A DEEP LEARNING APPROACH TO METRIC-BASED DAMAGE LOCALIZATION IN STRUCTURAL HEALTH MONITORING

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Recent advances in sensor technology offer the opportunity to make big steps ahead in structural health monitoring. Vibrations recorded in real-time by pervasive sensor networks enable the use of autonomous data-driven damage detection procedures aiming to increase the life/safety of the structures as well as optimize their maintenance planning. Within this framework, we propose a novel approach to damage localization, which leverages a deep neural network employing a Siamese convolutional architecture. The proposed method fuses dimensionality reduction and supervised pairwise learning to build a low-dimensional mapping under the guidance of data labels, providing a task-specific metric in the embedding space to discriminate the damage position. The prediction stage is performed in the mentioned low-dimensional space on the basis of the relative distances between testing and training data. Convolutional units are crucial to handle multivariate time series as input and also to detect local correlations within and across the time series. The training dataset is numerically generated through a physics-based model of the structure to be monitored, speeded up by a model order reduction strategy tailored to deal with parametrized systems. Unlike other strategies for damage localization, the proposed approach is suitable to identify the damage position with scalable accuracy, without requiring to define a large amount of target classes, and also provide interpretable results in terms of the identified damage position. Results relevant to a three-dimensional case study show how the procedure is insensitive to sensor noise and varying operational conditions.