InSAR Data Analysis using Deep Neural Networks

Ayush Kumar Agrawal¹, Himanshu Verma²*, Sumanta Pasari³

¹²³Department of Mathematics, Birla Institute of Technology and Science Pilani, Pilani Campus, Jhunjhunu - 333031, Rajasthan, India

¹f20180938@pilani.bits-pilani.ac.in

²vermahimanshu0008@gmail.com

³sumanta.pasari@pilani.bits-pilani.ac.in

Abstract. Among all natural disasters, earthquakes cause the most severe devastation to both infrastructure as well as human lives. The pattern of surface deformation from satellite-based measures, such as interferometric synthetic aperture radar (InSAR), helps understand crustal dynamics and associated seismic hazards in tectonically active areas. In the last few years, the exponentially rising volume of InSAR data has led to the formulation of automatic crustal deformation algorithms through data-intensive machine learning models. In this study, we propose the long-short-term memory (LSTM) architecture of deep neural networks to forecast InSAR-based line-of-sight displacement. The model suitably captures the inherent temporal variations of SAR interferograms. The method implementation on a region near Central and East Java, Indonesia shows satisfactory performance (mean absolute percentage error around 2%) of the proposed LSTM model comprising four layers, each consisting of 100 nodes. We therefore conclude that deep neural network is a promising avenue for InSAR time series analysis.

Keywords: InSAR, Machine learning, LSTM-RNN, Crustal deformation.

1. Introduction

Occurrence of earthquakes is commonly explained by the theory of plate tectonics [12]. The spatio-temporal dataset, that are used to understand earthquake dynamics and consequent seismic hazards, primarily include tabular seismicity data and Earth’s surface displacement from space geodesy [9, 11]. In recent years, the dependency on the dense InSAR data has increased manifold due to the inadequate resolution of global navigation satellite system (GNSS) stations [2]. As a consequence, several methods have been proposed to deal with InSAR data processing in order to infer the underlying crustal structure, fault kinematics, and earthquake potential in a defined region [4, 7]. Moreover, due to inherent diversity and exponentially rising volume of SAR interferograms, machine learning models may be employed to extract meaningful information in terms of “hidden-variables” [11]. Such models use feature vectors to simultaneously process millions of data points and they are less sensitive to human biases [1]. In this paper, we propose a long-short-term memory (LSTM) architecture of recurrent neural networks (RNNs) to capture inherent temporal variations of InSAR dataset.

A SAR data is a 2-D representation of the amplitude of target reflections inside the imaging region [12, 9, 11, 2, 4]. The amplitude represents target reflectance, while the phase represents surface variations. A SAR interferogram is formed by combining the phase of two SAR pictures obtained concurrently or at different times from satellite with slightly varying look angles [1, 3, 10, 13, 6]. The
phase difference of two pictures, called the master image and slave image, collected on the same region from two orbits separated by a given baseline distance is used in radar interferometry [2]. The InSAR data is useful in studying ocean currents, landscape studies, vegetation characteristics, terrain categorization, glacial motions, and landslide surveillance. It can be also used to study the ground surface displacement in the urban, rural or hilly regions [10]. Multiple SAR images can be combined to generate a radar interferogram. The interference pattern induced by the phase shift between these pictures can be used to quantify topography or small changes in terrain of order of a few millimetres along the spacecraft look path [1, 3, 10, 13, 6, 2, 14]. The changes in the returned phase can be accurately calculated using the phase difference between two radar picture obtained with the same point of look but at separate times. As a consequence, if the upper mantle moves closer or far from the satellite between two picture passes, phase difference may be computed with an efficiency equivalent to millimeter-level deformation [14]. Ding et al. [5] estimated crustal deformation of the eastern segment of the Altyg Tagh Fault (EATF) by using the D-InSAR technique. They used ERS-1/ERS-2 SAR data and Space Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) of the study area. Recently, Brengman and Barnhart [1] proposed a machine learning based SarNet method to identify surface deformation through InSAR data. Using convolutional neural network (CNN) architecture, they achieved an accuracy of 99.74% within synthetic interferograms. In this direction, the present study deploys an LSTM-RNN based neural network model to forecast InSAR-based line-of-sight (LoS) displacement.

2. Study Area & dataset
For illustration of the proposed method, a 100 km by 100 km region between central and east Java, Indonesia is selected (Fig. 1). Several unwrapped and coherent GeoTIFF files of Sentinel-1 (ascending) images from 08/12/2015 to 27/06/2021 with 1175 interferograms have been considered from the "COMET-LiCS Sentinel-1 InSAR" portal (https://comet.nerc.ac.uk/COMET-LiCS-portal/) to produce velocity map and time-series of velocity [8]. These velocity data will be used to forecast InSAR-based line-of-sight displacement using LSTM model.

Fig 1. Topography along the Java Island, Indonesia. The red rectangle near Central-East Java represents the region of interest.

3. Methodology and results
The methodology comprises three steps: pre-processing of data, processing (LSTM implementation), and post-processing analysis. A summary of the proposed methodology is provided in Fig. 2. As mentioned earlier, we use COMET-LiCS InSAR (LiCSAR) processing toolbox to extract the LoS velocity map of the study area. Using the LiCSAR toolbox, we downloaded the SAR data for the study
region in the first phase. Then to improve the accuracy of the velocity map, data from the Generic Atmospheric Correction Online Service (GACOS) has been used to account for the atmospheric correction [15]. Later, for time series analysis, erroneously unwrapped data that degrades the findings is discovered and deleted based on the unwrapped data's coherence and coverage, as well as loop closure [8]. To extract the displacement time series and velocity, the improved stacks of unwrapped data are inverted. The standard deviation of the velocity map (Fig. 3) shows millimeter level accuracy. We choose a pixel from the velocity map at location (7.08278°S, 110.60667°E) for observation and forecasting of InSAR time series.

Fig 2. Flowchart of the proposed methodology.

To analyze the trend pattern in displacement (e.g., upliftment or subsidence), a time series data for six years (2016-2021) is plotted in Fig. 4. The nature of the dataset (negative values) reveals subsidence of the area, with a mean displacement of 23.69 mm/yr. Two statistical tests, namely the ADF and KPSS tests, with their corresponding p-values 0.155 and 0.100, suggest that the trend is non-stationary. However, the dataset exhibits a seasonal behavior. Therefore, a time series decomposition would be useful to understand the trend, seasonality, and residual components. The dataset also exhibits a significant auto-correlation, indicating that the future value is correlated (or depends) on the occurrence of the past values. In fact, by inspection, it appears from Fig. 4 that a time lag of 20 would be appropriate to consider in forecasting models. The time-series decomposition plot is shown in Fig. 5. From Fig. 5, we can visualize that the dataset has a strong downtrend behavior (subsidence), seasonality, and random variation that may be related to localized geospatial effects and observational noise due to wrapping and unwrapping, vegetation cover, and atmospheric disturbances [2]. Having pre-processed the dataset and analyzing several components of the time-series, we construct LSTM
architecture for suitable forecasting of the LoS displacement. First, a single layered LSTM-RNN model with four nodes is considered. We consider a variable epoch size of 25, 50, and 100, split size as 0.8 (80% training data) and 0.9 (90% training data), and “Relu” as activation function. We consider two accuracy indicators, namely the root mean squared error (RMSE) and mean absolute percentage error (MAPE). Based on their values for several combination of models, it is found that a split size of

![Fig 3. InSAR-based LoS velocity map of the study area in mm/yr. Black dot at the upper left corner represents the pixel that was chosen for observation and forecasting of InSAR time series.](image1)

![Fig 4. Displacement (in mm) versus time plot.](image2)

![Fig 5. Time series decomposition of LoS displacement in mm/yr.](image3)
Fig. 6. Displacement versus time graph corresponding to the two types of LSTM architecture; (A) single-layered LSTM model with epoch size 100 and split size 0.9 provides an MAPE 4%, training RMSE score 8.27 and testing RMSE score 7.75; (B) Four-layered LSTM model with epoch size 100 and split size 0.9 provides MAPE 2%, training RMSE score 7.91 and testing RMSE score 8.10.

0.9 and epoch size of 100 provide better results (Fig. 6a). In fact, the model with epoch size 25 or 50 suffers heavy under-fitting. However, to further improve modeling accuracy, we have included three more LSTM layers to the previous model architecture. Epoch size 100 and split size 0.9 are chosen. This yields an MAPE score of 2%, with the training and testing RMSE values 7.91 and 8.10, respectively (Fig. 6b). The actual versus predicted values are plotted in Fig. 6.

4. Conclusions
This paper has provided a step-by-step implementation of the LSTM-RNN based machine learning technique to forecast InSAR-based LoS displacement of a pixel. It was observed that a multilayer LSTM model with four layers, each consisting of 100 nodes, provides desirable accuracy. In addition, the time series plots reveal land subsidence with a rate of 23.69 mm/yr. Although this study provides basic formulation of deep neural networks for InSAR data analysis in a selected pixel, the efficacy of the proposed approach may be assessed based on the results at several study regions. The deep-learning based LSTM model may also be implemented on a combined InSAR and GPS dataset to reveal better insights of crustal dynamics in a geographic area.

5. References
[1] Brengman, C. M., & Barnhart, W. D. (2021). Identification of Surface Deformation in InSAR Using Machine Learning. Geochemistry, Geophysics, Geosystems, 22(3), e2020GC009204.
[2] Bürgmann, R., Rosen, P. A., & Fielding, E. J. (2000). Synthetic aperture radar interferometry to measure Earth’s surface topography and its deformation. Annual Review of Earth and Planetary Sciences, 28(1), 169-209.
[3] Chelbi, S., Khireddine, A., & Charles, J. P. (2011, December). Interferometry process for satellite images SAR. In 2011 7th International Conference on Electrical and Electronics Engineering (ELECO) (pp. II-200). IEEE.
[4] Diao, F., Walter, T. R., Solaro, G., Wang, R., Bonano, M., Manzo, M., Ergintav, S., Zheng, Y., Xiong, X., Lanari, R. (2016). Fault locking near Istanbul: Indication of earthquake potential from InSAR and GPS observations. Geophysical Supplements to the Monthly Notices of the Royal Astronomical Society, 205(1), 490-498.
[5] Ding, X., & Huang, W. (2011). D-InSAR monitoring of crustal deformation in the eastern segment of the Altyn Tagh Fault. International Journal of Remote Sensing, 32(7), 1797-1806.
[6] Ferretti, A., Monti Guarnieri, A., Prati, C., Rocca, F., & Massonnet, D. (2007). InSAR Principles-Guidelines for SAR Interferometry Processing and Interpretation, Part A. Netherlands: European Space Agency.
[7] Liu, F., Elliott, J. R., Craig, T. J., Hooper, A., & Wright, T. J. (2021). Improving the resolving power of InSAR for earthquakes using time series: a case study in Iran. Geophysical Research Letters, 48(14), e2021GL093043.
[8] Morishita, Y., Lazecky, M., Wright, T. J., Weiss, J. R., Elliott, J. R., & Hooper, A. (2020). LiCSBAS: an open-source InSAR time series analysis package integrated with the LiCSAR automated Sentinel-1 InSAR processor. Remote Sensing, 12(3), 424.
[9] Pasari, S. (2015). Understanding Himalayan tectonics from geodetic and stochastic modeling. PhD Thesis, Indian Institute of Technology Kanpur, 376.
[10] Radutu, A., Nedelcu, I., & Gogu, C. R. (2017). An overview of ground surface displacements generated by groundwater dynamics, revealed by InSAR techniques. Procedia Engineering, 209, 119-126.
[11] Rundle, J., Stein, S., Donnellan, A., Turcotte, D. L., Klein, W., & Saylor, C. (2021). The complex dynamics of earthquake fault systems: New approaches to forecasting and nowcasting of earthquakes. Reports on Progress in Physics, 84, 076801.
[12] Scholz, C. H. (2019). The mechanics of earthquakes and faulting. Cambridge university press.
[13] Sreejith, K. M., Agrawal, R., & Rajawat, A. S. (2016). Crustal deformation studies using synthetic aperture interferometry. Proceedings of the Indian National Science Academy, 82(3), 737-746.
[14] Verma, H., Sharma, Y., & Pasari, S. (2022). Synthetic Aperture Radar Interferometry to Measure Earthquake-Related Deformation: A Case Study from Nepal. In Disaster Management in the Complex Himalayan Terrains (pp. 133-140). Springer, Cham.
[15] Yu, C., Li, Z., Penna, N. T., & Crippa, P. (2018). Generic atmospheric correction model for Interferometric Synthetic Aperture Radar observations. Journal of Geophysical Research: Solid Earth, 123(10), 9202-9222.