Anomaly Detection Model of Psychological Measurement Based on Low-scale Feature Constraint

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Abstract
Abnormality detection of psychometric measurement is very important to ensure the reliable operation of psychological measurement. However, the existing anomaly detection model only makes use of the temporal correlation or spatial correlation of measurement errors. Aiming at this shortcoming, considering the temporal and spatial correlation of the measurement error matrix, an anomaly detection model of psychometric measurement based on MSBSA is proposed. The method uses the multi-scale modeling capability of wavelet transform and the dimensionality reduction capability of BSA to model the normal measurement error. Then the Shewart control chart and the EWMA control chart are used to analyze the residual measurement error. In addition, the MSBSA anomaly detection model is extended online using the sliding window mechanism, and an online anomaly detection model of MSBSA is proposed. The results of Measured Data Analysis and of Simulated Experiment Analysis show that the detection performance of MSBSA algorithm is better than that of BSA algorithm and KLE algorithm.

Key words: Psychological measurement anomaly detection, Multi-scale modeling, Bias sampling analysis, Measurement error matrix, On-line detection.

1. INTRODUCTION

In today's psychological measurement environment, a variety of abnormal behavior occurs frequently. The effective detection of abnormal behavior of psychological measurement is important to ensure the reliable operation of psychological measurement. Because psychometric abnormal behavior usually has different patterns, and hidden in complex background measurement error, therefore, psychological measurement anomaly detection is a challenging task.

Most of the studies (Pohl, Gräfe and Rose, 2014; Sahranavard, Hassan, Elias and Abdullah, 2013) detect anomalies by passive monitoring and analyzing changes in the measurement error of a single psychometric measurement link, because most of the psychometric abnormalities are accompanied by significant changes in psychometric measurement error. For example, the paper (Pohl, Gräfe and Rose, 2014) uses wavelet transform to reveal four different measurement error anomalies. In this method, the temporal correlation of the measurement error of the psychometric measurement link is used, and the multiscale analysis method is adopted to obtain the better detection result. However, this method only takes into account the measurement error of a single psychometric measurement link, and its ability to detect anomalies is limited. The reason for this is that many anomalous behaviors affect the number of psychometric links and paths in psychometric measurements, and the anomalies that are present on a single psychometric link and path are sometimes not obvious. To solve this problem, a new network-wide anomaly detection model based on bias sampling analysis (BSA) is proposed for the first time using the measurement error matrix as a data source (Lally and Testa, 2015; Kröhne and Frey, 2013). This method uses multiple psychometric links to measure the spatial correlation between errors, map the high-dimensional data of the measurement error matrix to the normal subspace and the abnormal subspace, and then detect the highlighted anomaly in the abnormal subspace Behavior patterns. However, the BSA-based psychometric abnormality detection model belongs to the single-scale analysis method. It only considers the spatial correlation of the measurement error matrix data and does not take into account the temporal correlation of the measured error matrix data.

In view of the shortcomings of the existing two methods, this paper attempts to measure the time-space correlation of the error matrix with OD flow. Then, using the multi-scale modeling capability of wavelet transform and the dimension-reducing ability of BSA, we use Shewart and EWMA to control the error matrix of the OD flow measurement, and then use the wavelet transform and BSA to confirm the spatial-temporal correlation. (MSBSA) based on the low-scale feature constraint (multiscale BSA, short as MSBSA) is proposed. Furthermore, the MSBSA anomaly detection model is extended on-line using the sliding window mechanism, and an online MSBSA anomaly Detection model.

The main contribution of this paper lies in the following three aspects:
(1) Multidimensional analysis of the OD matrix error matrix data measured by the wavelet transform shows that it is time-dependent, and the bias sampling method is used to confirm the OD matrix error matrix data has spatial correlation at each time scale;

(2) An anomaly detection model of psychological measurement based on MSBSA and its online expansion are proposed;

(3) The validity of the algorithm was evaluated by two methods: psychological measurement data analysis and simulation experiment.

2. RELATED WORK

Since the literature (Pack and Cho, 2015) proposed anomaly detection statistical model, the psychological measurement anomaly detection model research has been widespread concern in academia. According to the different detection range, we can classify these methods into three categories: host-based anomaly detection model, psychometric measurement anomaly detection model based on single psychological measurement link error measurement error and psychological measurement anomaly detection model based on measurement error matrix.

The basic idea of the host-based anomaly detection model (Bartolucci, 2014; Südkamp, Kaiser and Möller, 2012; Woods, Cai and Wang, 2013; Wang, Tay and Drasgow, 2013) is to use the system log or audit record of the host system as the anomaly detection data source, to establish the normal behavior mode of the user by machine learning, and then measure it in some measure. The user deviates from the normal behavior pattern to detect the psychological measurement intrusion behavior.

The psychometric measurement anomaly detection model based on single psychometric measurement link measurement error (Pohl, Grafe and Rose, 2014; Sliter and Zickar, 2014; Kim, Yoon and Lee, 2012; Woods and Harpole, 2015) detects anomalies by passive monitoring and analyzing the changes in the error of a single psychometric measurement link. The basic idea of this method is to measure the time correlation of the error using the psychometric measurement link, and to analyze the measurement error data by multi-resolution analysis, such as wavelet transform, to separate the deterministic signal from the stochastic signal, a variety of abnormal behavior.

Abnormal detection of psychological measurement based on measurement error matrix is a kind of psychological measurement anomaly detection model which has arisen in recent years. It mainly focuses on the limitations of the single-psychometric measurement error detection model. By using the multidimensional statistical analysis method or the signal processing method, the spatial correlation and time correlation of the measurement error matrix are used to detect abnormal behavior from the perspective of psychological measurement. In (Lally and Testa, 2015; Kröhne and Frey, 2013), the measurement error matrix is used as the data source for the first time to reveal the low dimensionality of the measurement error matrix, and the characteristics of the feature flow are analyzed. Based on this, a BSA-based psychometric anomaly detection model is proposed. The experimental results show that the proposed method is superior to the traditional single-psychometric measurement error time series method (Pritikin, Hunter and Boker, 2015), which further points out the four challenges of the BSA anomaly detector, including the principal components in the normal subspace. The impact of measurement error aggregation level on the validity of the algorithm, the abnormal measurement error on the normal subspace poisoning; the literature (Schwarz, 2015; Ferrando, 2016) is the use of the BSA anomaly detector defects, proposed four kinds of data poisoning and proposes an anomaly detection model based on robust BSA. The basic idea of this method is to use multiple psychometric measurement links to measure the spatial correlation between errors. The BSA method is used to obtain the principal components of the high-dimensional data of the measurement error matrix. The normal subspace and the abnormal subspace are established respectively. Detection of abnormal behavior patterns is conducted in abnormal subspaces. The disadvantage of this method is that only the spatial correlation of the measurement error matrix is utilized, without taking advantage of the temporal correlation of the measured error matrices. In this paper, (Ferrando, 2016) considers the spatial correlation and time correlation of the measurement error matrix, extends BSA to the Karhunen-Loève transform (KLE), proposes a KLE calculation method based on Galerkin, and then uses KLE to establish A prediction model for anomaly detection. Experiments show that the KLE method has better detection performance than BSA. However, the KLE method only utilizes the temporal correlation between the measured data of a fixed time interval and does not have the capability of multi-resolution analysis of the wavelet transform. In addition, the KLE method is also an off-line algorithm and cannot detect anomalies in real time.

The MSBSA-based psychometric anomaly detection model also uses the measurement error matrix as the data source. It combines the multi-resolution analysis capability of wavelet transform and BSA's dimensionality reduction analysis ability, and makes full use of the spatial correlation and time correlation in the measurement error matrix data. The results of the data analysis and simulation experiments of the psychological measurements confirm that the detection performance of the MSBSA method is superior to the BSA method.
(Lally and Testa, 2015), and is superior to the recently proposed KLE method. In addition, this paper extends the MSBSA algorithm online, not only can detect anomalies in real time, but also has better detection performance.

3. ERROR MATRIX MODEL MEASUREMENT

Definition 1 (measurement error matrix), the measurement error matrix is a measure of the traffic demand between all the source and destination pairs (i.e. OD pairs) in a psychometric measurement. Depending on the type of psychometric node selected, a measurement error matrix of different granularities can be defined: psychometrically measured link-level, routing-level, and (PoP) point of presence measurement error matrices.

Definition 2 (PoP level measurement error matrix), assume that an autonomous system (AS) has n PoP points, passively measure the measurement error between any pair of PoP points at a certain time interval (period), and then arrange the obtained measurement values into one \( T \times p \) matrix \( X \) represents the time series of all these measurement error measurements. Where \( T \) indicates the number of cycles measured, \( p \) represents the number of measurement error measurements obtained during each cycle, i.e. \( p = n \times n \). The number \( t \) row represents the vector of the measured error measurements in the first \( t \) cycle, usually indicated by the first row \( x_1 \); the \( j \) column represents the time series of the measured error measurements between the pair of \( j \) PoP points. The matrix \( X \) is called the PoP measurement error matrix of the AS, or the measurement error matrix. In this paper, measurement error size takes (byte number, group number and flow number) as a measure of measurement error, therefore, measurement error matrix of any element \( x_{ij} \) that the first \( t \) interval time between the first pair of \( j \) OD measurement error size.

4. MSBSA ANOMALY DETECTION MODEL

In this section, we will make full use of the time-space correlation of the measurement error matrix, and combine the multi-scale modeling ability of wavelet transform and the dimension-reduction ability of bias sampling analysis, and then normal measurement error in the measurement error matrix. Two error analysis methods are adopted to achieve anomaly detection; finally, this section takes the MSBSA anomaly detection algorithm for time complexity analysis.

4.1. Normal Measurement Error Modeling

The ability of MSBSA combined with wavelet transform to extract the deterministic features of signals and the ability of BSA to extract the common models of multivariate variables well meet the requirements of normal measurement error modeling in measurement error matrix.

MSBSA-based normal measurement error modeling method includes the following four basic steps (as shown in Figure 1):

Step 1: Measure the wavelet decomposition of the error matrix.

Firstly, the standard orthogonal wavelet transform \( W \) is used to decompose the measurement error matrix \( X \) to obtain the wavelet coefficient matrix of each scale \( Z_L, \hat{Y}_m (m = 1, \cdots, L) \). Then the MAD method is used to filter the wavelet coefficients to obtain the filtered wavelet coefficient matrix:

\[
\hat{Z}_L, \hat{Y}_m (m = 1, \cdots, L)
\]

Step 2: Bias Sampling Analysis and Reconstruction of the Wavelet Coefficient Matrix.

Firstly, the wavelet coefficient matrix \( \hat{Z}_L, \hat{Y}_m (m = 1, \cdots, L) \) of each scale is filtered and analyzed by Bias Sampling Analysis. Then, the number of PC is selected according to the screeplot method (Lally and Testa, 2015). Finally, the wavelet coefficient matrix \( \hat{Z}_L, \hat{Y}_n (m = 1, \cdots, L) \) is reconstructed.

Step 3: Wavelet reconstruction of the measurement error matrix.

According to the wavelet coefficient matrix \( \hat{Z}_L, \hat{Y}_n (m = 1, \cdots, L) \) of all scales, the error matrix is reconstructed by wavelet inverse transform \( W^T \).

Step 4: Bias Sampling Analysis and Reconstruction of the Measurement Error Matrix.

The concrete steps are similar to the second step, and the reconstructed measurement error matrix \( \hat{X} \) is obtained.

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4.2. Residual Measurement Error Analysis

After establishing the normal measurement error model, the residual measurement error mainly consists of two parts: Noise and burst measurement error. Among them, the noise is mainly caused by the error of the measurement error model, while the burst measurement error is mainly caused by a variety of abnormal behavior. In order to analyze the residual measurement error, this paper introduces squared prediction error (SPE) as the detection threshold, Q statistic threshold is defined as follows:

$$Q = \sum_{j=1}^{p} (x_j - \hat{x}_j)^2$$

(1)

Due to the large variations in the magnitude of the various anomaly measurement errors, such as the flash crowd and DDoS attacks, the measurement error can be dramatically increased and the worm measurement error is small. And it increases with the spread of the propagation range, so this paper uses two control chart method to analyze the residual measurement error: Shewart and EWMA control chart. The Shewart control chart can detect the abrupt change of the measurement error quickly, but it is slow when detecting the abnormal measurement error of the slow change. The EWMA control chart can detect the abnormal measurement error which changes slowly but with longer duration after choosing the appropriate parameter.

4.2.1. Shewart control chart

Shewhart control chart method directly detects the SPE time series by using Q statistic (Lally and Testa, 2015) as the detection threshold, Q statistic threshold is defined as follows:

$$\delta_n^2 = \left[ c_n \sqrt{\frac{2\phi_2}{2\phi_2}} + \frac{\phi_1 h_0 (h_0 - 1)}{\phi_2} \right]^{\frac{1}{h_0}}$$

(2)

Here, $h_0 = 1 - \frac{2\phi_2}{3\phi_2^2}$, $\phi_1 = \sum_{j=1}^{p} \lambda_j$, $i = 1, 2, 3, \ldots$, the measured error matrix X is projected to the variance captured by the first $j$ principal axis, the first $j$ eigenvalue, and $c_n$ is the $1 - \alpha$ quantile in the standard normal distribution, $\alpha$ usually 0.001. For example $SPE \geq \delta_n^2$, an exception is considered, where $\delta_n^2$ the confidence threshold $1 - \alpha$ is the threshold for the SPE.

4.2.2. EWMA control chart

The EWMA control chart method predicts the value of the time series at the next moment based on the most recent historical data. At this time $t$, the predicted value of the residual measurement error is written as $\hat{Q}_{t}$, the actual value of the residual measurement error at the first time $t$ is written as $Q_{t}$, and the predicted value of the residual error at the time $t + 1$ of the measurement is written as $\hat{Q}_{t+1}$

$$\hat{Q}_{t+1} = \alpha Q_{t} + (1 - \alpha) \hat{Q}_{t}$$

(3)

Among them, $0 \leq \alpha \leq 1$ is the relative weight of historical data, also known as the smoothing index, the selection of values $\alpha$ is discussed in the Experimental section.
The absolute value of the difference between the actual value and the predicted value \( |Q - \hat{Q}| \) is obtained by iterating the equation (3), which is called the EWMA process statistic. The control limit of the EWMA control chart can be expressed asymptotically as follows

\[
UCL = u_s + L \times \alpha \sqrt{\frac{1}{2(1-\alpha)}} T
\]

Among them, \( u_s \) indicates the mean of the EWMA process statistics, \( \sigma_s \) indicates the mean square error of the EWMA process statistic, \( \alpha \) denotes a smoothing index, \( L \) denotes the control chart constant, the size of which directly affects the detection result; and denotes the length of the time series. If it is \( |Q - \hat{Q}| \geq UCL \), it will be considered abnormal.

### 4.2.3. Algorithm complexity analysis

In the MSBSA anomaly detection algorithm, the main computational cost is to measure the wavelet transform of the measurement error matrix and the biased sampling analysis of the wavelet coefficient matrix and the measurement error matrix. In the algorithm implementation, the wavelet transform using Mallat algorithm, the time complexity \( O(T) \); bias sampling analysis algorithm for the time complexity \( O(Tp^2) \). Therefore, the total time complexity of the MSBSA anomaly detection algorithm is \( O(Tp^2 + Tp) \) the same as \( O(Tp^2) \).

## 5. ONLINE EXPANSION

The MSBSA anomaly detection model requires that the anomaly detection is performed after the measurement of the error matrix data is completed. Therefore, the MSBSA anomaly detection model belongs to the off-line detection model and cannot meet the need of real-time online detection of anomalies. Therefore, this paper presents an on-line MSBSA anomaly detection model.

The basic principle of the on-line MSBSA anomaly detection model is shown in Fig.2. It uses a sliding window (gliding window) mechanism, and the detection process is divided into two phases: the initialization phase and sliding phase. In the initialization phase, the former WIN measurement data is selected to form the measurement error matrix, the MSBSA anomaly detection model is used to calculate the residual measurement error of the initial measurement error matrix and the EWMA control chart is used to issue the abnormal alarm timely. In the sliding phase, every other measurement interval Time, add the latest measurement data to the sliding window and the oldest measurement data removed to keep the sliding window length unchanged, and then apply the MSBSA anomaly detection model to calculate the residual measurement error of the latest measurement data, and the application of EWMA control chart timely abnormalities alarm. It should be pointed out that, in order to improve the speed of wavelet transform, the sliding window length should be a multiple of two, as selected in this paper, because the wavelet transform is usually used in the realization of the binary wavelet transform algorithm - Mallat algorithm. Therefore, in order to improve the speed of wavelet transform, the sliding window length should be a multiple of 2, as selected in this paper. \( WIN = 2^i \).

![Figure 2. The principle of the online MSBSA anomaly detection model](image-url)
Time complexity is an important index of online anomaly detection algorithm. The time complexity of the on-line MSBSA anomaly detection algorithm single step execution \(O(WIN \times p^2 + WIN)\), i.e. \(O(WIN \times p^2)\), if \(WIN = 2^9 = 512\) the computer is configured with 2.33GHz CPU and 2GB memory, the on-line MSBSA anomaly detection algorithm is performed on the data set F in Table 1, and the one-step running time is less than 1s, which fully satisfies the need of the psychometric abnormality detection abnormality.

Table 1 Abilene Measurement Error Matrix Data Set

<table>
<thead>
<tr>
<th>S/N</th>
<th>duration</th>
<th>interval(min)</th>
<th>measure</th>
<th>Matrix form</th>
<th>Date set</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2003.12.15-12.21</td>
<td>5</td>
<td>bytes</td>
<td>2010(\times)121</td>
<td>B</td>
</tr>
<tr>
<td>2</td>
<td>2003.12.15-12.21</td>
<td>5</td>
<td>groups</td>
<td>2010(\times)121</td>
<td>P</td>
</tr>
<tr>
<td>3</td>
<td>2003.12.15-12.21</td>
<td>5</td>
<td>streams</td>
<td>2010(\times)121</td>
<td>F</td>
</tr>
</tbody>
</table>

6. EXPERIMENTAL EVALUATION

There are two methods to evaluate the performance of anomaly detection algorithms: psychometric measurement data analysis and simulation experiment analysis. Taking into account the advantages and disadvantages of the two methods, this paper uses a combination of these two methods to evaluate the detection performance of anomaly detection algorithm.

6.1. Psychological Measurement Measured Data Analysis

6.1.1. Data sets

The measurement error matrix data set used in this paper comes from Abilene psychometric measurement, which is the backbone of psychometric measurement. Because Abilene psychometric measurements have high packet rates, the measurement device cannot capture each packet in the stream data, so the Abilene psychometrics uses the 1% sample rate to collect the stream data from the psychometric measurements. The measurement error matrix data set used in this paper is summarized in Table 1. It should be pointed out that the data set in Table 1 comes from the measured data of psychological measurement, including the burst measurement error and the abnormal measurement error. It will be confirmed by experiments that the MSBSA anomaly detection algorithm can detect abnormalities successfully in the background of burst measurement error Measurement error.

6.1.2. Evaluation methods

In order to evaluate the detection performance of the anomaly detection algorithm, we use the operating characteristic (ROC) curve. The x-axis of the ROC curve represents the false positive rate (FPR), and the y-axis represents the true positive rate (TPR). Each ROC curve corresponds to a pair of false positive rate and detection rate, each ROC curve reflects the detection algorithm in a variety of detection threshold false alarm rate and detection rate of the compromise. If the vertical coordinate of the ROC curve reaches the upper left corner of the graph as the abscissa increases gradually, it shows that the algorithm only achieves a high detection rate with a small false positive rate, that is, the algorithm has good detection performance. In order to quantitatively evaluate the detection performance of the algorithm, the area under the ROC curve is usually used as an index to measure the performance of the detection performance. The larger the area covered by the ROC curve is, the better the detection performance is.

6.1.3. Detection performance

The MSBSA and BSA algorithms are applied to Data Set B, Data Set P and Data Set F in Table 1, respectively. MSBSA algorithm uses Shewart control chart and db5 wavelet, detection results and detection performance shown in Figure 3. It can be seen that the detection performance of MSBSA algorithm is better than BSA algorithm for 3 different data sets. In particular, for the data set P, the MSBSA algorithm only achieves a detection rate of 0.95 with a false positive rate of less than 0.1; for the data set F, the MSBSA algorithm only achieves a detection rate of 0.85 with a false positive rate of less than 0.1.

The MSBSA algorithm and the KLE algorithm are applied to the data set B, dataset P and data set F in Table 1, respectively. MSBSA algorithm using Shewart control chart and db5 wavelet, KLE algorithm time correlation amplitude N = 2. The detection performance of the two algorithms is shown in Fig.4. It can be seen that the detection performance of MSBSA is better than KLE for three different data sets.
Figure 3. The detection results and detection performance of MSBSA and BSA algorithm for real measurement data

6.2. Simulation Experiment and Analysis

6.2.1. Experimental methods

In order to simulate the true psychological measurement and measurement error matrix under controlled conditions, based on the measured psychological measurement error matrix in Table 1, we use the following three steps to synthesize the measurement error matrix:
Step 1, for each OD measurement error in the measurement error matrix, the periodic normal measurement error is extracted by wavelet transform. In this paper, we use the db5 wavelet to decompose the OD measurement error to obtain the scale function coefficient vector. Then we reconstruct the smooth low frequency signal by wavelet reconstruction algorithm, and filter the high frequency signal containing noise and anomaly.

Step 2, the zero mean Gaussian noise is added to each OD measurement error of the reference measurement error matrix generated in the first step to obtain a reference measurement error matrix free of anomalies.

Step 3, in the noise-based reference measurement error matrix generated in Step 2, various typical anomalies are added by a certain rule.

Using the above three steps on the data set F in the OD1 measurement error processing, the results is shown in Figure 5.

![Original OD flow](image1)

(a) Original OD flow

![OD flow after removal of noise](image2)

(b) OD flow after removal of noise

![OD flow after adding noise](image3)

(c) OD flow after adding noise

![OD flow after adding anomaly](image4)

(d) OD flow after adding anomaly

Figure 5. Three Steps of Synthesizing Error Matrix

6.2.2. Detection performance

Based on the measurement error matrix data set F in Table 1, the measurement error matrix is synthesized and four types of measurement error anomalies are injected. In addition, 10 groups of alpha anomalies were injected from the 1st to the 500th time, and each group of anomalies lasted for 30 minutes. The abnormal measurement error was 50% of the original OD measurement error value, that is \( \delta = 0.5 \), the source-destination ODs involved was \((5,1)\), the abnormal shape function is a step function; 10 sets of DDoS attack anomalies are injected from the 501st to the 1000th time, each group is abnormal for 30 minutes, and the abnormal measurement error is 40% ~ 50% of the original OD measurement error \((0.4 \leq \delta \leq 0.5, 5,1)\), and the shape function of the anomaly is a slope function. One set of burst flow anomalies is injected from the 1101th to the 1150th, and the anomaly lasts for 250 minutes. The error of the abnormal measurement is 20% to 50% of the original OD measurement error \((i.e. 0.2 \leq \delta \leq 0.5, 5)\), the number of source-destination ODs involved was \((5,1)\), and the abnormal shape function was the slope function. One set of inlet / outlet movement anomalies was injected from 1981 to 2010, the anomaly lasted 150 minutes, 80% (i.e. \( \delta = 0.8 \)) of the original OD measurement errors, the number of
source-destination ODs involved is (1,1), and the shape function of the anomaly is a step function. MSBSA algorithm and BSA algorithm are applied to the synthesized measurement error matrix. MSBSA algorithm adopts Shewart control chart and db5 wavelet respectively. The detection results and detection performance are shown in Fig.6. It can be seen that the detection performance of MSBSA algorithm is better than BSA algorithm. In particular, the MSBSA algorithm only achieves a detection rate of 0.9 with a false alarm rate of 0.2.

The measurement error matrix is synthesized in the same manner as above, the MSBSA algorithm and the KLE algorithm are used respectively. MSBSA algorithm uses the Shewart control graph and db5 wavelet, and the time dependency amplitude of the KLE algorithm is N = 2. Detection performance of the two algorithms is shown in Figure 8, we can see, detection performance of MSBSA algorithm is better than KLE algorithm.

![ROC curve](image)

**Figure 6.** The detection results and detection performance of MSBSA and PCA algorithm for real measurement data

![ROC curve](image)

**Figure 7.** The detection results and detection performance of MSBSA and KLE algorithm for simulated experimental data

7. CONCLUSION

Existing anomaly detection models only exploit the temporal or spatial correlation of measurement errors alone. Considering this problem, this paper considers the spatial and temporal correlation of the measurement error matrix, synthetically utilizes the multi-scale modeling capability of wavelet transform and the dimensionality reduction capability of BSA, and uses Shewart control chart and EWMA control chart to analyze the residual measurement errors. A psychometric anomaly detection model based on MSBSA is proposed. And the MSBSA anomaly detection model is extended on-line using the sliding window mechanism, an on-line MSBSA anomaly detection model is proposed. Analysis of Measured Data and Analysis of Simulated Experiment show that the detection performance of MSBSA algorithm is better than that of BSA algorithm and KLE algorithm which was proposed recently. The detection performance of on-line MSBSA algorithm is very
close to that of MSBSA algorithm, and the single-step execution time is short, which fully satisfies the need for psychometric measurement anomaly detection. In addition, the experimental analysis confirms that the EWMA control chart is suitable for detecting small anomaly measurement errors, while the Shewart control chart is suitable for detecting large abnormal measurement errors. The next step, on the basis of anomaly detection, we will research on abnormal classification methods and how to deal with different types of anomalies and take appropriate defense measures.

REFERENCES


