Acta Clin Croat 2023; 62:131-140
doi: 10.20471/acc.2023.62.01.16

Original Scientific Paper

OPTIMIZATION OF PRE-HOSPITAL FIRST AID MANAGEMENT STRATEGIES FOR PATIENTS WITH INFECTIOUS DISEASES IN HUIZHOU CITY USING DEEP LEARNING ALGORITHM

Jing Zeng[1], WeiSheng Chen[2], WeiWei Chen[1], YaWei Wang[1] and XueSong Li[3]

[1]Department of Emergency, Huizhou Third People's Hospital, Guangzhou Medical University, Huizhou, China;
[2]Department of Emergency Intensive Care Unit, Huizhou Third People's Hospital, Guangzhou Medical University, Huizhou, China;
[3]Center for Neuromedicine, Huizhou Third People's Hospital, Guangzhou Medical University, Huizhou, Guangdong Province, China

SUMMARY – The aim of the study was to optimize the pre-hospital first aid management strategy for patients with infectious diseases in Huizhou city, which is expected to provide a basis for the epidemic prevention and control, to save lives, and increase the pre-hospital first aid efficiency. At the Department of Emergency, Huizhou Third People's Hospital as the research subject, the common pre-hospital first aid procedure for infectious diseases was identified. The Petri net was used to model and determine the execution time of each link of the pre-hospital first aid process. The isomorphic Markov chain was used to optimize the pre-hospital first aid procedure for infectious diseases. In terms of the emergency path, deep learning was combined with the reinforcement learning model to construct the reinforcement learning model for ambulance path planning. Isomorphic Markov chain analysis revealed that the patient status when returning to the hospital, the time needed for the ambulance to come to designated location, and the on-site treatment were the main problems in the first aid process, and the time needed for the pre-hospital first aid process was reduced by 25.17% after optimization. In conclusion, Petri net and isomorphic Markov chain can optimize the pre-hospital first aid management strategies for patients with infectious diseases, and the use of deep learning algorithm can effectively plan the emergency path, achieving intelligent and informationalized pre-hospital transfer, which provides a basis for reducing the suffering, mortality, and disability rate of patients with infectious diseases.

Key words: *Petri net; Isomorphic Markov chain; Infectious disease; Deep learning; Enhanced learning; Path planning*

Introduction

Pre-hospital first aid belongs to the public health field. Its reform is an important part of medical reform and a health dividend from economic supply-side structural reform. With the increase and aging of population, people have increasing demands for pre-hospital first aid[1]. At present, the novel coronavirus epidemic has been spreading worldwide, greatly affecting national public health security and social economic development. The transmission routes of infectious diseases of the respiratory system are mainly direct transmission, contact transmission, and aerosol

Correspondence to: *Jing Zeng*, Department of Emergency, Huizhou Third People's Hospital, Guangzhou Medical University, Huizhou, China 516001
E-mail: jingzeng120@163.com

Received July 8, 2021, accepted December 7, 2021

transmission. The incubation period is about 1 to 14 days. The clinical symptoms of patients mainly include fever, fatigue, and dry cough[2,3].

The response time of pre-hospital first aid is closely related to the mortality rate, and studies have pointed out that with every minute of the pre-hospital first aid process reduction, the mortality rate of patients with cardiac arrest can be reduced by about 24%[4]. Huizhou City initiated the first-level response to major public health emergencies in January 2020, and formulated effective measures for prevention and control. Department of Emergency at the Huizhou Third People's Hospital is the front line for the prevention and control of infectious diseases. It is responsible for the acceptance, dispatch, and transfer of out-of-hospital calls for help to suspected cases, confirmed cases, or cases with fever-related symptoms. There is more and more research on the pre-hospital first aid, but there is a lack of research on the optimization of pre-hospital first aid procedures.

Therefore, in the study, related tools were used to construct the pre-hospital first aid process model, and the bottleneck links were identified in the first aid process for optimization. At the same time, in view of the transportation route planning problem, a deep learning algorithm was constructed to optimize the transportation route, so as to reduce the time of pre-hospital first aid and improve the efficiency of first aid.

Methods

Basic requirements for pre-hospital first aid procedure for infectious diseases

Pre-hospital first aid is the treatment process for emergency patients out of hospital, including formulation of the dispatch plan, the out-call of the emergency team, emergency treatment at the scene, and monitoring and rescue of patients on their way to the hospital[5]. The requirements for pre-hospital first aid included three aspects, as follows: 1) safety and rapidity. Out of considering for the emergency, it is necessary to ensure the safety and rapidity of patient transfer when performing pre-hospital first aid, so as to save their lives as much as possible; 2) to save lives is the first priority. When emergency personnel arrive at the scene, they should quickly make judgments on the patient's injury, and then take corresponding first aid measures to save lives. When the patient's condition is under control, he/she is then transferred to the hospital for further rescue; and 3) emphasis on people-oriented protocol. Each link performed by the emphasized personnel during the rescue should be humanized. In addition, attention should be paid to the patient's and their family's psychological state. The emergency personnel should also carry out psychological care.

The pre-hospital first aid procedure model for patients with infectious diseases based on Petri net

Petri net model can be used to describe the structure and operation of the system, with very powerful and comprehensive functions[6]. In practice, Petri net is a dynamic structure system, and its structure is shown in Figure 1.

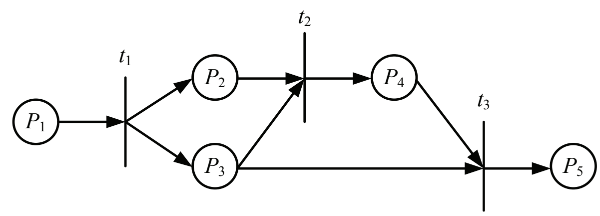

Fig. 1. Basic structure of Petri net.

When a triplet N=(P,T;F) can meet the following conditions, it can be called a Petri net: P∪T≠ ; P∩T= ; F (P×T)∪(T×P); Dom(F)∪Cod(F)= P∪T. Where T is the transition, P is the place, F is the flow relationship, Dom(F)={x| y: (x,y) F}, Cod(F)={y| x:(x-,y) F}, Dom(F) and Cod(F) are the domain and value domain of F, respectively.

Before construction of the Petri net model, it is necessary to determine the elements of the pre-hospital first aid process for patients with infectious diseases, including the specific work of pre-hospital first aid, the logical sequence of activities, the data flow and information flow in the process, emergency medical equipment and resources, and emergency personnel and rescued patients. Based on the investigation results of the pre-hospital first aid procedure of the Huizhou Third People's Hospital, the common pre-hospital first aid procedure is determined. The Petri net model is used to simulate the pre-hospital first aid procedure model according to correspondence between the first aid process and the Petri net elements. The model is analyzed for the execution time of each link, etc.

The common pre-hospital first aid procedure for infectious diseases is shown in Figure 2.

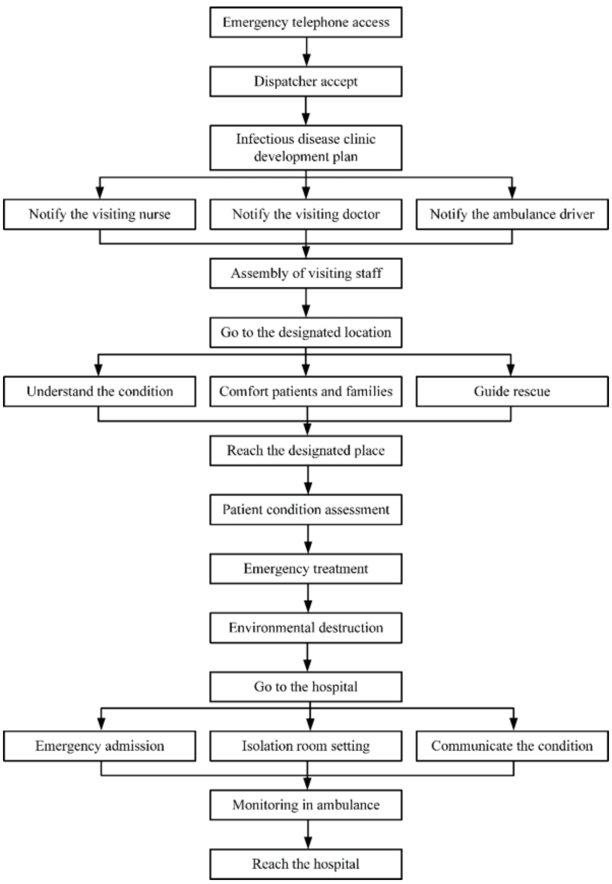

Fig. 2. Common pre-hospital first aid procedure for infectious diseases.

The pre-hospital first aid preparation activities are defined as the place, the pre-hospital first aid activities are defined as transition, and the resources needed for first aid are defined as tokens in the Petri net model. The final structure of the Petri net model of the emergency and severe patients with infectious diseases is shown in Figure 3. In this network, T is the activities in the pre-hospital first aid procedure, and P is the preparation activities in the pre-hospital first aid procedure. In Figure 3, T_{13} and T_{23} are instantaneous transitions; and T_0 is the substantive significance, which is a virtual transition; and the remaining T transitions all correspond to the variables of the pre-hospital first aid procedure in Figure 2.

In the traditional Petri net model, if the conditions cannot satisfy the model, the transitions in the model will be triggered immediately. If there is no delay, the result is generated, and the transition duration in the Petri net model is 0, which cannot reflect the time parameters in the system and lack the authenticity of feedback[7]. In the pre-hospital first aid procedure of emergency and severe patients with infectious diseases, all activities require time. Therefore, in order to further optimize the model, time parameters are introduced on the basis of the traditional Petri net model. In the actual situation, the duration of some links in the pre-hospital first aid procedure is relatively short. As a result, it is difficult to measure the time value. Therefore, some links are merged and the total execution time and delay

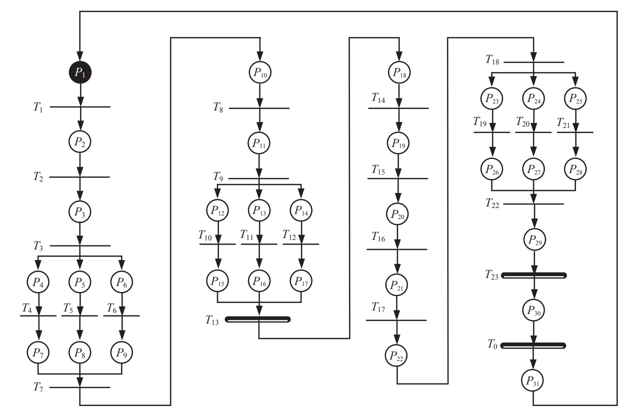

Fig. 3. Petri net model of pre-hospital first aid for emergency and severe patients with infectious diseases.

time of these links is determined. The simplified model is then obtained. The merging steps are as follows: step 1: T_3, T_4, T_5, and T_6 transitions are merged into a new transition T_3; step 2: T_9, T_{10}, T_{11}, and T_{12} transitions are merged into a new transition T_6; step 3: T_{14}, T_{15}, T_{16}, and T_{17} transitions are merged into a new transition T_8; step 4: T_{18}, T_{19}, T_{20}, and T_{21} transitions are merged into a new transition T_9.

After the above merging steps, the optimized structure of the Petri net model for the pre-hospital first aid procedure is shown in Figure 4. In Figure 4 T_1, T_2, T_4,

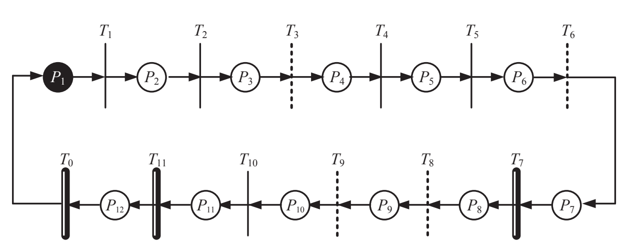

Fig. 4. Optimized Petri net model of pre-hospital first aid for emergency and severe patients with infectious diseases.

Table 1. Definition and execution time of each transition in the optimized Petri net model

Transition number	Definition	Minimum execution time (s)	Maximum execution time (s)
T_1	Emergency telephone access	0	6
T_2	Dispatcher acceptance	30	60
T_3	Sending scheduling notification	30	60
T_4	Out-call preparation of infectious emergency department	60	120
T_5	Assembly of out-call personnel	5	30
T_6	Ambulance to the designated place	180	900
T_7	Arriving at the emergency scene	0	0
T_8	Emergency personnel observing patients	120	300
T_9	Patient's first aid	480	720
T_{10}	Transferring back to hospital	300	1200
T_{11}	Reaching the hospital	0	0
T_0	Virtual variable	0	0

T_5, T_7, T_{10}, T_{11}, and T_0 are still equivalent to the transitions in the original model. T_7 and T_{11} are still instantaneous transitions and T_0 is still the virtual transition; T_3, T_6, T_8, and T_9 are the newly merged transitions, representing out-call preparations, emergency ambulances going to designated locations, on-site treatment, and transporting patients back to the hospital. The definition and execution time of each transition in the Petri net model after optimization are shown in Table 1.

Verification of pre-hospital first aid procedure for infectious diseases based on isomorphic Markov chain

The Petri net model can be used to determine the pre-hospital first aid for emergency and severe patients with infectious diseases and the execution time of each link, but it is not possible to determine which link is inefficient[8]. Therefore, the isomorphic Markov chain is used to evaluate the steady-state probability of each node in the pre-hospital first aid procedure, so as to find the bottleneck links in the procedure. Before the application of Markov chain, it is necessary to determine the implementation speed of each transition, and then determine the mark of the Petri net model, as shown in Figure 5.

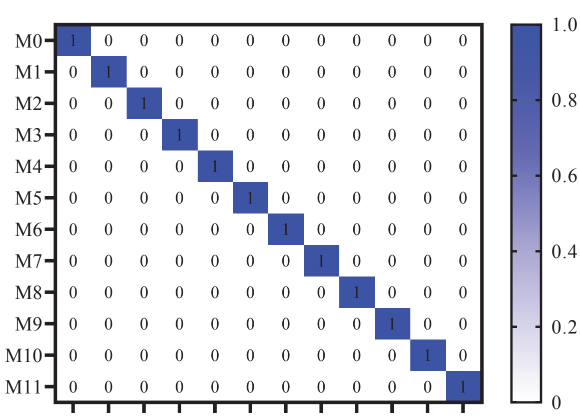

Fig. 5. Mark setting of Petri net model.

The mark of Petri net model is mapped to a Markov chain, and the specific structure is shown in Figure 6. The average implementation speed λ of each transition is the reciprocal of time, and the unit is times/min. The average implementation speed of each transition node λ_1, λ_2, λ_3, λ_4, λ_5, λ_6, λ_7, λ_8, λ_9, λ_{10}, λ_{11}, and λ_{12} are 21.4, 1.3, 1.2, 0.7, 4.8, 0.1, ∞, 0.3, 0.1, 0.1, ∞ and ∞.

The Markov chain based on the above Petri net model then calculates the steady-state probability of each Markov chain node.

Ambulance path planning based on deep reinforcement learning model

Deep reinforcement learning can combine perception and decision-making, and deep reinforcement learning based on value function was explored in the study. The Q learning algorithm in traditional reinforcement learning can be iterated using the following equation:

$$Q(u,v) = Q(u,v) + \alpha\left(R_{t+1} + \gamma \max_{a'} Q(u',v') - Q(u,v)\right) \quad (1),$$

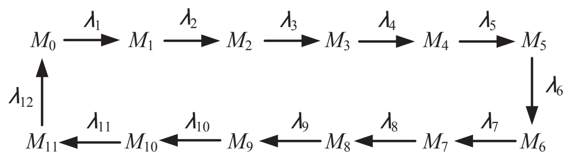

Fig. 6. Markov chain of Petri net model.

where u and v represent the current actual state and action, respectively; u' and *v*' represent the subsequent state and action, respectively, and α is the update step size.

In the deep Q network (DQN), the weight of the network needs to be updated iteratively, and the weight is differentiable. Therefore, the definition of the objective function is required, and then derivation of the weight function is performed. Therefore, the mean square loss function of the i-th iteration can be defined as follows:

$$L_i(\theta_i)=E_{(u,v,r,u')\sim U(D)}\left(R_{t+1}+\gamma\max_{a'}Q(u',v';\theta_i)-Q(u,v;\theta_i)\right)^2 \quad (2),$$

where θ is the network weight.

The DQN model has a convolutional layer that can be used for layered perception of images, while a fully connected layer can integrate image features and requires segmented state-action pairs for model training. Compared with traditional reinforcement learning, the application of DQN model to path planning needs to clarify the form of the input image and how to transform the path planning result into a state-action pair[9]. If the DQN model is directly applied to path planning, there are still shortcomings that the spatial location information cannot be fully retained in the model and the key location and local information cannot be used. Therefore, the full convolutional neural network (FCN) is used to improve DQN model to obtain the FCN-DQN model.

The FCN model based on the DQN reflectivity mechanism is designed first. The structure of the model is shown in Figure 7. The FCN model can retain the original relative position information of the image data while processing the data, fully representing the inherent properties of the path planning environment. Among them, the attention mechanism can also make full use of the local key information of image features, and it is intended to make up for the shortcomings of the above DQN model after combined with the FCN model. The FCN model is mainly composed of 4 convolutional layers of 3*3 spatial size and 1 special convolutional layer of 1*1 size. The activation function between each connected layer is ReLU; and the last layer is the Softmax function.

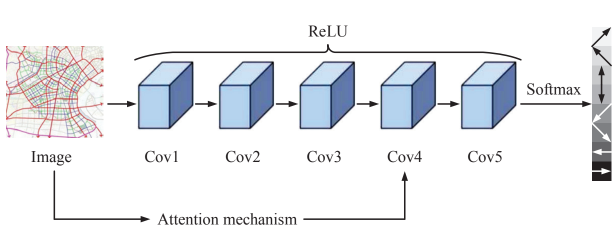

Fig. 7. Basic structure of the FCN-DQN model.

The convolutional layers 1 to 4 in the FCN-DQN model contain 150, 100, 100, and 50 filters, respectively. The size of the convolution kernel is 3*3, and the step size is 1. Assuming that the size of the input image is *A***B*, the filter size of the convolutional layer is *a***b*, the step size is *s*, and the number of unilateral pixels of the pixel expansion is *P*, the size of the output image needs to meet the following equation:

$$\begin{cases} A'=\dfrac{A-a+2P}{s}+1 \\ B'=\dfrac{B-b+2P}{s}+1 \end{cases} \quad (3)$$

The attention mechanism in this model is spatial attention, the input spatial size in the special convolution layer 5 is 1*1, the convolution kernel size of the convolution layer is 1*1, and the number of filters is 8. In this study, the imitation learning algorithm was used to perform the path planning algorithm based on the FCN-DQN model. The structure of this algorithm needs to optimize the weight value using the RMSProp algorithm. The optimized objective function in the model is the cross entropy calculated by the decision number and the output result of the FCN model. Assuming that *p* and *q* are different probability distributions, the cross entropy *H(p,q)* is expressed as follows:

$$H(p,q)=-\sum_x p(x)\log q(x) \quad (4)$$

The calculation equation for updating model weights using RMSProp algorithm is as follows:

$$\begin{cases} E(d_t)=(1-\rho)E(d_{t-1})+\rho d_t \\ E(d_t^2)=(1-\rho)E(d_{t-1}^2)+\rho d_t^2 \\ v_{t+1}=-\dfrac{\eta}{\sqrt{E(d_t^2)-E(d_t)^2+\varepsilon}}d_t \\ \theta_{t+1}=\theta_t-v_{t+1} \end{cases} \quad (5),$$

where θ_t is the current weight value; d_t is the weight gradient, η is the learning rate, η=0.001; ε is a constant, ε=1×10^{-6}.

The process of using the FCN-DQN model for path planning is as follows: 1) to read the map data and the FCN-DQN model is used to make decisions; 2) data are updated to plan the path. When the planning is overtime, the calculation ends, otherwise, it is determined whether the target point is reached; and 3) if the target point has been reached, the calculation ends, otherwise, it returns to the model decision.

Results and Discussion

Analysis of the status quo of the emergency centers in Huizhou city

The Emergency Medicine Center of our hospital is responsible for the pre-hospital first aid service within Huicheng District, including transfer of confirmed and suspected patients. There are 8 ambulances and a total of 26 people specialized in pre-hospital first aid, including 14 medical personnel, 6 drivers, and 6 stretcher workers. The standard configuration of the ambulance includes on-board monitoring defibrillator, ventilator, electrocardiograph, sputum suction device, shovel stretcher, and first aid kit. The total number of ambulance visits was 6,198 in 2018 and 6,206 in 2029. From January 21, 2020 to April 27, 2020, the total number of ambulance visits was 144, with a total of 230 people involved.

Simulation verification of the pre-hospital first aid procedure model

The simulation analysis of the pre-hospital first aid Petri net model for emergency and severe patients with infectious diseases is performed in the ExSpect platform. The number of simulations is 100. After statistics of the simulation data, the execution time of different nodes was analyzed. The results are shown in Figure 8. It is evident that the execution time after using the Petri model basically met the time range given in Table 1.

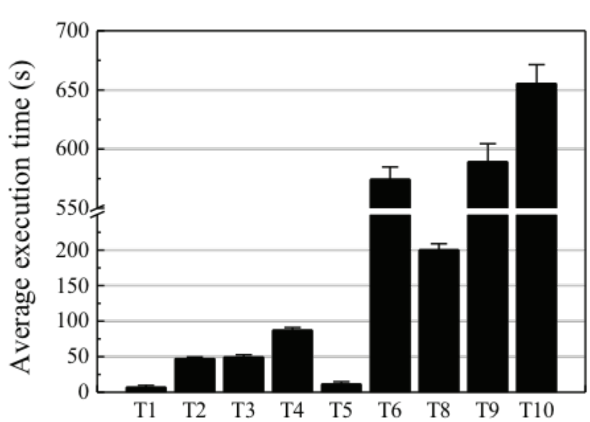

Fig. 8. Average execution time of different nodes.

Based on the above simulation results, the time index of the pre-hospital first aid procedure in Huizhou city was evaluated from January 21, 2020 to April 27, 2020. The results are shown in Figure 9. It is evident from Figure 9A that the dispatch time of the pre-hospital first aid procedure simulated by Petri net model was slightly higher than the actual average value, but there was no significant difference (p=0.079). It is evident from Figure 9B that the ambulance departure time simulated by Petri net model was lower than the actual average value, but there was no significant difference (p=0.062). It is evident from Figure 9C that the response time of the pre-hospital first aid procedure simulated by Petri net model was slightly higher than the actual average value, but there was no significant difference (p=0.063). The standards of pre-hospital first aid dispatch time, vehicle departure time, and response time formulated by Huizhou City are 0~1.5 min, 0~3 min, and 10~15 min, respectively. Obviously, the dispatch time and the response time simulated by the Petri net model were slightly higher than the standard time, suggesting that optimization is necessary. The average time needed by pre-hospital first aid was 42.338 min before optimization, while that after optimization was 31.683 min, which was reduced by 25.17%.

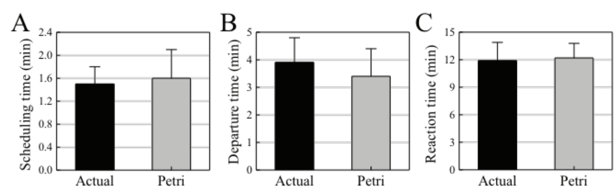

Fig. 9. Comparison of the time index of pre-hospital first aid procedure: (A) dispatch time; (B) ambulance departure time; (C) response time.

Evaluation of pre-hospital first aid procedure for infectious diseases

The Markov chain is used to calculate the steady-state probability of each node of the Petri net model.

The steady-state probability of Markov chain satisfies the following equation:

$$\begin{cases} XA=0 \\ \sum_{i=1}^{m} x_i = 1 \end{cases} \quad (6)$$

The steady-state probability of M_1, M_2, M_3, M_4, M_5, M_6, M_7, M_8, $M9$, M_{10}, M_{11}, and M_{12} was 0.004, 0.021, 0.021 0.038, 0.256, 0.000 0.091, 0.261, 0.305, 0.003 0.000, and 0.000, respectively.

Subsequently, the steady-state probability and cumulative percentage of different links in the pre-hospital emergency procedure were analyzed, and the results are shown in Figure 10. It is evident from Figure 10A and Figure 10B that the steady-state probability of $M9$, M_8 and M_5 was higher but their cumulative percentage was lower, indicating low efficiency in transferring the patient back to the hospital, in the patient's on-site emergency treatment, and in the ambulance going to the target location, which needs to be improved[10].

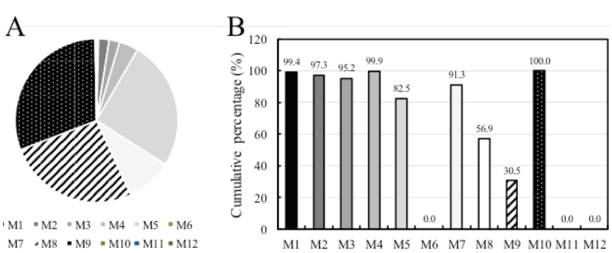

Fig. 10. Steady-state probability and cumulative percentage analysis of different links in the pre-hospital first aid procedure: (A) steady-state probability; (B) steady-state cumulative percentage.

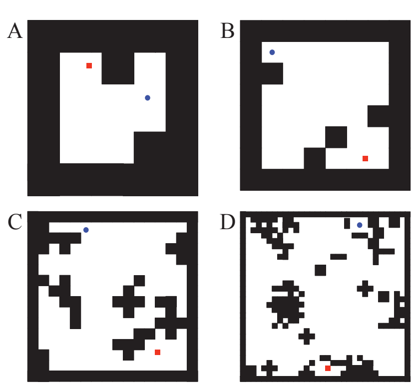

*Fig. 11. Path planning experiment of different sizes: (A) 4*4; (B) 8*8; (C) 16*16; (D) 24*24.*

The deep reinforcement learning model to plan the emergency route

To path planning performance of the FCN-DQN model constructed in the early stage was evaluated first, and four raster graphics of different sizes were used. The graphic model is shown in Figure 11, where the sizes of Figure 11A, Figure 11B, Figure 11C, and Figure 11D are 4*4, 8*8, 16*16, and 28*28, respectively. The black square is the obstacle area, and the white part is non-obstacle area. The blue dot is the starting position, and the orange square is the target position.

To evaluate the performance of the FCN-DQN model for path planning, 10 different starting positions are randomly generated in the 4*4, 8*8, 16*16, and 28*28 experimental environment, and then the model samples are generated. The images are divided into training set and verification set at a ratio of 7: 1, and 66639, 76052, 68361, 33679, and 40153 test samples are identified, respectively. The back-propagation algorithm is used to obtain the weight gradient in the FCN-DQN model, and the learning rate is unified to 0.001. The FCN-DQN model is evaluated for the training loss and error results in path test environment of different sizes. The training loss can reflect the error degree of the model on the training data, and the training error can be used to measure the error rate of the model on the training set. It is evident from Figure 12A and Figure 12B that as the number of iterations gradually increases, the training loss and training error of the FCN-DQN model show a gradually decreasing trend in path environment of different sizes. The FCN-DQN model performs better in the 4*4 size

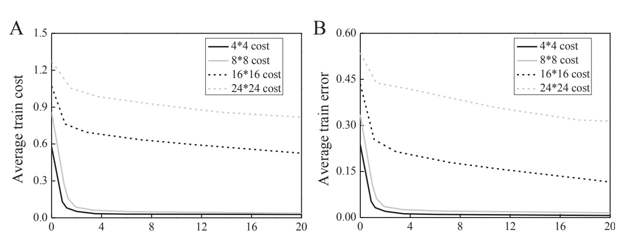

Fig. 12. Training results of the FCN-DQN model in path planning experimental environment of different sizes: (A) average training loss of the model; (B) average training error of the model.

and 8*8 size environment, while the training loss and training error in the 16*16 and 24*24 size environment gradually stabilize when the number of iterations reaches 16, suggesting that its planning performance in a larger-size graphic is relatively poor, and it cannot adapt to longer path planning problems.

The FCN-DQN model was then evaluated for prediction accuracy in path planning experimental environment of different sizes. It is evident from Figure 13 that the FCN-DQN model has excellent prediction accuracy in the 4*4 and 8*8 path planning environment; and its prediction accuracy in 16*16 and 24*24 path planning environment decreases obviously, indicating that the FCN-DQN model has

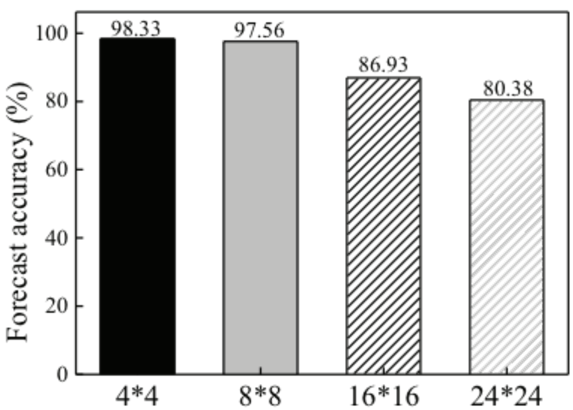

Fig. 13. Prediction results of the FCN-DQN model in the path planning experimental environment of different sizes.

a poor long-term planning capability, but the overall prediction accuracy rate of the FCN-DQN model is always higher than 80%.

The path planning results of FCN-DQN model and Dijkstra shortest path algorithm[11,12] in path planning images of different sizes are shown in Figure 14. It is evident from Figure 14A and Figure 14B that the FCN-DQN model and Dijkstra's shortest path algorithm have similar planned path lengths in the 4*4 and 8*8 path planning environment, and the optimal path prediction is successfully realized. It is evident from Figure 14C that Dijkstra's shortest path algorithm has a tortuous planning path in a 16*16 size image. This may be caused by factors such as a narrow and long path in the graphic environment. Therefore, the predicted planned path is slightly longer than that predicted by the FCN-DQN model. It is evident from Figure 14D that Dijkstra's shortest path algorithm also has longer planning paths in 24*24 size images, but the FCN-DQN model has successfully realized path planning for graphics of different sizes.

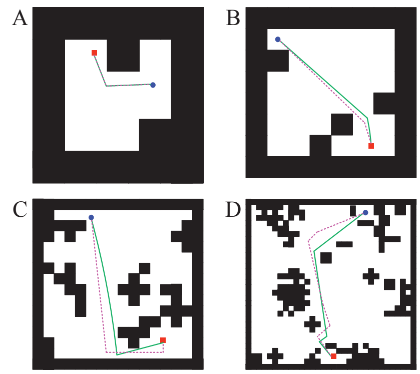

*Fig. 14. Path planning of different sizes of graphics based on the FCN-DQN model: (A) 4*4 experimental environment; (B) 8*8 experimental environment; (C) 16*16 experimental environment; (D) 24*24 experimental environment. Solid line is the path predicted by Dijkstra's shortest path algorithm; dotted line is the path predicted by the FCN-DQN model.*

Optimization of pre-hospital first aid procedure for infectious diseases

Based on the above results, it is necessary to explore the standards for the patient call for help and transfer process when dispatching and transferring the suspected, confirmed, or fever cases with infectious diseases. The optimized pre-hospital first aid procedures are as follows: 1) preparations: receiving instructions, preparing protective equipment, and reporting the actual time of departure; 2) transfer monitoring: reporting the time that patient gets on the ambulance, starting the negative pressure device, and contacting the hospital; 3) delivery to the designated hospital: turning off the negative pressure device, reporting the delivery time, and filling in the Transfer Handover Form; 4) disinfection and isolation: after disinfection, taking off the protective equipment and washing hands. The emergency vehicle will be further disinfected in the designated car wash room. The medical staff will report the completion time after bathing and changing clothes; and 5) path planning: inputting the graphic, setting the starting position, and the FCN-DQN model is used to plan the optimal route to heighten the patient transfer efficiency.

Conclusion

Based on the current situation, the Petri network model is used to construct a pre-hospital first aid procedure model in Huizhou, and the bottleneck links in the above-mentioned pre-hospital first aid procedure are analyzed with an isomorphic Markov chain. Subsequently, a deep learning algorithm for emergency path planning based on the FCN-DQN model is constructed. After verification, it is found that the operating efficiency was low for transporting patients back to the hospital, for on-site emergency treatment of patients, and for the ambulance to reach the target location. The route optimized by the FCN-DQN model is the best, which effectively solves the problem of low efficiency in transporting patients of emergency ambulances. However, in the study, only the emergency path planning efficiency of the FCN-DQN model was analyzed. In the follow-up, it is necessary to build a corresponding emergency platform to realize the automated research of the pre-hospital first aid procedure. In short, this research is of practical significance for improving the pre-hospital first aid procedure in Huizhou.

Acknowledgments

Support from the Huizhou Science and Technology Plan Project (2020Y537) in 2020 and Huizhou Science and Technology Plan Project (2020Y538) in 2020 is acknowled

References

1. Pek JH. Guidelines for Bystander First Aid 2016. Singapore Med J. 2017 Jul;58(7):411-7. doi: 10.11622/smedj.2017062
2. Baymakova M, Christova I, Panayotova E, Trifonova I, Chobanov A, Daskalov I, Popov GT, Plochev K. West Nile virus infection with neurological disorders: a case report and a brief review of the situation in Bulgaria. Acta Clin Croat. 2019 Sep 1;58(3):546-9. doi: 10.20471/acc.2019.58.03.21
3. Mrzljak A, Jemersic L, Savic V, Balen I, Ilic M, Jurekovic Z, Pavicic-Saric J, Mikulic D, Vilibic-Cavlek T. Hepatitis E Virus in Croatia in the “One-Health” Context. Pathogens. 2021 Jun 4;10(6):699. doi: 10.3390/pathogens10060699
4. Adib-Hajbaghery M, Kamrava Z. Iranian teachers’ knowledge about first aid in the school environment. Chin J Traumatol. 2019 Aug;22(4):240-5. doi: 10.1016/j.cjtee.2019.02.003
5. Bakke HK, Steinvik T, Angell J, Wisborg T. A nationwide survey of first aid training and encounters in Norway. BMC Emerg Med. 2017 Feb 23;17(1):6. doi: 10.1186/s12873-017-0116-7
6. Liu F, Heiner M, Gilbert D. Coloured Petri nets for multilevel, multiscale and multidimensional modelling of biological systems. Brief Bioinform. 2019 May 21;20(3):877-86. doi: 10.1093/bib/bbx150
7. Edhlund I, Lee C. A Petri net approach to physiologically based toxicokinetic modeling. Environ Toxicol Chem. 2019 May;38(5):978-87. doi: 10.1002/etc.4390
8. Shama G. The “Petri” dish: a case of simultaneous invention in bacteriology. Endeavour. 2019 Mar-Jun;43(1-2):11-6. doi: 10.1016/j.endeavour.2019.04.001
9. Rahman MM, Rashid SMH, Hossain MM. Implementation of Q learning and deep Q network for controlling a self-balancing robot model. Robotics Biomim. 2018;5(1):8. doi: 10.1186/s40638-018-0091-9
10. Bakke HK, Bakke HK, Schwebs R. First-aid training in school: amount, content and hindrances. Acta Anaesthesiol Scand. 2017 Nov;61(10):1361-70. doi: 10.1111/aas.12958
11. Perkowski Z, Tatara K. The use of Dijkstra’s algorithm in assessing the correctness of imaging brittle damage in concrete beams by means of ultrasonic transmission tomography. Materials (Basel). 2020 Jan 23;13(3):551. doi: 10.3390/ma13030551
12. Razzaq M, Shin S. Fuzzy-logic Dijkstra-based energy-efficient algorithm for data transmission in WSNs. Sensors (Basel). 2019 Feb 28;19(5):1040. doi: 10.3390/s19051040

Sažetak

OPTIMIZACIJA PREHOSPITALNIH STRATEGIJA UPRAVLJANJA PRVOM POMOĆI ZA BOLESNIKE SA ZARAZNIM BOLESTIMA U GRADU HUIZHOU POMOĆU ALGORITMA ZA DUBOKO UČENJE

Jing Zeng, WeiSheng Chen, WeiWei Chen, YaWei Wang i *XueSong Li*

Cilj istraživanja bio je optimizirati strategiju prehospitalnog upravljanja prvom pomoći za bolesnike sa zaraznim bolestima u gradu Huizhou, Kina, za koju se očekuje da pruži osnovu za prevenciju i kontrolu epidemije, da spasi živote te da poveća učinkovitost prehospitalne prve pomoći. Istraživanje je provedeno na Hitnom odjelu Treće narodne bolnice u gradu Huizhou, gdje je utvrđen opći prehospitalni postupak prve pomoći za zarazne bolesti. Petrijeva mreža je primijenjena kako bi se modeliralo i odredilo vrijeme izvršenja svake karike u procesu prehospitalne prve pomoći. Izomorfni Markovljev lanac primijenjen je za optimizaciju prehospitalnog postupka prve pomoći za zarazne bolesti. Za putanju hitnosti, duboko učenje je kombinirano s modelom pojačanog učenja kako bi se konstruirao model osnaživanja učenja za planiranje putanje vozila hitne pomoći. Analiza Markovljeva lanca pokazala je da su status bolesnika na povratku u bolnicu, vrijeme potrebno da vozilo hitne pomoći dođe na određenu lokaciju i skrb na mjestu događaja glavni problemi u procesu prve pomoći te da je vrijeme potrebno za prehospitalni proces prve pomoći smanjeno za 25,17% nakon optimizacije. Zaključeno je da Petrijeva mreža i izomorfni Markovljev lanac mogu optimizirati strategije upravljanja prehospitalnom prvom pomoći za bolesnike sa zaraznim bolestima te da primjena algoritma dubokog učenja može učinkovito planirati putanju tima hitne pomoći, čime se postiže pametan i informatizirani prehospitalni prijevoz, što čini osnovu za smanjenje patnje, smrtnosti i stope invalidnosti za bolesnike sa zaraznim bolestima.

Ključne riječi: *Petrijeva mreža; Izomorfni Markovljev lanac; Zarazne bolesti; Duboko učenje; Osnaženo učenje; Planiranje putanje*