Application of an adaptive weighted estimation fusion algorithm in landslide deformation monitoring data processing

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Abstract. For early warning and forecast of landslide disasters, several types of sensors are used to monitor landslide deformation at different locations. In practical applications, a simple comparative analysis of the data collected at each monitoring point cannot fully use the information provided by these data. In this contribution, the use of an adaptive weighted estimation fusion algorithm is implemented to fuse the landslide deformation data collected by the Global Navigation Satellite System (GNSS) receiver and the displacement meter. The fused data are utilized for a discriminant analysis of the landslide stage. In contrast to the fusion results obtained using the original monitoring data and a back-propagation neural network, the results obtained using the adaptive weighted estimation fusion algorithm reveal that the one-sidedness of the information can be overcome using a single monitoring method and single monitoring point data. Moreover, the algorithm can provide a reliable criterion for the analysis of landslide deformation.

1. Introduction

China is among the countries with the most serious landslide geological hazards. The gradual expansion of human activities and the influence of natural factors led to the occasional occurrence of landslide disasters. In China, landslide disasters are most severe in western regions, such as Yunnan, Guizhou, Chongqing, Gansu, and Shaanxi [1]. Frequent monitoring of landslides and early prediction of landslide hazards are necessary to minimize damages [2]. Currently, landslide monitoring includes surface deformation monitoring, deep displacement monitoring, and environmental impact factor monitoring. Surface deformation is considered important and is an effective means of landslide monitoring [3]. In the actual monitoring work, different types of equipment for deformation monitoring are installed in the landslide body to obtain a variety of data information that reflect the deformation state of the landslide. With the in-depth research on landslides, both local and overseas researchers have continuously discovered the factors that induce landslide disasters. Exploring how to analyze and rationally use these data is extremely necessary [4,5,6,7]. The traditional data analysis of landslide deformation only uses a single data value, which exhibits randomness, uncertainty, and fuzziness [8].
Comprehensive processing and analysis of the collected landslide deformation data is a necessary means to overcome the drawbacks of the traditional methods. Considering these drawbacks, the multisource heterogeneous sensor data fusion technology has been established as a new theoretical method. In the process of data fusion, the data collected using different landslide monitoring methods can be effectively used to obtain more comprehensive and reliable information. Consequently, more accurate landslide deformation information can be acquired, and the reliability and accuracy of landslide monitoring data and early warning can be improved \(^9\).

In recent years, multisource sensor data fusion, as an emerging interdisciplinary subject, has been widely used in high-tech fields, such as military, national defense, and aerospace. Moreover, it has become an area of concern \(^10\). In the field of landslide monitoring, multisource data fusion technology has been well developed with the application of sensor technology, computer technology, and network communication technology. Among them, Guo Ke et al. (2005, 2006) used multisensor target tracking fusion technology to process landslide displacement monitoring information, make full use of the monitoring information collected at each landslide monitoring point, and improve the accuracy of landslide prediction and forecast; Peng Peng et al. (2011) applied the multisensor valuation fusion theory in the dynamic deformation monitoring and analysis of a landslide in Southwest China, which proved that the method is effective and feasible; Fan Junqing et al. (2015) employed multiple stepwise regression analysis to create a correlation analysis model between the multi-factor variables of landslide, proving that data fusion is effective in improving the accuracy of landslide prediction results; Liu Chaoyun et al. (2015) used the Kalman filter data fusion model of displacement parameters to predict the stable state and deformation trend of the landslide; and Xie Mingli et al. (2019) used the multisource data fusion method to study the deformation and failure characteristics as well as the temporal and spatial evolution law of Huangnibazi landslide in the dynamic evolution process by utilizing the different characteristics and applicability of various data sources to the landslide body. In landslide monitoring and analysis, the most important thing is to conduct discriminant analysis on the landslide deformation stage. Determining whether data fusion is capable of optimizing the original monitoring data and whether it can improve the accuracy and reliability of discriminant analysis requires further evaluation and analysis.

This study uses the Heifangtai Dangchuan 7# landslide body in Gansu Province as an example, employs adaptive weighted estimation fusion algorithm to conduct fusion analysis on different types of landslide deformation monitoring data, and explores the application of data fusion in the processing of landslide deformation monitoring data. In addition, reliable criteria for landslide deformation analysis are provided in this study.

2. Adaptive weighted estimation fusion algorithm

At present, weighted fusion algorithm is among the simplest, most popular, and mature data-level fusion methods. Its advantages include optimality, unbiasedness, and minimum mean squared error, which have been proven by numerous researches \(^17,18,19\). However, the core problem of the weighted fusion algorithm is how to determine the weight, which directly affects the fusion result \(^20\). Thus, in this study, adaptive weighted estimation fusion algorithm is employed to determine the weights. This algorithm only obtains a set of data fusion values with the smallest mean squared error by relying on the sensor measurement data \(^17\).

Assume that there are \(n\) sensors with different accuracies, as presented in Figure 1, due to their different weighting factors, under the optimal condition of the smallest total mean squared error, according to the measurement value obtained by each sensor. Find the optimal weighting factor that adaptively corresponds to each sensor to obtain the best value for \(X\) after fusion \(^18\).
Figure 1. Multisensor data adaptive weighted fusion estimation model.

Assume that the mean square errors of the sensed data of the $n$ sensors are $\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2$; the measured values of the sensor nodes are $X_1, X_2, \ldots, X_n$, correspondingly; and the weight factors of the sensors are $W_1, W_2, \ldots, W_n$, respectively. Because the data are independent of each other and belong to the unbiased estimation of $X$, the truth and weight factors of $X^*$ after fusion respectively satisfy the following relationships:

$$X^* = \sum_{p=1}^{n} W_p X_p$$

(1)

$$\sum_{p=1}^{n} W_p = 1$$

(2)

The total mean squared error is

$$\sigma^2 = E \left[ \sum_{p=1}^{n} W_p^2 (X - X_p)^2 \right] = \sum_{p} W_p^2 \sigma_p^2$$

(3)

According to the above formulas, the mean squared error $\sigma^2$ is a multivariate quadratic function; thus, $\sigma^2$ must have a minimum value. In accordance with the extreme value theory of the multivariate function, the minimum weight factor is

$$W_p^* = \frac{1}{\sigma_p^2 \sum_{i=1}^{n} \frac{1}{\sigma_i^2}} (p = 1, 2, \ldots, n)$$

(4)

Thus, the corresponding minimum mean squared error is

$$\sigma_{min}^2 = \frac{1}{\sum_{p=1}^{n} \frac{1}{\sigma_p^2}}$$

(5)

Assume that there are any two different sensors, which are $p \neq q$; the measured values are $X_p, X_q$; and the corresponding observation errors are $V_p, V_q$,

$$X_p = X + V_p \quad X_q = X + V_q$$

where $V_p, V_q$ denote the zero-mean stationary noise; then, the variance of sensor $p$ is

$$\sigma_p^2 = E [V_p^2]$$

(6)

Because $V_p, V_q$ are not related to each other, and the mean is zero, as well as to $X$, the correlation coefficient $R_{pq}$ of $X_p, X_q$ satisfies

$$R_{pq} = E [X_p X_q] = E [X^2]$$

(7)

The autocorrelation coefficient $R_{pp}$ of $X_p$ satisfies

$$R_{pp} = E [X_p^2] = E [X^2] + E [V_p^2]$$

(8)

Subtract (7) from (8),

$$\sigma_p^2 = E [V_p^2] = R_{pp} - R_{pq}$$

(9)
After adaptive weighted data processing, the sensor data obtained from each monitoring point are fused into one data management center for the application of the landslide monitoring prediction and warning service.

3. Examples of landslide deformation monitoring data fusion

3.1. Monitoring area and data sources
Heifangtai is located in Yanpan Gorge Town, Yongjing County, Gansu Province, on the north bank of the Yellow River. In this study, the research area is near Heifangtai Dangchuan 7# landslide. This area is located in the arid and semiarid regions of the northwest inland, which has a temperate continental climate, with little annual rainfall, long sunshine duration, and large water resource evaporation. Due to the effect of precipitation and irrigation, the landslide has resulted in the formation of collapsed pits and a large number of fractures [21,22,23].

In this study, the monitoring data of 7# slump of Heifangtai are used. Figure 2 presents the layout of the monitoring points, which include two surface Global Navigation Satellite System (GNSS) monitoring points and three surface crack displacement monitoring points installed at the location of the landslide crack.

![Figure 2. Multisensor data adaptive weighted fusion estimation model.](image)

The monitoring data is from March 28 to October 4, 2019, and includes two sets of GNSS monitoring data (HF06 and HF07), three sets of displacement meter monitoring data (DCF11, DCF14, and DCF15), and humidity, cloudiness, cumulative three kinds of meteorological data of precipitation. The landslide occurred at 4 o’clock on October 5, 2019, and all five sets of monitoring equipment were able to obtain the displacement change data of the landslide deformation.

3.2. Monitoring data preprocessing
In landslide monitoring, the monitoring data are often influenced by sensor factors, surrounding environmental factors, and human factors, as well as the phenomenon of abnormal and missing values, as presented in Figure 3. Thus, it is necessary to perform preprocessing of missing interpolation, abnormal point elimination and equal interval data respectively on the monitoring data. For the GNSS monitoring data, the components along the main sliding direction were utilized as substitute for the measured data.
Figure 3. Monitoring data initial cumulative displacement deformation curve.

Figure 4. Cumulative displacement deformation curve after pretreatment.

Generally, a landslide undergoes a certain period of evolution from deformation to failure, and its cumulative displacement-time curve exhibits evident deformation characteristics in three stages: initial deformation stage, uniform deformation stage, and accelerated deformation stage [24]. However, the loess landslide often has a sudden occurrence, as reflected in the very short duration of the accelerated deformation stage, which can be seen from the cumulative displacement deformation [25]. Therefore, to more accurately analyze the accelerated deformation stage, the interval during equal interval processing should be reduced and the number of samples in the observation sequence of the accelerated deformation stage increased. In this study, the accelerated deformation stage is separated by 2 h, and the remaining two stages are separated by daily intervals. In addition, the data are averaged to achieve observation sequences with equal intervals. Thus, the monitoring sequence is divided into two stages, stage I (initial deformation stage + uniform deformation stage) and stage II (accelerated deformation stage), as presented in Figure 5.
3.3. Monitoring data fusion

Using adaptive weighted estimation fusion algorithm, the five sets of preprocessed monitoring data are fused in two stages. Under the principle of ensuring the minimum mean squared error, the fusion result is obtained, as presented in Figure 6.

Figure 5. The cumulative displacement deformation curve after constant interval.
In landslide deformation, an evident macroscopic deformation failure will occur, and there will be a precursor warning information during the accelerated deformation stage, thus making the early prediction and warning of landslide possible [24,25]. For predicting the occurrence of landslide and obtaining early warning, landslide displacement monitoring information is extremely important. Also, understanding the mechanism of landslide and providing a reliable threshold are also helpful [24,25]. The use of more reliable fused deformation data in landslide deformation monitoring data processing and analysis can further improve the accuracy of landslide prediction and imminent warning.

For the landslide displacement and deformation data after fusion, this study mainly analyzes the deformation rate, deformation acceleration, and improved tangent angle, as presented in Figure 7.

**Figure 6.** The cumulative displacement deformation curve after data fusion.

**Figure 7.** The fusion data analysis (RHI+RHI).
As can be seen from Figure 7, in the fusion data, from 2019-03-28 to 2019-09-19, the deformation rate, deformation acceleration, and improved tangent angle remain relatively stable as the cumulative displacement of the landslide increases, which is consistent with the data characteristics of the landslide uniform deformation stage. From 2019-09-20 to 2019-10-04, the improved tangent angle continues to increase as the cumulative displacement of the landslide increases. From 2019-09-30, the improved tangent angle of the deformation curve is greater than 80°, the landslide deformation rate is obviously accelerated; starting from 2019-10-02, the improved tangent angle of the deformation curve has been greater than 85°, and the deformation rate and deformation acceleration exhibit an increasing trend with time. It is consistent with the data characteristics of the landslide accelerated deformation stage.

3.4. Evaluation of fusion results
To analyze and evaluate the fusion results, the monitoring data and fusion data are analyzed and compared correspondingly to further reflect the application value of the fusion results. Through the above analysis, the GNSS HF07 monitoring data is chosen for the analysis of cumulative displacement, deformation rate, and improved tangent angle, etc. The results are presented in Figures 8 and 9.
fusion analysis result is better than the data analysis result of deformation data and can better reflect the deformation characteristics of the whole landslide. The results indicate that the landslide deformation enters the near-slip stage in 2019-9-20, and the landslide enters the near-slip stage. From the monitoring point DCF11 in Table 1, the landslide deformation enters the intermediate accelerated deformation stage in 2019-9-20, and the landslide enters the near-slip stage in 2019-9-27; from the monitoring point HF07, it can be seen that the landslide deformation enters the intermediate accelerated deformation stage in 2019-10-4; from the monitoring points DCF14 and HF06, it can be seen that the landslide deformation enters the intermediate accelerated deformation stage in 2019-9-30, and the landslide enters the near-slip stage in 2019-10-1; from the monitoring point DCF15 and adaptive weighted fusion and BP neural network fusion results, it can be seen that the landslide deformation enters the intermediate accelerated deformation stage in 2019-10-1, and the landslide enters the near-slip stage in 2019-10-2.

The results indicate that adaptive weighted estimation fusion algorithm can effectively fuse five sets of deformation data and can better reflect the deformation characteristics of the whole landslide. The fusion analysis result is better than the data analysis result of the single landslide deformation.
monitoring point; the BP neural network is an intelligent fusion algorithm with a high fusion accuracy, and the results of the adaptive weighted fusion analysis are similar to those of the BP neural network fusion analysis, which further indicates the reliability of adaptive weighted fusion results.

4. Conclusion
This study determines the current status of landslide multisource sensor monitoring and the characteristics of multisource sensor weighted fusion algorithm. Moreover, it applies the adaptive weighted estimation fusion algorithm in the processing of Heifangtai landslide deformation monitoring data. The adaptive weighted estimation fusion algorithm belongs to data-level fusion and only relies on sensor measurement data to obtain a set of data fusion values with the smallest mean squared error. The analysis and comparison of application examples make the adaptive weighted estimation fusion results more reliable and accurately reflect the deformation characteristics of the landslide body, thus providing more effective data support for subsequent analysis, prediction, and early warning of landslide.

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