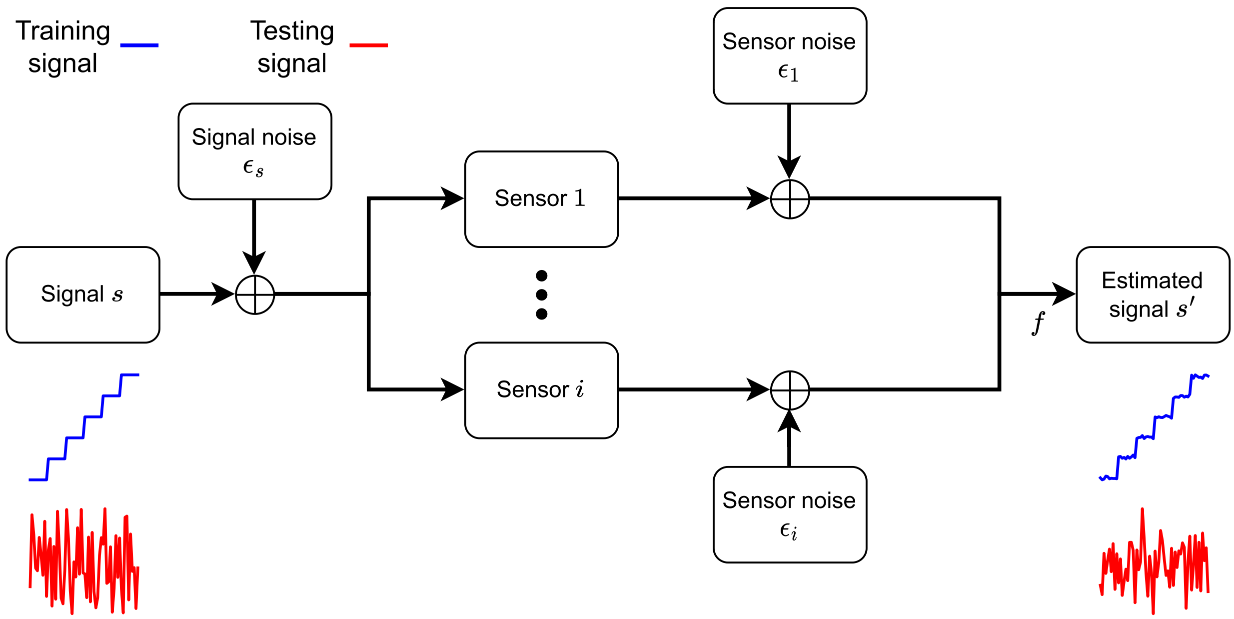


FIGURE 2. **Illustration of the signal estimation process from ground truth to estimated signal.**

on the input signal s_{in}. Machine learning techniques were employed to learn the mapping function f, which estimates the signal $\hat{s}$ from pairs of data $\mathcal{D}$. In the absence of explicit specification, linear regression was utilized as the default mapping function f. It is important to note that during the training process, both the signal noise and sensor noise were maintained at minimal levels to ensure the effective learning of f. In practical real-world applications, this requirement is typically fulfilled through the calibration process conducted in laboratory settings.

To denote the maximal performance any model could achieve given the noise in the signal, we adapted the concept of "noise ceiling" from the field of neuroscience [25]. The noise ceiling here was established by conducting training and testing procedures without the inclusion of sensor noise. Specifically, the training phase involved utilizing pairs of the ground truth signal s, and the ideal response $\mathbf{r}$.

IV. RESULTS

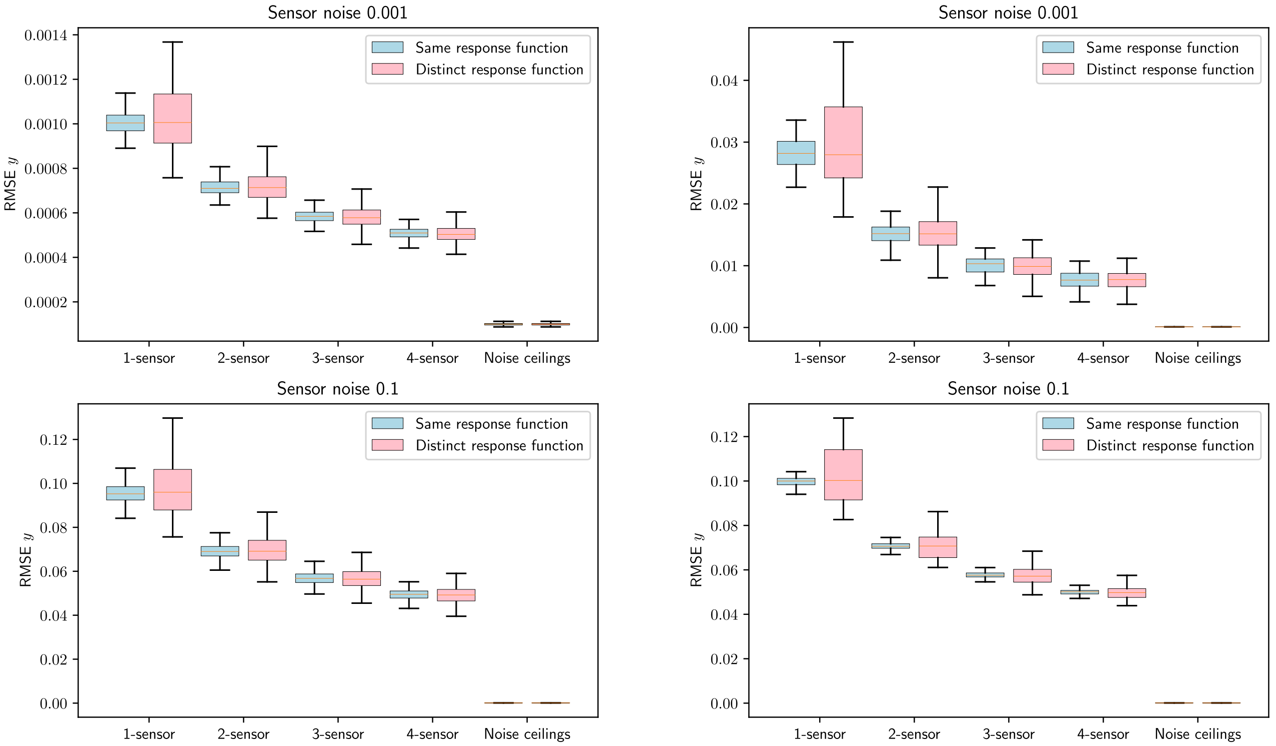
A. MULTI-SENSOR MEASUREMENT ACCURACY

The measurement accuracy of different numbers of sensors is depicted in Figure 3. Here, the sensor response functions were either set to an identity linear form ($w = 1, b = 0$) for each sensor or assigned random values for the parameters w and b, uniformly drawn from the range of 0.8–1.2 and -0.1–0.1, respectively. The evaluation of measurement accuracy was performed by computing the root mean squared error (RMSE) for varying numbers of sensors, ranging from 1 to 4. The signal noise level was fixed at 0.0001, while the sensor noise levels included a low noise level of 0.001 and a high noise level of 0.1. The sensor noise was assumed to be independent and exhibit the same variance, resulting in $(\epsilon_1(t), \epsilon_2(t), \cdots, \epsilon_M(t)) \sim \mathcal{N}(0, \mathbf{I}\sigma_{11}^2)$. To ensure the reliability of the findings, the evaluation process was repeated 100 times for each combination of signal noise level and sensor noise level.

To explore the appropriate noise levels for training, we conducted experiments comparing training and testing under the same or different noise conditions. In the case of training and testing on the same noise level, we employed a 5-fold cross-validation approach and calculated the validation error on each fold. For training and testing on different noise levels, the training was conducted on one noise level, and the testing error was computed on the other noise level.

As shown in Figure 3, the obtained RMSE for training and testing on the same noise level using a single sensor closely approximates the corresponding noise level. Notably, when training on a high noise level of 0.1, the testing accuracy on a lower noise level of 0.001 dropped to around 0.03. However, training on the low noise level still resulted in testing error on the 0.1-noise level that was comparable to training on the 0.1-noise level. Consequently, we adopted the low sensor noise level for training to ensure consistent performance across different noise levels.

Figure 3 highlights that the measurement accuracy increases with number of sensors, regardless of the differences in sensor response functions. This finding is particularly relevant for real-world applications, as actual sensors often exhibit similar characteristics with minor variations. This finding aligns with the concept of neurons displaying similar heterogeneous coding properties as in previously studies [26], [27]. The performance improvement



(a) Training and testing with identical noise levels

(b) Training and testing with distinct noise levels

FIGURE 3. Performance with regard to sensor noise levels and response characteristics.

TABLE 1. Error analysis for different numbers of sensors with distinct response functions.

Testing Sensor Noise	1-sensor	2-sensor		3-sensor		4-sensor	
	RMSE	RMSE	Error Reduction	RMSE	Error Reduction	RMSE	Error Reduction
1.00e-3	1.02e-3	7.20e-4	29.4%	5.83e-4	42.8%	5.07e-4	50.3%
1.00e-1	1.02e-1	7.13e-2	30.0%	5.75e-2	43.6%	4.98e-2	51.1%

associated with distinct response functions is summarized in Table 1. Comparison of error reduction was achieved by employing multiple sensors in contrast to single-sensor measurement. Empirically, employing four sensors resulted in an approximate 50% reduction in error compared to using a single sensor.

To explore the potential error reduction achievable by increasing the number of sensors, we conducted experiments with up to 64 sensors. The relationship between the number of sensors and the corresponding error is depicted in Figure 4. Notably, the error trend aligns well with an exponential curve of the form $y = y(1)/\sqrt{n}$, where $y(1)$ represents the error obtained from a single sensor. This observation suggests a connection between our proposed method and mean filters. In the context of a signal x that remains consistent over time and is corrupted by additive Gaussian noise $Z \sim \mathcal{N}(0, \sigma^2)$, employing a mean filter with a window length of n and input $Y_i = x + Z$ (where $i \in \{1, n\}$), the RMSE of the mean filter applied to x can be expressed as

$$y(n) = \sqrt{E\left(\frac{1}{n}\sum_{i=1}^{n} Y_i - x\right)^2} = \sigma/\sqrt{n}. \tag{3}$$

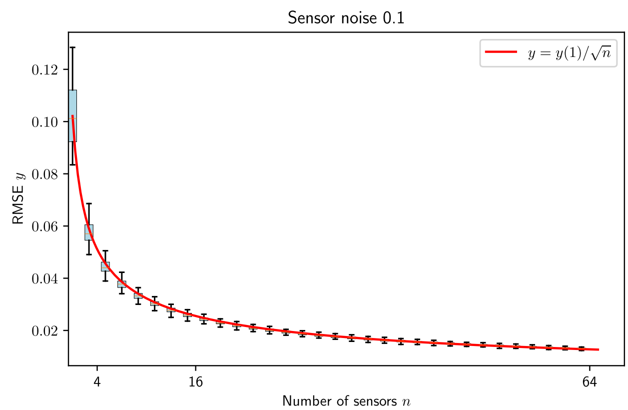
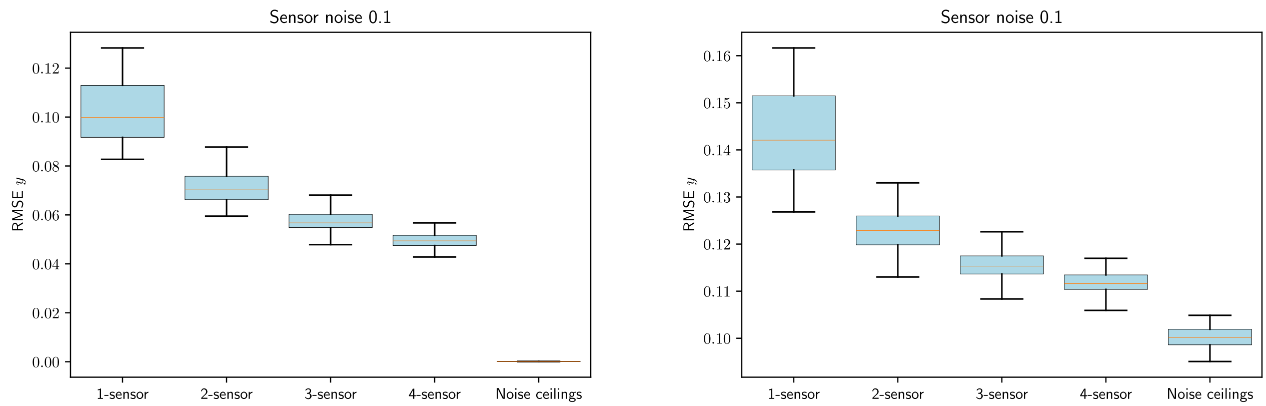


FIGURE 4. Performance analysis of our method in relation to the number of included sensors.

Given that $y(1) = \sigma$, we can derive the relationship $y = y(1)/\sqrt{n}$. Consequently, mean filters can be regarded as special cases of our proposed method, utilizing the same sensor response function and equal weights.

B. DYNAMIC PERFORMANCE

Cosine signals were employed to assess the performance of our method under dynamic conditions. To simulate a 50-Hz



(a) Testing on cosine signals with signal noise 0.0001 (b) Testing on cosine signals with signal noise 0.1

FIGURE 5. Performance of our method on 50-Hz cosine signals sampled at 4000Hz.

TABLE 2. Error analysis of varying number of sensors testing on cosine signals.

Testing Sensor Noise	Testing Signal Noise	Method	1-sensor	2-sensor		3-sensor		4-sensor	
			RMSE	RMSE	Error Reduction	RMSE	Error Reduction	RMSE	Error Reduction
1.00e-1	1.00e-4	Ours	1.02e-1	7.13e-2	30.1%	5.74e-2	43.7%	4.96e-2	51.4%
		KF	1.51e-1	1.04e-1	31.1%	8.19e-2	45.8%	6.89e-2	54.4%
	1.00e-1	Ours	1.43e-1	1.23e-1	14.1%	1.15e-1	19.4%	1.12e-1	22.0%
		KF	1.56e-1	1.14e-1	26.9%	9.66e-2	38.1%	8.80e-2	43.6%

cosine signal commonly encountered in field applications such as power system measurements, the signal was sampled at a rate of 4000 samples/s with 80 samples per period to test performance [28]. The testing results on cosine signals are shown in Figure 5 and Table 2. When signal noise is small, the performance is close to the results in Table 1. When signal noise is substantial, with more sensors added, it nonetheless approached the theoretical limits imposed by noise ceilings.

C. EFFECTS OF CORRELATION BETWEEN CHANNELS

Noise correlation in neurons has been shown to have a significant impact on information coding [23], [29]. To empirically test the effect of noise correlation on measurement error, we manipulated the covariance of noise distribution, transitioning it from independent to either positive or negative dependent. The positive noise covariance matrix was

$$\begin{bmatrix} 1 & 0.8 & 0.8 & 0.8 \\ 0.8 & 1 & 0.8 & 0.8 \\ 0.8 & 0.8 & 1 & 0.8 \\ 0.8 & 0.8 & 0.8 & 1 \end{bmatrix}, \tag{4}$$

and the negative noise covariance matrix was

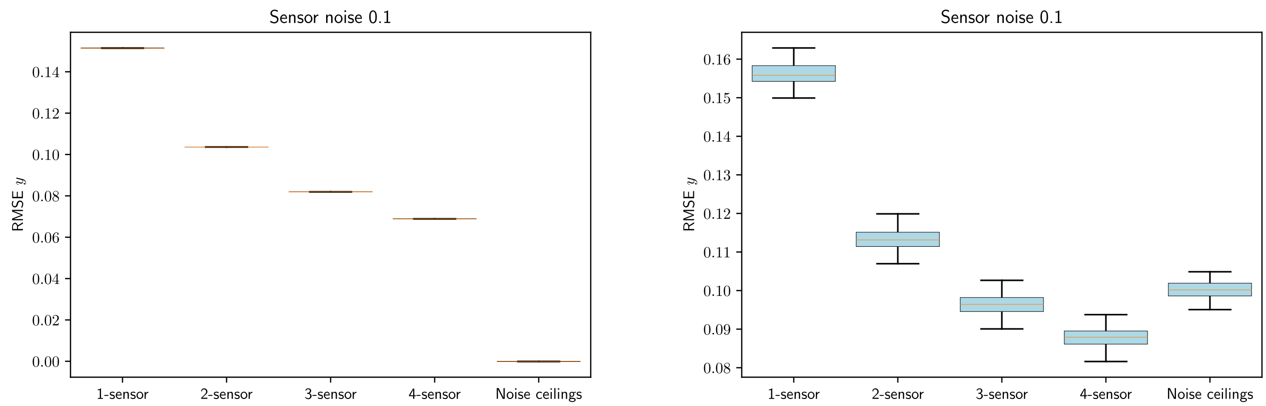
$$\begin{bmatrix} 1 & -0.8 & 0 & 0 \\ -0.8 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{5}$$

It is important to note that, due to the positive semi-definite constraint of covariance, negative correlation is present only between the first and second sensors, while the third and fourth sensors remain independent of the other sensors.

The findings are visually presented in Figure 7 and summarized in Table 3. In cases where noise correlation between sensors is highly positive, the addition of more sensors does not yield substantial improvements in measurement performance. Conversely, when negative noise correlation exists among sensors, the presence of just two sensors exhibiting strong negative correlation already leads to a significant 67.2% reduction in error compared to a single-sensor configuration. The presence of positive noise correlation among sensors leads to concurrent noise addition to the signal, posing a challenge for noise reduction, thus making multiple sensors akin to a single sensor. Conversely, in the case of negative noise correlation, noise originating from one sensor has the potential to be counteracted by the noise from another sensor exhibiting negative noise correlation with it. Considering under independent noise, the error decreases with $1/\sqrt{n}$, and under negative noise correlation, two sensors can already achieve substantial improvement, it is advisable to employ a two-sensor configuration to strike a balance between cost and performance in practical applications.

D. COMPARISON WITH KALMAN FILTER

Kalman filter (KF) [30] has been widely used in target tracking, navigation systems, control systems, etc., [31], [32], and [33]. In this study, we compared the performance of our method with KF [30]. The evaluation was conducted on cosine signals, as discussed in Section IV-B. All sensor inputs to the KF were derived from the noised signal with sensor

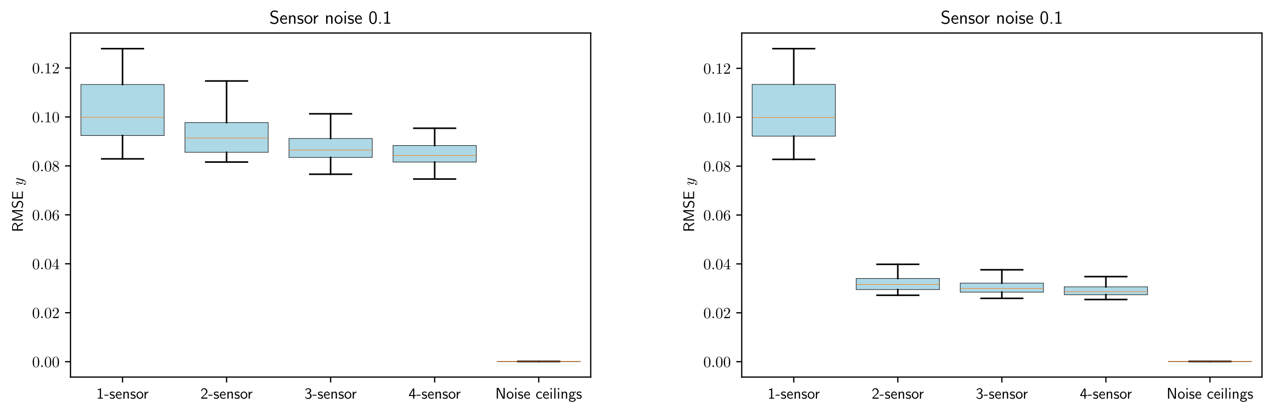


(a) Testing on cosine signals with signal noise 0.0001
(b) Testing on cosine signals with signal noise 0.1

FIGURE 6. **Performance of Kalman filter on 50-Hz cosine signals sampled at 4000Hz.**

TABLE 3. **Error analysis of varying number of sensors with sensor noise correlation.**

Testing Sensor Noise	Testing Signal Noise Correlation	1-sensor	2-sensor		3-sensor		4-sensor	
		RMSE	RMSE	Error Reduction	RMSE	Error Reduction	RMSE	Error Reduction
1.00e-1	Positive	1.02e-1	9.31e-2	8.7%	8.81e-2	13.6%	8.52e-2	16.4%
	Negative	1.02e-1	3.20e-2	68.6%	3.04e-2	70.2%	2.91e-2	71.4%



(a) Testing under positive sensor noise correlation
(b) Testing under negative sensor noise correlation

FIGURE 7. **Performance of our proposed method in the presence of correlated sensor noise.**

noise incorporated, effectively simulating an identity function for sensor response. The outcomes of KF are presented in Figure 6 and summarized in Table 2. Note that due to state estimation reducing signal noise, error lower than noise ceilings is achieved with 3 or more sensors when signal noise is 0.1, as shown in the right subplot of Figure 6.

Our method demonstrates superior performance compared to the KF in scenarios where the signal noise is low. While the KF, with its state estimation capabilities, exhibits higher accuracy under conditions of significant noise. However, our approach deviates from state estimation methods, such as the KF, as it relies solely on the current measurement. Consequently, it can avoid lag error problem, thereby leading to enhancement in dynamic performance.

E. CONNECTION BETWEEN MULTI-SENSOR APPROACHES AND INFORMATION THEORY

In order to elucidate the efficacy of our multi-sensor method, we employed a modeling framework that represents the process from ground truth signal to sensor output as parallel Gaussian channels. Each sensor functions as an independent channel, with the assumption that input signal noise is negligible and the sensor response function is identity. Figure 8 visually illustrates the model depicting the flow from the signal to the output of the sensors. Note that here we only discussed single channel input so that the input for every channel is X with a power constraint $EX^2 \leq P$. Moreover, the noise of different sensors $Z_1, Z_2, \cdots, Z_M$ is assumed to be independent from channel to channel. Thus we have channel

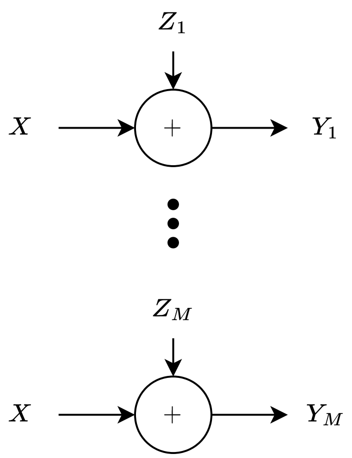


FIGURE 8. Modeling the process from ground truth signal X to sensor response $Y_i, i \in \{1, \cdots, M\}$ as parallel Gaussian channels.

output

$$Y_i = X + Z_i \tag{6}$$

where $i \in \{1, M\}$,$Z_i \sim \mathcal{N}(0, \sigma_i^2)$. As per information theory, the information capacity of the channel C is

$$C = \max_{EX^2 \leq P} I(X; Y_1, Y_2, \cdots, Y_M). \tag{7}$$

Since $Z_1, Z_2, \cdots, Z_M$ are independent,

$$I(X; Y_1, Y_2, \cdots, Y_M) \leq \sum_{i=1}^{M} \frac{1}{2} log(1 + \frac{P}{\sigma_i^2}). \tag{8}$$

Equality is achieved by $X \sim \mathcal{N}(0, P)$. Consequently, with the number of sensors increasing, more information of ground truth signal can be acquired from output of the sensors.

V. DISCUSSION

In this study, we explored the use of multiple sensors in improving measurement performance under noisy conditions. Our approach was inspired by the robustness of neurons in the brain and aimed to combine machine learning with diverse sensors to reduce measurement error. Our findings align with previous research that has demonstrated the benefits of using multiple sensors in various fields [34], [35].

One notable aspect of our approach is effectively reducing measurement error without relying on prior knowledge or historical measurement information. This simplicity makes our method easily applicable and accessible. Through empirical analysis and theoretical studies, we were able to quantify the performance improvement achieved by adding more sensors. Additionally, we established a connection between multiple-sensor methods and mean filters, highlighting mean filters as specific cases of our approach.

Interestingly, we discovered that strong negative noise correlation between sensors can contribute to better accuracy even with fewer sensors. This finding suggests that careful selection and placement of sensors, taking into account noise correlation, can further enhance measurement performance.

While our method does not incorporate historical measurement information, it demonstrates competitive performance compared to state estimation methods such as the Kalman filter. Future research should explore the potential synergy between our method and state estimation techniques to achieve even stronger performance. By combining the strengths of both approaches, we can potentially benefit from improved accuracy and better handling of complex measurement scenarios.

The theoretical linkage between multi-sensor methods and parallel Gaussian channels provides insights into the information theory aspects of the proposed approach. The study establishes a connection between the number of sensors and channel capacity, demonstrating that an increasing number of sensors facilitates the acquisition of more comprehensive signal information, leading to more precise estimations.

It is important to note that in this work, we focused on sensors with linear response characteristics. However, in reality, many sensors exhibit non-linear response functions. The impact of non-linear response on measurement accuracy warrants further investigation and discussion. Incorporating non-linearity such as neural networks and kernel projection into our approach could potentially improve its applicability to a wider range of sensors and measurement scenarios. In addition, more data points should be sampled for model training to reduce out-of-distribution.

VI. CONCLUSION

In this paper, we have presented a novel approach to improve measurement accuracy through the use of a neuro-inspired multi-sensor approach integrating multi-sensor information with machine learning techniques. By training a mapping function using pairs of ground truth signals and measured responses, the method effectively estimates the signal even under varying noise levels and dynamic signal properties. The findings indicate that increasing the number of sensors enhances measurement accuracy, with a reduction in error of approximately 50% when employing four sensors compared to a single sensor.

The research elucidates the influential role of noise correlation in the measurement process, highlighting the beneficial impact of negative correlation and the diminishing returns observed with positive correlation. The theoretical linkage between multi-sensor methods and parallel Gaussian channels provides insights into the information theory aspects of the proposed approach, establishing a connection between the number of sensors and channel capacity.

The integration of multi-sensor methodologies with machine learning techniques has significant potential for accurate measurement in various fields. The findings contribute to the advancement of measurement techniques and provide valuable insights for signal processing, robotics, and healthcare applications. We believe that our approach has the potential to make a significant impact in the field of measurement and sensing.

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