GTRF: A General Tuples Recognition Framework Towards Deep Learning-Driven Structural Health Monitoring Adapted to Diverse Supervision Paradigms

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ABSTRACT

Leveraging the powerful capabilities of deep learning (DL) techniques, the DL-driven tuple recognition approach has successfully addressed numerous challenges in SHM by associating tuples with structural patterns. However, the robustness and generalizability of the model are significantly compromised due to limitations in their designated feature extraction strategies, network architectures, and supervision learning schemas. To address these issues, this study proposes a novel General Tuple Recognition Framework (GTRF) that supports supervised (SL), unsupervised (UL), and semi-supervised learning (SSL) paradigms. The present article provides a detailed explanation of the mechanism and workflow of the proposed GTRF. Equipped with sophisticated networks and innovative components, the GTRF demonstrates competence in various tuple recognition tasks across different learning paradigms. The validation experiments conducted in the field of SHM include vibration SL-recognition of a prototype skyscraper, damage UL-detection of a laboratory RC beam, and condition SSL-assessment of a full-scale building model. To ensure the adaptability of diverse tuples, two commonly used data forms, namely acceleration measurements and piezoelectric signals, are employed in the experimental validations. The comprehensive results confirm the effectiveness and adaptability of the proposed GTRF. The flexible paradigm specialization, broad application, and potential for optimization make the proposed GTRF framework a promising prototype for bridging the gap between DL algorithm fusion and model integration across different learning paradigms.

INTRODUCTION

In recent decades, deep learning-based structural health monitoring (SHM) has gained significant attention, to which considerable efforts of scientific research and engineering applications have been dedicated [1-5]. Generally, these researches focus

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on establishing a mapping relationship between specific structural patterns (such as damage index and condition scenarios) and the corresponding measurement, utilizing a collected dataset from various deployed sensors, such as mechanical accelerators [6] and piezoelectric transducers [7]. Notably, Avci et al. conducted a comprehensive review of advanced deep learning (DL) algorithms for vibration-based damage detection, focusing on DL learning algorithms and their specific application scenarios [8]. However, they did not demonstrate a general DL framework capable of adapting to different supervision paradigms. This highlights the scarcity of studies dedicated to exploring a multi-paradigm framework. Developing a generalized DL framework that can adapt to SL, UL, and SSL regimes simultaneously is both appealing and challenging.

Activated by powerful capabilities of deep learning (DL) techniques, the DL-driven tuple recognition regime has facilitated plenty of problems settlement in SHM practice by mapping tuples with structural patterns. A multitude of algorithms and models have been proposed and successfully implemented, demonstrating exceptional performance surpassing human expertise in handling diverse data sources. However, these DL-based methods often face challenges due to fixed feature extraction approaches and limited sample label involvement. As a result, they can only address specific data forms under certain supervision patterns, compromising model robustness and generalization. Furthermore, the intricate design of DL network architectures hinders easy transferability to other tasks, reducing the overall value of the models in terms of transferability and generality. Therefore, there is an urgent need to investigate a DL framework that can be more universally applied.

To address this issue, this study introduces a generalized deep learning framework, named GTRF, for tuple recognition in SL, SSL, and UL patterns. In proposed framework, a novel approach for feature extraction is proposed, leveraging representation learning through deep autoencoders (DAE). This enables the extraction of sensitive features from diverse data sources, regardless of their type or length. To adapt the recognition framework to different supervision patterns, a novel pseudo-label propagation method is also presented, employing an optimized fuzzy c-means cluster (FCM) algorithm. The article provides a detailed explanation of the mechanism and workflow of the proposed GTRF.

PROPOSED FRAMEWORK

The present study introduces a novel feature extraction method within a generalized framework, utilizing signal representation learning through deep autoencoder (DAE). Building upon this method, a feature extractor is developed by quantifying the reconstruction error of the DAE. This process enables the definition and calculation of a set of pattern-sensitive features (PSF). The framework incorporates three distinct channels to cater to different recognition patterns: supervised classification pattern using linear classifiers, unsupervised fuzzy clustering pattern employing an optimized fuzzy-C-means (FCM) algorithm within the UL paradigm, and semi-supervised label propagation using an optimized FCM algorithm within the SSL paradigm. Figure 1 illustrates the workflow of the proposed generalized framework, GTRF, with detailed architecture and mechanisms explained subsequently.

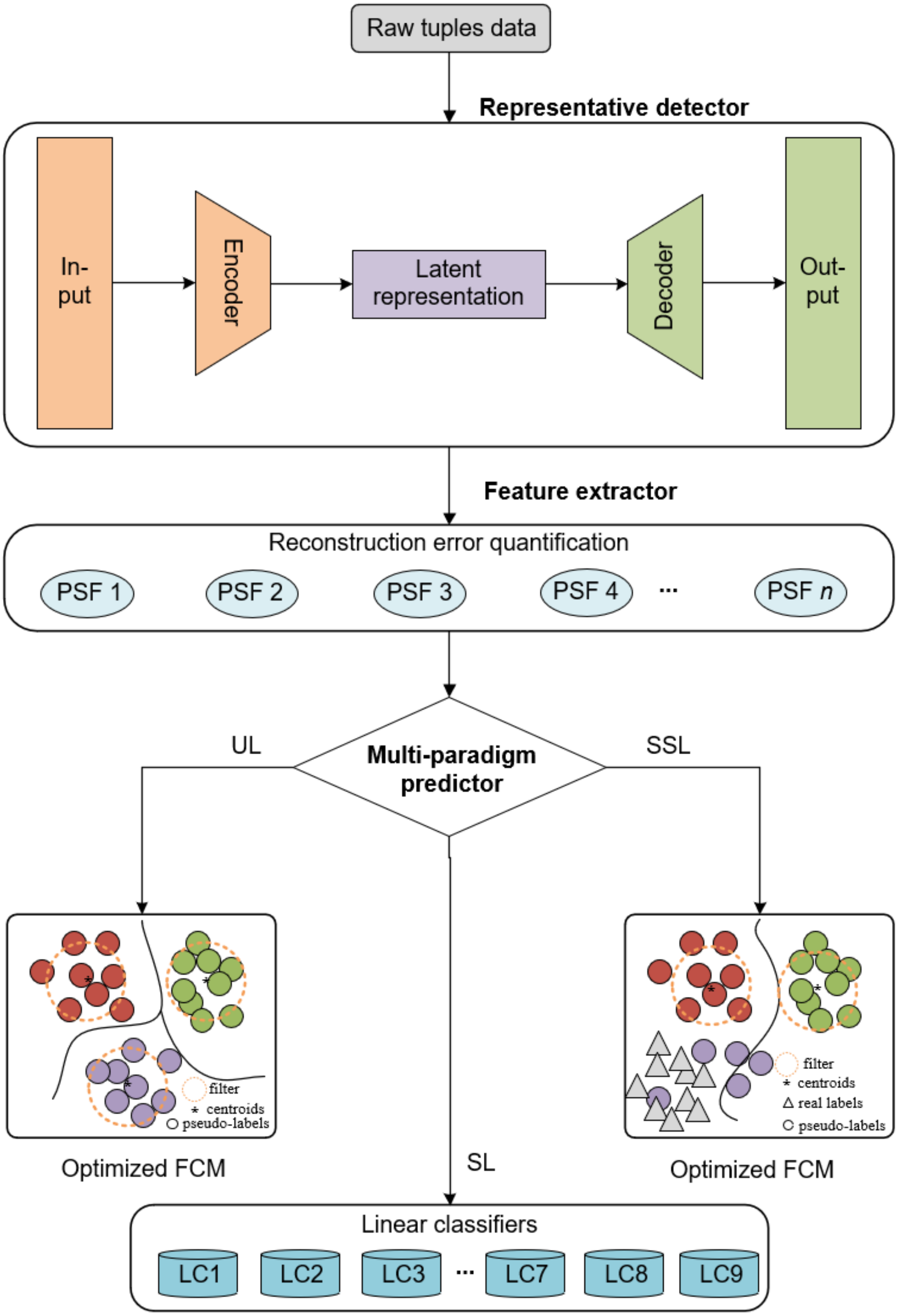

Figure 1. Workflow of proposed general framework GTRF

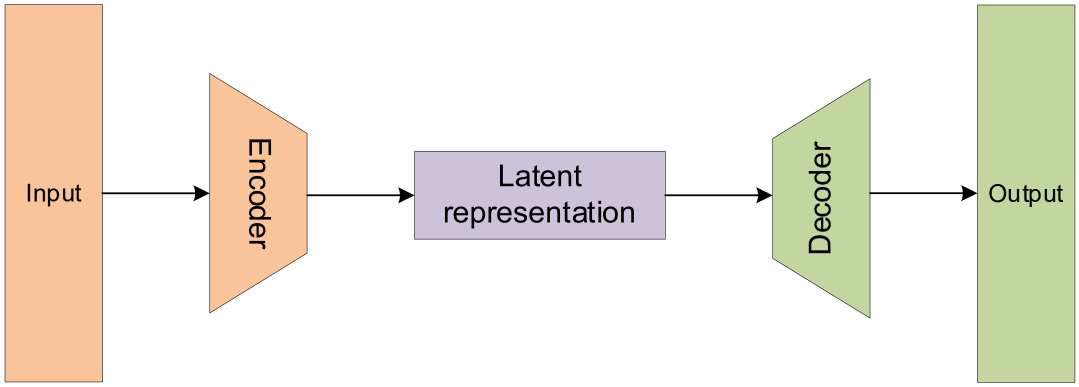

Figure 2. Schematic architecture of DAE

Representative Detector

In the broad family of DL techniques, DAE is a special type of self-supervised learning neural network regarded as a unique representation detector trained to duplicate its input to output as much as possible [9]. In a DAE, the encoder block initially transforms the input signal into a latent representation of lower dimensionality, while the decoder subsequently reconstructs it back into an output with the same dimension as the input, as shown in Figure 2.

While training a DAE with specific type of signals, the trained model will store the latent representative knowledge associated with designated structural patterns. Thus, when fed with signals affiliated to different patterns, the reconstruction performance of DAE shall exhibit corresponding discrepancies related to the divergence between testing signals to the trained one. Therewith, the kernel of building the representative detector is to quantify the reconstruction errors, which can be promising indicators to characterize the in-depth features of signals corresponding to different patterns.

Feature Extractor

In the proposed framework, the kernel strategy of feature extraction is to quantify the reconstruction error by DAE. Thus, it is natural to come up with such classical and readily indicators for evaluation. In this study, six renowned indicators are defined as PSFs, including mean square error (MSE), original-to-reconstructed signal ratio (ORSR), Correlation coefficients (CORR), cosine similarity (COSS), the root mean square error (RMSE) and the ratio of the sum of squares (RSS). The mathematic calculations are expressed as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \tag{1}$$

$$ORSR = 10\,log_{10}\frac{\sum_{i=1}^{n}{x_i}^2}{\sum_{i=1}^{n}{y_i}^2} \tag{2}$$

$$CORR = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2(y_i-\bar{y})^2}} \tag{3}$$

$$COSS = \frac{X\cdot Y}{\|X\|\|Y\|} = \frac{\sum_{i=1}^{n}x_i y_i}{\sqrt{\sum_{i=1}^{n}x_i^2}\sqrt{\sum_{i=1}^{n}y_i^2}} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \quad (5)$$

$$RSS = \frac{\sum_{i=1}^{n} {x_i}^2}{\sum_{i=1}^{n} {y_i}^2} \quad (6)$$

where n denotes the dimension of signals, x and y denotes the original and reconstructed sequences, respectively.

Hereby, a series of extracted PSFs is obtained, which can be allocated for downstream learning with multi-level supervision patterns. Without loss of generality, other modern and performing indices can be also exploited and allocated for error measurement here, which remains flexibility for potential designated specification.

Multi-paradigm Representor

Processed with the representative detector and feature extractor in the framework, the raw high-dimensional signals can be transferred into low-dimensional PSFs, which are beneficial for the downstream classification or clustering implementation.

Specifically, while solving the issue of SL classification, it can be readily performed via those mature classification algorithms, such as naïve Bayes (NB) [10], nearest neighbors (KN) [11], logistic regression (LR) [12], support vector machine (SVC) [13], decision trees (DT) [14], random forest (RF) [15], AdaBoost (AB) [16], gradient boosting (GB) [17] and neural perceptron network (MLP) [18]. With mature development and readily employment, those SL classifiers can be easily introduced for the classification tasks, relevant demonstration of which can be found in one our previous work [3].

Particularly, while switching the recognition paradigm into UL or SSL, an optimized clustering strategy based on the typical and renowned fuzzy C-means algorithm (FCM) [19] propounded in another work [20] of our team is introduced into the present framework. Having the basic truth that those points close to corresponding centroids are generally assigned a more reliable pseudo-label, while some inevitable fake labels among those pseudo-labels such as some outliers will come up occasionally. Thus, only the points with top 75% closest to centroids are selected to train the classifier in a supervised way. This kind of “filtering mechanism” is also applied into the UL clustering process in the framework. More details regarding the optimized clustering approach can be found on our related work [20].

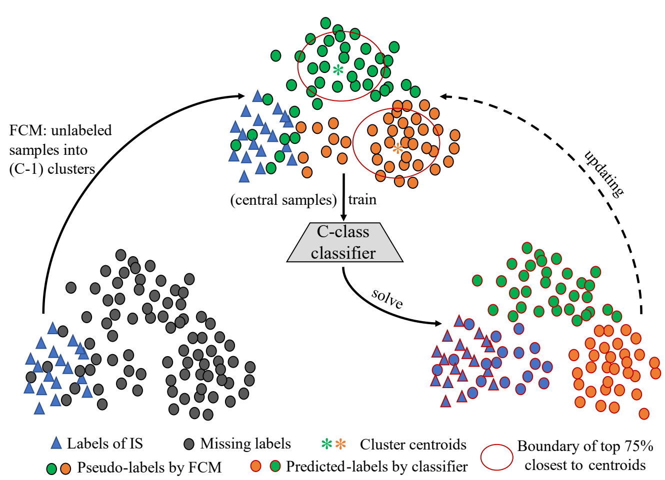

Figure 3. Optimized FCM algorithms for pseudo-label propagation [20]

Hereto, the methodological philosophy and translating mechanism of proposed framework have been thoroughly showcased and explained. Following are some experimental validations for verification.

EXPERIMENTAL VALIDATIONS

In this study, a series of multi-level experimental tasks were carried out to verify the effectiveness and potential superiority of the proposed GTRF in the field of SHM practice. These tasks encompassed various aspects, such as vibration recognition of a real-life skyscraper (representing the SL paradigm) [21], damage detection of a laboratory RC beam (representing the UL paradigm) [22], and condition assessment of a full-scale shear-wall structure (representing the SSL paradigm) [20]. To exhibit the adaptability of diverse tuples, i.e., diverse data form of SHM, two commonly utilized data formats: acceleration measurement and piezoelectric signals are involved in the validations.

Particularly, since the essence kernel of present study is to establish a general DL framework which can be readily switched to adapt to diverse learning paradigms, the major contribution and novelties cast in the sophisticated integration and regulation of all the involved translating mechanism. It is deemed to be reasonable to allocate the three individual works guided by the working principle of proposed framework conducted previously by our research team for experimental validations. Thus, this section will merely make a summarizing description of the three validating cases, as shown in TABLE I, while detail information and demonstrations can be referred to the reference [20-22], respectively.

Notably, to evaluate the prediction performance of validations corresponding to three learning paradigms, the prediction accuracy is utilized as the metric of overall models. The results turned to be 0.95, 0.84, and 0.86 associated to SL, UL, and SSL learning paradigms, respectively, suggesting the powerful capability and adaptability of proposed framework.

CONCLUSIONS

In this study, a new General Tuple Recognition Framework (GTRF) adapted to SL, UL, and SSL is developed to address DL-driven task implementations in SHM practice. The study provides detailed explanations of the advanced network architecture and innovative features incorporated into the framework. Three representative tasks in SHM practice were conducted for comprehensive validations, the results of which confirmed the convective performance of the proposed GTRF.

TABLE I. SUMMARY OF EXPERIMENTAL VALIDATIONS

Paradigm	Objective	Task	Tuple	Accuracy
SL	In-service skyscraper	Vibration recognition	acceleration	0.95
UL	Laboratory RC beam	Damage detection	piezoelectric	0.84
SSL	Full-scale shear-wall structure	Condition assessment	acceleration	0.86

Due to the flexible paradigm specialization, wide-ranging applicability, and opportunities for optimization, the proposed GTRF framework demonstrates promising potential as a prototype to bridge the gap between DL algorithm fusion and model integration across various learning paradigms.

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