Research and application of quantitative precipitation estimation based on optical flow method and ConvLSTM

Xuepeng Liu

***Abstract*—In recent years, precise meteorological monitoring in cities has been crucial for responding to natural disasters, traffic management, and environmental protection. Especially in extreme weather events such as heavy rainfall, timely and accurate prediction of rainfall not only concerns public safety, but also puts higher demands on urban planning and resource allocation. Quantitative rainfall estimation can not only better understand and predict rainfall phenomena in nature, but also provide important support and basis for flood warning, water resource management, agricultural production, and other aspects. In this context, accurate prediction of rainfall at urban monitoring stations and heavy rainfall warning have become key factors in ensuring public safety. In order to accurately and efficiently conduct quantitative rainfall estimation, this thesis takes the radar echo data and rainfall data collected by sensors at various monitoring stations as the research object, establishes corresponding radar echo extrapolation models and quantitative rainfall estimation models, and implements a quantitative rainfall estimation prototype system. The main job responsibilities are as follows: 1. A radar echo extrapolation model based on optical flow method and ConvLSTM (Convolutional Long Short Term Memory) neural network, called Flow-ConvLSTM network, is proposed to address the issues of insufficient consideration of different weather processes and cloud changes, as well as effective extrapolation time limits in existing radar echo extrapolation methods. This method first uses a wind field dynamic constraint filling optimization algorithm and multi-scale optical flow to obtain an optical flow field containing strongly correlated motion characteristics. Then, a multi-layer ConvLSTM simulation extrapolation effect is constructed, and the information of the optical flow field is input into ConvLSTM for radar echo extrapolation. The experimental results show that the error of the improved Flow-ConvLSTM network is the lowest compared to other selected models, and the time and resources required for training and prediction of this model are also relatively low.**

***Index Terms*—Optical Flow Method, Radar Echo Extrapolation, ConvLSTM, Quantitative precipitation estimation**

I. INTRODUCTION

Precipitation is a common phenomenon in nature and the most fundamental link in the water cycle process. It integrates with people's lives, not only bringing necessary water resources to our lives and becoming the main source of groundwater supply, but also improving the natural environment on which people rely for survival. However, heavy rainfall is one of the direct causes of natural disasters such as floods, floods, and droughts. With the global warming, the ecological environment is increasingly severely damaged, and the resulting climate anomalies are becoming more and more serious. Among the major natural disasters, such as the catastrophic flood disaster in the Yangtze River basin in 1998, and the extremely heavy rainstorm in western India in 2005, many flood disasters have caused serious damage to local urban construction and people's lives, resulting in huge economic losses, and even endangering people's life safety. It can be seen that the observation, forecasting, and early warning of heavy precipitation are all very important. Currently, radar echo extrapolation is commonly used for monitoring and warning of severe convective weather. The radar echo extrapolation method refers to tracking and predicting the velocity, direction, intensity, and shape changes of the echo. This is the main means of near precipitation forecasting. Its principle is to use the echo data detected by the radar to determine the intensity distribution of the echo and the movement speed and direction of the echo body, and predict the radar echo state after a certain period of time through linear or nonlinear extrapolation of the echo body. In traditional radar echo extrapolation methods, the cross correlation method has a low utilization rate of historical radar echo data, and performs well when the echo is stable. For echoes with large velocity gradients and fast evolution speeds, the prediction error is large and it is difficult to infer the actual weather conditions. The centroid tracking method can achieve good results in stable precipitation forecasting, but in local convective weather, the echo development is rapid and cannot meet the conservation conditions, and the forecasting effect will rapidly decline with time. The optical flow method has good motion tracking ability. Its principle is to calculate the optical flow field from a continuous image sequence. By utilizing the temporal changes of pixels in the image sequence and the correlation between adjacent frames, the corresponding relationship between the previous and current frames is established. Then, the motion information of objects between adjacent frames is calculated. For heavy convective precipitation with significant changes, a good overall motion trend can be obtained. However, due to the non conservation of reflectivity factors, the extrapolation error of the optical flow method for echoes with faster movement speed is relatively large

II. OPTICAL FLOW EXTRAPOLATION MODEL

Due to limitations in the quality of radar data, the optical flow field and the derived wind field may be affected by some disordered vectors, thus requiring quality control processing. The method of wind field dynamics constraint filling was adopted to ensure the physical consistency of the derived wind field, which involves multiple steps. Firstly, the horizontal and

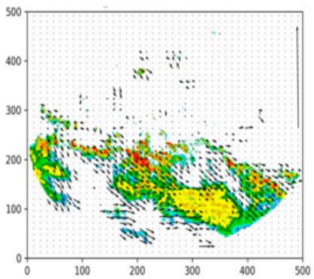

Fig. 1. The wind field obtained from the primitive optical flow method

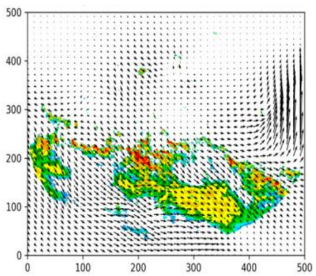

Fig. 2. Schematic diagram of the wind field obtained after filling

vertical components of the vector combination were used to calculate the wind speed of the optical flow field, and non physical values less than or equal to 0 were excluded from the radar reflectivity field to alleviate potential anomalies. Subsequently, the average wind speed and direction are calculated for the area where the product of reflectance and wind speed is positive, and the area where the product of reflectance and wind speed is non positive is adjusted. The wind speed and direction in this area are replaced with the calculated average value, and the wind speed exceeding the preset wind speed threshold is set to a threshold. The purpose of this process is to eliminate the interference of disordered vectors on the wind field through dynamic constraints, ensuring its physical interpretability throughout the entire area.

III. Improving Network Flow ConvLSTM

Traditional optical flow methods are usually based on assumptions such as constant brightness (the brightness values at the same point in adjacent frames remain basically unchanged), spatial consistency (the motion differences between adjacent pixels are small), and so on. These assumptions may not hold true in certain situations, especially in complex scenarios such as occlusion and lighting changes. stay

IV. Other Resources

Calculate the velocity of each pixel in the optical flow field, obtain a threshold by calculating the percentile of velocity, and set the portion of velocity that is less than the threshold to zero to filter out low velocity motion, which is beneficial for removing noise or insignificant motion.

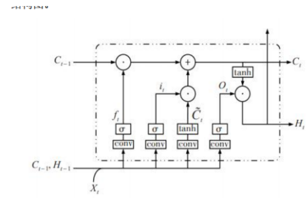

Fig. 3. Internal structure diagram of ConvLSTM loop unit

V. Text

There is a strong spatiotemporal dependence between radar echo image sequences. In order to achieve more accurate forecasting results, it is necessary to consider from the perspective of time series and spatial relationships. Although this article has generated high-quality optical flow fields through wind field dynamic constraint filling optimization algorithms and multi-scale optical flow methods, the theoretical basis of optical flow method is based on the assumption of constant brightness of the same object, which is difficult to fully meet in reality, resulting in optical flow method being unable to predict intensity changes in certain situations. The LSTM neural network model cannot predict position movement, while the ConvLSTM model combines CNN and LSTM, adding convolution operations that can extract spatial features from images on the basis of LSTM. Therefore, ConvLSTM has unique advantages in predicting spatiotemporal sequences of radar echo images. It can establish temporal relationships like LSTM and capture local spatial features like CNN, making the ConvLSTM model more effective in extracting temporal and spatial features. The expression of ConvLSTM can be found in formulas 3.6 to 3.11.

The deep structure of neural networks plays a crucial role in processing complex data, especially in learning deeper abstract features. In order to improve the fitting ability of the model, a multi-layer ConvLSTM structure was introduced. The single-layer ConvLSTM network has certain limitations in learning complex features of spatiotemporal sequences. Therefore, by stacking multiple layers and deepening the network in the time dimension, the model can better capture the subtle changes of spatiotemporal sequences. This hierarchical transmission method enables each layer to more fully consider the information from the previous layer, thereby improving the network's expressive power. The hierarchical structure helps the network better understand and abstract the complex relationships in input data, improving the overall performance of the model. For the extrapolation process, especially when dealing with information such as convergence, divergence, wind field rotation, and position shift in the optical flow field, the network can effectively learn the temporal and spatial evolution characteristics of radar echoes. By using these key factors as predictive factors, the network can more comprehensively capture the spatiotemporal dynamic characteristics of data, thereby improving the accuracy of predicting future moments. The introduction of this deep structure and the mechanism of information hierarchy transmission make neural networks more adaptable to complex environments and tasks, providing powerful tools for spatiotemporal sequence modeling.

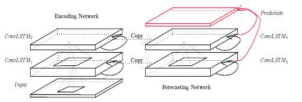

Fig. 4. Internal structure diagram of ConvLSTM loop unit

When solving the problem of radar echo extrapolation, the traditional optical flow method captures motion information at different time points by analyzing the changes in pixel intensity in the image sequence, which is used for precipitation prediction. However, due to the fact that radar data is not limited by the assumption of constant brightness, the optical flow method may produce incorrect motion estimation when processing radar data. To overcome this problem, this experiment adopts a combination of deep learning and optical flow method, which overcomes some limitations of optical flow method in processing radar data by introducing convolutional layers of neural networks. The advantages of convolutional layers in deep learning lie in parameter sharing, local perception, and evaluation invariance. They have significant advantages in feature extraction, especially in helping to capture the spatiotemporal correlation between adjacent frames of radar echo images. This creates conditions for deep learning to achieve better results in the field of radar echo extrapolation. Compared to traditional optical flow methods, deep learning is more adaptable to the particularity of radar data. In the problem of spatiotemporal sequence prediction, the convolutional loop model of deep learning can not only achieve extrapolation results similar to optical flow method, but also be better at capturing spatial information, thereby improving the accuracy of rainfall estimation. Especially by incorporating optical flow information derived from optical flow method into deep learning models, it can further enhance the accuracy of ConvLSTM models in predicting the true movement trajectory of radar echo data. Therefore, combining the advantages of deep learning and optical flow methods can better capture spatiotemporal relationships and improve the accuracy of precipitation prediction. The introduction of optical flow information not only helps to solve the problem of optical flow method in processing non constant brightness data, but also further enhances the model's understanding of real movement trajectories, providing important support for accurate prediction of radar echo data.aspel earcius.

$$x = \sum_{i=0}^{n} 2iQ. \tag{1}$$

Alis nime volorempera perferi sitio denim repudae pre ducilit atatet volecte ssimillorae dolore, ut pel ipsa nonsequiam in re nus maiost et que dolor sunt eturita tibusanis eatent a aut et dio blaudit reptibu scipitem liquia consequodi od unto ipsae. Et enitia vel et experferum quiat harum sa net faccae dolut voloria nem. Bus ut labo. Ita eum repraer rovitia samendit aut et volupta tecupti busant omni quiae porro que nossimodic temquis anto blacita conse nis am, que ereperum eumquam quaescil imenisci quae magnimos recus ilibeaque cum etum iliate prae parumquatemo blaceaquiam quundia dit apienditem rerit re eici quaes eos sinvers pelecabo. Namendignis as exerupit aut magnim ium illabor roratecte plic tem res apiscipsam et vernat untur a deliquaest que non cus eat ea dolupiducim fugiam volum hil ius dolo eaquis sitis aut landesto quo corerest et auditaquas ditae voloribus, qui optaspis exero cusa am, ut plibus.

VI. Some Common Elements

A. Sections and Subsections

Enumeration of section headings is desirable, but not required. When numbered, please be consistent throughout the article, that is, all headings and all levels of section headings in the article should be enumerated. Primary headings are designated with Roman numerals, secondary with capital letters, tertiary with Arabic numbers; and quaternary with lowercase letters. Reference and Acknowledgment headings are unlike all other section headings in text. They are never enumerated. They are simply primary headings without labels, regardless of whether the other headings in the article are enumerated.

B. Citations to the Bibliography

The coding for the citations is made with the LaTeX `\cite` command. This will display as: see [**?**].

C. Lists

In this section, we will consider three types of lists: simple unnumbered, numbered, and bulleted. There have been many options added to IEEEtran to enhance the creation of lists. If your lists are more complex than those shown below, please refer to the original "IEEEtran_HOWTO.pdf" for additional options.

Fig. 2(a) and 2(b) is an example of a double column floating figure using two subfigures. (The subfig.sty package must be loaded for this to work.) The subfigure `\label` commands are set within each subfloat command, and the `\label` for the overall figure must come after `\caption`. `\hfil` is used as a separator to get equal spacing. The combined width of all the parts of the figure should do not exceed the text width or a line break will occur.

Note that often IEEE papers with multi-part figures do not place the labels within the image itself (using the optional argument to `\subfloat[]`), but instead will reference/describe all of them (a), (b), etc., within the main caption. Be aware that for subfig.sty to generate the (a), (b), etc., subfigure labels, the optional argument to `\subfloat` must be present. If a subcaption is not desired, leave its contents blank, e.g.,`\subfloat[]`.

VII. Tables

In this experiment, considering that rainy weather does not occur every day, 30 rainy days were manually selected from the dataset, totaling 7200 radar echo images. 5760 images from the first 24 days of the dataset were used as the training set, and 1440 images from the remaining 6 days were used as the testing set.

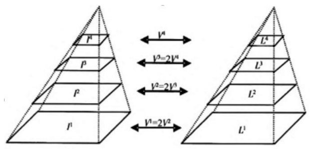

Fig. 5. Enter Caption

TABLE I
AN EXAMPLE OF A TABLE

One	Two
Three	Four

VIII. ALGORITHMS

Algorithms should be numbered and include a short title. They are set off from the text with rules above and below the title and after the last line.

Algorithm 1 Weighted Tanimoto ELM.

TRAIN($\mathbf{XT}$)
  select randomly $W \subset \mathbf{X}$
  $N_{\mathbf{t}} \leftarrow |\{i : \mathbf{t}_i = \mathbf{t}\}|$ **for** $\mathbf{t} = -1, +1$
  $B_i \leftarrow \sqrt{\textsc{max}(N_{-1}, N_{+1})/N_{\mathbf{t}_i}}$ **for** $i = 1, ..., N$
  $\hat{\mathbf{H}} \leftarrow B \cdot (\mathbf{X}^T\mathbf{W})/(\nVdash\mathbf{X} + \nVdash\mathbf{W} - \mathbf{X}^T\mathbf{W})$
  $\beta \leftarrow \left(I/C + \hat{\mathbf{H}}^T\hat{\mathbf{H}}\right)^{-1}(\hat{\mathbf{H}}^T B \cdot \mathbf{T})$
  return $\mathbf{W}, \beta$

PREDICT($\mathbf{X}$)
  $\mathbf{H} \leftarrow (\mathbf{X}^T\mathbf{W})/(\nVdash\mathbf{X} + \nVdash\mathbf{W} - \mathbf{X}^T\mathbf{W})$
  return $\textsc{sign}(\mathbf{H}\beta)$

IX. EXPERIMENTAL EVALUATION STRATEGY

Typographical conventions for mathematical formulas have been developed to **provide uniformity and clarity of presentation across mathematical texts**. This enables the readers of those texts to both understand the author's ideas and to grasp new concepts quickly. While software such as LaTeX and MathType® can produce aesthetically pleasing math when used properly, it is also very easy to misuse the software, potentially resulting in incorrect math display.

A. Display Equations

The simple display equation example shown below uses the "equation" environment. To number the equations, use the

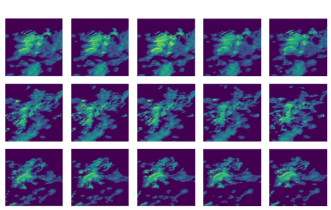

Fig. 6. Partial dataset data

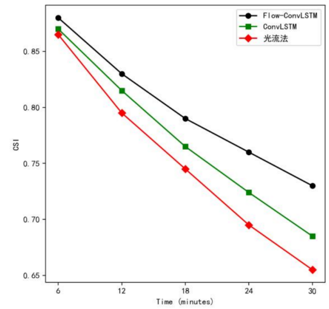

Fig. 7. Enter Caption

`\label` macro to create an identifier for the equation. LaTeX will automatically number the equation for you.

$$x = \sum_{i=0}^{n} 2iQ. \tag{2}$$

is coded as follows:

```
\begin{equation}
\label{deqn_ex1}
x = \sum_{i=0}^{n} 2{i} Q.
\end{equation}
```

To reference this equation in the text use the `\ref` macro. Please see (2)
is coded as follows:

```
Please see (\ref{deqn_ex1})
```

B. Equation Numbering

Consecutive Numbering: Equations within an article are numbered consecutively from the beginning of the article to the end, i.e., (1), (2), (3), (4), (5), etc. Do not use roman numerals or section numbers for equation numbering.
Appendix Equations: The continuation of consecutively numbered equations is best in the Appendix, but numbering as (A1), (A2), etc., is permissible.

Hyphens and Periods: Hyphens and periods should not be used in equation numbers, i.e., use (1a) rather than (1-a) and (2a) rather than (2.a) for subequations. This should be consistent throughout the article.

C. Multi-Line Equations and Alignment

Here we show several examples of multi-line equations and proper alignments.
A single equation that must break over multiple lines due to length with no specific alignment.

X. CONCLUSION

Based on the browser and server architecture, a prototype system for quantitative precipitation estimation was designed and implemented using a front-end and back-end separation design approach. This system integrates a radar echo extrapolation model based on optical flow method and ConvLSTM, as well as a quantitative rainfall estimation model based on multimodal data fusion. Through these models, the system can provide precise predictions of the next half hour rainfall at the current target site. In addition to the core prediction function, the system also implements a series of auxiliary functions, including dynamic data display, backend operation and maintenance personnel information management, log management, etc. This enables backend managers to efficiently understand the current changes in rainfall, take timely protective measures, and have the ability to provide early warning for future emergencies. Through this system, the feasibility of the two models can be verified, and a more comprehensive and efficient solution can be provided for environmental monitoring and prediction.