Multi-modal Landslide Monitoring Data Fusion Algorithm Based on Resistivity Imaging

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2 Resistivity Imaging

3 **Abstract** In the process of landslide deformation monitoring, the indicators of monitoring system based on surface
4 displacement cannot accurately reflect the deformation evolution law of deep geotechnical body. Although the joint
5 time curve of deep displacement monitoring of borehole and related monitoring data can reflect the deformation
6 characteristics inside the slope body, it cannot spatially describe and explain the overall deformation process of
7 geotechnical body completely due to the limitation of technical conditions such as borehole. In this paper, using the
8 characteristics of resistivity imaging technology with fast and accurate collection of electrical information of
9 subsurface medium and multi-dimensional imaging, we take resistivity imaging data as complete modal data and
10 fuse deep displacement and groundwater level and other modal data. Through joint depth matrix decomposition and
11 optimization, layer-by-layer modal semantic matching and updating, the distribution and representation differences
12 of modal data are compensated, and the analysis tasks such as classification and clustering of incomplete
13 multimodal data are completed, and the inversion results of resistivity data are updated according to the output
14 modal shared eigenvalues to realize effective multidimensional imaging monitoring of the internal deformation
15 process of landslide geological bodies.

16 **Keywords** Landslide monitoring·Multimodal data fusion·Resistivity imaging·Deep semantic matching

17 1 Introduction

18 Landslide geological hazards are complex physical systems with a long time evolutionary process (Xu et al.
19 2008). Studied in the direction of evolutionary mechanism, landslides are the result of the joint action of
20 fundamental, action and coupled fields generated by the structural, seepage, stress, chemical and temperature fields
21 of the geological body (Fan. 2015; Sun et al. 2017). Monitoring of landslide evolution process includes deformation
22 monitoring (displacement, tilt and stress), influencing factors monitoring (factors such as rainfall, groundwater and
23 earthquake) and macroscopic precursor monitoring (factors such as geoaoustics and macroscopic deformation). At
24 present, macroscopic deformation monitoring in large landslide areas mainly uses techniques such as synthetic
25 aperture radar (InSAR), 3D laser scanning and geographic information system (GIS) (Wang et al. 2020; Bovenga et
26 al. 2017; Wang et al. 2019). Focused monitoring in the hidden area focuses on the study of landslide deformation
27 evolution mechanism, mostly using total station, laser ranging and global positioning technology (GNSS) for
28 surface displacement monitoring, fixed borehole inclination technology for deep horizontal displacement
29 monitoring, and a combination of techniques for monitoring deformation and different influencing factors such as
30 water level, fractures, rainfall and stress (Zhang et al. 2018).

Geological hazards are characterized by frequency, hazard and complexity, and it is difficult for a single monitoring means to accurately reflect the landslide evolution process, and the integrated analysis and fusion of data obtained using different methods such as multi-temporal and multi-scale displacement monitoring, hydro-meteorological, and geological monitoring, and geotechnical interaction monitoring of the sky-lands is of great significance for predicting geological hazards (Lin et al. 2019; Mohammed et al. 2013). At present, some research results have been achieved in the field of data fusion technology in geological hazard monitoring and forecasting, such as the application of multiple sensor data to achieve the fusion of landslide multi-point displacement monitoring information, and then forecast landslides (Xie et al. 2020). At this stage, landslide monitoring data fusion is based on macroscopic the surface displacement monitoring such as GIS, InSAR and GNSS, but the magnitude, velocity and direction of surface displacement and displacement at the deep sliding surface are inconsistent, and the early warning indicators established based on the time series of surface displacement cannot accurately reflect the deformation evolution law of the deep geotechnical body (Chen et al. 2019). The joint time curve using monitoring data of deep displacement of borehole, soil moisture, groundwater level and stress can reflect the deformation characteristics inside the slope body and identify the depth range and deformation trend of potential sliding surface of the slope (Xie et al. 2019; He et al. 2012; Xu et al. 2012), but such methods are limited by technical conditions such as borehole and deployment, and cannot achieve an integral and continuous data acquisition on the internal space, resulting in incomplete modal data.

Multimodal information can describe the same data instance from different sides, and effective analysis of multimodal complementary information can obtain a more reasonable representation of data characteristics. The main causative factor of landslide generation is the weakening of soil shear strength in the process of rainwater infiltration caused by atmospheric precipitation, and the slope-sliding force is greater than the soil shear resistance. In this process, different stratigraphic structures within the geotechnical body, with the infiltration of rainwater, will form obvious resistivity differences near the slip surface. The resistivity imaging technique, based on the significant differences between the material composition, porosity, structure, and water content of the landslide weak body (face) and the surrounding rock (Carlo et al. 2013; Yin et al. 2018), measures the electrical conductivity information of the subsurface medium by scanning a large-area electrode array and can obtain a complete multidimensional electrical data set, reflecting the internal structure of the geological body. Therefore, a multimodal dataset consisting of monitoring data such as resistivity imaging data, deep horizontal displacement, soil moisture, groundwater level and rainfall can effectively reflect the process of obtaining structural deformation inside the landslide geotechnical body (Shao et al. 2013; Yin et al. 2017).

The multi-source data fusion technology can comprehensively analyze and reasonably utilize the multi-source heterogeneous data of landslide monitoring, eliminate the possible redundancy and mutual exclusion between data, and make all kinds of data complement and cooperate with each other, thus effectively improving the reliability of landslide monitoring data and increasing the utilization rate of landslide monitoring data (Qiu 2017; Zhao et al.

2019; Villalpando et al.2020). Common mathematical statistical models include logistic regression (Fan 2015), Gray Prediction Model (Xu et al. 2011; Gao et al.2020). Because landslides are subject to a variety of geological structural factors and environmental drivers coupled, the dynamical evolution process mechanism (type/model) is complex and nonlinear, and the correlation laws such as statistical regression and Gaussian distribution are not simply obeyed in space and time between state quantities and excitation drivers. Mathematical and statistical models can hardly express the nonlinear relationship between factors and landslide hazards accurately, so the analysis results still have some limitations. Shallow machine learning models, as a class of data-driven models, have gradually become the most widely used landslide susceptibility analysis models recently, and the commonly used machine learning models are Random Forest is an integrated learning method that combines bagging method to generate multiple mutually independent training sets and Classification and Regression Tree for prediction. Support Vector Machine is a machine learning method based on the principle of structured risk minimization, with the training error as the constraint of the optimization problem and the minimization confidence interval as the optimization objective (Wu et al. 2016; Huang et al. 2018; Zhang et al. 2021).Artificial Neural Network has a strong learning capability to obtain the characteristics and feature distribution of data through specific learning algorithms based on data sample information (Li et al. 2019; Yanget al. 2019; Liu et al. 2020; Guo et al. 2020). The essence of deep learning is to learn more features by constructing models with many hidden layers and a large amount of training data to achieve feature abstraction of the upper layers, which to some extent enhances and improves the problems of the objective function optimization and insufficient convergence exposed by traditional models, thus improving the accuracy of classification or prediction (Polykretis et al. 2017; Ji et al. al. 2019; Wang et al. 2020; Huang et al. 2021).

Shallow machine learning methods have been widely used in spatial prediction of time-series landslide hazards. However, compared to resistivity imaging datasets, modal feature values of soil moisture, groundwater level, the stress-strain and deep horizontal displacement are very seriously missing, and simple linear or nonlinear modal knowledge sharing become ineffective when there are large distributions or feature biases among modal data (Zhao 2018; Yin et al. 2015). Deep learning has stronger fitting and classification ability than it and can more fully utilize the neighborhood information. Exploring the applicability of deep learning methods in regional landslide hazard spatial prediction, using deep learning methods to build regional landslide hazard spatial prediction models, and applying them to multi-temporal landslide hazard spatial prediction has important research and application values (Zhang et al. 2020; Catani et al. 2020; Meena et al. 2021). To address the above-mentioned problems of missing and incomplete modalities, this paper proposes a landslide monitoring depth semantic matching multimodal data fusion algorithm, which takes resistivity monitoring data as a complete modal subspace and spatial and temporal discontinuities such as water level, deep displacement and soil moisture as incomplete modal data sets, fuses deep learning and incomplete multimodal analysis, and through joint depth matrix decomposition, optimization and layer-by-layer modal semantic matching and updating to obtain the depth semantic matching

features of multimodal data, complete the analysis of classification and clustering of incomplete multimodal data in the shared space, and improve the effectiveness of inversion profiles of dynamic changes of landslide seepage field, geological body structure field and deep displacement field generated by coupling.

2 Resistivity imaging technology

Since the material composition, structure, porosity, and water content of the landslide weak body (surface) are significantly different from the surrounding rock, the landslide body has a variety of physical properties such as density, electrical properties, and elasticity differences. Resistivity imaging technology collects the electrical conductivity data of the medium through the scanning measurement of electrode arrays, reflecting the detailed electrical structure and characteristics inside the medium, including landslide genesis mechanism, geological structure characteristics, potential slide size and slip surface, motion characteristics, mechanical and physical properties, etc. (Zhang et al. 2014; Lapenna et al. 2005), providing clear and concise two-dimensional and three-dimensional images (Perrone et al. 2014), and integrated analysis of the heterogeneity of landslide materials and landslide geotechnical characteristics (Carpentier et al. 2012) can further assess the dynamic characteristics of landslides for dynamic monitoring purposes (Yan et al. 2019; Sunaryo et al. al.2019; Akmam et al.2019; Samodra et al.2020). The resistivity imaging technique is used to study the distribution characteristics and variation patterns of artificial or natural electric fields through ground measurements to infer the subsurface resistivity distribution thus accurately inferring the distribution of different geological bodies. The resistivity is ρ_s expressed in $\Omega \cdot m$, and the resistivity is calculated by the formula:

$$\rho_s = K \frac{U_{MN}}{I_{AB}}, K = \frac{2\pi}{\frac{1}{AM} - \frac{1}{AN} - \frac{1}{BM} + \frac{1}{BN}} \quad (1)$$

U_{MN} is the difference in primary field potential between the measuring positive electrode (M-pole) and the measuring negative electrode (N-pole), is the current emitted to the earth through the supplying positive electrode (A-pole) and the supplying negative electrode (B-pole) I_{AB} , K is the device coefficient, and AM 、 AN 、 BM 、 BN is the distance between the points. The arbitrary quadrupole device (Fig.1), with a topographic correction, enables the inversion of 2D profiles of geological bodies with different topography.

In large landslide-monitoring sites, large-area, multi-dimensional resistivity data collection is required. The system controls multiple electrical measurement sub-stations (main functions include: measurement U_{MN} 、 I_{AB} control the collection sequence and data upload) through the host computer, and each sub-station controls the smart electrodes connected to it (the electrodes internally realize the function conversion between power supply A, B, and measurement M, N), and the collected data are stored in the electrical measurement sub-stations and transferred to the host computer (Fig. 2).

For example, one mainframe controls 16 sub-stations, and each sub-station are connected to 16 intelligent electrodes (data transmission between mainframe and sub-stations through CAN bus, the number of connected sub-stations can be expanded as needed). For different monitoring environments, the layout of the host, sub-stations and smart electrodes can be flexibly adjusted (Fig.3), is a layout designed for the need of long-distance monitoring of high slopes.

Aiming at the migration process of underground seepage field in landslide geological disaster evolution, which is often irregular and its transport speed and direction have the characteristics of sudden change, the initial scanning and collection of resistivity is performed in a large range (cross-electrode power supply and data collection) by rapidly changing the collection area. After determining the range of landslide-hidden trouble spots, the intelligent electrodes are encrypted and the electrode network is automatically coded, and the working state of electrodes is set according to the measurement needs, and the measurement is realized by completing the conversion of each electrode state through the host control to realize the resistivity monitoring data collection with real-time and dynamic variable monitoring point density and multi-dimensional resistivity dynamic collection grid structure in Fig.4 .

Fig.4a shows a schematic of the dynamic moving electrode grid when scanning the hidden area over a large area. In which, the solid circle on the left side is defined as the scanning area, and the dashed circle on the right side is defined as the area to be scanned. When a hidden spot is found, it can be switched to the encrypted scanning mode shown in Fig. 4b. Since the effective depth and accuracy of the inversion of resistivity imaging has been depending on the AB spacing, the flexible electrode grid layout can effectively reduce the pole spacing and improve the accuracy of the complete modal data set based on resistivity imaging data and the reliability of the multidimensional imaging of the internal structure of the fused landslide.

3 Fusion algorithm

In the actual situation of the landslide geological hazard monitoring process, there is a large correlation between resistivity imaging technology, deep displacement and related monitoring data, and the modal feature information of each monitoring data can describe the same data instance from different sides, but it is difficult for various monitoring data to constitute a modal data set with complete feature values in time and space due to technical conditions, to achieve effective analysis of multi-modal complementary information and be able to allow for effective analysis of multimodal complementary information and a more reasonable representation of data characteristics. The multimodal data fusion algorithm for landslide geology body deep displacement monitoring ensures the local similarity of each modal data by encoding the geometric structure of the data with graph regularization factors, constructs a deep semantic matching model that fuses modal deep neural networks and incomplete multimodal matrix decomposition, and then updates and optimizes the model (Liu et al. 2017; Zeng et al. 2016).

162 First, the modal private deep neural network converts all monitored data instances $X^{(n)} = \{X_C^{(n)}, X_I^{(n)}\}$ into deep
 163 feature representations $H^{(n)} = \{H_C^{(n)}, H_I^{(n)}\}$. Then each modal representation is decomposed into a basis matrix $H^{(n)}$
 164 $U^{(n)}$ and a consistent encoding matrix using a non-negative matrix with fused local invariant graph regularization
 165 $P^{(n)} = [P_C; P_I^{(n)}]$. By jointly training and optimizing the modal private depth network and the base matrix, as well as
 166 the modal consistent encoding matrix, multimodal depth semantic shared features in the subspace will be obtained.
 167 The flowchart is shown in Fig.5.

168 To ensure the consistency of each modal data with its geometric structure in the potential subspace, the learned
 169 shared encoding matrix is P_C represented regularly by the invariant graph model. Assuming that there are two data
 170 instances close to each other in the original data space $x_i^{(n)}$ and $x_j^{(n)}$, the low-dimensional representations of $p_i^{(n)}$
 171 and in the learned subspaces should also be close to each other $p_j^{(n)}$. The local geometric structure between data
 172 points is $G^{(n)}$ described by the nearest neighbor graph of each modality: each data instance in the n modality is
 173 $x_i^{(n)}$ represented as $G^{(n)}$ a point in the modality, and the nearest $x_i^{(n)}$ neighbor is p found to construct $G^{(n)}$ the
 174 weighted neighbor matrix $W^{(n)}$. The Euclidean distance can also be used to measure the similarity between two data
 175 instances $p_i^{(n)}$ and in the $p_j^{(n)}$ shared subspace. The local invariant graph embedding function of each modality can
 176 be obtained by fusing the similarity matrix in the original space of the modality $W^{(n)}$ and the similarity metric in
 177 the shared space as follows.

$$178 \quad \mathfrak{R} = Tr(P^{(v)} L^{(v)} P^{(v)T}) \quad (2)$$

179 where $Tr(\bullet)$ is the trace of the matrix, $D^{(n)}$ is the diagonal matrix, each data on the diagonal is $W^{(n)}$ the sum of
 180 each row or column, and $L^{(n)} = D^{(n)} - W^{(n)}$ is the Laplacian matrix of the graph $G^{(n)}$. By minimizing $\mathfrak{R}$, two similar
 181 data instances in the modal primitive space $x_i^{(n)}$ and $x_j^{(n)}$ will also be similar in the shared subspace. Integrating
 182 each modal local invariant graph embedding function with incomplete multimodal nonnegative matrix
 183 decomposition, the incomplete multimodal data fusion-learning model can be represented as follows.

$$184 \quad \min \sum_{n=1}^N (\| [X_C^{(n)}; X_I^{(n)}] - U^{(n)} [P_C; P_I^{(n)}] \|_F^2 + \alpha^{(n)} Tr(P^{(n)} L^{(n)} P^{(n)T})) \quad (3)$$

185 The incomplete multimodal deep semantic matching model can be represented as

$$186 \quad \min \sum_{n=1}^N (\| [H_C^{(n)}; H_I^{(n)}] - U^{(n)} [P_C; P_I^{(n)}] \|_F^2 + \alpha^{(n)} Tr(P^{(n)} L^{(n)} P^{(n)T})) \quad (4)$$

187 where $\alpha^{(n)} > 0$ denotes the regularization parameter, and the optimal value is selected by the monitoring
 188 results. $H^{(n)} = [H_c^{(n)}; H_l^{(n)}]$ is the feature output of the modal private depth network, and by jointly optimizing the
 189 modal private depth-learning network, the basis matrix and the consistent encoding matrix, a multimodal depth
 190 semantic shared subspace can be obtained, and multimodal data features can be fused and analyzed in the obtained
 191 subspace.

192 Given the basis matrix of each monitored data modality $U^{(n)}$ when the shared features $[P_c; P_l^{(1)}]$, $[P_c; P_l^{(2)}]$ and
 193 contain only $[P_c; P_l^{(n)}]$ a portion of, in the specific optimization process, the shared features P_c and are $P_l^{(n)}$
 194 updated separately and the invariant graph restriction is relaxed to

$$195 \quad \alpha^{(n)} Tr(P^{(n)} L^{(n)} P^{(n)T}) \approx \alpha^{(n)} Tr(P_c L_c^{(n)} P_c^T) \quad (5)$$

196 By sharing the characteristics P_c and $P_l^{(n)}$ minimizing the objective function Equation (5) can be written as
 197 minimizing the objective function.

$$198 \quad \min_{P_c \geq 0} \sum_{n=1}^N (\|H_c^{(n)} - U^{(n)} P_c\|_F^2 + \alpha^{(n)} Tr(P^{(n)} L^{(n)} P^{(n)T})) , \quad \min_{P_l^{(n)} \geq 0} \|H_l^{(n)} - U^{(n)} P_l^{(n)}\|_F^2 \quad (6)$$

199 Using the Lagrangian function optimization equation (7), restrict $P_c \geq 0$ and $P_l^{(n)} \geq 0$. The equations for
 200 $(P_c)_{ij}$ and $(P_l^{(n)})_{ij}$ can be obtained as follows

$$201 \quad \sum_{n=1}^N (-U^{(n)T} H_c^{(n)})_{ij} (P_c)_{ij} + (U^{(n)T} U^{(n)} P_c)_{ij} (P_c)_{ij} + \alpha^{(n)} (P_c L_c^{(n)})_{ij} (P_c)_{ij} = 0 \quad (7)$$

$$202 \quad (-U^{(n)T} H_l^{(n)})_{ij} (P_l^{(n)})_{ij} + (U^{(n)T} U^{(n)} P_l^{(n)})_{ij} (P_l^{(n)})_{ij} = 0 \quad (8)$$

203 The optimization update rules for shared features $(P_c)_{ij}$ and $(P_l^{(n)})_{ij}$ are as follows.

$$204 \quad (P_c)_{ij} \leftarrow \frac{\sum_{n=1}^N (U^{(n)T} H_c^{(n)} + \alpha^{(n)} P_c W_c^{(n)})_{ij}}{\sum_{n=1}^N (U^{(n)T} U^{(n)} P_c + \alpha^{(n)} P_c D_c^{(n)})_{ij}} (P_c)_{ij}, \quad (P_l^{(n)})_{ij} \leftarrow \frac{(U^{(n)T} H_l^{(n)})_{ij}}{(U^{(n)T} U^{(n)} P_l^{(n)})_{ij}} (P_l^{(n)})_{ij} \quad (9)$$

205 4 Experiments

206 The monitored slope is located on the west slope of Xiaonan Mountain, Xiangzhou District, Zhuhai (22°21'9.63"N,
 207 113°33'16.63"E), with the elevation of the top of the slope 152 m, the elevation of the foot of the slope 61 m, and
 208 the height of the slope about 90 m. The terrain is high in the south and low in the north, 260 m long in the east-west

direction, and about 120 m wide in the north-south direction, and the natural slope angle of the slope surface is 30°-37°. The cover of the front edge is mainly residual slope deposits and crumbling slope deposits, with a small number of fully weathered mudstone chips, while the middle and back edge cover are mudstone with different degrees of weathering respectively. The lithology is dominated by calcium-bearing mudstone in the upper part, calcareous siltstone in the middle part, interspersed with calcium-bearing mudstone, and conglomerate, sandstone and conglomerate-bearing sandstone in the bottom part. This stratigraphic structure is favorable for rainwater to continuously replenish groundwater from top to bottom and infiltrate into the lower mudstone, and the muddy debris and weak interlayer in the rock layer are immersed in the water for a long time, which will cause the strength of the soil body to decrease. Under the influence of multiple effects such as self-weight of the landslide body, rainfall infiltration, and vibration caused by human engineering activities, the cohesive force inside the landslide body gradually decreases, i.e., the slide force continues to increase due to rainfall infiltration and other effects, while the anti-slip force decreases rapidly due to shear damage, the landslide body shows increased cumulative deformation and contributes to further weakening of the weak zone inside the landslide body. A monitoring profile was set up in the middle of the slope in the form of the profile shown in Fig.6, and monitored for 182 consecutive days from June to December 2019.

The rainfall-monitoring point is arranged at the leading edge of the slope YL1, rainfall, and deep displacement data monitoring, sampling frequency (triggered acquisition). 182 consecutive days of daily average rainfall monitoring data at point YL1 are shown in Fig.7.

There is an obvious continuous precipitation process on the 90th-100th monitoring day, because the surface displacement rate of the landslide correlates well the rainfall, while the deep displacement rate of the landslide has a good correlation with the rate of deep displacement of the landslide has a certain lag with the amount of rainfall, which shows a greater influence on the deformation of the soil at the trailing edge and the central slip zone in the slope of this experiment.

The deep displacement is arranged in front edge borehole ZK1 (elevation 72 m, borehole depth 20 m), middle borehole ZK2 (elevation 37 m, borehole depth 20 m) and back edge borehole ZK3 (elevation 10 m, borehole depth 20 m), each monitoring node is spaced 0.5 m apart, and all three boreholes are deeper than the slip surface to reach the sandstone or conglomerate layer.

The monitoring frequency is 0.5 times/hour, and the monitoring period is 182 days. Figure 8 shows the average daily deformation results of ZK2 monitoring on monitoring days 85–120. From the 36-day continuous observation curve of the central monitoring hole ZK2 (Fig.8), it can be seen that the displacement is basically generated by the 0-5m hole section, the maximum sliding displacement at the mouth of the hole is 16.15mm, the curve forms a more obvious sliding surface at 3m, the sliding displacement above the sliding surface is larger, while the lower displacement is smaller, and the landslide is dominated by shallow overall sliding.

242 There are more than 10 kinds of acquisition devices commonly used in resistivity imaging technology, and the
243 Wenner device and Wenner-Schlumber device are used as experimental devices in this paper. Among them:
244 Wenner device: $AM=MN=NB$, A, M, N, B move to the right at the same time point by point, with the increase of
245 pole spacing, the depth through which the profile inversion is interpreted also gradually increases, the electric field
246 distribution of Wenner device is mainly directly below the center of the device, and the sensitivity function
247 becomes horizontal distribution. Wenner device is more sensitive to the vertical change of resistivity, used to detect
248 horizontal target body; Wenner-Schlumberger device-running pole way: this device between Wenner and
249 Schlumberger, the interval layer is $3a$ (a is the standard pole spacing), in 1-3 layer Schlumberger method running
250 poles, 4-6 layer MN interval becomes $3a$, 7-9 layer MN electrode spacing becomes $5a$, and so on, to get an inverted
251 trapezoidal cross-sectional map. Its high sensitivity value appears directly below between the measuring electrodes,
252 but the detection depth is small. The slip surface of landslide geological hazards is located within 30m below the
253 surface, and this depth is just within the sensitivity range of Wenner-Schlumber device with pole spacing ($a=1m$,
254 $a=0.5m$) (reducing the pole spacing can effectively improve the monitoring accuracy), and it is a more
255 ideal-monitoring device for landslide geological hazards because it takes into account both the horizontal and
256 vertical resolution.

257 Resistivity data collection was performed from the top to the bottom of the slope along the profile direction as
258 shown in Fig.6 with the measurement line , electrode spacing $a=4\text{ m}$, using a Wenner device (which has better
259 sensitivity to lateral structures) for resistivity data collection, the number of measurement electrodes was 60, the
260 supply voltage was 90 V, the maximum supply distance was $AB=236\text{ m}$, the effective measurement depth was 32
261 m, and on the 85th and 120th day of the monitoring process using DEM-3 distributed direct current meter with
262 smart electrodes was used to measure this profile 4 times/day. The Swedish high-density processing software
263 RES2Dinv was applied for topographic correction and data inversion processing, and the resistivity inversion
264 results were obtained as shown in Fig.9 for the 85th monitoring day (before rainfall) and the 120th monitoring day
265 (after continuous rainfall) in Fig.10 .

266 It can be seen that the inversion results of the two measurements at the front edge of the slope are basically the
267 same, but the resistivity of 5–10 meters at the deep displacement monitoring point of ZK1 has changed
268 significantly, from the maximum value of $460\ \Omega\cdot m$ to $285\ \Omega\cdot m$, which is consistent with the trend of ZK1
269 monitoring data in Fig.9 and Fig.10; In the middle of the slope, the maximum value of the horizontal coordinates of
270 the two maps can show that the rainfall process has led to a significant decrease in the resistivity of the surface and
271 the interior of the geological body. The resistivity of the sandstone layer in the middle of the slope decreased from
272 $853\ \Omega\cdot m$ to $462\ \Omega\cdot m$, and the internal structural stratification and slip surface of the geotechnical body were
273 clearly distinguished. In contrast with the maximum value of the deep part displacement data measured by ZK2 in
274 0–20 meters, the direction and change trend are consistent with the soil seepage field in the figure; ③In the back
275 edge of the slope, the surface mudstone is thicker, and the resistivity has changed before and after the rainfall, but

the structural stratification is still clear and obvious from the inversion results.

The deep displacement ZK1-3 and resistivity 85th and 120th monitoring days were selected to obtain 7689 data for multimodal data fusion. With the resistivity imaging technology Wenner device single complete profile collection as a data set consisting of 552 data, extracted extended ZK1-3 surrounding 2 m range of vertical downward 72 data for complete mode, deep displacement single ZK1-3 collection of 60 data for incomplete mode, different data instances missing ratio of 22.9%. Since it is impossible to realize the two-dimensional or three-dimensional real-time data ratio of the entire monitoring profile by the survey method, the resistivity imaging data, deep horizontal displacement data and rainfall data collected by the Wenner device are fused with the algorithm proposed in this paper, and the results are compared with the actual data measured by the Wenner-Schlumber device (because the Wenner-Schlumber device takes into account the horizontal and vertical resolution, it is a more ideal device for landslide geological hazard (because the Wenner-Schrempel device has both horizontal and vertical resolution, it is an ideal monitoring device for landslides). The results (Table 1) show the comparison of the deep horizontal displacement monitoring point profiles of boreholes, where the measured Wenner-Schlumberger data are referred to as W-S data.

Combining Table 1, Fig.9, Fig.10, Fig.13, and Fig.14, it can be seen that: ①with the increase of rainfall, the overall structural resistivity value of this slope has a significant decrease, and the data fusion results near the two boreholes ZK1 and ZK2, with three kinds of modal data fusion near the surface (0-5 m), the error is less than the deep data fusion results; ②at 6-8 m of ZK1 and 12-14 m of ZK2 are slip surface, the structure of the two parts above and below the slip surface are different, which leads to the obvious difference of discontinuity in resistivity data, and the error of the fusion result reaches 0.36%, which is lower than the fusion result of other depth data of uniform medium, indicating that the fusion algorithm proposed in this paper can effectively monitor the overall deformation and displacement of the slip surface. Fig.11 and Fig.12 show the measured data, fusion results and error analysis of the electrical data before and after the rain in the horizontal fourth layer (depth of 8 m), respectively.

As can be seen from Fig.11, the electrical data of the slope as a whole at the resistivity data collection points 3~8 and 13~40 at 8 m below the ground surface produced significant changes with rainfall infiltration, and the different water saturation of the rock body led to obvious differences in the electrical data. The results correspond to the main slip surface shown in Fig.6. From Fig.12, it can be seen that the error of the results of the fusion before the rain (-1.7% to 4.2%) is significantly larger than that after the rain (0.4% to 2.9%), and the error of data fusion is around 1% near both ZK1 (collection point 10) and ZK2 (collection point 28). Fig.13 and Fig.14 show the 2D inversion effect of the output after updating the resistivity imaging technique data by data fusion.

The deep displacement monitoring of the borehole can provide the most direct and effective correction and supplement to the resistivity imaging data, although continuous measurement cannot be achieved in space. From Fig.12 and Fig.13, it can be seen that: ①comparing Fig.9 and Fig.12, the results before and after data fusion at the leading edge of the slope are consistent, and the resistivity data decrease from $460 \Omega \cdot m$ to $355 \Omega \cdot m$ due to the fusion of ZK1 deep

displacement monitoring data with larger displacement near the elevation value of 60 m; ②comparing Fig.8 , Fig.9 and Fig.13 at the middle and leading edge of the slope, the resistivity data and ZK2 displacement data have consistent changes in numerical magnitude and direction The overall difference is small before and after fusion, and the slip surface is shifted by about 1 m after data fusion; ③From the inversion results of Fig.12 and Fig.13, it can be seen that the deep displacement monitoring data and resistivity imaging data at ZK1-ZK3 are fused by multi-layer modal semantic matching using the deep semantic abstraction feature, and the data of each modal are well converted to the deep semantic shared subspace, which can effectively compensate for the The large semantic deviation between the two modes is effectively compensated, and the process of geotechnical deformation of landslide is visualized. With the introduction of soil moisture, groundwater level and other data sets, the algorithm can obtain better clustering results on all test data sets by downscaling and exclude noise interference through the setting of depth network, to more accurately describe the process of internal structural changes of landslide geology.

5 Conclusion

More than 85% of landslide geological hazards are caused by the dynamic changes of soil seepage field caused by atmospheric precipitation and its resulting deep displacement, so the study of internal deformation evolution mechanism of landslide geological body is the key to landslide monitoring and prediction, and when the modal distribution or characteristics differ greatly, it is difficult to ensure the fusion by only using a linear or nonlinear transformation to compensate for the semantic deviation between multi-modal data for monitoring internal structural changes of landslide body The validity of the results. The depth semantic matching multimodal data fusion algorithm for landslide geology monitoring based on resistivity imaging technology uses the depth semantic matching mechanism of incomplete modal data, explores the depth semantic sharing features of modal data, and establishes multilayer nonlinear correlation among multimodal data by jointly optimizing the fused modal private depth network and the graph regularization-based incomplete modal data learning model, and then obtains the depth semantic matching features of multimodal data. The deep semantic matching features of multimodal data can effectively compensate for the large semantic bias between modalities and obtain more accurate data sharing semantics. In the later stage, by combining multiple surface displacement monitoring data sets, heterogeneous modal data migration fusion with multi-layer semantic matching can obtain the overall three-dimensional dynamic changes of landslide geological body, which provides powerful technical support for landslide geological disaster monitoring and prediction.

References

- Xu, Q., M.G. Tang, K.X. Xu, and X.B. Huang.2008. Research on the spatial and temporal evolution of landslides and early warning forecasting. *Journal of Rock Mechanics and Engineering* 27(6):1104-1104.
- Fan, J.Q.. 2015. Research on multi-source heterogeneous sensor information fusion method for landslide monitoring. *China University of Geosciences*.
- Sun, M.J, H.M. Tang, X.H. Wang, X.L. Hu, M.Y. Wang, and W.D. Ni. 2017. Study on creep properties of creep-type landslide slip zone soils. *Geotechnical Mechanics* 38(02):385-391+399.

343 Wang, L., S.M. Wang, G. Li, and L. Wang. 2020. Numerical analysis of reservoir landslide deformation considering the coupling effect
344 of seepage and creep. *Engineering Science and Technology* 52(1):66-74.

345 Bovenga, F., G. Pasquariello, R. Pellicani, A. Refice, and G. Spilotro. 2017. Landslide monitoring for risk mitigation by using corner
346 reflector and satellite SAR interferometry. The large landslide of Carlantino (Italy). *Catena* 151 (3) :49-62.

347 Wang, R.B., R. Xia, W.Y. Xu, H.L. Wang, and J. Qi. 2019. Experimental study on physical simulation of rainfall infiltration process in
348 landslide mounds. *Engineering Science and Technology* 51(4):47-54.

349 Zhang, Y., X.M. Meng, C. Jordan, A. Novellino, T. Dijkstra, and G. Chen. 2018. Investigating Slow-Moving Landslides in the Zhouqu
350 Region of China Using InSAR Time Series. *Landslides*, 15(7):1299-1315.

351 Lin, J., Q.F. Zhang, W.X. Long, and H.W. Zhang. 2019. Landslide early warning method based on multi-model fusion of early warning
352 affiliation function. *Journal of Jilin University (Earth Science Edition)* 49(02):477-484.

353 Mohammed, F., and M.F. Hermann. 2013. Correction to "Physical Modeling of Tsunamis Generated by Three-Dimensional
354 Deformable Granular Landslides". *Journal of Geophysical Research: Oceans*. 118(6):3221-3221.

355 XIE, M.L., J.J. ZHAO, N.P. JU, C.Y. HE, and J. WANG. 2020. Study on the spatial and temporal evolution law of landslide with
356 multi-source data-Example of Huangnibazi landslide. *Journal of Wuhan University (Information Science Edition)*
357 45(06):923-932.

358 Chen, H., H. Tang, X.R. Ge, and Y.J. Li. 2019. Research on early warning index and early warning forecast of creep-slip type landslide
359 based on deep displacement[J]. *Journal of Rock Mechanics and Engineering* 38(S1):3015-3024.

360 He, K.Q., D. Guo, P. Zhang, L. Guo, and G.D. Zhang. 2017. Research on vertical directional rate of rainfall-type landslide and its
361 displacement monitoring and early warning criterion. *Geotechnics* 38(12):3649-3659.

362 Xu, Q.. 2012. Deformation damage behavior and intrinsic mechanism of landslides. *Journal of Engineering Geology* 20(2):145-151.

363 Carlo, L.D., Maria T.P, M.C. Caputo, R. Deiana, M. Vurro, and G. Cassiani. 2013. Characterization of a dismissed landfill via
364 electrical resistivity tomography and mise-à-la-masse method. *Journal of Applied Geophysics* 98(07),1-10.

365 Yin, C.C., Z.L. Yang, Y.H. Liu, B. Zhang, Y.F. Qi, X.Y. Cao, C.K. Qiu, and J. Cai. 2018. Arbitrary anisotropy model response
366 characteristics of 3D DC resistivity method based on circular sweep measurements. *Journal of Jilin University (Earth Science
367 Edition)* 48(3):872-880.

368 Shao, W.X. Shi, and P.S. Yu. 2013. Clustering on multiple incomplete datasets via collective kernel learning. *Proceedings of 13th
369 IEEE International Conference on Data Mining* 2013:1181-1186.

370 Yin, Q., S. Wu, and L. Wang. 2017. Unified subspace learning for incomplete and unlabeled multi-view data. *Pattern Recognition* 67(7):
371 313-327.

372 Qiu, D.D.. 2017. Research on landslide risk analysis based on multi-source data fusion. *China University of Geosciences*.

373 Zhao, C.Y., X.J. Liu, Q. Zhang, J.B. Peng, and Q. Xu. 2019. Research on InSAR identification, monitoring and destabilization model
374 of Hefangtai loess landslide in Gansu. *Journal of Wuhan University (Information Science Edition)* 2019(07):996-1007.

375 Villalpando, F., J. Tuxpan, J.A. Ramos-Leal, and S. Carranco-Lozada. 2020. New Framework Based on Fusion Information from
376 Multiple Landslide Data Sources and 3D Visualization. *Journal of Earth Science* 31(01): 159-170.

377 Xu, F., Y. Wang, Z. Du, and L. Ye. 2011. Research on landslide displacement prediction model based on time series analysis. *Journal
378 of Rock Mechanics and Engineering* 30(04): 746-751.

379 Gao, W., S. Dai, and X. Chen. 2020. Landslide prediction based on a combined intelligent method using the GM and ENN: two cases
380 of landslides in the Three Gorges Reservoir, China. *Landslides* 17(01): 111-126.

381 Liu, J., S.L. Li, and T. Chen. 2018. Landslide susceptibility evaluation based on optimized random forest model. *Journal of Wuhan
382 University (Information Science Edition)* 43(07): 1085-1091.

383 Wu, R.Z., X.D. Hu, H.B. Mei, J.Y. He, and J.Y. Yang. 2021. Spatial susceptibility evaluation of landslides based on random forest: an
384 example of the Hubei section of the Three Gorges reservoir area. *Earth Science* 46(01): 321-330.

385 Wu, X.L., S.Q. Shen, and R.Q. Niu. 2016. Application of PSO-SVM model to predict landslide susceptibility with GIS support.
386 *Journal of Wuhan University (Information Science Edition)* 41(05): 665-671.

387 Huang, M.F., K. L. Yin, S.H. Jiang, J.S. Huang, and Z.S. Cao. 2018. Evaluation of landslide susceptibility based on cluster analysis
388 and support vector machine. *Journal of Rock Mechanics and Engineering* 37(01): 156-167.

389 Zhang, L., B. Shi, H. Zhu, X.B. Yu, H.M. Han, and X.D. Fan. 2021. PSO-SVM-based deep displacement prediction of Majiagou
390 landslide considering the deformation hysteresis effect. *Landslides* 18(01): 179-193 .

391 Guo, Z.Z., L.X. Chen, L. Gui, J. Du, K.L. Yin, and H.M. Do. 2019. A stepwise landslide displacement interval prediction method
392 considering dynamic switching of deformation states. *Journal of Rock Mechanics and Engineering* 38(11): 2272-2287.

393 Yang, B.B., K.L. YIN, S. Lacasse, and Z.Q. Liu. 2019. Time series analysis and long short-term memory neural network to predict
394 landslide displacement. *Landslides* 16(04): 677-694.

395 Liu, Y., C. Xu , B. Huang, X.W. Ren, C. Liu, B.D. Hu, and Z. Chen. 2020. Landslide displacement prediction based on multi-source
396 data fusion and sensitivity states. *Engineering Geology* 271(10): 560-578.

397 Guo, Z.Z., L.X. Chen, L. Gui, J. Du, K.L. Yin, and H.M. Do. 2020. Landslide displacement prediction based on variational mode
398 decomposition and WA-GWO-BP model. *Landslides* 17(03): 567-583.

399 Polykretis, C., and C. Chalkias. 2018. Comparison and evaluation of landslide susceptibility maps obtained from weight of evidence,
400 logistic regression, and artificial neural network models. *Natural Hazards* 93(03): 261-275.

401 Ji, S.P., D.W. Yu, C.Y. Shen, and Q. Xu. 2020. Landslide detection from an open satellite imagery and digital elevation model dataset
402 using attention boosted convolutional neural networks. *Landslides* 17(06): 1337-1352.

403 Wang, W.D., Z.L. He, Z. Han, and Y. Qian. 2020. Landslide sensitivity evaluation based on deep belief network. *Journal of*
404 *Northeastern University (Natural Science Edition)* 41(05): 609-615.

405 Huang, F.M., J. Zhang, C. Zhou, Y.H. Wang, and J.S. Hu. 2020. A deep learning algorithm using a fully connected sparse autoencoder
406 neural network for landslide susceptibility. *Landslides* 17(01): 217-229 .

407 Zhao, L.. 2018. Research on multimodal data fusion algorithm. *Dalian University of Technology*.

408 YIN, Q., S. WU, and L. WANG. 2015. Incomplete Multi-view Clustering via Subspace Learning. *Proceedings of the 24th ACM*
409 *International Conference on Information and Knowledge Management* 383-392.

410 Zhang, P.F., C. Xu, S.Y. Ma, X.Y. Shao, Y.Y. Tian, and B.Y. Wen. 2020. Automatic Extraction of Seismic Landslides in Large Areas
411 with Complex Environments Based on Deep Learning: an Example of the 2018 Iwate Earthquake, Japan. *Remote Sensing* 12(23) :
412 3992-3992.

413 Catani, F.. 2020. Landslide detection by deep learning of non-nadir and crowdsourced optical images. *Landslides*
414 <https://doi.org/10.1007/s10346-020-01513-4>.

415 Meena, S.R., O. Ghorbanzadeh, C. Westen, T.G. Nachappa, T. Blaschke, R.P. Singh, and R. Sarkar. 2021. Rapid mapping of landslides
416 in the Western Ghats (India) triggered by 2018 extreme monsoon rainfall using a deep learning approach. *Landslides*
417 <https://doi.org/10.1007/s10346-020-01602-4><https://doi.org/10.1007/s10346-020-01602-4>.

418 Zhang, M., R.L. Hu, Y.P. Yin, and R.A. Wu. 2014. Study on the mechanism of rainfall-induced landslides in the gently dipping red
419 layer in east Sichuan. *Journal of Rock Mechanics and Engineering* 33(S2): 3783-3790.

420 Lapenna, V., P. Lorenzo, A. Perrone, S. Piscitelli, E. Rizzo, and F. Sdao. 2005. 2D Electrical resistivity imaging of some complex
421 landslides in Lucanian Apennine Chain, Southern Italy. *Geophysics* 70(01): 11-18.

422 Perrone, A., V. Lapenna, S. Piscitelli. 2014. Electrical resistivity tomography technique for landslide investigation :A Review. *Reviews*

423 135(01):65-82.

424 Carpentier, S., M. Konz, R. Fischer, G. Anagnostopoulos, K. Meusburger, and K. Schoeck. 2012. Geophysical Imaging of Shallow
425 Subsurface Topography and Its Implication for Shallow Landslide Susceptibility in the Urseren Valley, Switzerland. *Journal of*
426 *Applied Geophysics* 83(2): 46-56.

427 Yan, Y.J., Y.S. Yan, G.Z. Zhao, T.L. Zhang, and Q. Sun. 2019. Research on water transport law of natural slopes based on high-density
428 electrical method. *Geotechnics* 40(07): 2807-2814.

429 Sunaryo, A. Susilo, M. Alamsyah, Yuwono, and Wiyono. 2019. Slope Stability Analysis for Landslides Natural Disaster Mitigation by
430 Means of Geoelectrical Resistivity Data in Gedangan of South Malang. *Materials Science and Engineering* 546(02): 334-346.

431 Akmam, H. Amir, A. Putra, R. Anshari, and N. Jalinus. 2019. Implementation of least-square constrain inversion method of
432 geoelectrical resistivity data Wenner-Schlumberger for investigation the characteristic of landslide. *Indian Journal of Public*
433 *Health Research & Development* 10(08): 2456 -2469.

434 Samodra, G., M.F. Ramadhan, J. Sartohadi, M.A. Setiawan, N. Christanto, and A. Sukmawijaya. 2020. Characterization of
435 displacement and internal structure of landslides from multitemporal UAV and ERT imaging. *Landslides* 17(10):2455-2468.

436 Liu, W.B., Z.D. Wang, X.H. LIU, N.Y. Zeng, and Y.R. Liu. 2017. A survey of deep neural network architectures and their applications.
437 *Neurocomputing* 234(10): 17-26.

438 Zeng, N.Y., Z.D. Wang, H. Zhang, and F.E. 2016. Alsaadi. Deep belief networks for quantitative analysis of a gold
439 immunochromatographic strip. *Cognitive Computation* 8(4): 684-692.

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441

Ethical Statement

442 I testify on behalf of all co-authors that our article submitted to “ Multi-modal Landslide Monitoring Data Fusion
443 Algorithm Based on Resistivity Imaging” :

444 Title :Multi-modal Landslide Monitoring Data Fusion Algorithm Based on Resistivity Imaging

445 All authors :Haning Xu • Juzhi Deng • Xiaoqing Xu • Jian Zhang • Gang Li • Qi Liu • Hui Xiao

446 1) this material has not been published in whole or in part elsewhere ;

447 2) the manuscript is not currently being considered for publication in another journal ;

448 3) all authors have been personally and actively involved in substantive work leading to the

449 manuscript , and will hold themselves jointly and individually responsible for its content .

450 Date :2021-09-23

451 Corresponding authors Signature :

**Ethical Statement for “Multi-modal Landslide Monitoring Data Fusion
Algorithm Based on Resistivity Imaging”**

I testify on behalf of all co-authors that our article submitted to “ Multi-modal Landslide Monitoring Data Fusion Algorithm Based on Resistivity Imaging” :

Title :Multi-modal Landslide Monitoring Data Fusion Algorithm Based on Resistivity Imaging

All authors :Haning Xu • Juzhi Deng • Xiaoqing Xu • Jian Zhang • Gang Li • Qi Liu • Hui Xiao

- 1) this material has not been published in whole or in part elsewhere ;
- 2) the manuscript is not currently being considered for publication in another journal ;
- 3) all authors have been personally and actively involved in substantive work leading to the manuscript , and will hold themselves jointly and individually responsible for its content .

Date :2021-09-23

Corresponding authors Signature :

Figures

Figure 1

The arbitrary quadrupole device (Fig.1), with a topographic correction, enables the inversion of 2D profiles of geological bodies with different topography.

Figure 2

In large landslide-monitoring sites, large-area, multi-dimensional resistivity data collection is required. The system controls multiple electrical measurement sub-stations (main functions include: measurement, control the collection sequence and data upload) through the host computer, and each sub-station controls the smart electrodes connected to it (the electrodes internally realize the function conversion between power supply A, B, and measurement M, N), and the collected data are stored in the electrical measurement sub-stations and transferred to the host computer (Fig. 2).

Figure 3

For different monitoring environments, the layout of the host, sub-stations and smart electrodes can be flexibly adjusted (Fig.3), is a layout designed for the need of long-distance monitoring of high slopes.

Figure 4

Fig.4a shows a schematic of the dynamic moving electrode grid when scanning the hidden area over a large area. In which, the solid circle on the left side is defined as the scanning area, and the dashed circle on the right side is defined as the area to be scanned. When a hidden spot is found, it can be switched to the encrypted scanning mode shown in Fig. 4b. Since the effective depth and accuracy of the inversion of resistivity imaging has been depending on the spacing, the flexible electrode grid layout can effectively reduce the pole spacing and improve the accuracy of the complete modal data set based on resistivity imaging data and the reliability of the multidimensional imaging of the internal structure of the fused landslide.

Figure 5

By jointly training and optimizing the modal private depth network and the base matrix, as well as the modal consistent encoding matrix, multimodal depth semantic shared features in the subspace will be obtained. The flowchart is shown in Fig.5.

Figure 6

A monitoring profile was set up in the middle of the slope in the form of the profile shown in Fig.6, and monitored for 182 consecutive days from June to December 2019.

Figure 7

The rainfall-monitoring point is arranged at the leading edge of the slope YL1, rainfall, and deep displacement data monitoring, sampling frequency (triggered acquisition). 182 consecutive days of daily average rainfall monitoring data at point YL1 are shown in Fig.7.

Figure 8

The monitoring frequency is 0.5 times/hour, and the monitoring period is 182 days. Figure 8 shows the average daily deformation results of ZK2 monitoring on monitoring days 85–120. From the 36-day continuous observation curve of the central monitoring hole ZK2 (Fig.8), it can be seen that the displacement is basically generated by the 0-5m hole section, the maximum sliding displacement at the mouth of the hole is 16.15mm, the curve forms a more obvious sliding surface at 3m, the sliding displacement above the sliding surface is larger, while the lower displacement is smaller, and the landslide is dominated by shallow overall sliding.

Figure 9

The Swedish high-density processing software RES2Dinv was applied for topographic correction and data inversion processing, and the resistivity inversion results were obtained as shown in Fig.9

Figure 10

for the 85th monitoring day (before rainfall) and the 120th monitoring day (after continuous rainfall) in Fig.10 .

Figure 11

As can be seen from Fig.11, the electrical data of the slope as a whole at the resistivity data collection points 3~8 and 13~40 at 8 m below the ground surface produced significant changes with rainfall infiltration, and the different water saturation of the rock body led to obvious differences in the electrical data.

Figure 12

show the measured data, fusion results and error analysis of the electrical data before and after the rain in the horizontal fourth layer (depth of 8 m), respectively.

Figure 13

the error of data fusion is around 1% near both ZK1 (collection point 10) and ZK2 (collection point 28).
Fig.13

Figure 14

show the 2D inversion effect of the output after updating the resistivity imaging technique data by data fusion.

Supplementary Files

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