Road Traffic Detection with a LSTM Autoencoder using State of Polarization on Deployed Metropolitan Fiber Cable

Fehmida Usmani*[1,2], Andrea D'Amico[2], Rudi Bratovich[3], Fransisco Martinez R.[3], Stefano Straullu[4], Emanuele Virgillito[2], Francesco Aquilino[4], Rosanna Pastorelli[3], and Vittorio Curri[2]
[1]*National University of Sciences & Technology (NUST), Islamabad, Pakistan*
[2]*Politecnico di Torino, Italy*; [3]*SM-Optics, Italy*; [4]*LINKS Foundation, Italy*
*fusmani.dphd18seecs@seecs.edu.pk

***Abstract*—We demonstrate the use of an unsupervised autoencoder-based Long Short Term Memory (LSTM) approach to automatically detect road traffic patterns. The model is trained on the dataset acquired from the deployed metropolitan fiber cable in the city of Turin.**

***Index Terms*—Unsupervised road traffic detection, optical fiber sensor, machine learning.**

I. Introduction

In recent years, optical transmission infrastructure has transformed the telecommunications sector to meet the enormous demands of quickly growing worldwide internet traffic. At the physical layer, most existing infrastructure utilizes wavelength division multiplexing (WDM) technology across core, metro and access networks. Consequently, optical fiber deployment is expanding throughout most of the world, especially in densely populated areas. In addition to providing high-capacity data transmission, optical fiber is the best candidate for use as a sensor to monitor the surrounding environment due to its exceptional intrinsic characteristics. Fiber optic sensing (FOS) has attracted a lot of interest from the research community and has been deployed in a number of applications over the past few decades. The core idea of all FOSs is to measure changes in the state of polarization (SOP), frequency, intensity and phase of light waves. Most FOS applications are based on dedicated equipment and rely on distributed acoustic sensors (DAS), phase-sensitive optical time-domain reflectometers (OTDRs), or interferometric setups. An alternative cost-effective solution is to compute the SOP fluctuations from the already deployed optical channels instead of using dedicated equipment. The solutions based on SOP computations are proposed in [1] and [2] for underwater earthquake detection and [3] demonstrates its application for road traffic monitoring.

Recently, use of artificial intelligence techniques has significantly improved the sensing capabilities of FOS, enabling the identification or segmentation of particular events based on the understanding of key characteristics that define them. Some works that demonstrate the advantages of employing machine learning in FOS include detection and classification of vehicles [4], real-time intruder detection in railways [5], and earthquake detection [6]. Although machine learning algorithms have made significant progress in traffic monitoring applications, the detection of road traffic in SOP observations is yet to be addressed, particularly for one based on a real SOP dataset acquired from an experimental setup. In this work, we demonstrate the use of an unsupervised machine learning approach trained on real SOP measurements over a period of 24 hours, collected from an optical link laid in the city of Turin. This approach is used to detect the road traffic patterns automatically for 96 hour SOP measurements, for the first time to the best of our knowledge. The goal of this approach is to extract and learn the relevant features of road traffic from the given time series data without employing any previous knowledge about the physical characteristics of the time series generation mechanism. In particular, we investigate the autoencoder long short term memory (LSTM) model for road traffic detection. It is believed that the proposed method presented in this work has the potential to contribute significantly to the development of an automatic road monitoring system based on SOP measurements.

II. Autoencoder-based LSTM approach for automatic traffic detection

We have acquired the real-time 96 hour SOP measurements from the experimental setup presented in [3]. A standard WDM card configured with an small form factor pluggable (SFP+) transceivers module is used at the transmitter end as an optical source. On the receiver side, a standard reconfigurable optical add/drop multiplexing (ROADM) integrated with a dense wavelength division multiplexing (DWDM) filter and an erbium-doped fiber amplifier (EDFA) is used, serving as a 10G dropping node and as a pre-amplifier. Two different receiver setups for polarization change detection based on a standard polarimeter (Novoptel PM-1000) and a polarization beam splitter (PBS) are examined. Both techniques were configured to store data for up to 96 hours at a sampling rate of 95 samples per second. The optical signal is intensity modulated at a rate of 10 Gbps to carry data traffic. The optical signal travels through the 38 km optical fiber laid in the city of Turin. Both ends of the fiber are accessible through an optical terminal box available at the LINKS lab where the SOP is measured in terms of the cartesian coordinates S_1, S_2 and S_3.

We propose an unsupervised methodology based on LSTM combined with an autoencoder for the automatic detection of road traffic. An autoencoder is an unsupervised artificial neural network (ANN) that leverages a backpropagation algorithm to obtain output identical to the input vector. Firstly, it reduces the input data dimension, and then this compressed representation is used to regenerate the actual data, learning the nonlinear underlying relationships in the data using multiple LSTM

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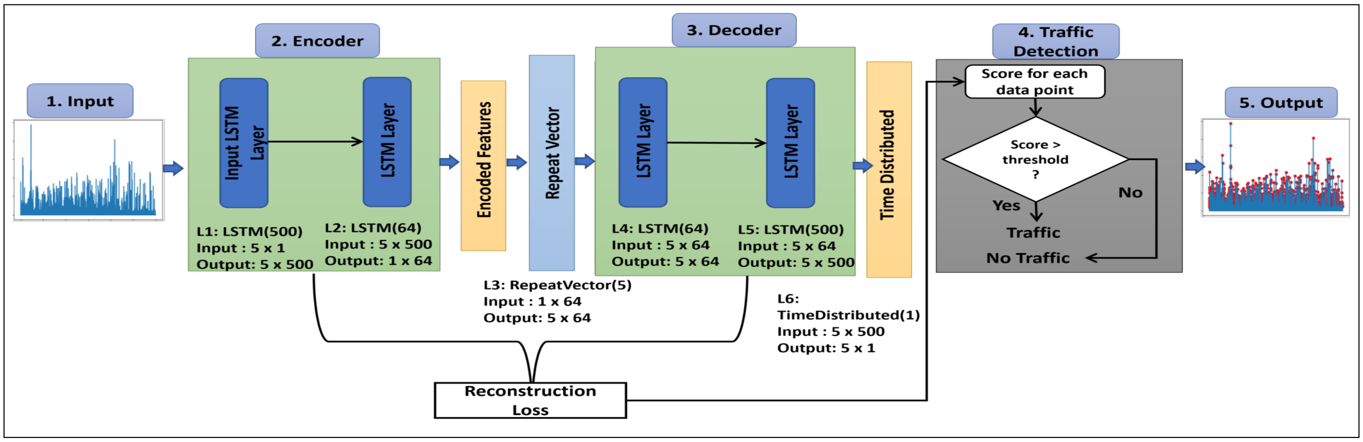

Fig. 1: Architecture of the proposed autoencoder LSTM

layers and a nonlinear activation function. The schematic diagram of our proposed approach is shown in Fig 1. We obtain a 96 hour time series which consists of a single feature. This feature has been define as the norm of the SOP variation in time.

Step 1: Input Data

We normalize the time series and then break it into different input sequences with a window size of 5 timestamps (with a time interval of 2 milliseconds). The input sequences are reshaped into a 2-dimensional (2-D) array comprising of timestamps and data samples, represented as a 5×1 vector.

Step 2: Encoder

We fed the input sequences into the encoder module which consists of the input layer, with 500 LSTM units operating in sequence to process the data samples. The major function of the LSTM encoder is to extract the important information from the input data and map it to a lower dimension. The input layer L1 process the data and outputs a vector of 500 features with 5 timestamps as a 5×500 vector. The L2 layer with 64 LSTM units takes an 5×500 input from L1. Each LSTM unit performs operations on a data sample to decide whether to keep the information or to discard it. If the LSTM unit marks the information as important, it is written into long-term memory and passed to the next LSTM unit. The last LSTM unit in L2 possesses all of the important information processed by the previous units and outputs it as a 1×64 encoded feature vector. Then we add the RepeatVector as the 3rd layer to link the encoder and decoder modules. This layer duplicates the encoded feature vector equal to the number of timestamps (5 in our case) and outputs a 5×64 vector. This layer is necessary to prepare a compatible 2-D input for the next LSTM layer of the encoder module.

Step 3: Decoder

In this step, the 5×64 output vector from L3 is fed to the decoder module, which contains layers 4 and 5. The purpose of the decoding module is to unfold the encoded representation in order to restore the original input data. Consequently, the LSTM layers in the decoder module are placed in the reverse order of the encoder module. In the proposed decoder module, the LSTM layer L4 consists of 64 units, with each unit generating an output that corresponds to the output learned from the encoded feature; this output is multiplied with the 1×64 vector generated by layer L3. Note that both the L4 and L5 layers in the decoder module are exact copies of L1 and L2 present in the encoder module. To get the final output, the TimeDistribution layer L6 is added at the end of the model. This layer is used to generate a vector equal to the number of features fed by the previous layer. In our case, L5 outputs 500 features, thus L6 generates a vector of 500 and matrix multiplication between the output of the 5×500 L5 vector and the output of the 5×1 L6 vector are performed, giving a final 5×1 output which is equal to the original input size. Our model uses a tanh activation function and adds two dropout layers with 0.3% and 0.2% rates in order to avoid overfitting. For model training, we have used a 24 hour portion (starting at 9.30 a.m. on Friday, Jan 21) of the given 96 hour dataset. The obtained training dataset is split into 80% training, 10% validation and 10% test datasets respectively. The model is trained on 100 epochs in order to minimize the loss function, and optimized using an ”Adam” optimizer with a learning rate of 0.05.

Step 4: Traffic Detection

For traffic detection, we compute the absolute mean error between the original input and the output to determine the reconstruction error. The distribution of computed loss in the training and test sets is plotted to determine the appropriate threshold value for traffic detection. Once the threshold is fixed, we have evaluated the performance of our model on the full 96 hour dataset to compute the predicted score for each data point. The data points with a loss greater than the threshold value are labeled as traffic detected while those with a loss below the threshold as traffic not detected.

III. Results and Discussion

The training and validation loss of the proposed model during training at various epochs is shown in Fig 2a. We observe a similar loss trend for both training and validation datasets, converging very quickly after a few epochs, demonstrating that the model is well-trained and performs well on unseen data during training. Fig 2b shows the performance of our model on 96 hours of data for traffic detection, where red

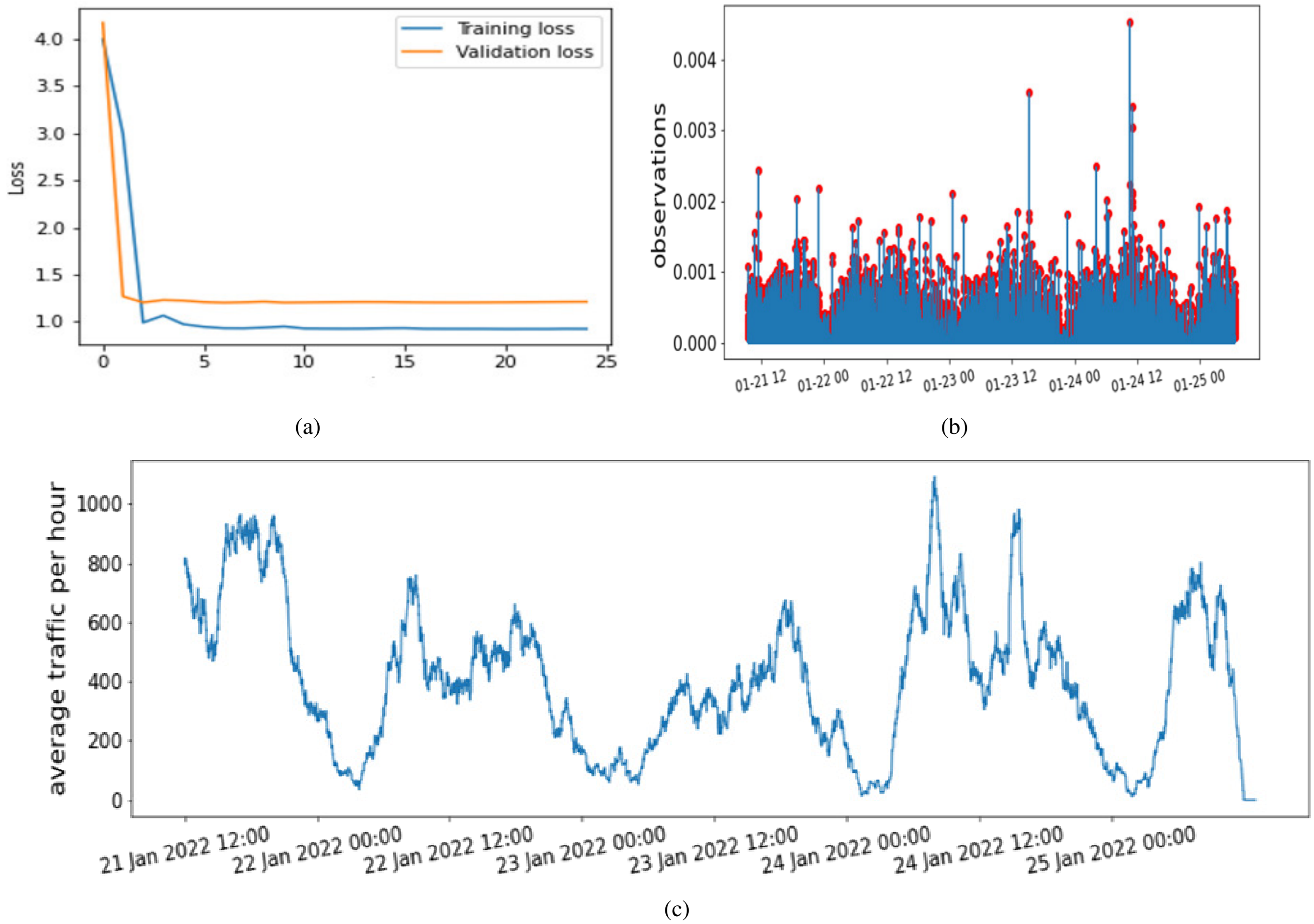

Fig. 2: (a) MSE loss versus epoch (x-axis) of the proposed model during training, (b) Traffic detected over 96 hours, red circles indicate the detected traffic, x-axis indicates month-date and time (c) Average count of detected traffic per hour versus time.

points indicate the detected traffic. Our model is visibly able to correctly distinguish traffic from noise, and able to detect all traffic peaks effectively in 96 hours of measurements. To further evaluate the performance of our proposed approach, we computed the number of traffic instances per minute on the complete 96 hours of data as shown in Fig 2c. The results show that our proposed approach is able to capture the hourly and daily traffic patterns very well. For instance, variations in patterns are clearly evident for day and night, weekdays and Sunday, Jan 23, and aligned well with the expected traffic pattern. We also compare the number of average traffic instances per hour with the statistics obtained from the experimental setup – our approach detected and computed traffic instances with approximately 97% accuracy.

IV. Conclusion

Our results demonstrate that training an autoencoder-based LSTM model with 24 hours of real SOP measurements, can capture and learn important features of road traffic, providing reliable detection of traffic in SOP measurements in an unsupervised manner. Our proposed method and findings can serve as a first step towards the development of an automatic traffic monitoring system based on SOP measurements. This approach is not limited to detecting road traffic, and can be further evaluated also for traffic classification, and other fiber sensing applications based on SOP measurements.

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