A Signal Quality Assessment Metrics for Vibration-based Human Sensing Data Acquisition

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ABSTRACT

Sensing signal quality affects signal processing efficiency, feature extraction, and learning accuracy. An efficient and accurate assessment of sensing system signal quality is essential for 1) large-scale cyber-physical system deployment and 2) datasets sharing and comparison. In this paper, we present a signal quality assessment – S-score – for vibration-based human sensing applications from two aspects – the hardware implementation and the deployment structure. The 1) signal-to-noise ratio and 2) the signal frequency response consistency over 2.1) sensing hardware, and 2.2) deployment structure are essential factors for structural vibration sensing signal evaluation. The S-score metrics combines these factors to a value between 0 and 1 with application-oriented weights. We compared the proposed metrics to two baselines, and our metrics achieved the highest correlation to the system performance, which is the indicator of the data quality.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**.

KEYWORDS

human-induced vibration, signal quality assessment, structural vibration, signal to noise ratio, signal consistency.

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1 INTRODUCTION

Structural-vibration sensing for people monitoring is widely used in many applications, such as elderly care, smart building resource management, and health care [1–4, 7, 9]. The intuition of vibration-based approaches is that people interact with ambient structures all the time and induce the structures to vibration. Vibration sensing systems detect people's interaction induced vibration and infer human information from the vibration signals. Vibration-based sensing approaches rely on the vibration sensor installed on the structural surface in the indoor environment to collect the vibration data. Due to the complexity and variation of the structure and hardware implementation, the quality of the collected data varies, which directly determines the performance of these applications.

Our prior works showed that the quality of acquired vibration signals is mainly influenced by two key factors: deployed structure and hardware implementation [6, 8, 9, 12]. The **structural factor** affects the impulsive excitation's response in two ways – 1) material properties, such as stiffness, determines the signal-to-noise ratio (SNR) and 2) structural elements, such as beam, pillar, and bearing walls, affects the propagation velocity and attenuation. The **hardware implementation** affects the signal quality in two ways – 1) signal resolution, and 2) hardware consistency over multiple sensing nodes as a sensor network. Prior work on acquiring high-fidelity human-induced vibration signals only focused on enhancing the signal resolution, which does not systematically assess the signal quality through the aforementioned factors [8].

In this paper, we propose a signal quality metric – S-score – to objectively assess the influence of the deployment structure and the hardware implementation for human-induced structural vibration signals. The S-score is a combination of SNR and signal consistency and can be used to evaluate the sensor deployment scheme and dataset quality. The contributions of this work are as follows.

- We present S-score, a signal quality metrics for structural vibration-based human sensing dataset or deployment assessment.
- We evaluate the proposed metrics through real-world experiments and applications performance.

The rest of this paper is organized as follows. We introduce the S-score metrics in Section 2 and evaluate the S-score through real-world experiments and analysis in Section 3. We further discuss the future directions in Section 4 and conclude this work in Section 5.

2 S-SCORE METRICS

The proposed S-score consists of two components: 1) SNR and 2) signal consistency. The SNR is a common index in signal processing, and measures the ratio between the power of the signal and the power of the background noise [10]. When the SNR is low, the detection accuracy of the human-induced vibration decreases and the original signal waveform is distorted by the additive noise. As a result, we define the S-score $\propto$ SNR.

The consistency of signals over 1) different hardware (sensing nodes), and 2) different locations in the same sensing structure affects the information learning performance in applications such as excitation source identification and localization. Low signal consistency of the same impulsive excitation detected by different sensing nodes indicates biased distortion over different sensors, which makes the comparison between these signals unfair for collaborative learning. Low signal consistency of different locations around the sensor indicates the heterogeneity of the structure, which makes the structural response near the sensor of high response variation. As a result, the data collected in this deployment will have a larger data distribution variation, which makes the accurate model of the structural response difficult. We consider this situation as low data quality due to deployment complexity.

The signal consistency component measures the similarity between two signals, we consider the candidate signals x and y and discuss their score's two components calculation in Section 2.1 and 2.2. We further discuss the selection of x and y for a deployment assessment in Section 2.4.

2.1 SNR component

Traditional SNR calculates the ratio between the signal power of the human-induced signal and the signal power of the noise, which usually is a value larger than 1. However, for the pairwise metric S-score, the component needs to take into account two signals SNR, and the value needs to be normalized to the range between 0 and 1.

We define the SNR component of the pairwise vibration signals x and y as $s(x, y)$, which is given by

$$s(x,y) = \frac{1}{2}\left(\frac{\log f(\mathrm{snr}(x))}{\log 20} + \frac{\log f(\mathrm{snr}(y))}{\log 20}\right) \tag{1}$$

where snr(x) and snr(y) is the traditional SNR value for signal x and y. The function $f(\mathrm{snr}(x))$ shown below is a piecewise linear function to constrain the SNR of signal x from the range of $[0, +\infty)$ in the range of $[1, 20]$. The threshold is selected based on the impulsive excitation signal detection algorithm through the ambient structural vibration's Gaussian noise model [9]. If the SNR of signal x is less than 3 dB, we consider the detection of the signal is not reliable and we define the SNR component of x as 0. On the other hand, if the SNR of x is 20 dB, it means that the amplitude of x is 10 times the amplitude of the background noise. In this circumstance, the threshold-based signal detection algorithm often achieve up to 100% accuracy within the sensing range. The signal detection rate will not increase when the SNR of the signal is larger than 20 dB, and we consider the SNR component as 1 when the SNR of the signal is equal or large than 20 dB.

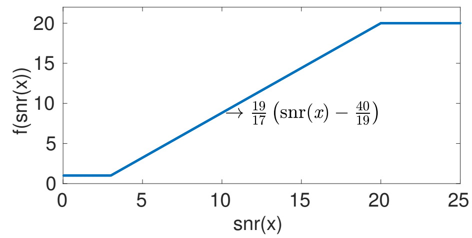

Figure 1: The plot of $f(\mathrm{snr}(x))$.

As shown in Figure 1, the value of slope and x-intercept is $\frac{19}{17}$ and $\frac{40}{19}$ to make sure the continuity of $f(\mathrm{snr}(x))$ at point snr(x) = 3 and snr(x)= 20.

$$f(\mathrm{snr}(x)) = \begin{cases} 20 & 20 < \mathrm{snr}(x) \\ \frac{19}{17}\left(\mathrm{snr}(x) - \frac{40}{19}\right) & 3 \le \mathrm{snr}(x) \le 20 \\ 1 & \mathrm{snr}(x) < 3 \end{cases} \tag{2}$$

2.2 Signal consistency component

We measure the signals consistency by calculating the similarity between two signals and use the maximum value of the correlation coefficient to define the similarity of two signals. If x and y are two vibration signals with N samples each, the similarity score $c(x, y)$ is given by

$$c(x,y) = \frac{\mathrm{MAX}\sigma_{xy}}{\sigma_x \sigma_y} \tag{3}$$

where $\mathrm{MAX}\sigma_{xy} = \max\limits_{-N/2 \le m,n \le N/2} \frac{1}{N-1} \sum_{i=1}^{N} (x_{i+m} - \mu_x)(y_{i+n} - \mu_y)$. σ_x, σ_y is the standard deviation of signal x and y. μ_x, μ_y is the mean value of x and y.

The two form of (1) and (3) also satisfy the following properities (where 'I' below can be either 's' or 'c'):

- Symmetry: $I(x, y) = I(y, x)$.
- Boundedness: $0 \le I(x, y) \le 1$
- $I(x, y) = 1$ if and only if each element of x is equal to the corresponding element of y.

2.3 S-score

The S-score is a linear combination of the SNR component and the signal consistency component as shown in Equation 4.

$$\textit{S-score}(x,y) = a \cdot s(x,y) + b \cdot c(x,y) \tag{4}$$

where $a + b = 1$, $a > 0$, $b > 0$. a and b are the weights of the two components. These weights are application oriented. For example, when used for the TDoA-based footstep localization, the variation between hardware and the sensing area would cause the inconsistency of the signal response, which will increase the error of signal arrival time estimation. As a result, the weight of the signal consistency component should be larger than the SNR component. On the other hand, for the application of pedestrian identification through footstep induced vibration, the identity information is buried in the detailed signal, which indicates that the SNR plays a more important role than it is in the localization application.

The S-score is in the range of $[0, 1]$ and a higher S-score value represents a higher signal quality. The S-score equal to 0 if and only if the SNR component and signal consistency component both equal to 0. The SNR component equal to 0 means that the SNR of two signals both less than 3 dB. The signal consistency component equal to 0 represents that the two signals are linear independent. The S-score equal to 1 if and only if the SNR component and signal consistency both equal to 1.

2.4 Dataset and deployment assessment with pairwise S-scores

For datasets sharing and comparing or a new deployment plan, two types of assessments with S-score can be conducted: structural variation and hardware variation. We used a standard excitation – dropping a tennis ball from 30 cm (1 ft) – in our assessments.

2.4.1 Structural variation. To assess the sensing structure or the deployment area signal quality, we place the sensor on the floor, and select K points d distance away around the sensor to apply consistent excitation source on. Multiple S-scores are calculated for 1) excitation of each pairwise location points or 2) excitation of one reference location point and the testing location points. The structural assessment for this sensing area is defined as the average of these measured S-scores.

2.4.2 Hardware variation. To assess the networked sensing system data quality, we place M sensing nodes at the same structural location, and apply the standard excitation at a same point d distance away from the sensors. Multiple S-scores are calculated for 1) excitation of each pairwise sensing nodes or 2) excitation of one reference hardware and the rest of the testing hardware. The hardware assessment for this sensor network is defined as the average of these measured S-scores.

3 EXPERIMENT AND RESULTS

To evaluate the S-score performance in the real applications, we conducted a set of experiments in different structures (office floor, dorm floor, and wooden table), and focus on the signal quality assessment which influenced by hardware implementation and deployed structure.

3.1 Example Application: Excitation Identification

We use the impulsive excitation identification as a general application to evaluate the proposed metrics. The excitation examples we used for the floor include hammer drop, tennis drop, and footstep, and we used hammer drop, tennis drop, and finger knock for the table. We define a **dataset** here as a set of data collected by one sensor at a designated location that contains three types of excitation. We use the classification accuracy of three types signals as the measurement of signal quality in each experiment.

We target at the classification applications with limited labeled data for training (only three data points each class from the reference dataset). As a result, the signal consistency component plays a more important role than SNR component in this case. We set the weight of SNR component as 0.3 and the weight of signal consistency component as 0.7 (i.e., $a = 0.3, b = 0.7$) as an example of the aforementioned application.

3.2 Baselines

We use the SNR index and the structural similarity (SSIM) index as baseline approaches to assess the signal quality. The SSIM index is widely used in many areas for signal quality evaluation, such as image [11] and audio quality assessment [5]. The SNR index is a pairwise measurement of SNR. The SNR index of signal x and y is given by

$$\text{SNR index}(x, y) = \frac{1}{2}\left(\frac{f\,(\text{snr}(x))}{20} + \frac{f\,(\text{snr}(y))}{20}\right)$$

The function $f\,(\text{snr}(x))$ is a piecewise linear function to constrain the SNR of signal x in the range of $[1, 20]$, and it's definition is shown in form (2).

3.3 Metrics

To evaluate the performance of the S-score, we measure the similarity of the **changing trend** over different scenarios investigated. The scenarios investigated include 1) same location, different hardware (Section 3.4), 2) same hardware, different structural materials (Section 3.5.1), 3) same hardware, different structural layouts (Section 3.5.2). For each investigated scenario, we first select a reference dataset, and then calculate the following four indexes: 1) performance index (classification accuracy), 2) S-score index, 3) SSIM index, and 4) SNR index, between the **reference dataset** and the **testing datasets**. The testing datasets have different data qualities affected by hardware or structural factors. The similarity of the trend is measured by comparing testing datasets 1) system performance index, i.e., classification accuracy, and 2) the dataset quality evaluation indexes.

Each investigated scenario includes at least two cases (x-axis in Figure 2, 4, and 5). We use one case as the reference case, and calculate the 'changing trend' for each of the index as an **index ratio** between the reference case and other cases. For example, in Table 2, when compare structural materials at three different buildings, we selected the office as the reference case, and calculated the accuracy index ratio for dorm as $\text{dorm}_{\text{acc ratio}} = \text{dorm}_{\text{acc}}/\text{office}_{\text{acc}}$. We calculated $\text{table}_{\text{acc ratio}}$ in the same way. Next, we compare the 'changing trend' between accuracy (ground truth) and the rest of the indexes measured by the mean square error (MSE) of the index ratio, which is referred to as **ratio MSE** later. For example, the ratio MSE of the S-score is calculated as the MSE between the vector $[\text{dorm}_{\text{acc ratio}}, \text{table}_{\text{acc ratio}}]$ and $[\text{dorm}_{\text{s-score ratio}}, \text{tables}_{\text{s-score ratio}}]$. A lower ratio MSE value means that the trend of this index is closer to the trend of the classification accuracy, indicating better performance of the metrics.

3.4 Hardware implementation factor

Due to the hardware variation, e.g., different version, resistor or capacitor variation, multiple sensing nodes with the same design may have different frequency response to the same excitation. We use S-score to assess two sensing nodes compared to a reference sensing node (used to collect the labeled data). The sensing node of

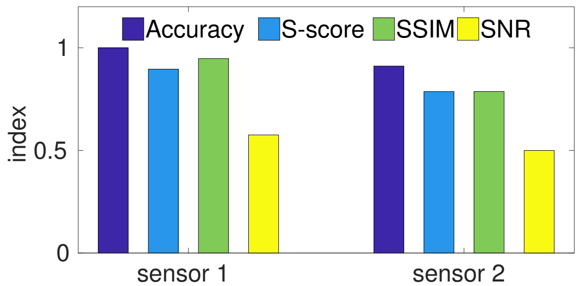

Figure 2: The classification accuracy, S-score, SSIM index and SNR index of two sensors in the office building.

Table 1: Hardware factor evaluation results.

	Accuracy	S-score	SSIM	SNR
sensor 1 ratio (ref)	1.00	1.00	1.00	1.00
sensor 2 ratio	0.91	0.88	0.83	0.87
ratio MSE	–	0.03	0.08	0.04

higher signal quality is the one that acquires signals with higher consistency to the reference sensing node.

We conducted experiments in an office building and applied excitations at a designated location 30 cm away from three sensors (placed together). We selected one sensor as the reference dataset and calculated the four indexes of the testing datasets as discussed in Section 2. We further calculated the classification accuracy for identifying these three types of excitation. We use data collected by the reference sensor to train a linear-SVM classifier. Then we apply this trained classifier to classify the signals collected by two testing sensors.

Figure 2 shows the four evaluated indexes of the two testing sensors deployed in the office. The classification accuracy of sensor 1 is higher than sensor 2. It indicates that the frequency response of the sensor 1 is more similar to the reference sensor than that of the sensor 2. We select the indexes of sensor 1 as the reference case and calculate the trend as discussed in Section 2 in Table 1. As shown in Table 1, the S-score has the lowest ratio MSE value compared to the SSIM index and the SNR index, indicating that the trend of the S-score is most similar to the classification accuracy.

3.5 Structural factor

In the vibration-based sensing system, the structure is one part of the sensing system: the medium of vibration wave transmission. The structural property might change the frequency features of the signal, and influence the signal quality. We consider the homogeneous structure more suitable for human-induced vibration sensing compared to heterogeneous structure. Because homogeneous structure can be modeled with the wave propagation distance, which is computational efficient. We investigate two structural factors – material and layout – that may affect the homogeneity.

For each investigated location, we selected four points 30 cm away around the sensor and apply consistent excitation as shown in

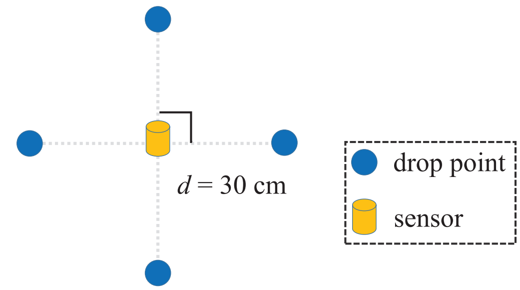

Figure 3: We select four points 30 cm away from the sensor to apply consistent excitation on.

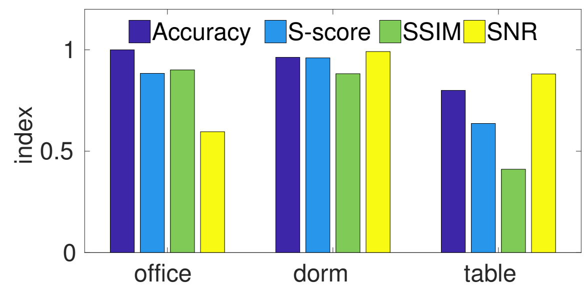

Figure 4: The classification accuracy, S-score, SSIM index and SNR index of the three kinds of structures.

Table 2: Structural material factor evaluation results.

	Accuracy	S-score	SSIM	SNR
office ratio (ref)	1.00	1.00	1.00	1.00
dorm ratio	0.96	1.09	0.98	1.66
table ratio	0.80	0.72	0.46	1.48
ratio MSE	–	0.10	0.24	0.69

Figure 3. We selected the data collected at one out of four points as the reference dataset, and the data collected at the rest three points as the testing dataset. We calculated the four indexes between the reference dataset and testing datasets as discussed in Section 2.

3.5.1 Structure material. We deployed the sensor and collected the data at three structures of different materials: 1) office building with concrete floor, 2) dorm building with concrete floor base and ceramic tile surface, 3) wooden table. We demonstrates the calculated four indexes in Figure 4. The classification accuracy of the office and dorm achieved 100% and 96%, and it decreased to 80% on the table. We believe that it is because of the heterogeneity of the wood material causing different distortion effects during propagation to different directions. We selected the office as the reference case to calculate the trend and the ratio MSE. As shown in Table 2, compared to the SSIM index, and SNR index, the S-score achieves the lowest ratio MSE, indicating better performance in estimating the influence of the structure material.

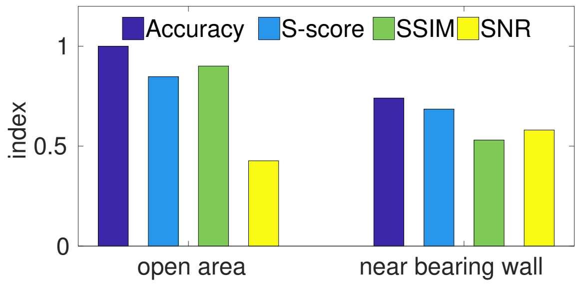

Figure 5: The classification accuracy, S-score, SSIM index and SNR index of the two different structural layout.

Table 3: Structural layout factor evaluation results.

	Accuracy	S-score	SSIM	SNR
open area ratio (ref)	1.00	1.00	1.00	1.00
bearing wall layout ratio	0.74	0.81	0.59	1.36
ratio MSE	–	0.07	0.15	0.62

3.5.2 Structure layout. We deployed sensors at two locations with different layouts in the office building. One location is 50 cm from a bearing wall, and the other location is an open area (the distance between the sensor location and the bearing wall is more than 3 meters). We calculated the four indexes of these two layouts, as shown in Figure 5. The sensor deployed in the open area has a higher classification accuracy than that of the sensor deployed closer to the bearing wall, indicating a higher signal quality from the open area deployment due to the homogeneity of the structure. We chose the open area location as the reference case and calculated the ratio MSE of the near bearing wall location. As shown in Table 3, compared to the SSIM index, and SNR index, the S-score achieves the lowest ratio MSE, indicating better performance in estimating the influence of the structure layout.

4 DISCUSSION

In this paper, we empirically selected assessment parameters based on the evaluated application, such as SNR component threshold, the wight of SNR component and signal consistency, and the excitation-sensor distance d. We plan to explore a systematical approach to determine the parameter values by combining heuristic rules and analytical models of the wave propagation. We will further conduct experiments to understand the parameters' effects on the S-score's signal assessing ability.

Another challenge we would like to explore is to assess the signal quality automatically without manual calibration with standard excitation. We plan to explore multi-modal IoT systems and utilize their shared context to assess signals of multiple sensing modalities simultaneously.

5 CONCLUSION

In this paper, we introduce a signal quality assessment metrics – S-score. The S-score can be used in many aspects of the vibration-based human sensing data acquisition, such as the signal quality assessment, hardware quality evaluation, and deployment scheme selection. The S-score consists of two parts: the SNR and the signal consistency. The weight of these two parts is determined by real applications requirements. Experimental results showed that S-score achieves the highest correlation to the dataset performance compared to two other baseline signal quality assessment metrics in the evaluation of hardware and deployed structure variations.

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