International Journal of Internet, Broadcasting and Communication Vol.15 No.3 94-102 (2023)
http://dx.doi.org/10.7236/IJIBC.2023.15.3.94

IJIBC 23-3-13

Detecting Abnormal Human Movements Based on Variational Autoencoder

Doi Thi Lan and Seokhoon Yoon*

Ph.D. Student, Department of Electrical, Electronic and Computer Engineering, University of Ulsan, Korea
Professor, Department of Electrical, Electronic and Computer Engineering, University of Ulsan, Korea
doilan151188@gmail.com, seokhoonyoon@ulsan.ac.kr

Abstract

Anomaly detection in human movements can improve safety in indoor workplaces. In this paper, we design a framework for detecting anomalous trajectories of humans in indoor spaces based on a variational autoencoder (VAE) with Bi-LSTM layers. First, the VAE is trained to capture the latent representation of normal trajectories. Then the abnormality of a new trajectory is checked using the trained VAE. In this step, the anomaly score of the trajectory is determined using the trajectory reconstruction error through the VAE. If the anomaly score exceeds a threshold, the trajectory is detected as an anomaly. To select the anomaly threshold, a new metric called D-score is proposed, which measures the difference between recall and precision. The anomaly threshold is selected according to the minimum value of the D-score on the validation set. The MIT Badge dataset, which is a real trajectory dataset of workers in indoor space, is used to evaluate the proposed framework. The experiment results show that our framework effectively identifies abnormal trajectories with 81.22% in terms of the F1-score.

Keywords: *Anomalous trajectory detection, VAE, Bi-LSTM, D-score, anomaly score.*

1. Introduction

With the occurrence of location positioning equipment (e.g., GPS, smartphone, sensors), the trajectory of moving objects may be recorded. Analyzing these objects' trajectories allows us to understand their movement behaviors, which opens a lot of new applications. For example, in smart transportation systems, detecting outliers in drivers' behavior may help prevent drivers' fraud and detect traffic accidents and jams [1-2]. Besides, the drivers' driving preferences may be realized through their trajectories, which enable us to recommend personalized routes to drivers [3]. In maritime, analysis and extraction patterns in trajectories of ships are also crucial, which help to predict marine vessel movement and detect their abnormal trajectories [4].

The anomalous trajectory detection methods may be divided into two main categories: traditional detection methods (i.e., distance-based, density-based, clustering-based methods) and deep learning-based detection

Manuscript Received: June. 10, 2023 / Revised: June. 15, 2023 / Accepted: June. 18, 2023
Corresponding Author: seokhoonyoon@ulsan.ac.kr
Tel: +82-52-259-1403, Fax: +82-52-259-1687
Professor, Department of Electrical, Electronic and Computer Engineering, University of Ulsan, Korea

Copyright© 2023 by The Institute of Internet, Broadcasting and Communication. This is an Open Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (http://creativecommons.org/licenses/by-nc/4.0)

methods. In the first category, abnormal trajectory detection is often based on the trajectories' relationship in the dataset (i.e., the distance between the checked trajectory and remaining trajectories, the number of trajectory's neighbors and the relationship between the trajectory and clusters in the dataset). The studies in [5-6] proposed anomalous trajectory detection frameworks using distance metrics and density method. First, they proposed new metrics to measure the distance between trajectories. Then, the trajectory's density was determined using a distance threshold. A trajectory was detected as an anomaly if its density is smaller than a given density threshold. The authors in [7] proposed an abnormal trajectory detection method based on clustering algorithm. To find trajectory clusters in dataset, the hierarchical clustering algorithm was applied using a distance matrix of trajectories. A trajectory was marked as an anomaly if it belongs to cluster with only one trajectory.

The second category focuses on learning trajectories' embedding vectors through deep learning models, which capture latent representations of trajectories. In works [8-9], RNN-based deep learning models are trained to learn trajectory embeddings. The embedding vectors keep the internal characteristics of trajectories, which may be used to distinguish between normal and abnormal trajectories. In these works, models were trained in a supervised manner where normal and abnormal trajectories are labelled in the training set. Besides, the autoencoder (AE) architecture was also used in [10] for anomalous trajectory detection. In this work, the authors proposed LSTM-AE and 2DCNN-AE to learn the latent space of trajectories. Anomalous trajectories were detected using their reconstruction errors through AEs. If the reconstruction error of one trajectory is higher than a threshold, the trajectory is marked as an anomaly.

Our work proposes a framework for detecting anomalies in human trajectories, which is based on a variational autoencoder (VAE) with Bi-LSTM layers. In Bi-LSTM architecture, trajectories' embeddings are learned following both sides of the original trajectories. VAE is trained to capture latent representations of normal trajectories. VAE also constrains the latent space of trajectories, approximating the latent space's distribution to the standard Gaussian distribution. This helps to distinguish more clearly between normal and abnormal trajectories in latent space. In the anomaly detection phase, the reconstruction error of trajectories by the trained VAE is used as the trajectory anomaly score. If the anomaly score exceeds a threshold, the trajectory is detected as an anomaly. Since the anomaly threshold's value directly affects the anomaly detection performance, the choice for its value is challenging. In this work, we propose a new *D-score* metric to choose an appropriate anomaly threshold. The *D-score* represents the difference between two performance metrics: recall and precision. Note that selecting the anomaly threshold is based on the framework performance on the validation set. The contribution in this work can be summarized as follows:

- ✓ A variational Bi-LSTM autoencoder-based framework is designed for detecting anomalies in human movements. First, a VAE is trained to learn the trajectory representations and constraint them to the standard Gaussian distribution. Then, the reconstruction error of trajectories through the trained VAE is used to detect anomalies.
- ✓ To choose the anomaly threshold, a new metric called *D-score* is proposed. The *D-score* measures the difference between recall and precision. The algorithm performance on the validation set is used in this step. The anomaly threshold is chosen so that the role of recall and precision is the same.
- ✓ The proposed framework is evaluated using the MIT Badge dataset, which is a real trajectory dataset of humans. The results show that our framework detects abnormal trajectories, achieving 81.22% of the F1-score.

The layout of this paper is organized as follows. First, Section 2 presents the background of Bi-LSTM and

VAE architectures. Then, the proposed framework is introduced in Section 3. Section 4 shows the evaluation results of the proposed framework performance. Finally, Section 5 consists of the conclusion of the paper.

2. Background

In this section, we present architectures of Bi-LSTM layer and VAE.

2.1. Bi-LSTM

Bi-LSTM architecture is used effectively in sequence tasks. This layer captures the input sequence's sequential information and internal characteristics from both directions. Bi-LSTM contains two LSTM layers independently [11]. One gets the input from left to right of the input sequence, known as the forward layer. The other receives the input from the reversed direction, called a backward layer. The output of the Bi-LSTM layer is a combination of the outcomes from two LSTM layers. Since the Bi-LSTM layer learns the sequences from both directions, it may improve the model's performance compared to the basic LSTM layer. The architecture of Bi-LSTM is shown in Figure 1.

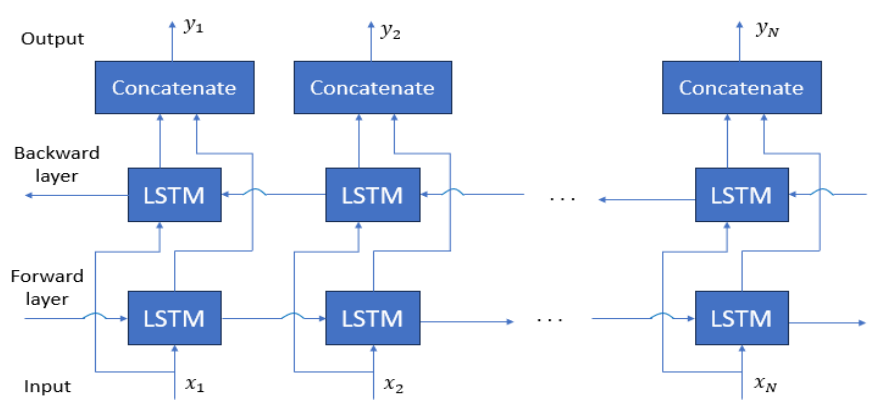

Figure 1. Bi-LSTM architecture

2.2. Variational Autoencoder

The main architecture of VAE is similar to a basic autoencoder (AE), which is presented in Figure 2.

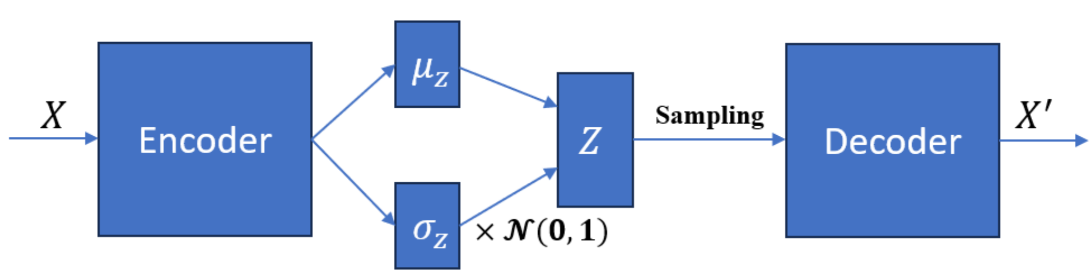

Figure 2. Variational autoencoder

VAE consists of two main parts: an encoder and a decoder. In the encoder, the distribution parameters of a latent representation space Z of input sequences are learned. These parameters are the mean value μ_Z and the standard deviation σ_Z. The decoder aims to obtain an output sequence X', which is reconstructed from the input sequence X. Besides, the latent space is constrained to approximate to the standard Gaussian distribution

$\mathcal{N}(\mathbf{0}, \boldsymbol{I})$. The decoder input is sampled from the distribution $\mathcal{N}(\mu_Z, \sigma_Z)$ with parameters be learned from the encoder.

The training objective of VAE is to minimize the distance between the target distribution $\mathcal{N}(\mathbf{0}, \boldsymbol{I})$ and the distribution of the latent space $\mathcal{N}(\mu_Z, \sigma_Z)$. Besides, VAE also aims to minimize the reconstruction error of the input sequence from the decoder output. The loss function of VAE is shown in the following equation [12].

$$L_{VAE} = MSE(X, X') + \beta \times \frac{1}{2} \sum_{i=1}^{z_{dim}} \left(\mu_i^2 + \sigma_i^2\right) - 1 - \log\left(\sigma_i^2\right) \tag{1}$$

where the first term $MSE(X, X')$ is the mean-squared error between the input sequence X and the output sequence X', and the second term is the Kullback-Leibler Divergence between the standard Gaussian distribution and the latent space's distribution. μ_i and σ_i are the mean value and the standard deviation of the dimension i^{th} in the latent space Z, respectiverly. z_{dim} is the dimension number of the latent space. β is a parameter to control the role of the Kullback-Leibler Divergence in the total loss function.

After training VAE, the decoder may generate new sequences using the input samples from the standard Gaussian distribution. The generated sequences belong to the same space as the original input sequences.

3. Methodology

First, we introduce a framework for detecting anomalies in human movements. Then, the anomaly detection phase is presented.

3.1 Variational Autoencoder-based Anomaly Detection in Human Movements

In this subsection, a framework is proposed for anomaly detection in human movements, which is depicted in Figure 3.

A variational Bi-LSTM autoencoder is trained to learn the latent space distribution of the normal trajectories. Our model contains two stacked Bi-LSTM layers in each encoder and decoder. The final hidden state of the second Bi-LSTM layer in the encoder is input to two fully connected layers to obtain the parameters μ_Z and σ_Z of the latent space distribution. The decoder input is sampled from the latent space Z. Then a reconstructed trajectory is from the decoder output.

The training and validation sets of the model are obtained after pre-processing raw human trajectories. In the training phase, only normal samples are in the training and validation sets.

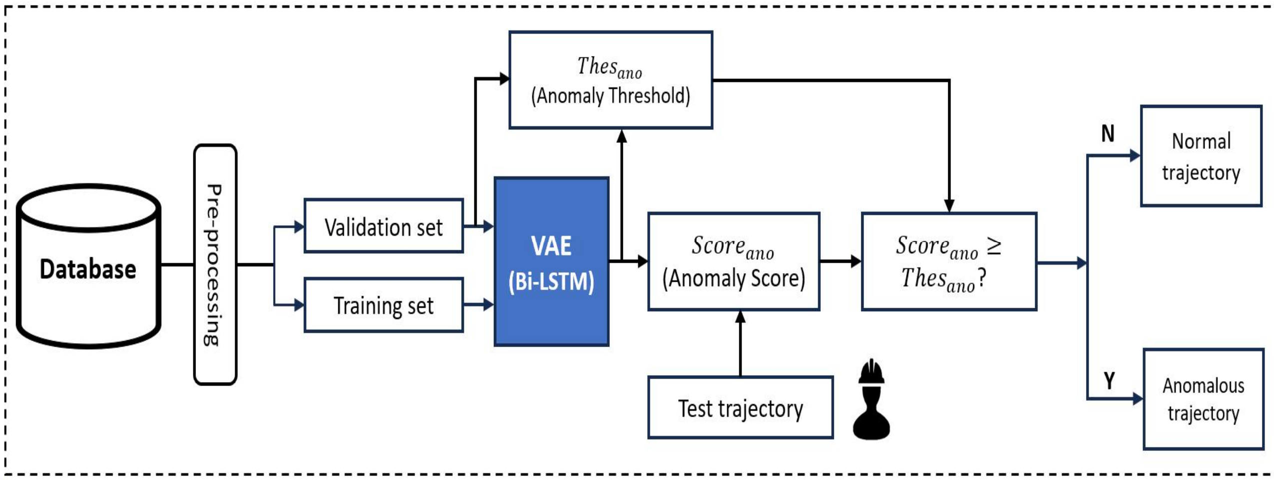

Figure 3. The proposed framework

In the anomaly detection phase, the trained model is used. In particular, the reconstruction error of the original trajectory by the trained VAE is used as the anomaly score. Since the VAE captures the internal characteristics of normal trajectories, the abnormal trajectories may fail to be reconstructed. This means that the anomaly score of abnormal trajectories often is high. From this viewpoint, a test trajectory is detected as an anomaly if its anomaly score exceeds an anomaly threshold.

To determine the anomaly score of each trajectory, the reconstruction error of trajectory through the VAE is used in this work.

$$Score_{ano} = LSED(X, X') \tag{2}$$

where $LSED(X, X')$ is the lock-step Euclidean distance between the input and reconstructed trajectories [13].

3.2 Determine the Anomaly Threshold

Since the value of the anomaly threshold directly affects the anomaly detection performance, we proposed a method, which uses a new metric, to determine the anomaly threshold.

In our method, the anomaly threshold is chosen based on the proposed framework performance on the validation set. This step ensures that choosing the anomaly threshold independents with unseen samples in test set. A new metric that measures the difference between recall and precision called *D-score* is proposed in equation [3].

$$D - score = Recall - \alpha \times Precision \tag{3}$$

where α is a parameter that controls the role of the terms in the *D-score.* If $\alpha = 1$, recall and precision have the same role. If $\alpha > 1$, recall is more importance than precision, and otherwise.

If the anomaly threshold is small, the number of true positives is high. However, the number of false positives is also high. In this case, recall is high, and precision is low. In contrast, if the anomaly threshold is large, false positives are low. Besides, the number of true positives could be higher. This means that the anomaly detection ability of the method is low. Therefore, we aim to find an anomaly threshold that balances recall and precision. At this threshold value, the anomaly detection ability and the detection precision may be ensured well. To do this, the anomaly threshold is chosen according to the minimum value of the D-score.

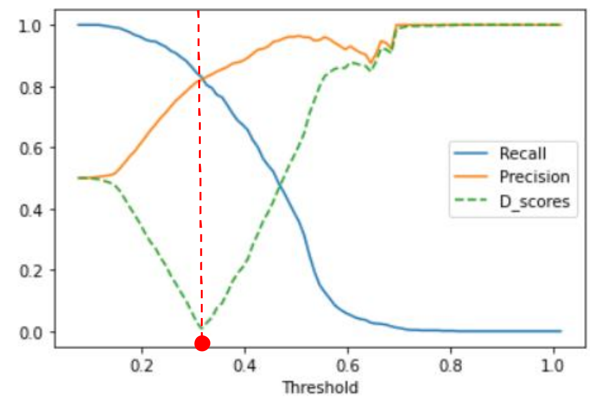

Figure 4. Choosing the anomaly threshold based on the performance on validation set

The determination of the anomaly threshold is shown in Figure 4. In this work, α equals to 1 in equation [3]. The chosen value of the anomaly threshold equals 0.315 according to the minimum value of *D-score.*

4. Performance Evaluation

In this section, the proposed framework performance is evaluated using a real dataset: MIT Badge dataset [14].

4.1 Dataset

In the MIT Badge dataset, there are 39 participated workers in the data collection in a Chicago-area data server configuration firm for one month [15]. Each worker was assigned a badge with a unique ID. This dataset contains three groups of workers: configuration group, pricing group, and coordinate group, with the number of workers being 28, 7 and 4, respectively. However, since there are 3 workers in the configuration group having data within only a few days, we dropped them.

The sampling speed of the location is 10 points over 1 minute. To detect anomaly movements of workers as early as possible, we sample trajectories using a time window. In this work, the time window is set as 2 minutes. This means that each trajectory consists of 20 points. Since the abnormal samples are not available in the MIT Badge dataset, they need to be made for evaluation. The authors in the studies [15,16] gave the hypothesis for assigning labels to abnormal trajectories based on the behavior difference of groups in the dataset. In [15], the hypothesis is that if one group occurs less frequently than another in the datasets, it may be considered anomalies. In particular, the pricing group only accounts for about 18%, and the configuration group is approximately 72% in the MIT Badge dataset. Therefore, we assume that the configuration worker's trajectory is normal, and one of the pricing workers is abnormal.

The dataset of trajectories is divided into three sets: the training set with 10537 trajectories, the validation set with 4211 trajectories and the test set with 3228 trajectories.

4.2 Parameter Learning

Table 1. List of hyper-parameters

Hyperparameters	Value
Num_Bi-LSTMs (Encoder)	2
Num_Bi-LSTMs (Decoder)	2
Dim_Bi-LSTMs	32, 64
Learning rate	0.0005
Epochs	20

To update the parameters for the variational Bi-LSTM autoencoder, a total loss function, which is based on equation in [1], is designed:

$$L_{VAE} = LSED(X, X') + \beta \times \frac{1}{2} \sum_{i=1}^{z_{dim}} \left(\mu_i^2 + \sigma_i^2\right) - 1 - \log\left(\sigma_i^2\right) \quad (4)$$

where β is increased linearly with the training step number [17]. This helps VAE focus on reconstructing the input trajectory in the first training steps. When the training step number increases, VAE pays more attention to learning the latent space distribution.

The hyper-parameters of the model are summarized in Table 1. The model is chosen at the epoch that achieved the minimum value of loss function on the validation set.

4.3 Results

To evaluate the framework performance, we use three performance metrics: recall, precision, and F1-score.

$$recall = \frac{TP}{TP+FN} \quad (5)$$

$$precision = \frac{TP}{TP+FP} \quad (6)$$

$$F1 - score = 2 \times \frac{recall \times precision}{recall + precision} \quad (7)$$

In this work, the proposed method is compared with the anomalous trajectory detection method using the spectral clustering algorithm. Besides, we also evaluate the performance of a variant of the proposed method, which replaces Bi-LSTM layers in VAE with LSTM layers. With the spectral clustering-based method, a trajectory is identified as an anomaly if it does not belong to any clusters. Clusters in the dataset are obtained by applying the spectral clustering algorithm.

The experiment results are shown in Table 2. The proposed method, which is based on the variational Bi-LSTM autoencoder, may detect abnormal trajectories of workers well, with 81.22% in terms of the F1-score. The abnormal detection ability and precision also achieve above 80%. Besides, the performance of the proposed method is better than the spectral clustering-based method. In particular, the VAE architecture with LSTM and Bi-LSTM outperforms the baseline by about 9% and 10% in terms of F1-score, respectively. This may be explained by the clustering-based method detecting anomalies based on the relationship between the checked trajectory and clusters. This method does not discover the internal characteristics and sequence information of trajectory well as the VAE-based method. Besides, using Bi-LSTM layers in the VAE also achieves better outcomes by about 1% in F1-score than using LSTM layers. Since Bi-LSTM learns information from both sides of the input trajectory while LSTM only learns from one side, Bi-LSTM may improve the model's performance.

Table 2. Results of the proposed framework

Method	Recall (%)	Precision (%)	F1-score (%)
Spectral clustering-based	0.745	0.6903	0.7162
Variational LSTM-AE-based	0.7949	0.8151	0.8049
Variational Bi-LSTM-AE-based	80.54	81.91	81.22

5. Conclusion

The paper proposed a variational Bi-LSTM autoencoder-based framework for detecting abnormal human trajectories. First, the VAE was trained and validated using normal historical trajectories. The VAE captures the latent representation of normal trajectories. Then, a new trajectory is tested to determine whether it is an anomaly using the trained VAE. If the new trajectory's anomaly score, which is its reconstruction error by the VAE, exceeds a threshold, this trajectory is detected as an anomaly. Besides, this paper proposed a new metric called *D-score* for determining the anomaly threshold. Finally, the proposed framework was evaluated using the MIT Badge dataset. The results show that our work identified abnormal trajectories with 81.22% in F1-score and outperformed the baseline.

Acknowledgement

This work was supported by the Institute of Information and Communication Technology Planning and Evaluation (IITP) Grant by the Korean Government through MSIT (Development of 5G-Based Shipbuilding and Marine Smart Communication Platform and Convergence Service) under Grant 2020-0-00869.

References

[1] Matousek M, Mohamed EZ, Kargl F, Bösch C. " Detecting anomalous driving behavior using neural networks. " *In 2019 IEEE Intelligent Vehicles Symposium* (IV) 2019 Jun 9 (pp. 2229-2235). IEEE. DOI: 10.1109/IVS.2019.8814246.

[2] Zhang M, Chen C, Wo T, Xie T, Bhuiyan MZ, Lin X. " SafeDrive: Online driving anomaly detection from large-scale vehicle data. " *IEEE Transactions on Industrial Informatics*. 2017 Feb 24;13(4):2087-96. DOI: 10.1109/TII.2017.2674661.

[3] Dai J, Yang B, Guo C, Ding Z. " Personalized route recommendation using big trajectory data." In 2015 IEEE 31st international conference on data engineering 2015 Apr 13 (pp. 543-554). IEEE. DOI:10.1109/ICDE.2015.7113313

[4] Karataş GB, Karagoz P, Ayran O. "Trajectory pattern extraction and anomaly detection for maritime vessels." *Internet of Things*. 2021 Dec 1; 16:100436. DOI: doi.org/10.1016/j.iot.2021.100436

[5] Lee JG, Han J, Li X. " Trajectory outlier detection: A partition-and-detect framework." *In 2008 IEEE 24th International Conference on Data Engineering* 2008 Apr 7 (pp. 140-149). IEEE. DOI: 10.1109/ICDE.2008.4497422.

[6] Zhu, Z.; Yao, D.; Huang, J.; Li, H.; Bi, J. " Sub-trajectory-and trajectory-neighbor-based outlier detection over trajectory streams." *In Proceedings of the Pacific-Asia Conference on Knowledge Discovery and Data Mining*, Melbourne, VIC, Australia, 3–6 June 2018.

DOI: 10.1109/CGiV.2016.65
[7] Wang, Yulong, et al. "Detecting anomalous trajectories and behavior patterns using hierarchical clustering from taxi GPS data." *ISPRS International Journal of Geo-Information* 7.1 (2018): 25.
DOI: doi.org/10.3390/ijgi7010025
[8] Song L, Wang R, Xiao D, Han X, Cai Y, Shi C. Anomalous trajectory detection using recurrent neural network. In Advanced Data Mining and Applications: 14th International Conference, ADMA 2018, Nanjing, China, November 16–18, 2018, Proceedings 14 2018 (pp. 263-277). Springer International Publishing.
[9] Cheng Y, Wu B, Song L, Shi C. Spatial-temporal recurrent neural network for anomalous trajectories detection. In Advanced Data Mining and Applications: 15th International Conference, ADMA 2019, Dalian, China, November 21–23, 2019, Proceedings 15 2019 (pp. 565-578). Springer International Publishing.
[10] Kieu T, Yang B, Jensen CS. Outlier detection for multidimensional time series using deep neural networks. In2018 19th IEEE international conference on mobile data management (MDM) 2018 Jun 25 (pp. 125-134). IEEE.
DOI: 10.1109/MDM.2018.00029.
[11] M. Schuster and K. K. Paliwal, “Bidirectional recurrent neural networks,” IEEE Transactions on Signal Processing, vol. 45, no. 11, pp. 2673–2681, 1997.
DOI: 10.1109/78.650093
[12] Matias P, Folgado D, Gamboa H, Carreiro AV. Robust Anomaly Detection in Time Series through Variational AutoEncoders and a Local Similarity Score. In Biosignals 2021 (pp. 91-102).
DOI: 10.5220/0010320500002865
[13] Tao Y, Both A, Silveira RI, Buchin K, Sijben S, Purves RS, Laube P, Peng D, Toohey K, Duckham M. A comparative analysis of trajectory similarity measures. GIScience & Remote Sensing. 2021 Jul 4;58(5):643-69.
DOI: doi.org/10.1080/15481603.2021.1908927
[14] Olguín DO, Waber BN, Kim T, Mohan A, Ara K, Pentland A. "Sensible organizations: Technology and methodology for automatically measuring organizational behavior." *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 39.1 (2008): 43-55.
DOI: 10.1109/TSMCB.2008.2006638
[15] SzekéR, M. "Spatio-Temporal Outlier Detection in Streaming Trajectory Data." Master’s Thesis, School of Computer Science and Communication (CSC), Stockholm, Sweeden, 2014.
[16] Banerjee, P.; Talwalkar, P.; Ranu, S. "Mantra: A scalable approach to mining temporally anomalous sub-trajectories." *In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, CA, USA, 13–17 August 2016; pp. 1415–1424.
DOI: 10.1145/2939672.2939846
[17] Pereira J, Silveira M. " Learning representations from healthcare time series data for unsupervised anomaly detection." *In 2019 IEEE international conference on big data and smart computing* (BigComp) 2019 Feb 27 (pp. 1-7). IEEE.
DOI: 10.1109/BIGCOMP.2019.8679157