CLASSIFICATION OF UNDERWATER PIPELINE EVENTS USING DEEP CONVOLUTIONAL NEURAL NETWORKS

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Our Contributions

- Implementation of a Deep Convolutional Neural Network (CNN) algorithm for underwater event classification;
- Empirical selection of optimal CNN architecture and parameters;
- Comparison to Multilayer Perceptron (MLP) classification algorithm preceded by manually selected wavelet-based feature extraction;
- Collection and usage of large datasets – 200,000 samples for each event class.

Problem Statement:

- Intensification of subsea oil and gas field exploitation has turned the inspection of underwater pipelines into a progressively demanding task;
- Visual inspection by humans is a tedious endeavor, particularly in the cases of long inspections, low image quality and search for multiple targets;
- Autonomous Underwater Vehicles (AUVs) are able to automatically detect and track underwater pipelines;
- Event classification methods based on machine learning can be used in order to automatically inspect the pipelines;
- Classic neural network techniques, such as the MLP, are strongly dependent on feature extraction methods, which are often manually carried out;
- Recently, deep learning algorithms have been able to iteratively extract their own features from original data.

Event Classes and Data Sets

- The classifier developed in this work was used to detect four different event classes:
  - Inner coating exposure (ICE):
    - Occurs when pipeline surface is damaged;
    - Caused by the object impact and by natural circumstances, such as waves and sea currents;
    - Can be described as a texture region containing parallel stripes, possibly surrounded by homogeneous regions.
  - Presence of algae:
    - Can be characterized by a variety of shapes, colors and textures;
    - Might hide damages on the pipeline surface, hampering their detection.
  - Flanges:
    - Commonly found at pipeline junctions, used for holding pipeline sections together;
    - When seen from a frontal view, these events are outlined by hexagonal prisms surrounding cylinders;
    - When seen from a side view, they are characterized by thinner rectangles emerging from thicker structures.

Event Classes and Data Sets

- Concrete blankets (CB):
  - Placed under or over the pipelines;
  - Constructed to give support or protect the pipelines from vibrations;
  - Usually identified by a regular brick array.

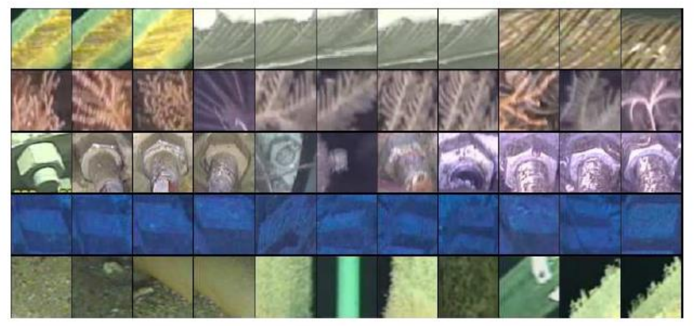

Fig. 1. Samples from different event datasets. From top to bottom rows, ICE, algae, flange, CB and negative samples.

- Windows containing event samples were extracted from high resolution images (1280 x 720), in order to train, validate and test the implemented classification system;
- For ICE, algae and CB samples, 60 x 60 pixel windows were extracted;
- For flanges, 80 x 80 pixel windows were extracted, due to the need to include their entire geometry in each sample.

CNN Algorithm

- The implemented CNN topology consists of two convolutional, two max-pooling and two fully-connected (FC) layers.

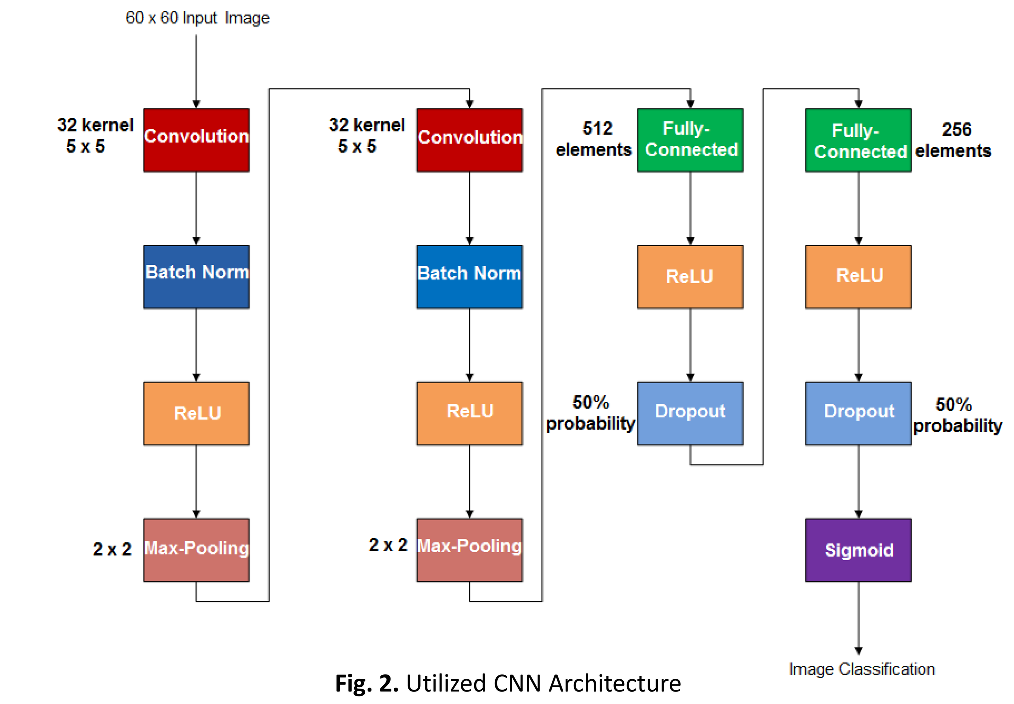

Fig. 2. Utilized CNN Architecture

- Adam optimizer [5] was utilized, with learning rate set to 0.001;
- Cross-entropy loss function was utilized;
- Batch size was set to 100;
- Keras API was utilized for the implementation.

MLP Algorithm

- The CNN classification accuracy was compared to the one from a system comprised of a multilayer perceptron preceded by a wavelet-based feature extractor;
- A 3-level Daubechies 2 (Db2) wavelet was employed, and the mean and the variance of the wavelet coefficients at each subband within each level were used as features for the neural network [7];
- Empirically optimal MLP architecture was composed of a 23-element input layer and a 12-element hidden layer.

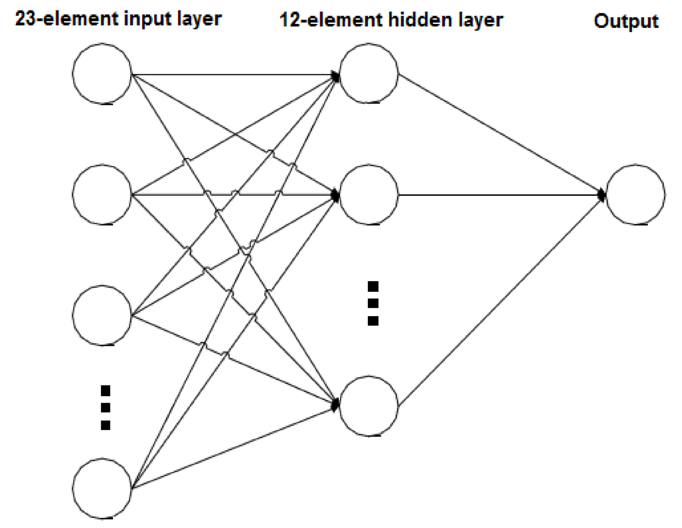

Fig. 3. Utilized MLP Architecture

Classification Results

- For each event class, 100,000 positive and 100,000 negative samples were randomly mixed;
- 162,000 samples were used for training, 18,000 for validating and 20,000 for testing the networks;
- Before being applied to the neural network input, each window is converted to grayscale, in order to eliminate color dependence;
- Results obtained by the CNN and by the MLP for the four classes of events are shown in Table 1.

Accuracy (%)	ICE	Algae	Flange	CB
CNN	96.5	98.3	83.0	95.0
MLP	94.6	97.0	82.4	90.8

Table 1. Classification accuracy for the four different event classes.

Conclusions

- CNN was shown to efficiently classify underwater pipeline events in comparison with the MLP based on wavelet computed features;
- Inner coating exposure, presence of algae, flanges and concrete blankets were the event classes considered;
- CNN obtained higher classification accuracy on all four event classes;
- 93.2% classification accuracy was achieved on average, whereas the perceptron accuracy reached 91.2% on average;
- Classification was preformed without the need of manually selected feature extraction.

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