A COMBINATION OF DEEP LEARNING AND DENSITY METHOD IN ANOMALOUS HUMAN TRAJECTORY DETECTION

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Abstract

Abnormal human trajectories in working places are often associated with problems such as terrorism, violent attacks, and fire. Therefore, detecting anomalous human trajectories can improve safety and security in working areas. In this work, a novel framework of abnormal trajectory detection is proposed based on combining deep learning and density method. In particular, a Long Short-Term Memory-Autoencoder is first applied to learn informative representations of normal trajectories. Then, the density of trajectory representation in the latent space and reconstruction error of trajectory are used to detect anomalies. A novel metric is also proposed to determine the anomaly scores of trajectories. The proposed framework is evaluated using two real trajectory datasets: the MIT Badge and the sCREEN datasets. The experimental results show that our work effectively detects anomalies, achieving a f1-score of 81.08% on the MIT Badge dataset and 89.57% on the sCREEN dataset.

Index terms

Anomalous trajectory detection; LSTM-AE; density method; anomaly score.

1. Introduction

In recent years, abnormal trajectory detection has attracted more attention from researchers in different fields. For example, abnormal taxi trajectory detection can help prevent problems such as traffic congestion, accidents, and taxi driver fraud. Therefore, the quality of this vehicle type can be improved considerably through anomalous trajectory detection [1]–[3]. Besides, detecting abnormal ship trajectories is necessary to ensure the safety and security of maritime activities, such as shipment of goods, maritime travel, and fishing [4], [5]. Moreover, detecting human trajectory anomalies in public and working areas can identify dangerous situations like terrorism, violent attacks, and fire [6], [7]. Therefore, in this study, we focus on detecting human trajectory anomalies to improve workplace safety and security.

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Existing anomalous trajectory detection approaches can be grouped into two main categories: traditional detection methods and deep learning-based detection methods. The former category focuses on discovering the relationship between trajectories in a dataset (i.e., the distance between trajectories, trajectories' density, and clusters of trajectories in the dataset). For example, the works in [8], [9] proposed the frameworks of abnormal trajectory detection based on distance measures and density method. However, these works do not discover each trajectory's internal features and sequential information for anomaly detection.

In the latter category, deep learning models are trained to capture representations of trajectories in a latent space. Specifically, the authors in [10] proposed RNN-based deep learning models to learn trajectories' embedding vectors. These embedding vectors were used to identify normal and abnormal trajectories. In addition, autoencoder (AE) architectures were also applied to detect abnormal trajectories in the study [11]. First, AEs were trained to keep informative representations of trajectories in a latent space. Then, if a trajectory was reconstructed well from its latent representation, it is detected as normal. In contrast, if a trajectory failed to be reconstructed, it was marked as an anomaly. However, these studies only used reconstruction errors of trajectories through trained AEs to detect anomalies. They do not consider the relationship between trajectory representations in the latent space (e.g., the distance between representations and representations' density in the latent space) for anomaly detection.

From the above aspects, in this work, a novel anomalous human trajectory detection framework is proposed based on deep learning and density method. In particular, a Long Short-Term Memory-Autoencoder (LSTM-AE) architecture is first trained to capture internal characteristics and sequential information of normal trajectories in a latent space. Then, the density of trajectory representations in the latent space is determined. Since the latent space captures more informative representations of trajectories, determining density is performed better on the latent space than on the raw trajectory space. A new metric is also proposed to determine the anomaly scores of trajectories. This metric is designed based on the reconstruction error of the trajectory and the density of the trajectory representation in the latent space. To detect an anomaly, an anomaly threshold is chosen based on the anomaly scores of trajectories in the training set. In this work, both trajectory reconstruction error through learning trajectory characteristics and the relationship between trajectory representations in the latent space (i.e., trajectory representation's density) are used to detect anomalies. Thus, the performance of the proposed framework may be improved compared with existing works that just use one of the above two factors.

To evaluate the proposed framework, two real trajectory datasets are used: the MIT Badge and the sCREEN datasets. Experiments show that our framework achieves 81.08% and 89.57% in terms of f1-score on the MIT Badge and sCREEN, respectively. These results outperform the methods only based on either reconstruction error of deep learning models or density method.

The contribution of this work can be summarized as follows:

- An anomaly detection framework in human trajectories is proposed based on trajectory reconstruction error through an LSTM-AE and trajectory representation's density in the latent space. First, an LSTM-AE is trained to keep internal features and sequential information of normal trajectories in a latent space. Then, trajectory reconstruction error and trajectory representation's density in the latent space are used to detect anomalies.
- A new metric is proposed to determine trajectories' anomaly scores using reconstruction errors and latent representations' density. If the anomaly score is larger than an anomaly threshold, the trajectory is detected as an anomaly. In contrast, it is normal if the anomaly score is smaller than the anomaly threshold.
- The proposed anomaly detection framework is evaluated using two real trajectory datasets. The experimental results depict that our method efficiently detects human trajectory anomalies, achieving the f1-score of 81.08% on the MIT Badge and 89.57% on the sCREEN.

The layout of this work is organized as follows. First, Section 2 presents the related works. In the Section 3, the proposed anomaly detection framework is shown. Then, the framework performance is given in Section 4. Finally, a conclusion of this paper is given in Section 5.

2. Related works

This section first reviews related works in anomaly detection based on the LSTM-AE. Then, studies in anomalous trajectory detection are briefly presented.

In AE networks, the encoder learns a latent representation of the input data, while the decoder works to reconstruct these compressed features. Typically, AEs are trained using data that reflects normal behavior, allowing them to learn effective latent representation. When anomalous data is processed by the trained AE, it leads to a noticeable reconstruction error, as the model struggles to reconstruct abnormal patterns accurately. Hence, the trained AEs can be used to detect anomalies. A combination of LSTM and AE was introduced in [12]. This model learned short-term and long-term dependencies regarding temporal lower-dimensional features for detecting complex time-variant anomalies. In [13], a variational LSTM-AE was proposed for anomaly detection, employing probabilistic projection techniques within both the encoder and decoder. The method incorporates a log-likelihood-based approach for anomaly detection by comparing log-likelihood scores between real and reconstructed outputs. Another method was proposed in [14], where an LSTM-AE was employed to model the typical behavior of discrete manufacturing processes. The trained decoder worked as an inverse process model, allowing the system to detect anomalies by comparing the input data with the reconstructed ones. In the above LSTM-AE-based works, only reconstruction error of input data through trained LSTM-AE is used to detect anomalies. In contrast, in our work, both reconstruction error and density of representation in latent space are used to detect anomalies. In other words, the proposed method further discovers the relationship of informative representation in latent space for detecting abnormal trajectories. Therefore, the proposed method can improve the anomaly detection performance compared with methods that only use reconstruction error.

For anomalous trajectory detection, different methods have been proposed over the past years. For example, an extensible Markov model (EMM)-based method was introduced in [6] for anomalous human trajectory detection. In this approach, the EMM integrates a Markov chain with a clustering algorithm. Each node in the EMM represents a cluster of location points, modeled by a cluster representation. A point is identified as an anomaly in one of two cases: either it creates a new node, or it belongs to a node where the occurrence probability or transition probability falls below a specified threshold. A trajectory is classified as anomalous if it includes at least one such abnormal point. A density-based method was proposed for detecting anomalies in human trajectory [9]. In particular, they first determined the distance between trajectories. Then, the density of trajectories was identified based on its distance from other ones. Finally, a trajectory was detected as an anomaly if its density was smaller than a density threshold. In [15], clustering-based abnormal human trajectory detection was studied. In this work, the authors proposed an anomaly detection method using DBSCAN. To improve detection performance, an algorithm for determining the input parameter of DBSCAN was proposed. In studies [16], [17], RNN-based deep learning models were utilized to learn trajectory embeddings. These embedding vectors capture the most representative features of trajectories, enabling the distinction between normal and abnormal trajectories. The models were trained in a supervised manner, with the training set containing labeled normal and abnormal trajectories. In addition, the anomaly detection methods for trajectory applied LSTM-AE was given in [11] and [18]. In LSTM-AE, the encoder's role is to map each trajectory into a semantically meaningful latent space, while the decoder aims to reconstruct the trajectory using the information encoded in the latent vector. During detection, the reconstruction error for each trajectory is calculated and used as an anomaly score. Anomalies are detected when this score exceeds a predefined threshold. Meanwhile, our work uses the trained LSTM-AE and density-based method for detecting anomalies. In particular, the trajectory reconstruction error through the LSTM-AE and density of trajectory representation in latent space are combined to determine the anomaly score of the trajectory.

3. Methodology

3.1. Proposed framework for abnormal human trajectory detection

In this section, a proposed framework for detecting abnormal human trajectories is first presented. Then, the determination of the trajectory anomaly score and the anomaly threshold are discussed.

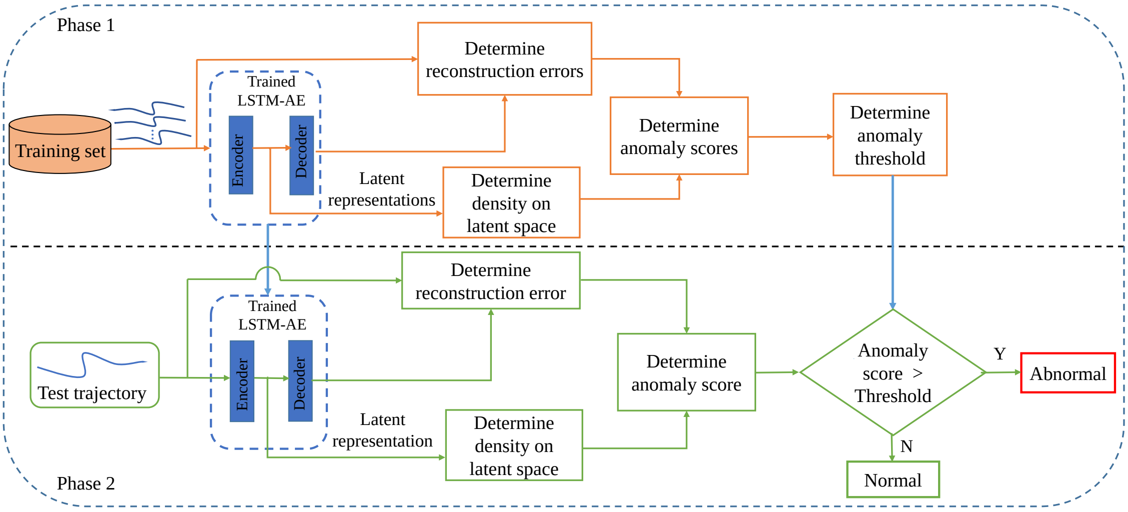

Fig. 1. Proposed framework for abnormal human trajectory detection.

The abnormal human trajectory detection framework is proposed in Figure 1. The proposed framework is divided into two phases. In phase 1, the LSTM-AE is first trained to capture internal characteristics and sequential information of normal trajectories in a latent space. Note that the training set only contains normal trajectories. Then, training trajectories' anomaly scores are determined using reconstruction errors and the density of trajectory representations in the latent space. Finally, an anomaly threshold is determined to detect anomalies using anomaly scores of the training set.

In phase 2, anomaly detection of the test trajectory is shown. In particular, if a test trajectory comes, its abnormality is checked using the trained LSTM-AE. First, the test trajectory's anomaly score is determined through reconstruction error and representation's density in the latent space. Then, if the anomaly score is larger than the anomaly threshold, the test trajectory is detected as an anomaly. Note that the anomaly threshold is determined in phase 1.

To train the LSTM-AE, a loss function is used as the following equation:

$$Loss_{AE} = \frac{1}{M}\sum_{i=1}^{M} \text{LSED}(\tilde{T}_i, T_i) \tag{1}$$

Here, M is the number of trajectories in a batch for each parameter update when training the model. LSED$(\tilde{T}_i, T_i)$ is the lock-step Euclidean distance between the reconstructed and original trajectories $\tilde{T}_i$ and T_i, respectively. This distance metric was introduced in [19] as follows:

$$\text{LSED}(\tilde{T}_i, T_i) = \frac{1}{n}\sum_{j=1}^{n} dist(\tilde{p}_j, p_j), \tag{2}$$

where $\tilde{p}_j$ and p_j are reconstructed and original trajectory points, respectively. n is the number of points of a trajectory, and $dist(.)$ is the Euclidean distance.

3.2. Determine anomaly score of trajectory

In the subsection, a new metric for determining the anomaly score of trajectory is proposed. Specifically, this work discovers both the reconstruction error of trajectory and the relationship between trajectory representations in the latent space (i.e., density of representation) for determining the anomaly score of trajectory.

Following previous works [8], [9], the density of a trajectory is defined by the number of its neighbors in data space. In this work, the density of a trajectory's representation in the latent space is used to detect anomalies. Specifically, Euclidean distances between representations in the latent space are determined. If the distance between two representations is smaller than a predefined threshold, they are considered neighbors. The density of a representation is defined as the number of its neighbors in the latent space, and is given by:

$$Den(Z) = \sum_{i=1}^{N} I(||Z - Z_i|| < r), \tag{3}$$

where $Den(Z)$ is the density of a trajectory representation in the latent space. $||Z - Z_i||$ denotes the distance between a specific representation Z and the remaining representations Z_i. N is the total number of representations in the latent space, and r is the distance threshold used to determine whether two representations are considered neighbors. $I(.)$ is an indicator function, which is 1 if the condition is true and 0 otherwise. Note that the mean value of distances between latent representations in the training set is used as the distance threshold in this work.

In Figure 2, a UMAP plot displays the distribution of representations in latent space. Each point corresponds to a representation in the latent space: blue points represent normal trajectories, while red points represent abnormal trajectories. As shown in Figure 2, abnormal points are far from normal ones, resulting in lower density. In contrast, normal points are close together, showing higher density. Thus, the latent representations' density can effectively be used for anomaly detection.

Besides, the reconstruction error of a trajectory, determined as the difference between the reconstructed trajectory and the original trajectory, is also used to detect anomalies. The trajectory reconstruction error is determined using the equation (2).

A proposed metric for determining anomaly score of trajectory is defined as follows:

$$Ano - Score = \frac{Err}{\text{min}(Err)} - \frac{Den}{\text{max}(Dens)}, \tag{4}$$

where Den is the density of trajectory representation in the latent space. Err is the trajectory reconstruction error through LSTM-AE. $\text{max}(Dens)$ is the maximum value of density of latent representations in training set. $\text{min}(Err)$ is the minimum value

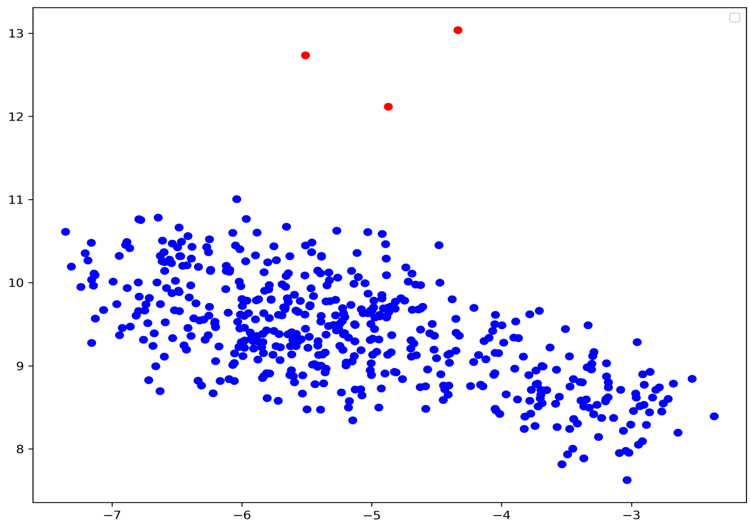

Fig. 2. The UMAP plot showing distribution of latent space. Each point in plot represents a trajectory representation in the latent space. Blue points represent normal trajectories, while red points represent abnormal ones.

of reconstruction errors of trajectories in training set. When a trajectory shows high abnormality, its latent representation deviates from others, leading to low density in the latent space. Additionally, since the AE is trained to capture the internal characteristics of normal trajectories, an anomalous trajectory fails to be accurately reconstructed from

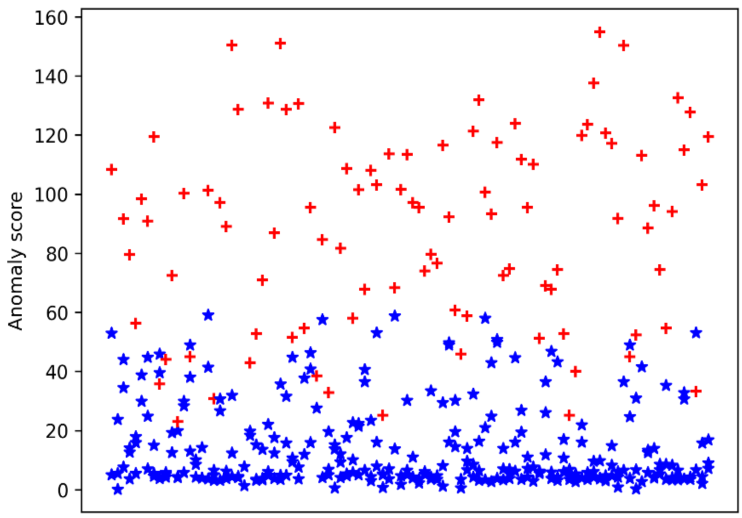

Fig. 3. The plot showing anomaly scores of trajectories. Blue points represent scores of normal trajectories and red points represent scores of abnormal trajectories.

its latent representation, resulting in a large reconstruction error. In such a case, the anomaly score is high. In contrast, if a trajectory is normal, the first element is small, and the second one is high, meaning the anomaly score is low.

In Figure 3, anomaly scores of trajectories are shown. Specifically, blue points represent the scores of normal trajectories, while red points indicate those of abnormal trajectories. As shown, abnormal trajectories typically have higher anomaly scores compared to normal ones. Based on this observation, anomaly detection can be achieved using an anomaly threshold. In particular, if a trajectory's anomaly score exceeds the anomaly threshold, it is classified as an anomaly.

For anomaly detection methods based on AE architectures, the anomaly score of samples is determined solely by the reconstruction error [11], [13], [14], and [18]. In contrast, in our work, both reconstruction error Err and the density of latent representation Den are used to calculate the anomaly score. As the anomaly score is based on more informative features, the anomaly detection performance is improved in the proposed method.

3.3. Determine anomaly threshold

Choosing the anomaly threshold is challenging for detecting anomalies. If the anomaly threshold is set with a high value, the truth anomalies can be ignored. In contrast, if the threshold value is low, many false alarms occur. Therefore, in this work, the anomaly threshold is selected based on the framework's performance on the validation set. It is expected that the selected threshold value also has a good performance on the test set. In particular, the anomaly threshold is chosen according to the maximum value of the f1-score on the validation set. Figure 4 shows the result of determining the anomaly threshold based on framework's performance on the validation set on the MIT Badge dataset. Specifically, when the anomaly threshold is too small or large, the f1-score is small. In this work, the chosen threshold is 2.37 according to the maximum value of the f1-score. Besides, the anomaly threshold should be larger than the mean value of normal trajectories' anomaly scores. Our work shows the mean value of anomaly scores in the training set is 1.85. Thus, the anomaly threshold of 2.37 is reasonable with the above statement.

4. Experimental results

4.1. Dataset

In this work, the proposed framework is evaluated using two real trajectory datasets: MIT Badge and sCREEN.

The MIT Badge dataset contains the position information of workers in a data server configuration firm in Chicago [20]. Workers' position is recorded using an indoor positioning system with information of x-y coordinates. The sample speed is 10 points over one minute. Since our objective is to detect anomalies as soon as

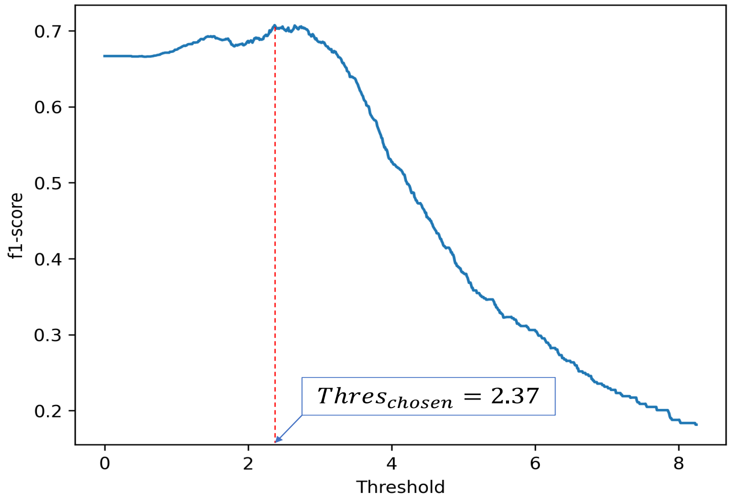

Fig. 4. Choose anomaly threshold using the performance on validation set on the MIT Badge dataset.

possible, a time window is used to collect trajectory data. If the time window is long, the anomaly detection can be more exact. However, the time requirement is not ensured. In contrast, when the time window is too short, the anomaly detection can be failed. In this work, the time window is chosen to be two minutes. In this case, the trajectory length can ensure both of the above requirements. Besides, the data is collected from 9:00 am to 6:00 pm each day. The total number of days for collecting data is 17. The data is divided into training, validation, and test sets. The training set contains 10,537 trajectories, and the validation is 4,211. The number of trajectories chosen in the test set is equal for abnormal and normal samples. This ensures that the framework performance is evaluated correctly. There are 1,614 trajectories for each type in the test set. To evaluate the proposed framework, both normal and abnormal trajectories are required in the dataset. However, anomalous samples may not be available in datasets. Thus, they need to be generated for evaluation. A trajectory is considered anomalous if it significantly deviates from most other trajectories in the dataset. Conversely, a trajectory is classified as normal if it closely resembles the majority of trajectories in the dataset. From this point, the works [6], [15], [21] created anomalies based on differences in frequency of occurrence between different groups in the dataset. Specifically, in the MIT Badge dataset, the Configuration group consists of 25 users, while the Pricing group includes just 7 users. This means that the Configuration group makes up about 78.2% of the total, and the Pricing group only 21.8%. Based on this distribution, employees in the Pricing group could be considered anomalies, while those in the Configuration group may represent normal behavior. An example of normal and abnormal trajectories on the MIT Badge dataset is shown in Figure 5. Blue trajectories are normal and red one is abnormal. From Figure 5, the abnormal trajectory is different from remaining ones in the dataset.

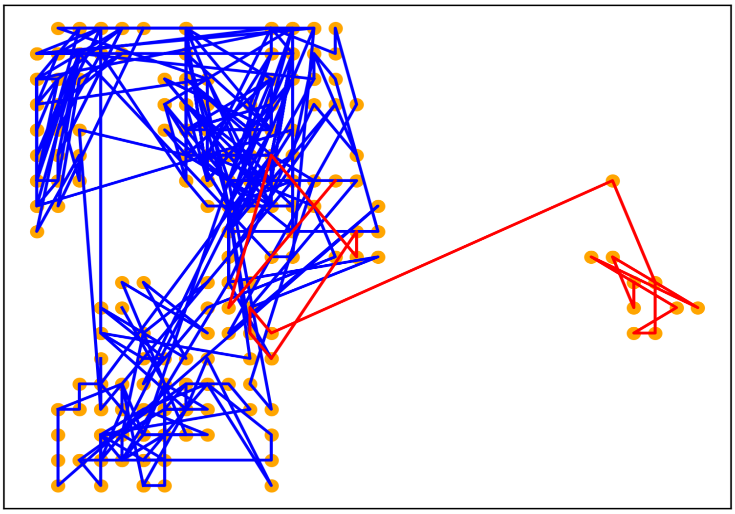

Fig. 5. The plot showing normal and abnormal trajectories on MIT Badge dataset. Blue trajectories are normal and red one is abnormal.

For the sCREEN dataset, customers' trajectories in a German supermarket are collected [22]. The real-time location system is used to determine the location of customers in the supermarket. Each data point in the sCREEN dataset also contains information about the coordinates and timestamps. The data is available from 8:00 am to 10:00 pm each working day in the supermarket. Note that, in the sCREEN dataset, there are no abnormal trajectories. Therefore, abnormal trajectories are generated for evaluation performance. In particular, in indoor spaces (e.g., factories, supermarkets), some locations, such as engine rooms, security areas, and warehouses, where humans rarely enter or are prohibited from entering, are referred to as rare locations. Hence, if a person visits these rare locations, his/her trajectory is abnormal. From the above point, anomalies by visiting rare locations are created using original trajectories in the sCREEN dataset. This step is performed by shifting some points in normal trajectories to rare locations in the supermarket for the sCREEN dataset. To train and validate the model, the number of normal trajectories used is 11,107 and 4,445, respectively. The test set contains 3,470 trajectories for each type of normal and abnormal trajectory.

4.2. Results

This work evaluates the method using three performance metrics: recall, precision, and f1-score. Recall shows the method's ability to detect anomalies, and precision represents the correct detection. Besides, the f1-score is a harmonic mean of recall and precision.

To detect abnormal trajectories, the LSTM-AE is first trained. The model is implemented in Python 3.9.5 using TensorFlow 2.10.1 on a computer with Intel(R) Core(TM) i7- 14700K and NVIDIA GeForce RTX 4060 Ti graphics cards. The

Table 1. Parameters of model

Parameters		**Value**
Encoder	LSTM layer	128
	LSTM layer	64
Decoder	LSTM layer	64
	LSTM layer	128
Learning rate		0.015
Batch size		32
Epochs		100

summary of model parameters is presented in Table 1. In our work, the AE contains two LSTM layers of 128 and 64 output dimensions for the encoder. The decoder has two LSTM layers of 64 and 128 latent dimensions. The last output of the decoder is mapped to a vector with the same dimension as the input trajectory.

The learning curves of model on training and validation sets are shown in Figure 6. The model is chosen at epoch with the minimum loss on validation set. In this work, the

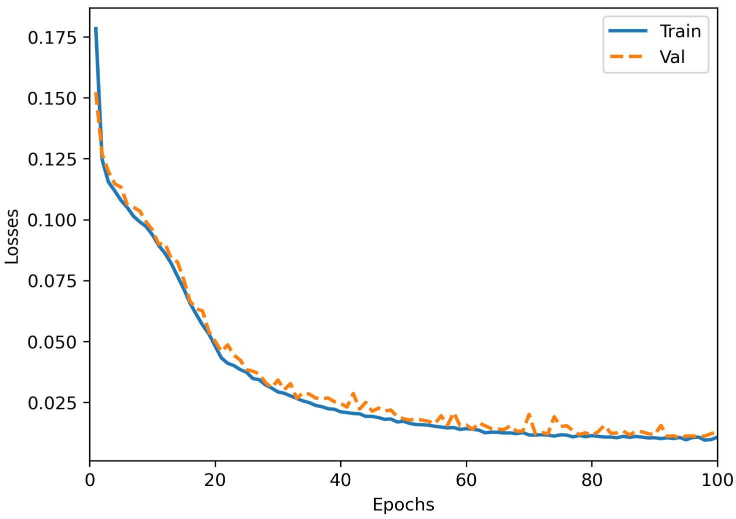

Fig. 6. Learning curves on training and validation sets.

proposed method is compared with existing methods such as EMM-based [6], LSTM-AE-based [18], density-based [8], and DBSCAN-based [15], which were proposed in 2014, 2019, 2022, and 2023, respectively. Note that, in DBSCAN-based method, the

Table 2. Results for detecting trajectory anomalies on the MIT Badge dataset

Method	Recall	Precision	f1-score
EMM [6]	0.899	0.6596	0.7609
Density-based (Original space) [8]	0.8087	0.7009	0.7468
DBSCAN-based [15]	0.7930	0.8102	0.8015
LSTM-AE-based [18]	0.8637	0.7208	0.7858
Density-based (Latent space)	0.9046	0.7067	0.7935
Proposed method	0.9306	0.7173	**0.8108**

Table 3. Results for detecting trajectory anomalies on the sCREEN dataset

Method	Recall	Precision	f1-score
EMM [6]	1	0.6004	0.7503
Density-based (Original space) [8]	0.9432	0.7543	0.8382
DBSCAN-based [15]	0.9801	0.7842	0.8712
LSTM-AE-based [18]	1	0.8082	0.8939
Density-based (Latent space)	1	0.7735	0.8723
Proposed method	1	0.8110	**0.8957**

Euclidean metric is used to determine distance between trajectories.

Tables 2 and 3 show experimental results on the MIT Badge and sCREEN datasets, respectively. In particular, in all compared baselines, EMM-based method obtains a highest recall while precision is lowest on both datasets. This can be explained that EMM-based method assesses abnormality at the trajectory point level, marking a trajectory as anomalous if even a single point is identified as abnormal. Therefore, abnormal trajectories can be detected easily. Besides, many normal trajectories are incorrectly identified as anomalies, leading to a low precision in EMM.

In density-based method, the trajectories' density in both original and latent spaces was evaluated. Note that the result of density-based method in the original space for the MIT Badge dataset is obtained from the study [8]. From Tables 2 and 3, the density-based method on the latent space outperforms the original space in terms of f1-score (e.i., better than about 5% on the MIT Badge and about 3% on the sCREEN). It is explained that the latent space trained by LSTM-AE captures the more informative features and sequential information of trajectories. Thus, the density-based method performs more efficiently in the latent space than in the original space. In addition, the DBSCAN-based method is quite effective for detecting anomaly. For example, the DBSCAN-based method achieves 80.15% and 87.12% in terms of f1-score on the MIT Badge and sCREEN datasets, respectively. In DBSCAN-based method, the Epsilon parameter affects directly the quality of clustering trajectories and detecting anomaly. In this method, they proposed a new DCVI metric for choosing the appropriate Epsilon value. Therefore, the DBSCAN-based method achieves high performance in detecting anomaly.

For LSTM-AE-based method, the trajectory reconstruction error is used to detect anomalies. In the LSTM-AE model, the normal trajectories are used for training to capture informative features. This training process enables the LSTM-AE to reconstruct normal trajectories with minimal error. As a result, the model tends to achieve the lowest false alarm rate. Thus, the LSTM-AE often obtains a high precision. For instance, compared to density-based method on latent space, the LSTM-AE-based method obtains higher precision (i.e., about 2% on the MIT Badge and about 3% on the sCREEN). Besides, the density-based method on latent space outperforms the LSTM-AE in terms of recall on the MIT Badge and detect correctly all anomalies in the sCREEN dataset. In other words, the density-based method tends to obtain a high recall while precision may be low. Therefore, a combination of LSTM-AE and density method in the proposed method improves precision compared with the density method, while the recall is better than the LSTM-AE-based method. Note that the precision of the proposed method may be lower than that of the LSTM-AE-based method (e.g., by less than about 1% on the MIT Badge dataset). This can be attributed to the combination of the density-based method, which may lead to a decrease in precision. However, the f1-score of the proposed method is still improved due to the increase in recall achieved by the density-based method. In particular, Tables 2 and 3 show that the proposed method outperforms all others in f1-score (i.e., achieving 81.08% on the MIT Badge and 89.57% on the sCREEN). In addition, in the sCREEN dataset, since the abnormal trajectories may be easy to detect, all methods achieve a high recall (e.g., the LSTM-AE achieving a recall of 1). Therefore, with this dataset, it is difficult to demonstrate an improvement in recall for the density method compared with the LSTM-AE-based method. This explains why the contribution of the density method in latent space for the proposed method is not evident in the sCREEN dataset.

5. Conclusion

In this paper, a framework for anomalous human trajectory detection based on deep learning and density method is proposed. In particular, the LSTM-AE was trained to keep the trajectory representations in a latent space. The anomalous trajectory detection was performed using the density of latent representations and trajectory reconstruction error. To determine the trajectory anomaly score, the new metric is proposed. If the anomaly score of a trajectory is larger than or equals a threshold, this trajectory is detected as anomaly. The experimental results showed that the proposed framework identified well anomalies achieving 81.08% and 89.57% of f1-score on the MIT Badge dataset and the sCREEN datasets, respectively.

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MỘT SỰ KẾT HỢP CỦA HỌC SÂU VÀ PHƯƠNG PHÁP MẬT ĐỘ TRONG PHÁT HIỆN QUỸ ĐẠO CON NGƯỜI BẤT THƯỜNG

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Tóm tắt

Quỹ đạo bất thường của con người ở những nơi làm việc thường liên quan đến các vấn đề như: hỏa hoạn, tấn công bạo lực hay khủng bố. Vì vậy, việc phát hiện các quỹ đạo bất thường của con người có thể cải thiện độ an toàn và an ninh ở những nơi làm việc. Trong công việc này, một khung làm việc mới cho việc phát hiện quỹ đạo bất thường được đề xuất dựa trên sự kết hợp của học sâu và phương pháp mật độ. Đầu tiên, một bộ tự động mã hóa sử dụng mạng nơ-ron LSTM (Bộ nhớ ngắn-dài hạn) được áp dụng để học các thể hiện mang thông tin hữu ích của các quỹ đạo bình thường. Sau đó, mật độ của các thể hiện quỹ đạo trong không gian tiềm ẩn và lỗi khôi phục quỹ đạo được sử dụng để phát hiện bất thường. Một phép đo mới được đề xuất để xác định mức độ bất thường của quỹ đạo. Khung làm việc đã đề xuất được đánh giá sử dụng hai bộ dữ liệu quỹ đạo thực tế: MIT Badge và sCREEN. Các kết quả thí nghiệm chỉ ra rằng công việc của chúng tôi phát hiện các bất thường hiệu quả và f1-score đạt 81,08 % trên bộ dữ liệu MIT Badge và 89,57% trên bộ dữ liệu sCREEN.

Từ khóa

Phát hiện quỹ đạo bất thường; LSTM-AE; phương pháp mật độ; mức độ bất thường.