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Current and Emerging Deep Learning Methods for Flood Simulation

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ABSTRACT

In today's world, the development of flood simulation technology is crucial for urban planning and disaster management. However, traditional flood simulation methods are often constrained by the complexity of terrain and meteorological changes, making it difficult to accurately predict the occurrence and impact range of floods. In order to overcome these challenges, the introduction of deep learning technology has brought new ideas and possibilities for flood simulation. By using deep learning models to learn and analyze a large amount of flood data, researchers can more accurately predict the occurrence time, intensity, and impact range of floods, providing strong support for urban planning and emergency response. This article summarizes and discusses traditional flood simulation methods and deep learning based flood simulation methods, and provides prospects for future development.

KEYWORDS

Flood evolution; Artificial Intelligence; Deep Learning; Numerical Method

1. INTRODUCTION

Floods are one of the most common natural disasters on Earth, and the losses they cause to human society and economy are often enormous. In the past few decades, with the acceleration of climate change, urbanization, and changes in land use patterns, the trend of frequent floods has become increasingly significant. In the face of this challenge, the ability to predict and evaluate flood disasters is particularly important. Flood simulation technology, as an important tool, can help us better understand and respond to flood disasters, providing support for urban planning, water resource management, and emergency response.

However, traditional flood simulation methods often rely on physical models and empirical formulas, limited by the complexity of terrain and the impact of meteorological changes, and their prediction accuracy and timeliness often fail to meet practical needs. In recent years, with the rapid development of deep learning technology, especially the widespread application of models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short Term Memory Networks (LSTM), new opportunities and challenges have been brought to the field of flood simulation. Deep learning models can learn and train from a large amount of flood data, thereby improving the accuracy and timeliness of flood prediction, and providing more reliable decision-making basis for disaster management departments and decision-makers.

In this article, we will comprehensively review and analyze current and emerging deep learning methods for flood simulation. We will explore the principles, application cases, and future development trends of these methods, aiming to provide a comprehensive reference material for relevant researchers and practitioners, and promote the further development and application of flood simulation technology.

2. TRADITIONAL FLOOD SIMULATION METHODS

Numerical simulation of flood evolution can identify the areas with the highest risk, the greatest harm and the most serious impact during flood, and take targeted measures to solve or mitigate the harm caused by flood in advance. In the early stage, zero-dimensional models such as discharge process line were widely used to solve the flood peak process formed by precipitation at the basin outlet, while the lumped hydrological model ignored the basin topographic features and the dynamic mechanism of flood evolution, and lacked the solution to the hydrological and hydrodynamic evolution process. Since then, hydrodynamic models have entered a rising stage, and a large number of one-dimensional and two-dimensional hydrodynamic models based on fluid motion governing equations (DHI Mike, Wallingford Inforworks, HEC-RAS, etc.) have been developed successively, and a complete flood evolution research method has been established [1,2]. After entering the modern stage, people gradually realized that assumptions in two-dimensional shallow water numerical simulation (such as static pressure assumption, ignoring vertical acceleration and free surface curvature) inevitably lead to errors in the results. With the improvement of model accuracy requirements and the visual display of flow field information, people began to try three-dimensional hydrodynamic numerical simulation[3-5]. Zhang Ting used Floodity to study the flood inundating process of Glasgow based on radar data. The model realized the 3D flood simulation solution with higher precision and resolution [6]. Yang Dong et al. adopted the GPU-accelerated GAST model to solve the flood in Morpeth urban area and realized the high-precision solution of the floodplain flood. Two-dimensional flood numerical simulation can solve the problem at a higher speed and obtain the change of physical parameters of the flow field earlier, which provides references for flood control schemes and has wide application value in practical projects [7].

The numerical simulation of 3D flood evolution is based on Navier-Stokes equation, and other hydrodynamic equations can be derived from it. The strong nonlinearity of Navier-Stokes equation makes it difficult to solve theoretically, and the uncertainty of turbulence further increases the difficulty of Navier-Stokes equation. Therefore, Direct Numerical Simulation (DNS), Large Eddy Simulation (LES) and Reynolds-averaged Navier-Stokes, RANS is gradually improved to approximate turbulent flows. DNS does not need to make any simplification and approximation of turbulent flow, and directly adopts instantaneous Navier-Stokes equations to solve turbulent flow. The mesh size must be fine enough to capture the vortex structure, which is difficult to be used in engineering calculation. LES can only solve vortices larger than the size of the grid, and the precision of the grid directly affects the generation of turbulence. Reynolds mean RANS equation is the most common turbulence solving algorithm. By time homogenizing the unsteady Navier-Stokes equations, a set of unclosed equations is obtained with the time mean of the product of the time mean physical quantity and the pulsation quantity as the unknown quantity. Then other equations are added to describe the time mean of the product of the pulsation quantity to ensure the closure of the equations.

Reynolds mean RANS equations are generally solved discretely by difference method. The discretization of the governing equation mainly includes the discretization of the time term and the space term, and the discretization of the space term includes the discretization of the convection term and the discretization of the diffusion term, so a series of numerical solutions are derived. Finite element method [8] based on variational principle and with good conservation property, spectrum method [9] suitable for high-precision calculation of simple shapes, particle class method based on discrete elements that can deal with complex shapes, etc., are widely used in flood evolution [10,11]. Among them, finite difference method based on spatiotemporal discretion with high order accuracy and Taylor series expansion is used as a tool. The derivative term in the differential equation of water flow motion is approximated by the difference formula, and the high-precision solution can be achieved by using the higher-order scheme in the simple shape structure [12]. The finite element method, which approximates the solution by unit and minimizes the weighted residual of the space integral of the differential equation, is suitable for solving the boundary value problems of elliptic equations, but it is difficult to solve the transport problems mainly dominated by convection. The finite volume method with good conservation property can effectively solve the motion of large gradient water surface by discretization with unstructured mesh and discontinuous solution on the boundary of the control body. Particle class method does not need to grid the computational space, and can represent more delicate fluid motion states, and can accurately display fluid details such as spray [13-15].

3. FLOOD SIMULATION METHOD BASED ON DEEP LEARNING

The applications of deep learning algorithms include predicting future flood events - deep learning algorithms can be trained on important historical flood datasets, such as rainfall data, river flow data, and satellite images. These algorithms help to provide more accurate and faster flood warning, thereby achieving better preparation and response [16]. Flood monitoring - using deep learning algorithms for near real-time analysis of satellite images and other remote sensing data, can be used for flood monitoring. These algorithms help identify locations that are vulnerable to flooding by detecting changes in water levels [17]. Flood risk assessment - Deep learning algorithms can conduct extensive analysis of terrain, infrastructure, and land use data. This helps to locate flood prone locations and provides information for managing flood risks [18]. Flood loss assessment - Deep learning algorithms can be used to examine satellite images and other data sources to determine the extent of flood losses. This helps to assess the extent of floods and provides information for decision-making in rescue and recovery activities [19].

Wang et al. proposed a data-driven approach based on NASA Global Land Data Assimilation System (GLDAS) data for flood prediction with the help of gamma testing in order to solve the difficult problem of building a physics-based hydrological flood prediction model in a catchment with no or limited data. [20] Based on the most advanced deep learning model, Long short-term memory (LSTM) network, the runoff generation model and routing model are established. Based on Nash-Sutcliffe efficiency coefficient (NSE), it is found that the surface runoff generation model has good performance. Nevo et al. used this framework to build a flood prediction model without any satellite rainfall support for small watersheds with frequent flash floods in China[21]. The evaluation showed that the EF5 model performed well in the flood prediction scenario, with Pearson linear correlation coefficient (PCC) values exceeding 0.9 and Nash-Sutcliffe efficiency coefficient (NSE) values exceeding 0.85 during the validation period, and a large number of indicators and graphs demonstrated the good effect of the model prediction. Wan et al. introduced a general framework to uniformly describe different dynamic networks, including focused delay networks (FTDN), hierarchical recursive networks (LRN), and nonlinear autoregressive networks (NARX) with exogenous inputs, and constructed 1080 models with 6 different lead times and 10 neuron numbers[22]. And six different time delays to predict reservoir inflow in eastern China. The numerical and experimental results show that the training error of the model changes significantly with the number of neurons and the time delay. Indra et al. provided an optimal deep learning flood prediction model with big data analysis based on Twitter data (ODLFF-BDA) [23]. The proposed ODLFF-BDA technique aims to use tweets in a big data environment to predict the presence of floods. ODLFF-BDA technology includes data preprocessing to convert incoming tweets into a usable format; A gated recursive unit (GRU) with a multi-layer convolutional neural network (MLCNN) is used to extract local data and predict flooding.

4. CONCLUSION

Traditional flood simulation methods play an important role in flood prediction and defense. Through physical models, empirical formulas, terrain analysis, historical data analysis, and meteorological forecasting, they model and calculate the process of flood formation and evolution to predict the water level, flow velocity, and flood range of floods, providing important support for disaster management and urban planning.

However, traditional methods also have some limitations and challenges. Firstly, traditional methods typically require a large amount of computing resources and data support, are sensitive to parameter settings such as terrain, soil, and vegetation, and their prediction accuracy is constrained by various factors. Secondly, traditional methods often struggle to consider nonlinear and dynamic factors, resulting in poor predictive performance for complex terrain and meteorological conditions. Finally, traditional methods need to be continuously improved and enhanced when facing new challenges such as climate change and urbanization processes.

With the development and application of deep learning technology, traditional flood simulation methods are gradually being replaced by deep learning models to improve the accuracy and timeliness of flood prediction. Deep learning models can better capture nonlinear relationships and dynamic changes by learning flood features and patterns from large-scale datasets, providing new ideas and methods for flood prediction and defense.

In summary, traditional flood simulation methods still have important significance in flood prediction and defense, but they also need to be combined with new technologies and methods, continuously improved and enhanced to cope with increasingly severe flood risks and challenges.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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