Spatial Information Research
https://doi.org/10.1007/s41324-023-00532-2

Spatio–temporal attention based real-time environmental monitoring systems for landslide monitoring and prediction

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Received: 16 March 2023 / Revised: 2 June 2023 / Accepted: 8 June 2023

Abstract
Due to their intense concealment and tremendous destructiveness during the course of their lengthy growth, landslides are difficult to monitor. Landslide data gathering exhibits traits such as incomplete local data, unbalanced data sampling, and dynamic changes in monitoring points, which obstructs research on landslide prevention and control and introduces new needs for data collection and analysis. This article proposes a spatiotemporal attention-based Kriging interpolation approach (STAK) based on the conventional Kriging method. Three key sections make up the model: Create a graph and specify the adjacency relationship at various levels, then build a spatial–temporal mask matrix so that the model can incorporate spatial–temporal information, and finally combine ordinary kriging and a multi-head attention network to perform interpolation and correction for missing data. This study compares many frequently used interpolation methods in order to reflect the properties and performance of the STAK model, namely: Ordinary Kriging, KPMF algorithm and kNN algorithm. This methodology has some universality and may be used to tackle any spatiotemporal graph network interpolation problem, such as predicting urban traffic flow. It can also address the issue of incomplete and unequal features brought on by different sensor failures or economic factors.

Keywords Environmental monitoring · Context-aware intelligent landslide data · Spatiotemporal · Discrete multi-head attention · Kriging interpolation method

1 Introduction

A landslide is one of the most common geological disasters in the world. It refers to a natural phenomenon in which rock and soil move integrally along a certain direction under the action of gravityconstruction and other human factors. The first item on our list is an avalanche, which is characterized as any sizable amount of snow that is sliding, falling, or flowing. Given that they can also contain stones and other debris, avalanches might be considered a

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sort of landslide. The term "drought" refers to a prolonged period during which drier-than-normal circumstances cause a shortage of water or other problems with water. Earthquakes, one of nature's most erratic tragedies, happen whenever the tectonic plates of the Earth suddenly and violently move apart. The Earth's surface may shake in a very serious way when these plates abruptly glide past one another. A landslide, according to the USGS, is any significant movement of a mass of rocks or debris down a slope. Landslides are a type of "mass wasting," which is essentially the sliding of soil or rock under the influence of gravity. Unfortunately, landslides may cause a significant amount of damage depending on their magnitude and are relatively common in some regions of the world.Any geological process that causes a downhill motion from a slope of rock, soil, artificial fill, or a mix of the three under the effect of gravity is referred to as a landslide. Erosion, chemical weathering, earthquakes, volcanic activity, and mechanical weathering are a few of the factors that can create landslides. Slides, flows, falls, topples, and lateral spreads are the five basic forms of landslides. The solid components of the slope (such as rocks, debris, or dirt) may slide down a slope or fall over a cliff as a single unit or in several units, depending on the kind of landslide (this occurs in slides, falls, and topples). Alternatively, a mixture of loose soil, rock, air, and water (such as inflows) might flow down the slope like a river.

Landslides can cause traffic jams, damage various buildings, and seriously threaten people's lives and property safety. In China, landslides cause thousands of deaths every year, and direct or indirect economic losses amount to tens of billions. Therefore, preventing and controlling landslides, exploring their causes, and continuously monitoring sensitive areas have attracted widespread attention from academia and industry [1–4].According to the landslide susceptibility assessment concept, a region's susceptibility to landslides may be predicted using the data that is now accessible, including conditional variables and past landslides. These numbers were taken from the inventory of landslides. Landslide susceptibility evaluation has proven useful as a static tool for geographical analysis, but it is devoid of data on the possibility of a landslide occurring in the future. Because of the intricate geodynamic and microphysical processes involved, it is difficult to analyze the aforementioned steps in landslide prevention. Machine learning techniques, which can make judgments based on data, conduct clustering, extract association features, and provide predictions, have recently gained prominence as analytics tools. Machine learning techniques have been effectively applied across several areas to finish certain challenging jobs. Similar to this, the field of landslide prevention has started to utilize the majority of machine learning techniques to precisely, efficiently, and effectively handle issues.

At present, there have been many landslide prediction studies and cases for landslide-sensitive areas, but most of them are very dependent on the knowledge of experts in related fields, using the rich experience of people to analyze and judge various geological indicators and topological structures on the site, and finally get a relatively accurate professional conclusion [4, 5]. To automatically monitor and predict landslides, various machine learning methods have been applied in this field [6, 7]. In landslide research, machine learning techniques handle challenging and nonlinear high-dimensional data sets the best. Among the techniques employed are tree inductions, probabilistic strategies, artificial neural networks (ANN), and support vector machines (SVM). In many geotechnical applications, machine learning and artificial intelligence algorithms have shown to be useful and promising tools. Machine learning techniques are being applied to landslide forecasting to increase model accuracy and, in particular, the adaptability of such models to handle a broad variety of conditioning factors. In the last ten years, land-slide mapping has significantly improved, thanks in large part to machine-learning approaches. Thanks to the Geographic Information System (GIS) with the development of wireless sensor networks, various machine learning methods can obtain enough information to make predictions for landslides. The main methods include but are not limited to Bayesian models, logistic regression, decision trees, random forests, and support vector machines [8–11].

Two optimized landslide susceptibility mapping (LSM) models—logical regression (LR) and random forest (RF) models—are based on the Bayesian approach for hyperparameter optimization. The use of prediction models is crucial for landslide early warning. The Bayesian algorithm is used to optimize the model's parameters to increase its accuracy. Hyperparameter optimization for both models, based on the Bayesian approach, had a significant influence on the models' accuracy; as a result, hyperparameter optimization is crucial for models of LSM. The optimized RF model based on hyperparameter optimization has greater stability and predictive power in the case region, even though both models have acceptable results. The models describing the links between landslide-conditioning variables and landslide incidence are created using a logistic regression model.

The performance of all models was evaluated using pre-existing landslide bodies and the area under the relative operative characteristic (ROC) curve. One of the more established classification techniques is the use of decision trees, which has the advantages of a straightforward model structure, simple understanding, and quick training. One classification and regression tree has limits, and overfitting frequently happens throughout the model training phase, according to practical application. The merging of the Ensemble technique with the decision tree model was created to address the drawbacks of the single decision tree. The two integration techniques now in use, gradient-boosted trees and random forests are based on a decision tree model.

The regression or classification model was created using the RF algorithm, an ensemble learning technique created by merging predictions from decision trees. This approach provides several benefits. It is more frequently applied in multivariate regression or classification techniques, for instance, and no assumptions about the probability distribution of explanatory variables are necessary. Similar to how interactions and non-linearities between variables can be taken into consideration, the combined usage of category and numerical variables is permitted without the use of indicator (or dummy) variables. The RF offers a wide range of outstanding applications in several sectors. It has also had success predicting landslides and pinpointing where they would occur.

A supervised learning technique called an SVM is based on minimizing structural risk and statistical learning theory. The SVM implicitly converts the original input space into a high-dimensional feature space using the training data. The best hyperplane in the attribute space is then found by maximizing the margins of the class borders. By maximizing the space between the separating hyperplane and the data, the SVM aims to reduce the upper bound of the generalization error. Support vectors are the training locations most near the ideal hyperplane. Finding the best-separating hyperplane that can discriminate between the two classes (i.e. landslides and no landslides) is the goal of SVM classification. The training data set is used to do this.

In recent years, deep learning (Deep Learning) has developed rapidly, and some studies have proposed applying deep learning to the geological feature capture of landslides. There are two mainstream solutions, one is to send photos of the mountain surface into the convolution Convolutional Neural Networks (CNNs) use the convolution operation to learn the spatial characteristics of the target [3, 12], but this scheme has two obvious problems: (1) it relies heavily on image pixels; (2) it lacks the accuracy of altitudemodeling. Therefore, another solution uses Graph Neural Networks (GNN), which can use geographical location information of any dimension to represent different monitoring points. By learning the characteristics of graphs such as adjacency matrix to obtain the spatial structure of the target, combined with various time-aware modules to predict the spatiotemporal data such as mountain surface subsidence [13–15], however, most graph neural network research is based on static graphs, which cannot adapt to dynamically changing mountain monitoring data. Spatial, temporal, and spatiotemporal correlations are common characteristics of environmental spatiotemporal data. Identifying these dependencies is a critical effort. Deep Learning (DL) is a promising approach to addressing this challenge, particularly because of its ability to automatically extract features in both the spatial (via Convolution Neural Networks (CNNs)) and temporal domains (via the recurrent structure of Recurrent Neural Networks (RNNs)). Subsidences are primarily caused by various mechanisms, many of which interact with one another, such as aquifer-system compaction caused by natural processes or artificial groundwater extraction for agricultural and industrial uses. Rapid urbanization can impact unconsolidated alluvial or basin-fill aquifer systems in some situations.

In the dynamic graph,there have been some effective methods in the field of problem areas, but there are few studies on graph problems with space–time properties, we will further introduce them in related work [16–20] is widely used in geographic related research, it can provide high-precision surface change point cloud (Point-cloud) data, combined with GNN can realize the extraction of more abundant features of the mountain surface. Mountains are often mapped manually using fieldwork and visual evaluation of topographic maps, that is is a labor-intensive and time-consuming process. Digital elevation models (DEMs) have been used as the input data for extraction procedures as they have progressed from manual to computer-aided to automated approaches in recent years. The dimensionality reduction method, which divides and condenses a starting set of raw data into smaller, easier-to-manage groupings, includes feature extraction. As a result, processing will be simpler. The fact that these enormous data sets contain a lot of different variables is their most crucial feature. Processing these variables takes a lot of computational power. To efficiently reduce the amount of data, feature extraction helps to extract the best feature from such large data sets by selecting and integrating variables into features. These characteristics are simple to use while still accurately and uniquely describing the real data set.

Related research has achieved excellent results [21, 22]. To sum up previous studies, there are several difficulties in landslide prediction: firstly, how to model spatiotemporal features so that the model can simultaneously capture features from two dimensions of time and space; secondly, in actual situations, due to sensor.Due to problems such as failure, thunderstorm interference, cloud cover, etc., the data collection of the target area is often lacking, and this lack is characterized by local aggregation; moreover, due to insufficient funds and other conditions, it is not possible to conduct a sufficiently uniform analysis of the entire area. and sufficient monitoring, resulting in sparse monitoring in some areas and dense monitoring in other areas, which ultimately makes the learning of the model unbalanced; finally, the monitoring area is not static, and will expand or shrink due to changes in terrain., so the corresponding graph (Graph) structure is often dynamic, including but not limited to the addition and reduction of various nodes, and the increase or decrease of connections between nodes. Unbalanced data are those where only a very tiny percentage of one or more categories of samples were included in the initial sample set. In this approach, skewed data is another name for uneven data. Most classes are often referred to be negative classes, while just a few classes are referred to as positive classes. In reality, the data sets are typically quite unbalanced, yet they are frequently more significant than those big class samples. The present methods largely concentrate on building a suitable algorithm to address the disparity of samples within diverse data sets.

The settlement caused by applying stress to a compressible material's surface relies on the material's stiffness and the current boundary conditions. By taking into account the settling of a solid that acts by the theory of elasticity, these effects may be quantitatively studied. Tremors from earthquakes, alter slope equilibrium and raise the possibility of a mass movement, as well as groundwater flow, which places pressure on soil particles and reduces slope stability. Together with meteorological elements like precipitation and frost activity, these slope-affecting forces frequently induce downslope mass flow. Subsidence and settlement are two different terms for sinking mass motions that take place gradually and relatively quickly, respectively. Subsidence is the breakup of a subterranean hollow, such as a cave, or the collapse of the ceiling.

This work differs from earlier research through a number of significant contributions. First, it offers a structure for a graph neural network that combines a spatial–temporal mask matrix with multi-head attention, enabling the modelling of spatiotemporal aspects while also allowing for flexibility to dynamic networks. Second, by combining an attention network with the Kriging interpolation technique, the suggested method addresses the problem of missing and sparse data in landslip prediction. This effectively fills in missing values and creates virtual monitoring points to improve map data and geological features. Additionally, the model can adjust to dynamic graphs as the monitoring region changes thanks to the accessibility sub-graph sampling strategy, producing predictions that are more accurate. Last but not least, the research offers experimental validation utilising high-precision SAR point cloud data, showcasing the effectiveness of the suggested strategy by contrast with current interpolation techniques.

To solve the above problems, this paper proposes a new graph neural network structure in combination with the representative algorithm Ordinary Kriging (OK) [23] for geographic feature interpolation. The contributions of this paper are as follows:

(1) Referring to the existing research [19], the basic graph attention network structure is transformed. By controlling the shape of the Spatio-Temporal mask matrix and the shape of the multi-head attention, the ability to model spatiotemporal features is obtained, and the ability to model spatiotemporal features is obtained. The accessibility sub-graph sampling method makes the model adaptable to dynamic graphs.
(2) Combining the attention network with the Kriging interpolation method enables the model to automatically supplement the missing values of a certain monitoring point, and constructs virtual monitoring points in relatively sparse observation areas to obtain more comprehensive map information and geological features.
(3) A series of high-precision SAR point cloud data were collected from the real geographic location, related experiments were carried out, and the effectiveness of the model was verified in the comparison with the existing interpolation methods.

2 Related work

2.1 Inductive graph neural networks

The existing graph neural network for modeling spatiotemporal data cannot adapt to the dynamically changing graph structure, because the dynamic change of the graph will lead to the global change of the graph in the spectral domain, making the Laplacian matrix of the graph outdated, so it needs to be recalculated. The spatial structure relationship of the graph [13–15, 24, 25]. This kind of model that cannot adapt to the dynamic changes of the graph is called transudative learning (Transudative), otherwise, it is called inductive learning (Inductive). Hamilton et al. [16] in 2017 the inductive neural network based on Graph Convolution Network (GCN) [24] were proposed for the first time in 2010. The network can realize inductive learning through techniques such as sub-graph and mini-batch. Similar studies [17] used The method of graph clustering to make the complete graph be divided into multiple sub-graphs or proposed an unbiased graph sampling for GCN [18], both of which build larger dynamic graphs by training the sub-graphs. Different clustering procedures are employed by algorithms. Divisive or cut-based approaches repeatedly divide a graph into smaller networks until a halting condition is satisfied. Agglomerative techniques begin by isolating each node into a separate cluster, which is subsequently combined. Iterative methods start with some basic clustering, which is then refined with minor adjustments like moving a single node across clusters. A seed node is chosen for graph building or seed expansion, which then uses methods like best-first search to progressively expand a cluster. Another large class of inductive graph networks is a model based on the attention mechanism [19]. Some studies [20] propose an inductive graph attention network, which enables the model to adapt to dynamic dynamics by controlling the scope of attention and the number of neighbors of nodeschanging graphs. The attention mechanism is not limited to natural language processing and image fields and is widely used in graph networks. It has an excellent performance in graph problems with spatiotemporal properties such as human action detection and video processing [26, 27].

2.2 Ordinary kriging and other interpolation algorithms

The kriging method is based on such a simple intuition: similar nodes have similar features, so the target position can be filled with features based on the information around the target position. The ordinary Kriging method considers the physical distance of two points and the similarity of features there is a certain functional relationship between degrees, and the unbiased estimator of the target can be obtained by fitting the objective function [28]. There are many strong assumptions about node characteristics in Ordinary Kriging, to get a better it is estimated that many studies have proposed Kriging variants based on the same idea, such as Universal Kriging, Co-Kriging, etc. [23].

On the other hand, some studies have combined neural networks and traditional Kriging methods, which have enhanced traditional methods from multiple perspectives. This paper [29] used Kriging methods to perceive space and neural networks to perceive time, to obtain a model of spatial–temporal data perception. This research article [28] used a deep neural network to generate weight coefficients to achieve super-resolution of images. This research [27] used diffusion map convolution technology to enhance the spatial complex feature. The ability to capture, and spread to the time dimension. Scale-dependent (it changes depending on the degree of generalization at which it is evaluated) and perception-dependent are all terms used to describe spatial complexity. Superficial ground characteristics make up geographical features spatially. It is made up of several ground features. Convolutional Neural Networks (CNNs) produce feature representations of complicated objects by gathering hierarchical and various semantic sub-features. These sub-features, which represent distinct semantic items, may often be delivered in a grouped form in the feature vector of each layer. However, identical patterns and noisy backgrounds frequently alter how these sub-features are activated spatially, leading to inaccurate localization and identification. Each semantic group may independently improve its learned expression and reduce potential noise thanks to the Spatial Group-wise Enhance (SGE) module, which can alter the relevance of each sub-feature by creating an attention factor for each spatial position. The resemblances between the local and global feature descriptors within each group serve as the only basis for the attention factors, making the SGE module's design incredibly simple with few additional parameters and computations.

In addition to the classic Kriging method and its variants, there are some traditional algorithms applied to the interpolation problem. The k-Nearest Neighbors (kNN) method first finds the k-nearest neighbors, and then directly takes the average as a supplement to the target position. Kernelized Probabilistic Matrix Factorization (KPMF) includes the kernel information of the graph in the matrix decomposition technology through the Laplacian kernel and can gather the spatial features to the target position for interpolation [26].

However, the existing methods do not simultaneously capture the spatiotemporal attributes of features, do not establish a Spatio-Temporal integrated perception system, and cannot be adapted to the learning of dynamic graphs. Therefore, this paper proposes a Kriging variant using attentional neural networks. This method can model the interdependence of spatiotemporal features for dynamically changing graphs with any missing values, to realize spatiotemporal interpolation, improve the original data information, and provide more complete information for subsequent data mining.

3 Spatio-temporal attention G-kriging interpolation method

Based on the ordinary Kriging method, this paper proposes a Kriging interpolation method based on spatiotemporal attention (Spatio-Temporal Attention-based Kriging, STAK). The model framework is shown in Fig. 1. The model is mainly divided into three parts: Construct a graph and define the adjacency relationship at different levels; secondly, construct a Spatio-Temporal mask matrix so that the model can capture Spatio-Temporal information; finally, combine Ordinary Kriging and Multi-Head Attention (Multi-Head Attention) network, and correct missing data Perform interpolation and correction.Ordinary Kriging is a dependable estimate technique that uses a continuous model of spatial randomness for data interpolation. It has the advantages of unbiased estimation and minimal estimation error variance. Although the spatiotemporal Kriging approach for interpolating missing data completely takes into account the spatiotemporal correlations of monitoring sites, there are still problems with variogram models, parameter estimation, and a lengthy spatiotemporal modeling process. The standard spatial Kriging approach is mostly based on structural analysis and correlation theories of variation functions. It does a linear unbiased optimum estimate for the values of unsampled points using a small number of variables that represent known monitoring point data. By completely accounting for the geographical and temporal importance of monitoring sites, the

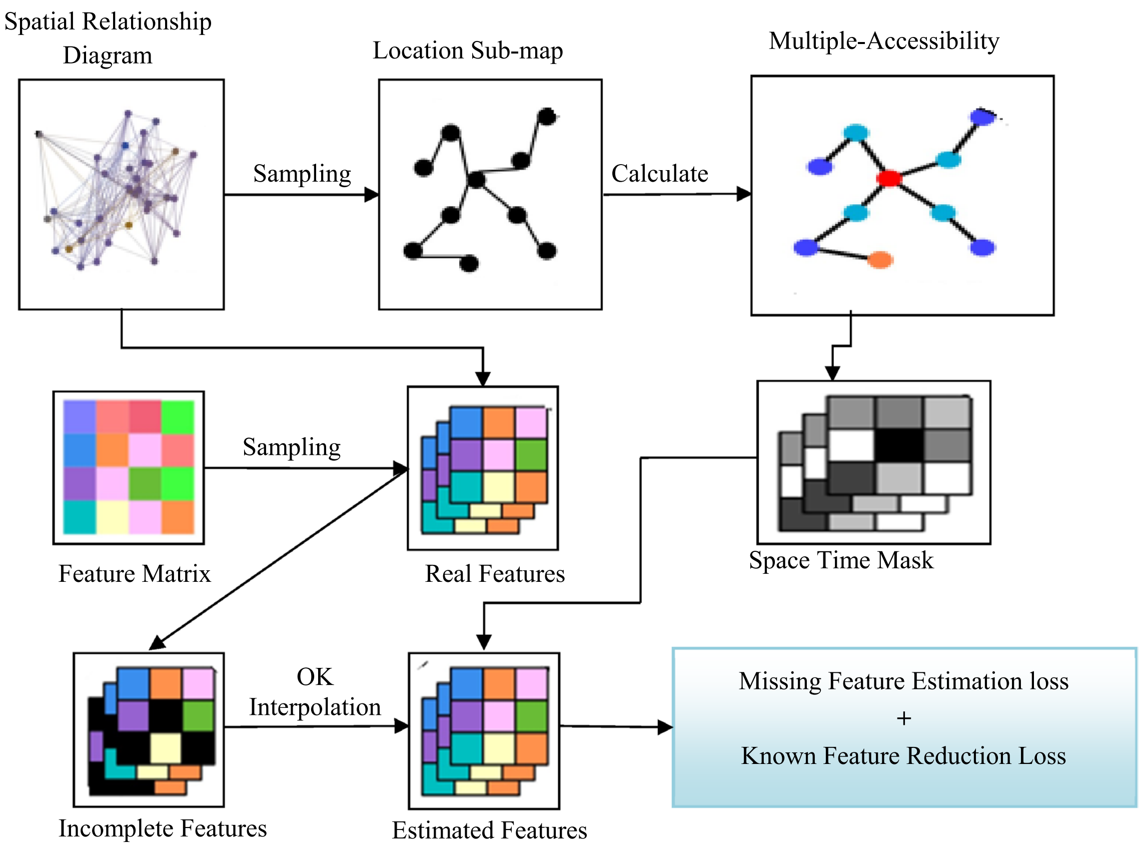


Fig. 1 Architecture of STAK

spatiotemporal Kriging interpolation stretches data from the spatial to the spatiotemporal domain. It is necessary to get the estimated values of the unknown points before beginning the spatiotemporal Kriging interpolation procedure.

3.1 Problem description and graph creation

To better describe the geological interpolation problem, without loss of generality, point cloud data is used to define N geographic location vectors z as the unique identifiers of landslide monitoring points. This location vector is generally 3-dimensional and consists of a matrix $Z \in \mathbb{R}^{N\times 3}$. Each position has a set of mountain surface settlement records corresponding to the position. The monitoring duration is T, and the feature vector is q, which forms a feature matrix $\widetilde{Q} \in \mathbb{R}^{N\times T}$. To divided into two parts: one part is marked as missing, which is recorded as Q_{miss}. If there is no additional explanation in the following, the rest represents no missing features, which is recorded as Q, and there is $\widetilde{Q} = Q + Q_{miss}$. Assume that there is incompleteness at z_i the eigenvector qi of the neighbor node is recorded as $N(z_i)$. If there are enough neighbor nodes, q_i can be supplemented by the corresponding features of the neighbor node $z_j \in N(z_i)$. The geological interpolation problem can be generally described as is: according to the known feature Q and position information Z, estimate the missing feature Q_{miss} and all features.

In this paper, a multi-head attention network is used to represent the complex spatiotemporal relationship of different distances. To use the powerful analysis ability of the graph neural network to the graph structure, it is first necessary to define a graph structure. Each point in the graph does not need to be connected to all other points, whichis to maintain a certain degree of sparsity, because each point should only interact with the nearest node, and does not need and cannot be connected with distant nodes. Therefore, first, construct a fully connected adjacency matrix A, and then define A threshold ε, all edges higher than this distance threshold are cut off, and those within the threshold are considered as 1-hop (1-hop) neighbors, that is: if$\|z_i - z_j\|2 \leq \varepsilon$, then$A_{(i,j)} = 1$, which means that there is an edge eij between the nodes z_i and z_j in the graph. The $\|\|_2$ operations here and in the following, all represent the L2 norm (Norm), also known as the Euclidean norm (Euclidean Norm). For any the vector x has $\|x\|_2 = \sqrt[2]{x_1^2 + \cdots + x_n^2}$. After finishing the operation of clipping edges, a graph $g(Z, E)$ is obtained.

After constructing the basic graph multiple accessibilities can be defined,the reachability matrix is represented by A^h, and each point can be connected with neighbors of h hops. Under the specification of multiple accessibilities, this paper uses different attention heads Neighbors with different reachability levels are learned so that the attention network can capture a richer spatial dependency. It should be noted that the same reachability matrix can be paid as much attention as possible when the computing power is satisfiedin Litou's study to ensure a more stable effect.

3.2 Build a spatio-temporal mask matrix

In the field of natural language processing, the position encoding and mask matrix used by attention have only one dimension [19]. In the context of this paper, position encoding exists naturally, but the mask matrix has two dimensions, namely time and space. We design a Spatio-Temporal mask matrix, so that the attention network can assign different weights to nodes in different spatiotemporal positions, and then realize the capture of spatiotemporal features. If there is no additional description, the subsequent model descriptions are based on an attention head Above For the two nodes whose spatial position and temporal position are respectively at (z_i, t_i) and (z_j, t_j), construct the space–time mask of the corresponding position as follows:

$$\boldsymbol{M}_{z_i,t_i,z_j,t_j} = 1\ if\left\{z_j \epsilon N\left(z_i\right)\right\} \wedge \left\{t_j < t_i\right\} \ldots \quad (1)$$

Among them, $M \in \mathbb{R}^{NT \times NT}$. If $A^h_{(\mathrm{i,j})} = 1$, then z_j is considered to be the neighbor of z_i, that is, $z_j \in N(z_i)$. In the Spatio-Temporal mask matrix, some node features marked as 1 are can be perceived, others will be ignored. In different attention heads, using different accessibility matrices will result in different spatiotemporal mask matrices, so the model can model Spatio-Temporal features at different levels.

Since there are missing values in the data, even with interpolation, we cannot consider this non-real data to be reliable. Therefore, for missing values, we need to further correct their masks. Two types of missing values are defined: One is the missing records that cause observation failure due to special circumstances; the other is the missing records that do not observe some positions due to cost and other reasons. For the latter case, directly define a position vector z that needs to be supplemented to solve the problem Unified as missing values at a certain observation point. These missing features will first be filled with ordinary kriging, and then corrected with the attention network. The specific steps will be described later. To represent this missing, the mask matrix marks the dependence position of other points on missing points as the $\delta \in [0, 1]$, so that other points can reduce their dependence on missing point features in subsequent corrections. The calculation method is as follows:

$$\boldsymbol{M}_{z_i,t_i,z_j,t_j} = \delta, if\ Q_{(j,t_j)}\ is\ not\ complete \ldots \quad (2)$$

It is worth noting that δ is not a hyper-parameter, but a parameter that can be learned, which depends on the contribution of the ordinary kriging method to the final filling effect. Generally, a fixed initial value $\delta = 0.5$ can be set, the closer the learned δ is to 1, the better the effect of Ordinary Kriging.

3.3 Spatial interpolation based on multi-head spatio-temporal attention

The use of multiple accessibility matrices and the spatiotemporal mask matrix are defined above, and the main part of the model is introduced below: the spatiotemporal interpolation method based on multi-head attention. To realize inductive learning, refer to the existing research [16], the model it does not learn directly from $g(Z, E)$, but learns the features on a subgraph sub. Due to the local characteristics of the spatiotemporal mask matrix, the design of this paper cannot understand the spatial structure of the graph from a global perspective. This feature is exactly in line with the graph attention network.

We design a sub-graph interception method based on the accessibility. Using the space–time mask matrix defined above, we can allocate attention to the local part of the graph and train on this sub-graph. Constructing an adjacency matrix is the first step in saving a graph as a memory representation in a computer. Assume that our network has n vertices, each one numbered from 1 to n. A binary matrix of dimension n × n is referred to as an adjacency matrix. Each cell in the matrix has a potential value of either 0 or 1. Let's assume that there is an edge connecting vertices v_i and v_j. It signifies that in this matrix, the value in the ith row and jth column is equal to 1. Importantly, the matrix is symmetric if the graph is undirected. The construction of such a matrix has a temporal complexity of $O(n^2)$, assuming the graph has n vertices. Additionally, the space complexity is also $O(n^2)$. To generate the adjacency matrix for a given graph, we need to make a square n × n matrix and fill its values with 0 and 1. We pay $O(n^2)$ space for it. We must determine if there is an edge between each pair of vertices (v_i, v_j) to populate every value of the matrix. Because of this, the matrix construction has an $O(n^2)$ time complexity. Define the maximum possible reachability H, and use A^H to cut the nodes of $g(Z, E)$. Since the vacant values have the characteristics of clustering appearance, a group of positions Z_{miss} and the corresponding sub-graph g_{sub} that need to be filled are discussed later. For a group that needs the filled position Z_{miss} is:

$$z_j \in g_{sub} if \left\{z_i \in Z_{miss}\right\} \wedge \left\{A^H_{(i,j)} = 1\right\} \ldots \quad (3)$$

After constructing all sub-graphs, count the maximum number of nodes contained in the sub-graph, which is recorded as N′, as the unified input size of the graph attention network. For sub-graphs with nodes less than N′, additional nodes are added without changing the Each sub-graph has a set of corresponding sub-adjacency matrices $\{A^h_{sub}\}_{h=1}^{H}$ with a size of $N\prime \times N\prime$, which are used to construct different spatiotemporal mask matrices.

Ordinary Kriging method is used for the initial interpolation of Z_{miss}, the purpose is to enable the self-attention neural network to obtain the reference information of the missing position, and on this basis, use the feature attention of the surrounding area to correct the reference value, to achieve better the interpolation effect ofrecord $\overset{\vee}{\underset{i}{q}}$ as the estimated value of the target point. According to the uniform assumption of the characteristic attribute q of the ordinary kriging method, there is an expectation $E[q] = c$ and a variance $Var[q] = \sigma^2$, so it can be deduced Draw the following conclusions:

$$E\left[\overset{\vee}{q}_i - q_i\right] = E\left[\sum_{j=1}^{n} \lambda_j q_j - q_i\right] = c\sum_{j=1}^{n} \lambda_j - c \ldots \tag{4}$$

Finally, a multi-head attention model is constructed, and the benchmark estimation obtained earlier is corrected by using the spatiotemporal mask matrix, as shown in Fig. 2.

Each attention head is calculated as follows:

$$Head\left(\overline{Q}_i, W, V, h\right) = softmax\left(\frac{\overline{Q}W^T}{\sqrt{NT}} \odot M^h\right)V \ldots \tag{5}$$

Among them, ⊙ is the Hadamard Product of the matrix, that is, the multiplication of the corresponding position elements, $\overline{Q}$, W and V are the queries (Queries), keys (Keys) and value (Values) matrix respectively, and are composed of $\overline{Q}$ Initialize, h represents the reachability order used by this attention head. Finally, we stitch all the heads together and correct the baseline estimate.

$$MultiHead\left(\overline{Q}_i, W, V, h\right) = concat\left(Head_1, Head_2. \cdots\right)\phi \ldots \tag{6}$$

ϕ is the parameter of the trainable fully connected (Fully Connected) network used to fuse the attention heads together, and can control the shape of the final output $\overline{Q}$. This structure can be repeated three times to output $\overline{Q}$, which contains the feature estimation of all points. Calculating the loss needs to balance the restoration accuracy of known features and unknown features. Completely ignoring the restoration ability of known features will lead to a decrease in the generalization ability of the model, but considering the two losses equally will lead to the attention to the target position decreases., so the loss function is defined as follows:

$$Loss = \sum_{graphs} \left(\|\overline{Q}_{miss} - Q_{miss}\|_2^2 + \gamma \|\overline{Q} - Q\|_2^2 \right) \ldots \tag{7}$$

Among them, γ is a hyper-parameter to adjust the two losses,In a region sub, the missing part Z_{miss} is a minority, so it can be approximately understood that formula (7) is the recovery loss of points without missing features. The overall description of the algorithm is as in Algorithm 1.

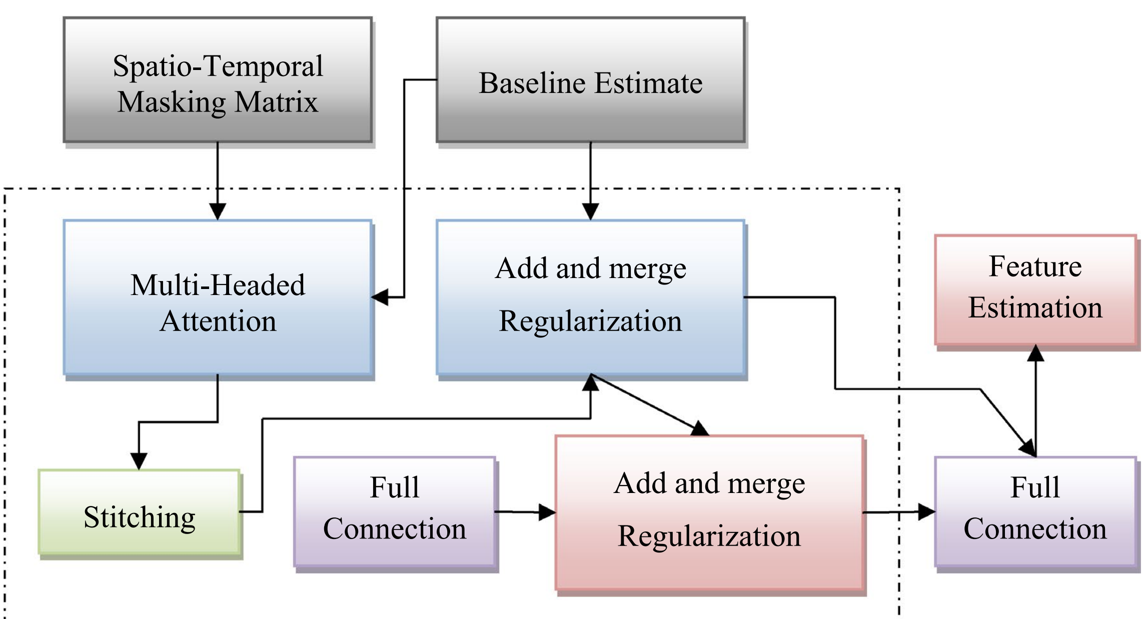


Fig. 2 Spatio temporal multi-headed attention

Algorithm 1: Spatiotemporal Attention Kriging Interpolation Method
Inputs: Geographic Location **Z**, Feature Matrix **Q**, Missing Markers Z_{miss} and Q_{miss} , Clipping Threshold **ε**, Maximum Reachability **H**, Loss Tuning Parameter**γ**;
Output: Training Parameters ϕ;
$Step$ 1: $for\ i \leftarrow 1\ to\ N\ do$;
$for\ j \leftarrow 1\ to\ N\ do$;
$if\ \left(\|z_i - z_j\|_2 \le \varepsilon\right) A_{(i,j)} = 1$;
$Step$ 2: $Calculate\ \{A^h\}_{h=1}^{H}, based\ on\ A^H\ random\ sampling\ subgraph\ \{A_{sub}^h\}_{h=1}^{H}$;
$Step$ 3: $for\ h \leftarrow 1\ to\ H\ do$
$Calculate\ M\ according\ to\ formula\ (1)\ and\ formula\ (2)$;
$Calculate\ the\ benchmark\ \tilde{Q}\ according\ to\ the\ Kriging\ method[24]$;
$Initialize\ \bar{Q}\ , W\ and\ V\ with\ \tilde{Q}, compute\ Head(\bar{Q}\ , W, V, h)$;
$Calculate\ \breve{Q} = MultiHead(\bar{Q}, W, V, h)$;
$Step$ 4: $Calculate\ Loss, and\ use\ the\ gradient\ descent\ method\ to\ optimize\ the\ parameter\ \phi$;
$Step$ 5: $Repeat\ steps\ 2-4\ until\ convergence.$

4 Experiment

4.1 Dataset construction

The data set in this paper is taken from the hillside near the Houziyan Hydropower Station on the Dadu River at the junction of Danba County and Kangding City, Ganzi Tibetan Autonomous Prefecture, Sichuan. The surface subsidence point cloud data of the target area lasted for 8 months, and each time was one week apart. There were 4569 monitoring points on the west bank of the Dadu River and 2164 monitoring points on the east bank. Each time the subsidence data ranged from -29.06 mm to 30.05 mm. Figure 3 shows the point cloud view of the data set (see Fig. 3a) and the feature view of the West Bank at a certain time point (see Fig. 3b–d). From In the feature view, it can be seen that the subsidence features have continuity in the spatial dimension, that is, dark and dark points are clustered. Comparing Fig. 3b, c and d, it can be found that The features in the time dimension also have continuity. This dual continuity observation of time and space is the motivation for STAK to analyze time and space at the same time.

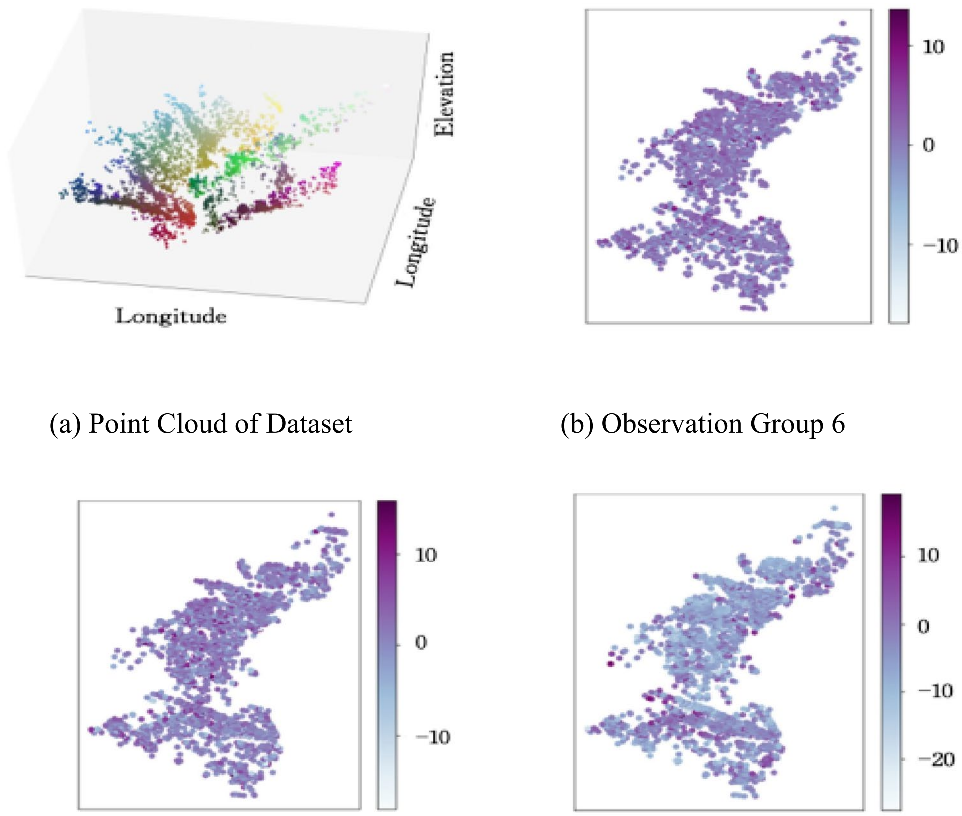
To test the recovery effect of STAK on missing values, we marked some features as missing values from the complete data set, and then used these values for comparison. In this paper, three different missing value construction schemes were designed to test the interpolation algorithm: (1) For the incomplete data, we assume that the missing positions are distributed in a local concentration, and the number of feature vacancies in each incomplete position is less than or equal to 5; the rest of the positions are all intact; (3) For the compound problem, we have the combined data of the above two cases. The number of missing values in the three cases is the same, accounting for 10% of the total. It can reflect the interpolation performance of STAK and apply it to real interpolation problems. To prevent overfitting on the same sub-graph, we randomly split different combinations of missing sub-graphs into two parts, 70% of which are used as training sets, and the remaining 30% is used as the test set, and the average value of 10 experiments is taken as the result shown in this paper.

4.2 Experiment settings

To reflect the characteristics and performance of the STAK model, several widely used interpolation methods are compared in this paper, namely: (1) Ordinary Kriging (OK), which has been tested in geological interpolation problems; (2) KPMF algorithm, the traditional graph processing algorithm uses matrix decomposition technology to gather the features of the graph, and then performs interpolation; (3) kNN, finds the nearest k nodes in the Euclidean space around the target position, and then through them features are averaged to obtain predictions.

To learn the dynamic graph structure, STAK needs to learn from sub-graphs. To maintain fairness, similar sub-graphs are used for other comparison algorithms. There are a total of 100 sub-graphs. STAK uses a maximum of 3-order

Fig. 3 Monitoring area point cloud view and feature view



(a) Point Cloud of Dataset (b) Observation Group 6

(c) Observation Group 7 (d) Observation Group 19

Table 1 Interpolation performance comparison of different models

Algorithms	RMSE	MAE	ACC	R^2
KPMF	0.125	0.093	0.854	0.243
kNN	0.109	0.071	0.931	0.586
OK	0.096	0.065	0.947	0.636
STAK(1)	0.072	0.050	0.978	0.763
STAK(2)	0.091	0.063	0.952	0.662
STAK(3)	0.087	0.060	0.957	0.689

accessibility matrix, namely A3. For the 1st, 2nd, and 3rd-order accessibility matrices, 5, 4, and 3 attention heads are used for learning. In multi-head attention, threeSpatio-Temporal attention layers are used inside the force, as shown in Fig. 2. When constructing a map from point cloud data, let ε = 200. The initialization of the Spatio-Temporal mask matrix is $\delta = 0.5$, and the lost weight is reconstructed without missing values $\gamma = 0.5$. Finally, the initial learning rate is set to 0.002, and the learning rate is adjusted to 0 after every 100 rounds of training. 8. The loss will stop after 20 rounds without decreasing, and the parameters corresponding to the optimal loss in the entire training are used for testing. For the kNN algorithm, we use K = 100 for calculation.

4.3 Performance comparison and results analysis

This paper uses root mean square error (Root Mean Square Error, RMSE), mean absolute error (Mean Absolute Error, MAE), accuracy (Accuracy, ACC), and determination coefficient (Coefficient of Determination, R2) to measure the level of interpolation performance. The smaller the RMSE and MAE, the closer the ACC and R2 are to 1, and the better the interpolation performance.

Table 1 lists the interpolation performance comparison of four different types of models, where the best results are represented by bold fonts. Overall, KPMF has the worst performance, kNN is slightly worse than OK, and STAK is generally better than other models. In the experiments in this paper, except for STAK, the performance of other algorithms in different scenarios is very close. This is because other algorithms always only consider spatial features, resulting in three scenes with similar problem structures in terms of space, so in the table,there are no three different situations. The effect of STAK in scenario 1 is better than that in scenario 2, and the performance in scenario 3 is relatively balanced. This is because, in scenario 1 and scenario 3, STAK can be estimated using historical data, this makes the feature estimation have continuity in time. This is intuitively true because surface subsidence is always continuous and does not change abruptly. The comparison of the three missing scenarios proves the effectiveness of the strategy for estimating features, this point of view will be further verified in the follow-up case analysis.

The comparison between STAK and OK can be regarded as a correction effect ablation experiment of Spatio-Temporal attention. It can be seen from the table that the performance of STAK is better than that of OK, and the improvement effect of Spatio-Temporal attention in scenario 1 is better than that in scenario 2 and scenario 3., the reason is: in Scenario 1, STAK can rely on the historical data of missing locations to estimate Spatio-Temporal dependence; while in Scenario 2, STAK, like OK, can only be predicted by spatial features. We can draw the following conclusions: Spatio-Temporal attention to the force can effectively improve the effect of the OK algorithm, and the perception of the time dimension can significantly improve the effect of the interpolation algorithm. In addition, the final learning results of the δ parameter in the mask matrix are all around 0.7 in the three scenarios, which shows that STAK has an important effect on the interpolation algorithm. The effect of OK has improved to a certain extent.

When calculating the accuracy, we set that the prediction is correct when the absolute error is less than 1. To describe the accuracy of different methods more intuitively, we counted the overall errors predicted by each algorithm in missing scenario 3, as shown in Fig. 4. It can be seen from the figure that STAK is at 0. 3 The error level has obvious advantages over other methods. In high-precision prediction, kNN performs very poorly, because kNN predicts by calculating the average value, which depends heavily on the uniformity of the surrounding points of the estimated position. Susceptible to extreme changes in the characteristics of a neighbor, which leads to a rapid decline in estimation accuracy, especially in steeper domains and areas with uneven sampling.OK uses high-order linear simulation to overcome this problem to a certain extent, but the flexibility of linear solutions accuracy is insufficient, so STAK is used to correct it through the attention network, so it is significantly improved compared to OK.

Different feature missing rates have a very direct impact on the effects of different algorithms. Taking accuracy as the evaluation standard, as the missing rate increases from 5 to 10% and 20%, the interpolation effects of all algorithms decline to vary degrees. As shown in Fig. 5. Among them,

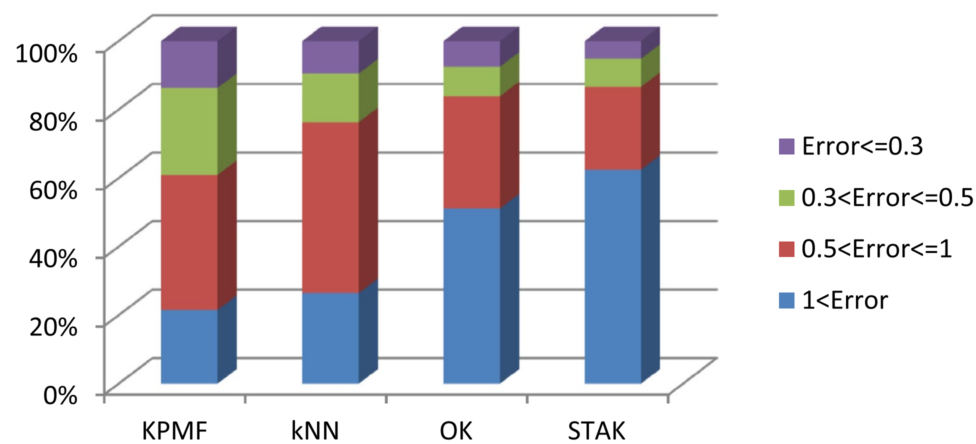


Fig. 4 Estimation error distributions

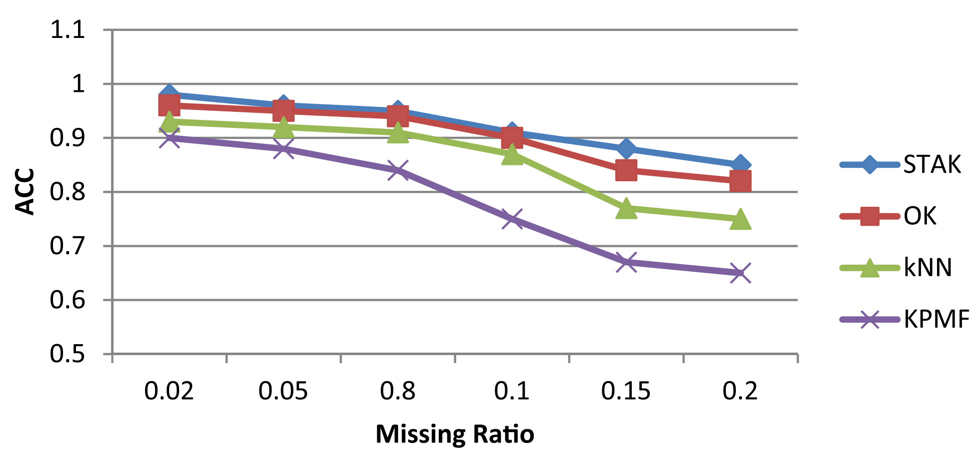


Fig. 5 Impact of missing ratio on performance

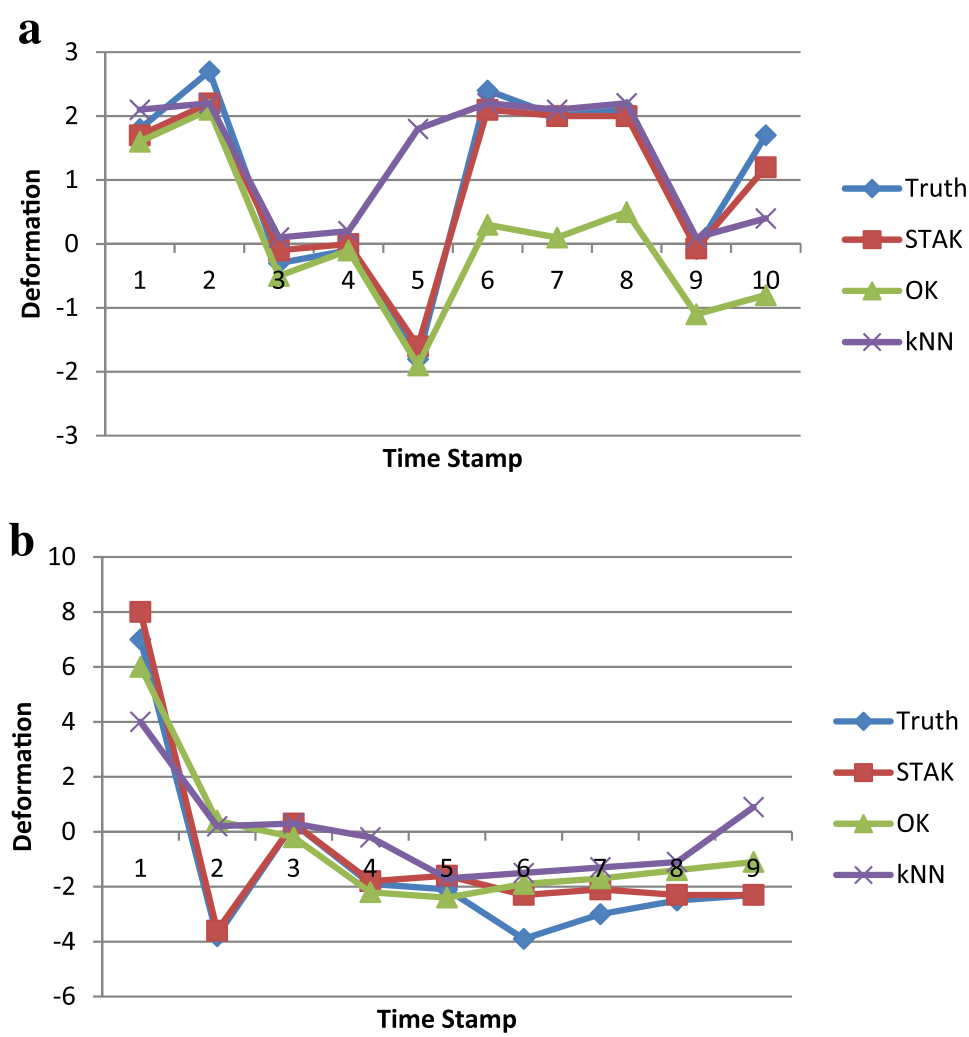


Fig. 6 **a** Interpolation of location 1. **b** Interpolation of location 2

STAK has the smallest decline, compared with kNN and KPMF, the decline is very large, which shows that STAK has the best performance on the sensitivity of the missing degree, and can be adapted to the interpolation of different missing degreesproblem, and consistently outperforms other methods.

Finally, the interpolation performance of each algorithm is visualized from two perspectives of time and space.The first is the time dimension. Randomly select 10 historical

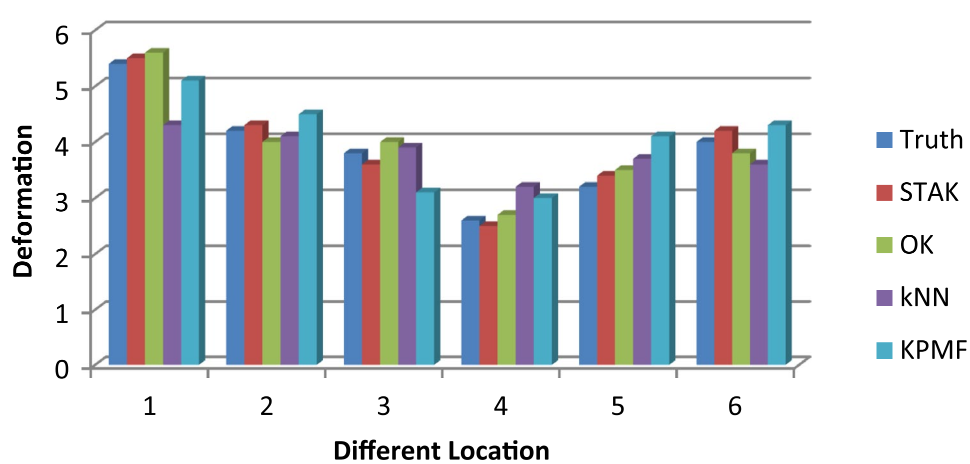


Fig. 7 Visualization of spatial dimension interpolation effect

characteristic data of two monitoring points with different deformation variables, divide them into two times, and process 5 missing data each time, then estimate the missing data and organize them together. To avoid cluttered lines, the interpolation result of KPMF is removed here. It can be seen from Fig. 6 that STAK is closest to the trend of real features, and the overall degree of deviation is the smallest. In addition, other algorithms can only rely on the characteristics of neighbor nodes to maintain the coherence of the time dimension. STAK directly perceives the characteristics of different times. We believe that this ability enables STAK to better maintain the smoothness of the time dimension, which is more in line with the gradient property of the slope deformation interpolation problem.

Secondly, this paper selects 6 adjacent positions at a certain time, and visualizes the interpolation effect from a spatial perspective, as shown in Fig. 7. It can be seen that KPMF is the worst overall, and STAK and OK have always maintained relatively good characteristics. At the same time, STAK maintains its superiority over OK. kNN presents the characteristics that the features at the 5 positions are very close because kNN considers a large number of surrounding neighbor features equally but at 3 and 4 such relatively It is difficult for kNN to obtain a better estimate of the target feature from the neighbor features. On the contrary, OK and STAK do not refer to the neighbor nodes equally, so they can get more accurate results.

5 Conclusion

This paper proposes a Kriging interpolation method based on spatiotemporal attention. This algorithm can effectively capture Spatio-Temporal features by using a Spatio-Temporal mask matrix, and use a multi-head attention mechanism to learn spatial features at different levels, and finally obtain interpolation results. By comparing with several other interpolation algorithms on the real ground data set, the effectiveness of the algorithm in this paper is verified from the overall performance and case analysis, and it is proved that time and space can be learned simultaneously in the slope deformation interpolation problem. This idea can be applied to the deformation interpolation problem of landslides. This framework has certain universality, and is also applicable to any graph network interpolation problem with spatiotemporal attributes, such as urban traffic flow prediction; It can also solve the problem of incomplete and uneven features caused by various sensor failures or economic reasons. In future work, not limited to using the powerful feature learning ability of neural networks, we consider mining more features for feature estimation and interpolating valuable deep features, further studying the inherent laws of geological data and explicitly analyzing and learning, to enhance the interpretability and interpolation effect of the model. In addition, the lack of features in real situations is often more serious than in the experiments we designed. Complicated, for example, missing values will appear in large numbers or evenly distributed on each monitoring point, we will study how to design a missing algorithm that is closer to reality to further improve the practicability of the auxiliary interpolation algorithm.

Funding This research work is self-funded.

Data availability Data shall be made available on request from the corresponding author.

Declarations

Conflict of interest The authors declare no conflicts of interest. Also, no human or animal participation is involved in this research.

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Spatio–temporal attention based real-time environmental monitoring systems for landslide monitoring and prediction

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Abstract

Due to their intense concealment and tremendous destructiveness during the course of their lengthy growth, landslides are difficult to monitor. Landslide data gathering exhibits traits such as incomplete local data, unbalanced data sampling, and dynamic changes in monitoring points, which obstructs research on landslide prevention and control and introduces new needs for data collection and analysis. This article proposes a spatiotemporal attention-based Kriging interpolation approach (STAK) based on the conventional Kriging method. Three key sections make up the model: Create a graph and specify the adjacency relationship at various levels, then build a spatial–temporal mask matrix so that the model can incorporate spatial–temporal information, and finally combine ordinary kriging and a multi-head attention network to perform interpolation and correction for missing data. This study compares many frequently used interpolation methods in order to reflect the properties and performance of the STAK model, namely: Ordinary Kriging, KPMF algorithm and kNN algorithm. This methodology has some universality and may be used to tackle any spatiotemporal graph network interpolation problem, such as predicting urban traffic flow. It can also address the issue of incomplete and unequal features brought on by different sensor failures or economic factors. © 2023, The Author(s), under exclusive licence to Korea Spatial Information Society.

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Author keywords

Context-aware intelligent landslide data; Discrete multi-head attention; Environmental monitoring; Kriging interpolation method; Spatiotemporal

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Published: 26 June 2023

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Data availability

Data shall be made available on request from the corresponding author.

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Funding

This research work is self-funded.

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Ethics declarations

Conflict of interest

The authors declare no conflicts of interest. Also, no human or animal participation is involved in this research.

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to me

Thu, Jun 1, 12:00 AM

You are being carbon copied ("cc:'d") on an e-mail "To" "VIJAY SEKHAR BABU MANCHILI" mvijaysekhar.rs@andhrauniversity.edu.in
CC: shabaz.cse@mietjammu.in, "N. Ashok kumar" ashoknoc@gmail.com, "Anjali Joshi" anjali.joshi@mmit.edu.in, "Pallavi Sagar Deshpande" pallavisd@rediffmail.com, "Ismail Keshta" imohamed@mcst.edu.sa, "Renato R. Maaliw III" rmaaliw@slsu.edu.ph

Dear Dr Maaliw,

We have received the reports from our advisors on your manuscript, 'Spatio-Temporal Attention Based Real-Time Environmental Monitoring Systems for Land Deformation', which you submitted to Spatial Information Research.

Based on the advice received, I have decided that your manuscript could be reconsidered for publication should you be prepared to incorporate major revisions. When preparing your revised manuscript, you are asked to carefully consider the reviewer comments which can be found below, and submit a list of responses to the comments. You are kindly requested to also check the website for possible reviewer attachment(s).

Please submit your revised manuscript online by using the Editorial Manager system.

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We look forward to receiving your revised manuscript before 15 Jul 2023.

Thank you very much.

With kind regards,
Jung-Sup Um, PhD
Editor in Chief
Spatial Information Research

Comments to the author (if any):
What differentiates this paper from previous studies is land deformation.

The content of the paper does not match with the title

The first word of the title needs to be capitalised, while the remaining letters in lowercase.

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