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A Novel Framework to Identify Damage in Bridges Based on Recurrent Neural Network with Long Short-Term Memory Blocks Algorithm Hybrid with LiDAR Scanning

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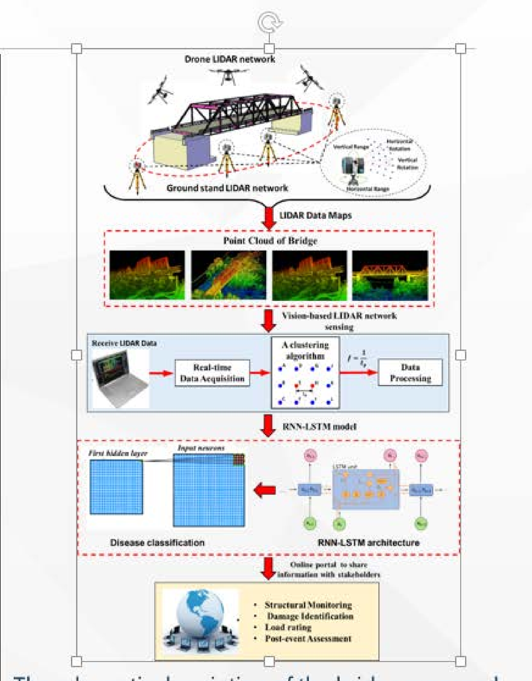
Main Methodology

This work aims specifically at developing an efficient but low-cost methodology that can help detect early transportation infrastructure damages either by permanent or periodic monitoring. In this research, we used LiDAR scanning units (ground units fixed on holders and movable units fixed on UAV) integrated with a novel deep neural network (DNN) for disease monitoring of bridges. The monitoring model is based on a recurrent neural network with long short-term memory blocks (RNN-LSTM) since the LiDAR scanning datasets have a time-dependent and memory-dependent behavior.



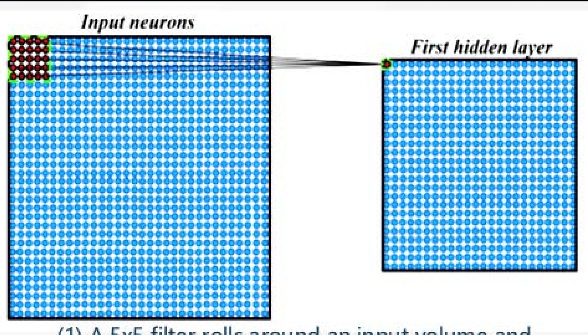
The schematic description of the bridge proposed monitoring system

LiDAR Technology

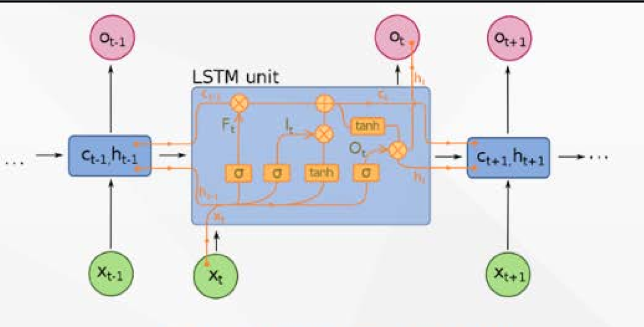
- LiDAR technology is the application of the remote sensing method. It is usually used to examine the surface of the earth, assess information about the ground surface, create a digital twin of an object or detail a range of geospatial information. LiDAR systems harness this technology, using LiDAR data to map three-dimensional models and digital elevation.
- LiDAR data, in the form or a point cloud, can be used to map entire cities, enabling decision makers to accurately pinpoint structures or areas of interest in millimetre perfect detail. Features and objects such as road networks, bridges, infrastructures and vegetation can be classified and extracted.
- LiDAR maps can also be used to highlight changes and abnormalities such as surface degradation and slope changes of infrastructures .

RNN- LSTM Configuration

Figure 1 shows the internal architecture of a single LSTM unit used in certain RNNs to reduce the common problems called disappearing gradient problems. This problem greatly improves the performance of RNN. There are three types of doors in each LSTM cell: input doors, forgetting doors, and output doors. These doors use SIGMOID as the activation function to define the state of each storage unit to transmit information selectively. Keeping a long-term state c_t storage unit is a key structure of each LSTM unit. There are architectures proposed by RNN-LSTM with a single cell (Figure 2).



(1) A 5x5 filter rolls around an input volume and generates an output



(2) A single block diagram in an RNN-LSTM

Bridge overview

The Huangshan River Bridge is located in the Zhuji section. The bridge length is 439.52m, and the bridge width is 12 m. The upper structure adopts a 14×30m simply supported and then continuously prestressed concrete compo-site box beam. The lower part structure adopts pile-type piers for bridge piers and is U-shaped. The bridge's design load is cars 20 tons, trailers 120 tons

Huangshan River Bridge

Geographical location plan

Bridge Test via LiDAR

In this study, we performed a group of ground LiDAR units fixed on holders and movable units fixed on UAVs in shooting places to apply the field test on bridges in common use for disease monitoring in places where the visual inspection is impossible beyond human control and verify of reliability of proposed method as shown in Figure.

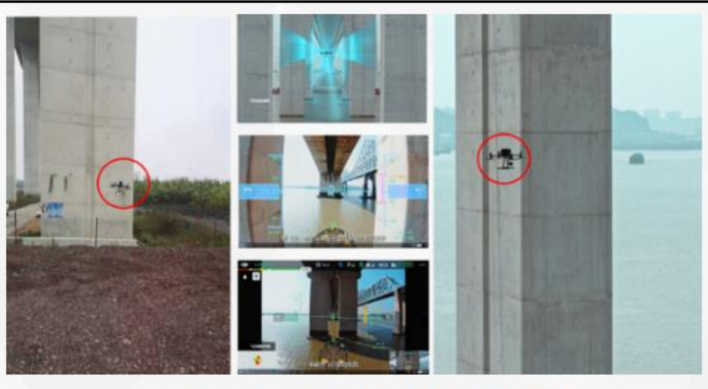
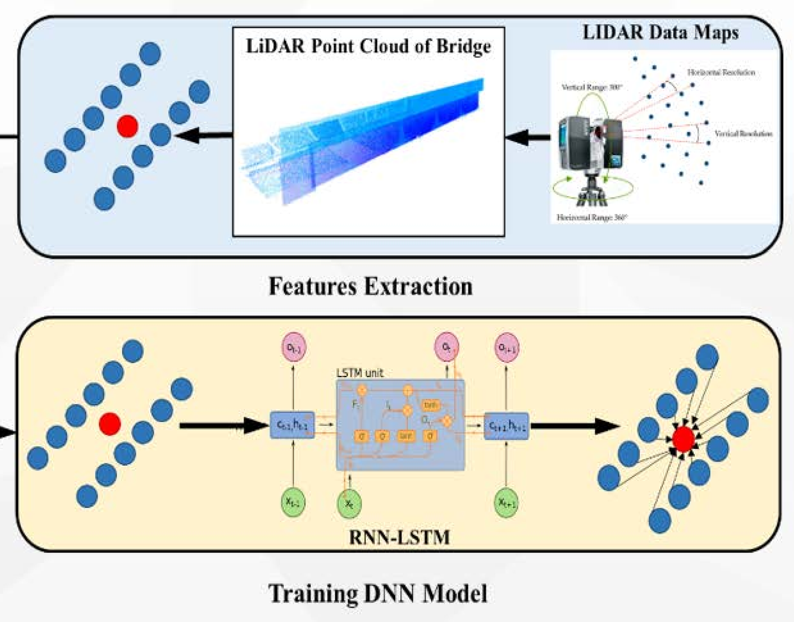


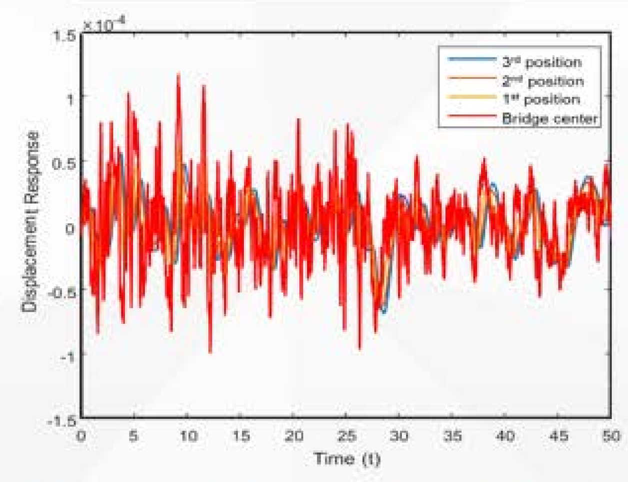
Image acquisition from UAV and LiDAR

Features Extraction

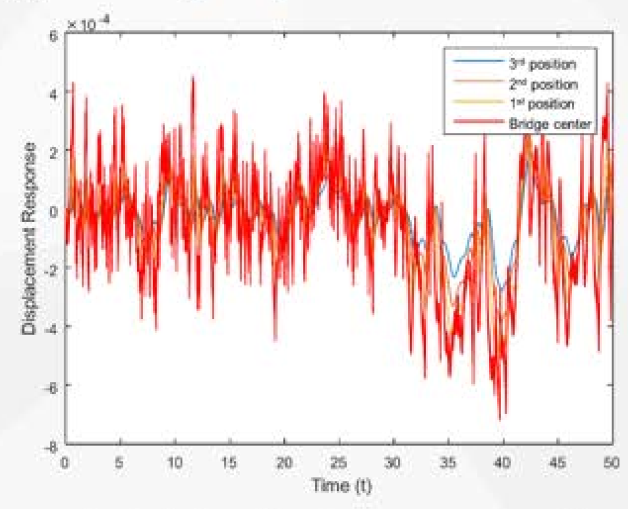


Representation of the workflow architecture. Feature extraction from LiDAR scans (blue dots) and training the Deep NN model using RKRNN to estimate the real position (red dot).

Displacement Analysis



(1) The bridge displacement before diseases



(2) The bridge displacement after diseases

Laser scanning was performed at four positions on the bridge for 50 sec for each load case, and scanning data of 40 scans were obtained, including those for the case without load. The displacement estimation technique was applied using the point cloud of the bridge. The maximum displacement occurred at the center of the bridge at 219.76 m, and the displacement results are presented in Figure 1 and Figure 2 before and after bridge diseases occurred respectively, where the 1st position at 109.88 m from the bridge center, the 2nd position at 164.82 m from the bridge center, and the 3rd position at 192.29 m from the bridge center

Conclusion

1. The integration of LiDAR scanning units—for time-synchronized collection of laser measurements can be processed into a 3D visualization known as a 'point cloud'.
2. The development of a Long Short-Term Memory RNN-LSTM model updating technique for structural system identification and Temporal Estimation of the LiDAR data (Displacement, vibration mode, load, …, etc).
3. The integration of LiDAR scanning units with RKRNN model updating to obtain a reliable and cost-effective structural health monitoring and damage identification solution for bridges.
4. The development and maintenance of digital twins for bridge management and decision support
5. The response of the proposed DNN achieved high rates of P%, R%, and F% equal to 96.43%, 93.77%, and 91.65% respectively. In this way, the monitoring of a real lifeline can be analyzed by combining it with the data from LiDAR and DNN models.