

Signal Processing Techniques For Structural Health Monitoring In Civil And Mechanical Engineering Applications

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Abstract

Impact-based structural health monitoring is based on sensor measurements to gain a structural behavior understanding, although complex wave propagation effects often make relationships between measured quantities and impact location without a direct causation. This work examines signal processing techniques for feature-based impact localization using multi-sensor transient response data in civil and mechanical engineering applications. Time-domain impact responses were preprocessed, segmented, and converted into statistical feature representations for each sensor. Feature standardization and exploratory principal component analysis were used to examine spatial trends in the feature space, while Pearson correlation analysis assessed the sensitivity of individual features to impact location. Impact localization was formulated as a regression problem using Ridge regression, and performance was evaluated with a group-aware holdout strategy to reduce information leakage across repeated experiments. The results show that spatial information is reflected through gradual variations in the feature space rather than explicit separation. Individual features exhibited moderate sensitivity to location, while feature fusion enabled consistent localization performance, with a mean coefficient of determination of 0.696 across validation splits. These findings indicate that interpretable, feature-based signal processing approaches can support impact localization in controlled settings and provide a practical baseline for further SHM studies.

Keywords: structural health monitoring, signal processing, impact localization, feature extraction, regression.

1. Introduction

The concept of structural health monitoring (SHM) has become an inseparable part of the modern civil and mechanical engineering practice because of the necessity to provide the

engineering structures with the safety, reliability and long service. Growth of structural complexity, ageing structures, and exposure to changeable operations and environmental conditions have enhanced the need to adopt systematic methods of monitoring that are capable of determining the structural condition with time [1]. SHM structures strive to derive useful information out of recorded structural reactions to aid in maintenance planning and informed decision-making. Improved sensing technologies and data acquisition systems have contributed to making continuous and large-scale SHM deployments much more viable. The current SHM systems are based on sensor networks that are used to measure structural responses during ambient excitation or controlled loading conditions [2]. To achieve the usefulness of these measurements, it is necessary to use strong analytical methods that will be able to transform the raw data into valuable indicators of structural behavior.

The basis of most SHM methodologies involves signal processing techniques that can be used to extract features that can be used to describe structural responses in both the time and frequency domains. Various types of sensors have been investigated to achieve this aim such as accelerometers, strain sensors, piezoelectric transducers and acoustic sensors all with various capabilities of measuring structural dynamics [3]. Machine learning techniques have also enriched the analysis arsenal of SHM as they can offer data-driven solutions to damage detection, classification, and localization problems [4]. The choice of sensors and approaches to their deployment has become one of the most popular topics of research, and it directly affects the quality and interpretability of obtained data. SHM sensing systems reviews underscore the significance of sensor design to obtain spatially informative structural responses [5]. These considerations are especially important in systems that include sophisticated materials, which include composite structures, in which the mechanisms of damage and wave propagation are more complicated [6].

The recent advances in sensing technologies have presented new opportunities in the SHM applications. Fiber-optic sensors have shown excellent potential in terms of long-term monitoring of civil infrastructure, as they are very sensitive and durable [7]. Simultaneously, the methods of SHM based on vibration are still popular due to their non-invasive characteristic and the possibility to monitor the global behavior of the structure [8]. The new smart sensing technologies also enable scalable and distributed monitoring architectures [9]. Along with signal-based methods, computer vision methods have also been explored as SHM applications, especially in the detection of surface damage and displacement [10]. Although these techniques are useful in offering useful spatial information, they can be constrained by environmental factors and accessibility requirements, which explain the ongoing interest in signal-based SHM solutions. The piezoelectric sensing methods are one of them and have been widely investigated due to their ability to capture wave-based signals using localized impacts and defects [11]. SHM strategies and data management practices also determine the effectiveness of SHM systems. The placement of sensors has been identified as a primary consideration in enhancing the detectability of damage and the accuracy in localization of damage [12]. Moreover, the expanding access to bulk data has facilitated the use of statistical pattern recognition and big data analytics in SHM, which allows analyzing structural behavior in a more comprehensive manner during long durations of monitoring [13].

Even though the topic of sensing technologies and data-driven SHM approaches is well-researched, there are still a number of challenges. Numerous of the available studies are mainly concerned with damage detection or classification when controlled conditions are considered, whereas the ones that deal with spatial localization, based on experimentally obtained multi-sensor impact response data, are fewer. Besides, many signal-based features have been developed; however, the spread of spatial information among features

and sensors is not always explored directly. In the situation of an impact-based SHM, the wave propagation effect, the reflection on the boundaries and multi-path interference tend to produce more complicated patterns of responses that restrict the applicability of a single-feature approach or only physics-based methods. A need thus exists to carry out systematic studies where the feature-based localization performance is assessed using experimentally based data and validation protocols that guarantee generalization of the repeated measurements.

This paper aims to review signal processing methodology in structural health monitoring with a specific focus on impact localization of a feature in the context of civil and mechanical engineering. Multi-sensor transient response signals in controlled impact events are extracted to obtain statistical features, and the correlation between those and impact location is determined to evaluate the reflection of spatial information by the data. Moreover, a multivariate regression is also implemented and tested with the help of a group-conscious validation protocol to make an indication of localization performance.

2. Methodology

2.1 Data source

The impact-event data that were analyzed in this study were taken into account by utilizing a publicly available impact-event dataset [14]. The data set was created by means of a structural specimen that was instrumented with various surface-mounted sensors that measured transient responses due to controlled impact events. It comprises the data of four sensors placed on the facility to record wave propagation throughout the area under observation. Impact excitations were imposed in preset points over the surface to cover the space as per the experimental protocol mentioned in the data. Signal processing and analysis of the presented work were done based on the recorded time-domain response signals and the coordinates of the impact location as well.

2.2 Signal Preprocessing

The signals recorded were preprocessed before the feature extraction so that there would be more consistency between experiments. Baseline correction was performed to eliminate offsetting components, and amplitude normalization was done to curb the variation among measurements. Signal segments that were characterized by a lot of noise outside the impact response window were ignored. The same preprocessing operations were applied to all the data of each sensor and each experiment. Signals that result is the temporary structural response of each impact event and are utilized as input for feature extraction.

2.3 Feature Extraction

Each of the preprocessed signals was extracted to provide a set of statistical features that characterize the temporal and amplitude variations of the impact response. Such characteristics are the first- and second-order (mean, variance, and standard deviation), extrema-based (minimum, maximum, and absolute maximum), and higher-order statistics (skewness and kurtosis). Other characterizations of signal distribution and time were also taken into account. Each sensor was extracted individually. The characteristics of all sensors were subsequently appended together to create one feature vector to represent each impact event, allowing information collected in different locations to be used in concert with each other.

2.4 Feature Standardization and Dimensionality Analysis

All extracted features were standardized to unit variance and zero mean in order to make them numerically stable and limit the impact of feature magnitude. Principal Component Analysis (PCA) was used as an exploratory method to investigate the feature space structure, as well as to determine whether spatial patterns are represented in the most salient means of variance. Visualization and qualitative analysis were only performed with PCA, which was not utilized in training the model as a dimensionality reduction method.

2.5 Feature-Location Relationship Analysis

Pearson correlation coefficients were calculated between each of the extracted features and spatial coordinates in order to test the connection between the individual features and the location of the impact. The analysis gives an understanding of how linear individual features are sensitive to location and whether there is spatial information that is shared among multiple features or not. Correlation of both positive and negative types was taken into account, since the meaning of the correlation is directional dependence, and is not the relevance of a feature.

2.6 Multivariate Localization Model

Impact localization was developed as a monitored regression difficulty, in which spatial coordinates were anticipated based on the feature vectors extracted. A Ridge regression was also used in response to the high dimensionality of the feature set and to mitigate the impact of multicollinearity by regularizing. The regularization parameter was chosen in an empirical manner. A group-based holdout validation strategy was used in order to minimize the risk of information leakage between repeated measurements at the same location of impact. The samples were clustered by repetitions of the experiments, and training and testing were done on fragmented groups. Standard regression measures such as the coefficient of determination, the mean absolute error and the root mean square error were used to evaluate the localization performance.

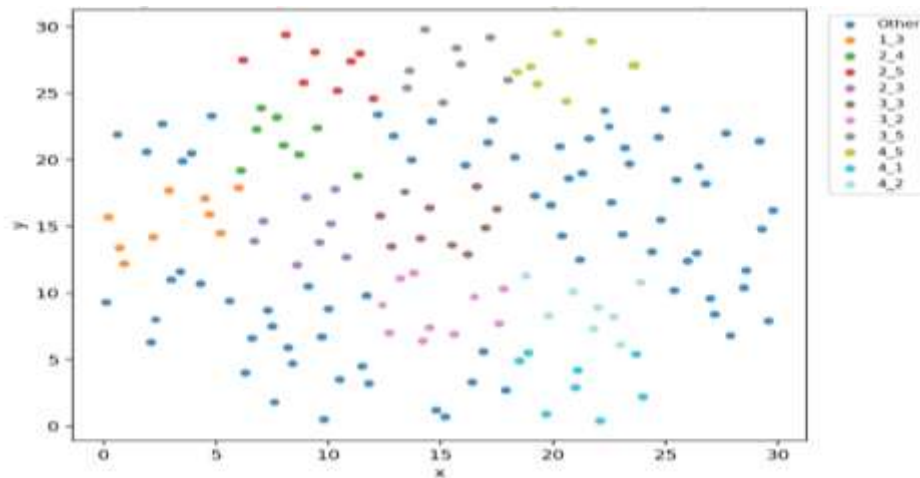
2.7 Evaluation Protocol

The analyses were made in accordance with the same evaluation protocol in various validation splits to determine the soundness of the suggested method. The performance measures were provided both at the level of the individual splits and in the aggregated form so that the variability in the conditions of the experiment could be considered. This assessment process gives a clue to the generalization behavior of the suggested signal processing and feature-based localization structure.

3. Results

3.1 Spatial Distribution of Impact Events

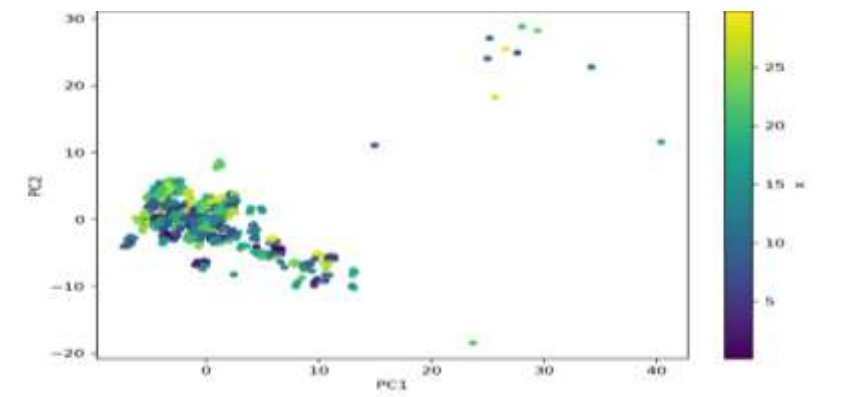
Figure 1 shows the spatial distribution of impact events, in which the impact positions are mapped to the x-y plane and colored by impact position. This figure depicts that the effects have good distribution at the surface under monitoring, and spatial clusters are made with respect to pre-determined excitation points. The fact that the entire space is covered, which means that the dataset does not have strong positional bias, is a good indication that the dataset would be useful in terms of localization analysis. It is also obvious that the experiment is arranged in a clear space, which proves the integrity of the experimental arrangement and the validity of the labels on the recorded locations. Table 1 gives a summary of the dataset characteristics.

Figure 1. Impact locations colored by position**Table 1. Dataset overview**

Parameter	Value
Number of samples	772
Number of sensors	4
Number of extracted features	128
Spatial dimensions	x, y
Experimental repetitions	Multiple per position

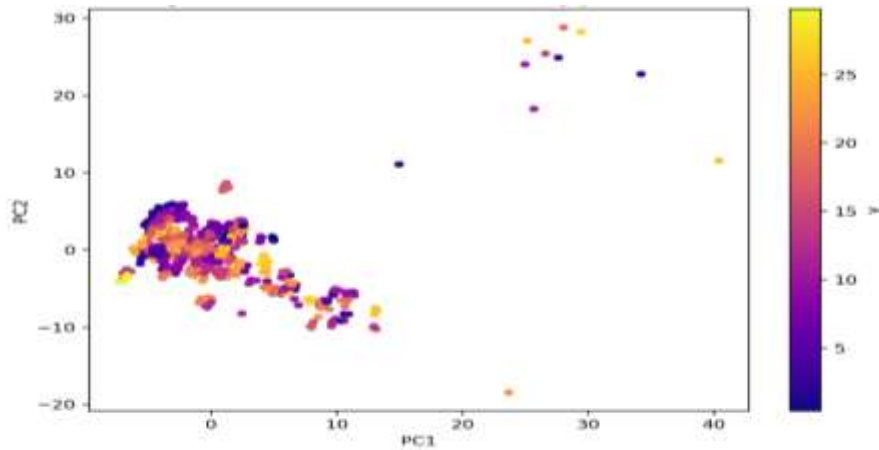
3.2 Feature Space Structure and Spatial Sensitivity

In order to analyze whether the features extracted capture spatial information, the Principal Component Analysis (PCA) was used on the standardized feature set. Figure 2 draws the PCA projection that has been colored by the x-coordinate. The color difference in the overriding direction of the feature space is smooth, which means that the variations in the location of impact are represented in the principal components. The samples are not arranged in well-separated clusters but rather are in a continuous overlap, which is a characteristic of wave-based structural responses. This behavior is an indication of the progressive change of signal properties with position and the effect of boundary reflections and multi-path propagation.

Figure 2. PCA of features colored by x-location

The respective y-coordinated colored PCA projection is depicted in Figure 3. Though the spatial difference in the vertical direction is not so high, nonetheless, there is still a constant gradient. When put together, these findings show that the extracted features represent two-dimensional spatial information in a distributed fashion as opposed to explicit clustering.

Figure 3. PCA of features colored by y-location



3.3 Feature-Location Correlation Analysis

The Pearson correlation coefficients between each of the features extracted and the x-coordinate were calculated to determine the sensitivity of each feature to impact location. Other features were moderately correlated with each other, with absolute values of nearly 0.4. These characteristics are a result of various sensors and they contain statistical measures like variance, minimum, standard deviation and higher-order moments. It was found that there were both positive and negative correlations, the directional character of wave propagation and attenuation in relation to sensor positions. The moderate values of the magnitudes of the correlations are in line with the experimental structural health monitoring data, where the spatial information is not represented by one single feature, but by a set of features. Table 2 summarizes representative spatially informative features.

Table 2. Examples of features correlated with x-location

Feature type	Sensor	Correlation trend
Variance	Sensor A	Positive
Minimum value	Sensor B	Negative
Kurtosis	Sensor C	Positive
Standard deviation	Sensor D	Negative

3.4 Multivariate Feature Fusion and Localization Performance

Although the individual features only have moderate correlation with the impact location, impact localization is, by its nature, a multivariate problem where the spatial information is shared among various sensors and feature types. In order to measure the joint predictive skill of the extracted features, a multivariate regression model was used to predict the x-value of the impact point. It was decided to use the Ridge regression model because it is effective when working with high-dimensional feature spaces and addresses multicollinearity. A group-based holdout strategy was considered to avoid leakage of

information between repeated experiments and to provide a fair evaluation; samples were divided based on repetitions of the experiment. Table 3 presents the localization performance of five group holdout splits, and an overview of the results is given in Table 4.

Table 3. Ridge regression performance for x -localization (group holdout splits)

Split	Test groups	R^2	MAE	RMSE
1	155	0.776	2.535	3.587
2	155	0.708	2.627	4.236
3	155	0.584	2.809	4.715
4	155	0.684	2.616	3.948
5	155	0.730	2.710	3.829

Table 4. Summary of multivariate localization performance

Metric	Mean $\pm$ Std
R^2	0.696 ± 0.071
MAE	2.659 ± 0.104
RMSE	4.063 ± 0.433

The findings indicate that, in spite of the fact that the individual features alone do not offer much spatial discrimination, together with the features, they can be used to offer a much higher localization performance. The obtained R^2 values demonstrate that a substantial part of the spatial variance is explained by the fact of multivariate features fusion, which proves that the extracted features are suitable to be used in data-driven impact localization.

4. Discussion

The findings show that the signal features obtained can be used to retrieve useful spatial information, albeit in a distributed as opposed to clearly separable form. The continuous cloud of samples in the PCA projections has an observable gradient instead of discrete clusters, indicating that the variability based on location is concealed in more than one axis of features, which is not concentrated on a single topical axis. The nature of this pattern is in line with impact-driven wave responses, whereby the overlapping signal characteristics are found in the reflections and multipath propagation even between distinct excitation points. This interpretation is also supported in the correlation analysis. There is a moderate linear sensitivity of individual features to the location coordinate, where absolute values are near about 0.4, as well as the negative and positive correlations among sensors. It is not surprising that there are negative correlations since the sign of the sign basically indicates coordinate orientation and direction of attenuation/propagation, and not feature usefulness. Most importantly, when all the sensor combinations of features are used, the multivariate model has significantly greater localization than many single-feature trends would indicate. The Ridge regression obtained comparable accuracy between group-holdout splits, mean $R^2 = 0.696 \pm 0.071$, MAE = 2.659 ± 0.104 and RMSE = 4.063 ± 0.433 . It helps in coming up with a practical conclusion that the localization information exists, but it is not homogenized on sensors and descriptors, and it is more accessible when feature fusion and regularized regression are used.

The perceived advantage of multivariate feature fusion is consistent with the existing SHM practice, in which raw sensing data is generally converted and summarized prior to making a decision. Schools of thought Sensor-to-cloud architectures focus on scalable piping where sensing to analytics pipelines are moved, and this is compatible with the feature-extraction and regression pipeline that was used in this study [15]. When it comes to applications-oriented SHM signal processing, it is regularly observed that individual indicators are hardly adequate, and effective inference can be based on a variety of descriptors and aggregation policies. In particular, signal processing processes used in large-scale infrastructure monitoring (e.g., dams) generally utilize a combination of several features or transformed representations to provide stable interpretation within the complex operating conditions [16]. The literature on SHM data science more broadly also highlights the idea that the utility of analytics is frequently due to a combination of heterogeneous features and learning algorithms that are capable of leveraging weak but consistent patterns between streams of data [17]. The move towards data-driven approaches in damage identification studies is driven by the inability to have signatures that are uniquely separable with measured responses, particularly when operating and boundary effects play a role with measured signals [18]. This recurring overlap in the feature space in this work is in line with this more general perspective: the lack of distinct clustering does not mean that the data is unusable; it provides an incentive to supervised models that can acquire subtle multivariate structure.

The current method gives more importance to a simpler and more interpretable pipeline compared to deep learning-based ones. Deep learning reviews suggest a lot of potential in SHM, although they also emphasize that it is sensitive to the size of the dataset, the domain, and that close attention is required to ensure generalization [19]. Here, the group-aware holdout method applied in this situation gives a conservative estimate of localization capacity in a repeated experimental situation, which is consistent with the advice frequently given in data-driven SHM studies. In deployment terms, the literature of wireless sensor networks focuses on the limitations of bandwidth, power and reliability of communication, which tend to lean towards feature-level transmission rather than raw waveform transmission [20]. This study uses the feature-based approach, which can be compatible with such constraints, especially when processing edges and in a low-latency monitoring requirement. Lastly, despite the growing interest in the use of fiber-optic sensing in civil SHM, certain value is determined by how measured signals are processed and interpreted; the current workflow has potentially been scaled to these sensing modalities when transient responses or vibration signals exist [21].

The findings indicate that feature-based spatial localization of impact can be practically achievable without the need to have visually distinguishable clusters of features. The existence of a continuous, location-dependent gradient in reduced dimensions, moderate correlations between features and location, and stable multivariate regression performance all signify that a sensor signal can be used to extract location information and be applied to monitoring application. Regularized regression also has implications of allowing robust localization whilst controlling composition and over-modelling of the model, and sensitivity to multicollinearity. In civil and mechanical applications, this means that a comparatively lightweight analytics pipeline, which includes preprocessing, statistical features extraction and regularized regression, can make meaningful localization estimates with controlled effects, and can act as the benchmark of more complex models.

The present research has multiple limitations that propose the way forward in future research. The analysis is based on a controlled impact-event data set and a given specimen configuration, but additional verification is needed to determine the performance of various structures and operation conditions. Only PCA was employed to perform the

exploratory analysis, and other dimensionality reduction methods can also be taken into account in the future. Moreover, localization was proved through the application of a linear regression model; nonlinear models can be considered with strong validation. Future research can also be on sensor placement and integration by scalable SHM systems to make them more practical.

5. Conclusion

The signal processing-related methods were explored in structural health monitoring by concentrating on features-based localization of impacts upon the use of multi-sensor transient response measurements. The statistical characteristics derived from the preprocessed signals were compared in order to study their correlation with impact location. The findings show that the spatial information is represented by a gradual change in the feature space instead of explicit clustering, implying that individual features provide complementary information about location. In cases where a combination of features in different sensors was used, a regularized regression framework was used and showed uniform localization performance in a group-aware validation condition. The findings indicate that feature fusion and interpretable models can be effectively used to realize localization of impacts without the usage of complex architectures or image-based information. The general findings of the study contribute to the notion that signal-based feature extraction and multivariate analysis can be applied as a viable baseline to impact-induced SHM in a controlled experimental scenario. The given workflow offers a starting point in further research of the various structural setups, feature representations and scaled-out monitoring systems.

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