

Testing Equality of Multivariate Normal Populations with Three-step Monotone Missing Data

Remi Sakai^{*}, Ayaka Yagi^{*}, and Takashi Seo^{*}

^{*}*Department of Applied Mathematics, Tokyo University of Science
1-3, Kagurazaka, Shinjuku-ku, Tokyo 162-8601, Japan*

Abstract

In this paper, we consider simultaneous tests of the mean vectors and the covariance matrices under three-step monotone missing data for a multi-sample problem, that is, the problem of testing the equality of multivariate normal populations with three-step monotone missing data. We provide the likelihood ratio test (LRT) statistic and propose test statistics for improving the accuracy of the χ^2 approximation. These test statistics are derived by decomposing of the likelihood ratio (LR) using the coefficients of the modified LRT statistics with complete data. As an alternative approach, we derive an approximate upper percentile of the LRT statistic with three-step monotone missing data using linear interpolation based on an asymptotic expansion of the LRT statistic with complete data. Finally, we investigate the asymptotic behavior of the upper percentiles of these test statistics and the accuracy of approximate upper percentiles via Monte Carlo simulation. In addition, we give an example for test statistics and approximate upper percentiles proposed in this paper.

Key Words and Phrases. Asymptotic expansion, likelihood ratio test, linear interpolation, maximum likelihood estimator, modified likelihood ratio test statistic.

1 Introduction

In this paper, we consider simultaneous tests of the mean vectors and the covariance matrices under three-step monotone missing data for a multi-sample problem. MLEs for general k -step monotone missing data were discussed by Jinadasa and Tracy (1992) and Kanda and Fujikoshi (1998). For the simultaneous test, the LRT statistic and the modified LRT statistic with Bartlett correction for the

case of complete data were discussed by Muirhead (2005) and Srivastava (2002). Further, the LRT statistic and the test statistics for improving the accuracy of the χ^2 approximation for three-step monotone missing data were proposed by Hao and Krishnamoorthy (2001) and Hosoya and Seo (2015, 2016). In particular, Hosoya and Seo (2015, 2016) presented test statistics by decomposing the LR; this paper is an extension of the work presented by Hosoya and Seo (2016). Indeed, an LRT statistic and test statistics for general k -step monotone missing data, which are obtained by correcting only a part of the missing data, were given by Yagi, Yamaguchi, and Seo (2016).

The remainder of this paper is organized as follows. In Section 2, we describe the MLEs of the mean vectors and covariance matrices and its LRT statistic in the case of three-step monotone missing data for a multi-sample problem. In Section 3, the modified LRT statistics in the case of complete data are described, which are used to derive the test statistics in Section 4. In Section 4, we propose three test statistics for improving the accuracy of the χ^2 approximation using the coefficients of the modified LRT statistics with complete data. In Section 5, we derive an approximate upper percentile of the LRT statistic. In Section 6, using Monte Carlo simulation, we investigate the χ^2 approximation accuracy of the test statistics and the accuracy of approximate upper percentiles of the LRT statistic. In Section 7, the results are illustrated using an example. Finally, in Section 8, we state our conclusions.

2 Likelihood ratio with three-step monotone missing data

In this section, we will consider simultaneous tests of the mean vectors and the covariance matrices under three-step monotone missing data for a multi-sample problem. Let $\mathbf{x}_1^{(\ell)}, \mathbf{x}_2^{(\ell)}, \dots, \mathbf{x}_{N_1^{(\ell)}}^{(\ell)}$ be independent p -dimensional sample vectors, $\mathbf{x}_{(12), N_1^{(\ell)}+1}^{(\ell)}, \mathbf{x}_{(12), N_1^{(\ell)}+2}^{(\ell)}, \dots, \mathbf{x}_{(12), N_1^{(\ell)}+N_2^{(\ell)}}^{(\ell)}$ be independent $(p_1 + p_2)$ -dimensional sample vectors and $\mathbf{x}_{1, N_1^{(\ell)}+N_2^{(\ell)}+1}^{(\ell)}, \mathbf{x}_{1, N_1^{(\ell)}+N_2^{(\ell)}+2}^{(\ell)}, \dots, \mathbf{x}_{1N^{(\ell)}}^{(\ell)}$ be independent p_1 -dimensional sample vectors from the ℓ th population ($\ell = 1, \dots, m$). We suppose that the data is normally distributed as follows:

$$\begin{aligned} \mathbf{x}_1^{(\ell)}, \mathbf{x}_2^{(\ell)}, \dots, \mathbf{x}_{N_1^{(\ell)}}^{(\ell)} &\stackrel{i.i.d.}{\sim} N_p(\boldsymbol{\mu}^{(\ell)}, \boldsymbol{\Sigma}^{(\ell)}), \\ \mathbf{x}_{(12), N_1^{(\ell)}+1}^{(\ell)}, \mathbf{x}_{(12), N_1^{(\ell)}+2}^{(\ell)}, \dots, \mathbf{x}_{(12), N_1^{(\ell)}+N_2^{(\ell)}}^{(\ell)} &\stackrel{i.i.d.}{\sim} N_{p_1+p_2}(\boldsymbol{\mu}_{(12)}^{(\ell)}, \boldsymbol{\Sigma}_{(12)(12)}^{(\ell)}), \\ \mathbf{x}_{1, N_1^{(\ell)}+N_2^{(\ell)}+1}^{(\ell)}, \mathbf{x}_{1, N_1^{(\ell)}+N_2^{(\ell)}+2}^{(\ell)}, \dots, \mathbf{x}_{1N^{(\ell)}}^{(\ell)} &\stackrel{i.i.d.}{\sim} N_{p_1}(\boldsymbol{\mu}_1^{(\ell)}, \boldsymbol{\Sigma}_{11}^{(\ell)}), \end{aligned}$$

where

$$\boldsymbol{\mu}^{(\ell)} = \begin{pmatrix} \boldsymbol{\mu}_1^{(\ell)} \\ \boldsymbol{\mu}_2^{(\ell)} \\ \boldsymbol{\mu}_3^{(\ell)} \end{pmatrix} = \begin{pmatrix} \boldsymbol{\mu}_{(12)}^{(\ell)} \\ \boldsymbol{\mu}_3^{(\ell)} \end{pmatrix},$$

$$\boldsymbol{\Sigma}^{(\ell)} = \left(\begin{array}{cc|c} \boldsymbol{\Sigma}_{11}^{(\ell)} & \boldsymbol{\Sigma}_{12}^{(\ell)} & \boldsymbol{\Sigma}_{13}^{(\ell)} \\ \boldsymbol{\Sigma}_{21}^{(\ell)} & \boldsymbol{\Sigma}_{22}^{(\ell)} & \boldsymbol{\Sigma}_{23}^{(\ell)} \\ \hline \boldsymbol{\Sigma}_{31}^{(\ell)} & \boldsymbol{\Sigma}_{32}^{(\ell)} & \boldsymbol{\Sigma}_{33}^{(\ell)} \end{array} \right) = \left(\begin{array}{c|c} \boldsymbol{\Sigma}_{(12)(12)}^{(\ell)} & \boldsymbol{\Sigma}_{(12)3}^{(\ell)} \\ \hline \boldsymbol{\Sigma}_{3(12)}^{(\ell)} & \boldsymbol{\Sigma}_{33}^{(\ell)} \end{array} \right).$$

and

$$\begin{aligned} \mathbf{x}_j^{(\ell)} &= (\mathbf{x}_{1j}^{(\ell)'}, \mathbf{x}_{2j}^{(\ell)'}, \mathbf{x}_{3j}^{(\ell)'})', j = 1, \dots, N_1^{(\ell)}, \\ \mathbf{x}_{(12),j}^{(\ell)} &= (\mathbf{x}_{1j}^{(\ell)'}, \mathbf{x}_{2j}^{(\ell)'})', j = N_1^{(\ell)} + 1, \dots, N_1^{(\ell)} + N_2^{(\ell)}, \\ N^{(\ell)} &= N_1^{(\ell)} + N_2^{(\ell)} + N_3^{(\ell)}, p = p_1 + p_2 + p_3. \end{aligned}$$

Such a dataset has three-step monotone missing data for the ℓ th population:

$$\left(\begin{array}{ccc} \overbrace{\hspace{1.5cm}}^{p_1} & \overbrace{\hspace{1.5cm}}^{p_2} & \overbrace{\hspace{1.5cm}}^{p_3} \\ \left(\begin{array}{ccc} \mathbf{x}_{11}^{(\ell)'} & \mathbf{x}_{21}^{(\ell)'} & \mathbf{x}_{31}^{(\ell)'} \\ \vdots & \vdots & \vdots \\ \mathbf{x}_{1N_1^{(\ell)}}^{(\ell)'} & \mathbf{x}_{2N_1^{(\ell)}}^{(\ell)'} & \mathbf{x}_{3N_1^{(\ell)}}^{(\ell)'} \\ \mathbf{x}_{1,N_1^{(\ell)}+1}^{(\ell)'} & \mathbf{x}_{2,N_1^{(\ell)}+1}^{(\ell)'} & * \cdots * \\ \vdots & \vdots & \vdots \quad \vdots \\ \mathbf{x}_{1,N_1^{(\ell)}+N_2^{(\ell)}}^{(\ell)'} & \mathbf{x}_{2,N_1^{(\ell)}+N_2^{(\ell)}}^{(\ell)'} & * \cdots * \\ \mathbf{x}_{1,N_1^{(\ell)}+N_2^{(\ell)}+1}^{(\ell)'} & * \cdots * & * \cdots * \\ \vdots & \vdots \quad \vdots & \vdots \quad \vdots \\ \mathbf{x}_{1N^{(\ell)}}^{(\ell)'} & * \cdots * & * \cdots * \end{array} \right) \end{array} \right),$$

where “*” indicates a missing observation.

We consider the following hypothesis:

$$H_0 : \boldsymbol{\mu}^{(1)} = \boldsymbol{\mu}^{(2)} = \dots = \boldsymbol{\mu}^{(m)}, \boldsymbol{\Sigma}^{(1)} = \boldsymbol{\Sigma}^{(2)} = \dots = \boldsymbol{\Sigma}^{(m)} \text{ vs. } H_1 : \text{not } H_0$$

To derive the MLEs of the mean vectors and the covariance matrices, we consider the following transformation matrix $\mathbf{Z}^{(\ell)}$:

$$\mathbf{Z}^{(\ell)} = \left(\begin{array}{cc|c} \mathbf{I}_{p_1} & \mathbf{O} & \mathbf{O} \\ -\boldsymbol{\Sigma}_{21}^{(\ell)} \boldsymbol{\Sigma}_{11}^{(\ell)-1} & \mathbf{I}_{p_2} & \mathbf{O} \\ \hline -\boldsymbol{\Sigma}_{3(12)}^{(\ell)} \boldsymbol{\Sigma}_{(12)(12)}^{(\ell)-1} & \mathbf{I}_{p_3} & \mathbf{O} \end{array} \right).$$

The transformed vector $\mathbf{y}_j^{(\ell)} = (\mathbf{y}_{1j}^{(\ell)'}, \mathbf{y}_{2j}^{(\ell)'}, \mathbf{y}_{3j}^{(\ell)'})'$ is

$$\begin{aligned}\mathbf{y}_j^{(\ell)} &= \mathbf{Z}^{(\ell)} \mathbf{x}_j^{(\ell)} \\ &= \begin{pmatrix} \mathbf{x}_{1j}^{(\ell)} \\ -\boldsymbol{\Sigma}_{21}^{(\ell)} \boldsymbol{\Sigma}_{11}^{(\ell)-1} \mathbf{x}_{1j}^{(\ell)} + \mathbf{x}_{2j}^{(\ell)} \\ -\boldsymbol{\Sigma}_{3(12)}^{(\ell)} \boldsymbol{\Sigma}_{(12)(12)}^{(\ell)-1} \begin{pmatrix} \mathbf{x}_{1j}^{(\ell)} \\ \mathbf{x}_{2j}^{(\ell)} \end{pmatrix} + \mathbf{x}_{3j}^{(\ell)} \end{pmatrix}.\end{aligned}$$

The transformed parameters $(\boldsymbol{\eta}^{(\ell)}, \boldsymbol{\Delta}^{(\ell)})$ are defined as

$$\begin{aligned}\boldsymbol{\eta}^{(\ell)} &= \begin{pmatrix} \boldsymbol{\eta}_1^{(\ell)} \\ \boldsymbol{\eta}_2^{(\ell)} \\ \boldsymbol{\eta}_3^{(\ell)} \end{pmatrix} = \begin{pmatrix} \boldsymbol{\mu}_1^{(\ell)} \\ -\boldsymbol{\Sigma}_{21}^{(\ell)} \boldsymbol{\Sigma}_{11}^{(\ell)-1} \boldsymbol{\mu}_1^{(\ell)} + \boldsymbol{\mu}_2^{(\ell)} \\ -\boldsymbol{\Sigma}_{3(12)}^{(\ell)} \boldsymbol{\Sigma}_{(12)(12)}^{(\ell)-1} \begin{pmatrix} \boldsymbol{\mu}_1^{(\ell)} \\ \boldsymbol{\mu}_2^{(\ell)} \end{pmatrix} + \boldsymbol{\mu}_3^{(\ell)} \end{pmatrix}, \\ \boldsymbol{\Delta}^{(\ell)} &= \left(\begin{array}{cc|c} \boldsymbol{\Delta}_{11}^{(\ell)} & \boldsymbol{\Delta}_{12}^{(\ell)} & \boldsymbol{\Delta}_{13}^{(\ell)} \\ \boldsymbol{\Delta}_{21}^{(\ell)} & \boldsymbol{\Delta}_{22}^{(\ell)} & \boldsymbol{\Delta}_{23}^{(\ell)} \\ \hline \boldsymbol{\Delta}_{31}^{(\ell)} & \boldsymbol{\Delta}_{32}^{(\ell)} & \boldsymbol{\Delta}_{33}^{(\ell)} \end{array} \right) = \left(\begin{array}{c|c} \boldsymbol{\Delta}_{(12)(12)}^{(\ell)} & \boldsymbol{\Delta}_{(12)3}^{(\ell)} \\ \hline \boldsymbol{\Delta}_{3(12)}^{(\ell)} & \boldsymbol{\Delta}_{33}^{(\ell)} \end{array} \right),\end{aligned}$$

where

$$\begin{aligned}\boldsymbol{\Delta}_{11}^{(\ell)} &= \boldsymbol{\Sigma}_{11}^{(\ell)}, \\ \boldsymbol{\Delta}_{12}^{(\ell)} &= \boldsymbol{\Delta}_{21}^{(\ell)' } = \boldsymbol{\Sigma}_{11}^{(\ell)-1} \boldsymbol{\Sigma}_{12}^{(\ell)}, \\ \boldsymbol{\Delta}_{22}^{(\ell)} &= \boldsymbol{\Sigma}_{22 \cdot 1}^{(\ell)} = \boldsymbol{\Sigma}_{22}^{(\ell)} - \boldsymbol{\Sigma}_{21}^{(\ell)} \boldsymbol{\Sigma}_{11}^{(\ell)-1} \boldsymbol{\Sigma}_{12}^{(\ell)}, \\ \boldsymbol{\Delta}_{(12)3}^{(\ell)} &= \boldsymbol{\Delta}_{3(12)}^{(\ell)' } = \boldsymbol{\Sigma}_{(12)(12)}^{(\ell)-1} \boldsymbol{\Sigma}_{(12)3}^{(\ell)}, \\ \boldsymbol{\Delta}_{33}^{(\ell)} &= \boldsymbol{\Sigma}_{33 \cdot 12}^{(\ell)} = \boldsymbol{\Sigma}_{33}^{(\ell)} - \boldsymbol{\Sigma}_{3(12)}^{(\ell)} \boldsymbol{\Sigma}_{(12)(12)}^{(\ell)-1} \boldsymbol{\Sigma}_{(12)3}^{(\ell)}.\end{aligned}$$

We note that the pair $(\boldsymbol{\mu}^{(\ell)}, \boldsymbol{\Sigma}^{(\ell)})$ is in one-to-one correspondence with $(\boldsymbol{\eta}^{(\ell)}, \boldsymbol{\Delta}^{(\ell)})$. Under H_1 , we define the MLEs of $(\boldsymbol{\eta}^{(\ell)}, \boldsymbol{\Delta}^{(\ell)})$ as $(\widehat{\boldsymbol{\eta}}^{(\ell)}, \widehat{\boldsymbol{\Delta}}^{(\ell)})$,

$$\begin{aligned}\widehat{\boldsymbol{\eta}}_1^{(\ell)} &= \frac{1}{N^{(\ell)}} (N_1^{(\ell)} \bar{\mathbf{x}}_{(1)1}^{(\ell)} + N_2^{(\ell)} \bar{\mathbf{x}}_{(2)1}^{(\ell)} + N_3^{(\ell)} \bar{\mathbf{x}}_{(3)}^{(\ell)}), \\ \widehat{\boldsymbol{\eta}}_2^{(\ell)} &= \frac{1}{N_1^{(\ell)} + N_2^{(\ell)}} \{N_1^{(\ell)} \bar{\mathbf{x}}_{(1)2}^{(\ell)} + N_2^{(\ell)} \bar{\mathbf{x}}_{(2)2}^{(\ell)} - \widehat{\boldsymbol{\Delta}}_{21}^{(\ell)} (N_1^{(\ell)} \bar{\mathbf{x}}_{(1)1}^{(\ell)} + N_2^{(\ell)} \bar{\mathbf{x}}_{(2)1}^{(\ell)})\}, \\ \widehat{\boldsymbol{\eta}}_3^{(\ell)} &= \bar{\mathbf{x}}_{(1)3}^{(\ell)} - \widehat{\boldsymbol{\Delta}}_{3(12)}^{(\ell)} \bar{\mathbf{x}}_{(1)(12)}^{(\ell)}, \\ \widehat{\boldsymbol{\Delta}}_{11}^{(\ell)} &= \frac{1}{N^{(\ell)}} (\mathbf{W}_{(1)11}^{(\ell)} + \mathbf{W}_{(2)11}^{(\ell)} + \mathbf{W}_{(3)}^{(\ell)}), \\ \widehat{\boldsymbol{\Delta}}_{22}^{(\ell)} &= \frac{1}{N_1^{(\ell)} + N_2^{(\ell)}} (\mathbf{W}_{(1),(12)(12)}^{(\ell)} + \mathbf{W}_{(2)}^{(\ell)})_{22 \cdot 1}, \quad \widehat{\boldsymbol{\Delta}}_{33}^{(\ell)} = \frac{1}{N_1^{(\ell)}} \mathbf{W}_{(1)33 \cdot 12}^{(\ell)}, \\ \widehat{\boldsymbol{\Delta}}_{12}^{(\ell)} &= \widehat{\boldsymbol{\Delta}}_{21}^{(\ell)' } = (\mathbf{W}_{(1)11}^{(\ell)} + \mathbf{W}_{(2)11}^{(\ell)})^{-1} (\mathbf{W}_{(1)12}^{(\ell)} + \mathbf{W}_{(2)12}^{(\ell)}),\end{aligned}$$

$$\widehat{\Delta}_{(12)3}^{(\ell)} = \widehat{\Delta}_{3(12)}^{(\ell)'} = (\mathbf{W}_{(1),(12)(12)}^{(\ell)})^{-1} \mathbf{W}_{(1),(12)3}^{(\ell)},$$

where

$$\bar{\mathbf{x}}_{(1)}^{(\ell)} = \begin{pmatrix} \bar{\mathbf{x}}_{(1)1}^{(\ell)} \\ \bar{\mathbf{x}}_{(1)2}^{(\ell)} \\ \bar{\mathbf{x}}_{(1)3}^{(\ell)} \end{pmatrix} = \begin{pmatrix} \bar{\mathbf{x}}_{(1)(12)}^{(\ell)} \\ \bar{\mathbf{x}}_{(1)3}^{(\ell)} \end{pmatrix},$$

$$\bar{\mathbf{x}}_{(1)1}^{(\ell)} = \frac{1}{N_1^{(\ell)}} \sum_{j=1}^{N_1^{(\ell)}} \mathbf{x}_{1j}^{(\ell)}, \quad \bar{\mathbf{x}}_{(1)2}^{(\ell)} = \frac{1}{N_1^{(\ell)}} \sum_{j=1}^{N_1^{(\ell)}} \mathbf{x}_{2j}^{(\ell)}, \quad \bar{\mathbf{x}}_{(1)3}^{(\ell)} = \frac{1}{N_1^{(\ell)}} \sum_{j=1}^{N_1^{(\ell)}} \mathbf{x}_{3j}^{(\ell)},$$

$$\bar{\mathbf{x}}_{(2)}^{(\ell)} = \begin{pmatrix} \bar{\mathbf{x}}_{(2)1}^{(\ell)} \\ \bar{\mathbf{x}}_{(2)2}^{(\ell)} \end{pmatrix}, \quad \bar{\mathbf{x}}_{(2)1}^{(\ell)} = \frac{1}{N_2^{(\ell)}} \sum_{j=N_1^{(\ell)+1}^{N_1^{(\ell)}+N_2^{(\ell)}} \mathbf{x}_{1j}^{(\ell)}, \quad \bar{\mathbf{x}}_{(2)2}^{(\ell)} = \frac{1}{N_2^{(\ell)}} \sum_{j=N_1^{(\ell)+1}^{N_1^{(\ell)}+N_2^{(\ell)}} \mathbf{x}_{2j}^{(\ell)},$$

$$\bar{\mathbf{x}}_{(3)}^{(\ell)} = \frac{1}{N_3^{(\ell)}} \sum_{j=N_1^{(\ell)}+N_2^{(\ell)}+1}^{N^{(\ell)}} \mathbf{x}_{1j}^{(\ell)},$$

$$\mathbf{W}_{(1)}^{(\ell)} = \sum_{j=1}^{N_1} (\mathbf{x}_j^{(\ell)} - \bar{\mathbf{x}}_{(1)}^{(\ell)}) (\mathbf{x}_j^{(\ell)} - \bar{\mathbf{x}}_{(1)}^{(\ell)})' = \begin{pmatrix} \mathbf{W}_{(1)11}^{(\ell)} & \mathbf{W}_{(1)12}^{(\ell)} & \mathbf{W}_{(1)13}^{(\ell)} \\ \mathbf{W}_{(1)21}^{(\ell)} & \mathbf{W}_{(1)22}^{(\ell)} & \mathbf{W}_{(1)23}^{(\ell)} \\ \mathbf{W}_{(1)31}^{(\ell)} & \mathbf{W}_{(1)32}^{(\ell)} & \mathbf{W}_{(1)33}^{(\ell)} \end{pmatrix} = \left(\begin{array}{c|c} \mathbf{W}_{(1),(12)(12)}^{(\ell)} & \mathbf{W}_{(1),(12)3}^{(\ell)} \\ \hline \mathbf{W}_{(1),3(12)}^{(\ell)} & \mathbf{W}_{(1)33}^{(\ell)} \end{array} \right),$$

$$\begin{aligned} \mathbf{W}_{(2)}^{(\ell)} &= \sum_{j=N_1^{(\ell)}+1}^{N_1^{(\ell)}+N_2^{(\ell)}} \begin{pmatrix} \mathbf{x}_{1j}^{(\ell)} - \bar{\mathbf{x}}_{(2)1}^{(\ell)} \\ \mathbf{x}_{2j}^{(\ell)} - \bar{\mathbf{x}}_{(2)2}^{(\ell)} \end{pmatrix} \begin{pmatrix} \mathbf{x}_{1j}^{(\ell)} - \bar{\mathbf{x}}_{(2)1}^{(\ell)} \\ \mathbf{x}_{2j}^{(\ell)} - \bar{\mathbf{x}}_{(2)2}^{(\ell)} \end{pmatrix}' + \frac{N_1^{(\ell)} N_2^{(\ell)}}{N_1^{(\ell)} + N_2^{(\ell)}} \begin{pmatrix} \bar{\mathbf{x}}_{(1)1}^{(\ell)} - \bar{\mathbf{x}}_{(2)1}^{(\ell)} \\ \bar{\mathbf{x}}_{(1)2}^{(\ell)} - \bar{\mathbf{x}}_{(2)2}^{(\ell)} \end{pmatrix} \begin{pmatrix} \bar{\mathbf{x}}_{(1)1}^{(\ell)} - \bar{\mathbf{x}}_{(2)1}^{(\ell)} \\ \bar{\mathbf{x}}_{(1)2}^{(\ell)} - \bar{\mathbf{x}}_{(2)2}^{(\ell)} \end{pmatrix}' \\ &= \begin{pmatrix} \mathbf{W}_{(2)11}^{(\ell)} & \mathbf{W}_{(2)12}^{(\ell)} \\ \mathbf{W}_{(2)21}^{(\ell)} & \mathbf{W}_{(2)22}^{(\ell)} \end{pmatrix}, \end{aligned}$$

$$\begin{aligned} \mathbf{W}_{(3)}^{(\ell)} &= \sum_{j=N_1^{(\ell)}+N_2^{(\ell)}+1}^{N^{(\ell)}} (\mathbf{x}_{1j}^{(\ell)} - \bar{\mathbf{x}}_{(3)}^{(\ell)}) (\mathbf{x}_{1j}^{(\ell)} - \bar{\mathbf{x}}_{(3)}^{(\ell)})' + \frac{(N_1^{(\ell)} + N_2^{(\ell)}) N_3^{(\ell)}}{N^{(\ell)}} \left(\bar{\mathbf{x}}_{(3)}^{(\ell)} - \frac{1}{N_1^{(\ell)} + N_2^{(\ell)}} (N_1^{(\ell)} \bar{\mathbf{x}}_{(1)1}^{(\ell)} + N_2^{(\ell)} \bar{\mathbf{x}}_{(2)1}^{(\ell)}) \right) \\ &\quad \times \left(\bar{\mathbf{x}}_{(3)}^{(\ell)} - \frac{1}{N_1^{(\ell)} + N_2^{(\ell)}} (N_1^{(\ell)} \bar{\mathbf{x}}_{(1)1}^{(\ell)} + N_2^{(\ell)} \bar{\mathbf{x}}_{(2)1}^{(\ell)}) \right)'. \end{aligned}$$

In contrast, under H_0 , we define MLEs of $\boldsymbol{\eta} (= \boldsymbol{\eta}^{(1)} = \dots = \boldsymbol{\eta}^{(m)})$, $\Delta (= \Delta^{(1)} = \dots = \Delta^{(m)})$ as $(\tilde{\boldsymbol{\eta}}, \tilde{\Delta})$. Then, we obtain

$$\tilde{\boldsymbol{\eta}}_1 = \frac{1}{N} \sum_{\ell=1}^m (N_1^{(\ell)} \bar{\mathbf{x}}_{(1)1}^{(\ell)} + N_2^{(\ell)} \bar{\mathbf{x}}_{(2)1}^{(\ell)} + N_3^{(\ell)} \bar{\mathbf{x}}_{(3)}^{(\ell)}),$$

$$\tilde{\boldsymbol{\eta}}_2 = \frac{1}{N_1 + N_2} \sum_{\ell=1}^m \{N_1^{(\ell)} \bar{\mathbf{x}}_{(1)2}^{(\ell)} + N_2^{(\ell)} \bar{\mathbf{x}}_{(2)2}^{(\ell)} - \tilde{\Delta}_{21} (N_1^{(\ell)} \bar{\mathbf{x}}_{(1)1}^{(\ell)} + N_2^{(\ell)} \bar{\mathbf{x}}_{(2)1}^{(\ell)})\},$$

$$\tilde{\boldsymbol{\eta}}_3 = \frac{1}{N_1} \sum_{\ell=1}^m N_1^{(\ell)} \{ \bar{\mathbf{x}}_{(1)3}^{(\ell)} - \tilde{\Delta}_{3(12)} \bar{\mathbf{x}}_{(1)(12)}^{(\ell)} \},$$

$$\tilde{\Delta}_{11} = \frac{1}{N} \sum_{\ell=1}^m \sum_{j=1}^{N^{(\ell)}} (\mathbf{x}_{1j}^{(\ell)} - \tilde{\boldsymbol{\eta}}_1) (\mathbf{x}_{1j}^{(\ell)} - \tilde{\boldsymbol{\eta}}_1)',$$

$$\begin{aligned}
\tilde{\Delta}_{22} &= \frac{1}{N_1 + N_2} \sum_{\ell=1}^m \sum_{j=1}^{N_1^{(\ell)} + N_2^{(\ell)}} (-\tilde{\Delta}_{21} \mathbf{x}_{1j}^{(\ell)} + \mathbf{x}_{2j}^{(\ell)} - \tilde{\boldsymbol{\eta}}_2) (-\tilde{\Delta}_{21} \mathbf{x}_{1j}^{(\ell)} + \mathbf{x}_{2j}^{(\ell)} - \tilde{\boldsymbol{\eta}}_2)', \\
\tilde{\Delta}_{33} &= \frac{1}{N_1} \sum_{\ell=1}^m \sum_{j=1}^{N_1^{(\ell)}} (-\tilde{\Delta}_{3(12)} \mathbf{x}_{(12)j}^{(\ell)} + \mathbf{x}_{3j}^{(\ell)} - \tilde{\boldsymbol{\eta}}_3) (-\tilde{\Delta}_{3(12)} \mathbf{x}_{(12)j}^{(\ell)} + \mathbf{x}_{3j}^{(\ell)} - \tilde{\boldsymbol{\eta}}_3)', \\
\tilde{\Delta}_{21} &= \tilde{\Delta}'_{12} \\
&= \sum_{\ell=1}^m \left[\sum_{j=1}^{N_1^{(\ell)} + N_2^{(\ell)}} \mathbf{x}_{2j}^{(\ell)} \mathbf{x}_{1j}^{(\ell)'} - \frac{1}{N_1 + N_2} \left\{ \sum_{k=1}^m (N_1^{(k)} \bar{\mathbf{x}}_{(1)2}^{(k)} + N_2^{(k)} \bar{\mathbf{x}}_{(2)2}^{(k)}) \right\} (N_1^{(\ell)} \bar{\mathbf{x}}_{(1)1}^{(\ell)} + N_2^{(\ell)} \bar{\mathbf{x}}_{(2)1}^{(\ell)})' \right] \\
&\quad \times \sum_{\ell=1}^m \left[\sum_{j=1}^{N_1^{(\ell)} + N_2^{(\ell)}} \mathbf{x}_{1j}^{(\ell)} \mathbf{x}_{1j}^{(\ell)'} - \frac{1}{N_1 + N_2} \left\{ \sum_{k=1}^m (N_1^{(k)} \bar{\mathbf{x}}_{(1)1}^{(k)} + N_2^{(k)} \bar{\mathbf{x}}_{(2)1}^{(k)}) \right\} (N_1^{(\ell)} \bar{\mathbf{x}}_{(1)1}^{(\ell)} + N_2^{(\ell)} \bar{\mathbf{x}}_{(2)1}^{(\ell)})' \right]^{-1}, \\
\tilde{\Delta}_{3(12)} &= \tilde{\Delta}'_{(12)3} \\
&= \sum_{\ell=1}^m \left\{ \sum_{j=1}^{N_1^{(\ell)}} \mathbf{x}_{3j}^{(\ell)} \mathbf{x}_{(12),j}^{(\ell)'} - N_1^{(\ell)} \left(\frac{1}{N_1} \sum_{k=1}^m N_1^{(k)} \bar{\mathbf{x}}_{(1)3}^{(k)} \right) \bar{\mathbf{x}}_{(1),(12)}^{(\ell)} \right\} \\
&\quad \times \sum_{\ell=1}^m \left\{ \sum_{j=1}^{N_1^{(\ell)}} \mathbf{x}_{(12),j}^{(\ell)} \mathbf{x}_{(12),j}^{(\ell)'} - N_1^{(\ell)} \left(\frac{1}{N_1} \sum_{k=1}^m N_1^{(k)} \bar{\mathbf{x}}_{(1),(12)}^{(k)} \right) \bar{\mathbf{x}}_{(1),(12)}^{(\ell)} \right\}^{-1},
\end{aligned}$$

where $N = \sum_{\ell=1}^m N^{(\ell)}$, $N_1 = \sum_{\ell=1}^m N_1^{(\ell)}$, $N_2 = \sum_{\ell=1}^m N_2^{(\ell)}$. From the preceding MLEs, the LR can be given by

$$\lambda_m = \frac{\prod_{\ell=1}^m |\hat{\Delta}_{11}^{(\ell)}|^{\frac{N^{(\ell)}}{2}} |\hat{\Delta}_{22}^{(\ell)}|^{\frac{N_1^{(\ell)} + N_2^{(\ell)}}{2}} |\hat{\Delta}_{33}^{(\ell)}|^{\frac{N_1^{(\ell)}}{2}}}{|\tilde{\Delta}_{11}|^{\frac{N}{2}} |\tilde{\Delta}_{22}|^{\frac{N_1 + N_2}{2}} |\tilde{\Delta}_{33}|^{\frac{N_1}{2}}}.$$

Thus, we obtain LRT statistic $-2 \log \lambda_m$. $-2 \log \lambda_m$ is asymptotically distributed as a χ^2 distribution with $f_m = p(p+3)(m-1)/2$ degrees of freedom. However, it is known that the accuracy of this approximation is not good for small samples. Therefore, we propose test statistics that are a good approximation to χ^2 distribution using several methods.

3 Complete data

In this section, we discuss the LRT statistic in the case of complete data and the modified LRT statistics with Bartlett correction. The results will be used to propose the test statistics in the next section. First, we consider a simultaneous test with complete data as follows:

$$H_{01} : \boldsymbol{\mu}^{(1)} = \boldsymbol{\mu}^{(2)} = \dots = \boldsymbol{\mu}^{(m)}, \boldsymbol{\Sigma}^{(1)} = \boldsymbol{\Sigma}^{(2)} = \dots = \boldsymbol{\Sigma}^{(m)} \text{ vs. } H_{11} : \text{not } H_{01}$$

Let $\mathbf{x}_1^{(\ell)}, \mathbf{x}_2^{(\ell)}, \dots, \mathbf{x}_{N^{(\ell)}}^{(\ell)}$ be independently distributed as $N_p(\boldsymbol{\mu}^{(\ell)}, \boldsymbol{\Sigma}^{(\ell)})$, and let λ_{S_m} be the LR for the complete data. Then, the LR is given by

$$\lambda_{S_m} = \frac{\prod_{\ell=1}^m \left| \frac{1}{N^{(\ell)}} \mathbf{V}^{(\ell)} \right|^{\frac{1}{2} N^{(\ell)}}}{\left| \frac{1}{N} (\mathbf{V} + \mathbf{B}) \right|^{\frac{1}{2} N}},$$

where

$$\begin{aligned} \mathbf{V}^{(\ell)} &= \sum_{j=1}^{N^{(\ell)}} (\mathbf{x}_j^{(\ell)} - \bar{\mathbf{x}}^{(\ell)}) (\mathbf{x}_j^{(\ell)} - \bar{\mathbf{x}}^{(\ell)})', \quad \mathbf{V} = \sum_{\ell=1}^m \mathbf{V}^{(\ell)}, \\ \mathbf{B} &= \sum_{\ell=1}^m N^{(\ell)} (\bar{\mathbf{x}}^{(\ell)} - \bar{\mathbf{x}}) (\bar{\mathbf{x}}^{(\ell)} - \bar{\mathbf{x}})', \\ \bar{\mathbf{x}}^{(\ell)} &= \frac{1}{N^{(\ell)}} \sum_{j=1}^{N^{(\ell)}} \mathbf{x}_j^{(\ell)}, \quad \bar{\mathbf{x}} = \frac{1}{N} \sum_{\ell=1}^m N^{(\ell)} \bar{\mathbf{x}}^{(\ell)}, \quad N = \sum_{\ell=1}^m N^{(\ell)}. \end{aligned}$$

Furthermore, the modified LRT statistic with Bartlett correction can be given by $-2\rho_3 \log \lambda_{S_m}$ (Muirhead (2005, p.513)), where

$$\rho_3 = 1 - \frac{2p^2 + 9p + 11}{6N(p+3)(m-1)} \left(\sum_{\ell=1}^m \frac{N}{N^{(\ell)}} - 1 \right).$$

Next, we consider the covariance test in the case of complete data as follows:

$$H_{02} : \boldsymbol{\Sigma}^{(1)} = \boldsymbol{\Sigma}^{(2)} = \dots = \boldsymbol{\Sigma}^{(m)} \quad \text{vs.} \quad H_{12} : \text{not } H_{02}$$

The modified LRT statistic $-2\rho_4 \log \lambda_{V_m}$ was provided by Muirhead (2005, p.308), where

$$\rho_4 = 1 - \frac{2p^2 + 3p - 1}{6(p+1)(m-1)} \left(\sum_{\ell=1}^m \frac{1}{n^{(\ell)}} - \frac{1}{n} \right), \quad \lambda_{V_m} = \frac{\prod_{\ell=1}^m \left| \frac{1}{n^{(\ell)}} \mathbf{V}^{(\ell)} \right|^{\frac{n^{(\ell)}}{2}}}{\left| \frac{1}{n} \mathbf{V} \right|^{\frac{n}{2}}},$$

and

$$n^{(\ell)} = N^{(\ell)} - 1, \quad n = \sum_{\ell=1}^m n^{(\ell)}.$$

4 Test statistics

Using LR of the simultaneous test with complete data from the previous section, we propose test statistics by decomposing the LR λ_m with three-step monotone missing data. First, the LR can be decomposed as $\lambda_m = \xi_1 \xi_2 \xi_3$, where

$$\xi_1 = \frac{\prod_{\ell=1}^m \left| \widehat{\boldsymbol{\Delta}}_{11}^{(\ell)} \right|^{\frac{N^{(\ell)}}{2}}}{\left| \widetilde{\boldsymbol{\Delta}}_{11} \right|^{\frac{N}{2}}}, \quad \xi_2 = \frac{\prod_{\ell=1}^m \left| \widehat{\boldsymbol{\Delta}}_{22}^{(\ell)} \right|^{\frac{N_1^{(\ell)} + N_2^{(\ell)}}{2}}}{\left| \widetilde{\boldsymbol{\Delta}}_{22} \right|^{\frac{N_1 + N_2}{2}}}, \quad \xi_3 = \frac{\prod_{\ell=1}^m \left| \widehat{\boldsymbol{\Delta}}_{33}^{(\ell)} \right|^{\frac{N_1^{(\ell)}}{2}}}{\left| \widetilde{\boldsymbol{\Delta}}_{33} \right|^{\frac{N_1}{2}}}.$$

Because ξ_1 is of the form of LR for H_{01} in the case of without missing data, the modified LRT statistic $-2\rho_{\xi_1} \log \xi_1$ is given, where

$$\rho_{\xi_1} = 1 - \frac{2p_1^2 + 9p_1 + 11}{6N(p_1 + 3)(m - 1)} \left(\sum_{\ell=1}^m \frac{N}{N^{(\ell)}} - 1 \right).$$

Next, ξ_2 can be decomposed as $\xi_2 = \xi_2^\dagger \xi_2^\ddagger$, where

$$\xi_2^\dagger = \frac{\prod_{\ell=1}^m \left| \widehat{\Delta}_{22}^{(\ell)} \right|^{\frac{N_1^{(\ell)} + N_2^{(\ell)}}{2}}}{\left| \frac{1}{N_1 + N_2} (\mathbf{V}_{p_2} + \mathbf{B}_{p_2}) \right|^{\frac{N_1 + N_2}{2}}}, \quad \xi_2^\ddagger = \frac{\left| \frac{1}{N_1 + N_2} (\mathbf{V}_{p_2} + \mathbf{B}_{p_2}) \right|^{\frac{N_1 + N_2}{2}}}{\left| \widetilde{\Delta}_{22} \right|^{\frac{N_1 + N_2}{2}}},$$

and

$$\mathbf{V}_{p_2}^{(\ell)} = \sum_{j=1}^{N_1^{(\ell)} + N_2^{(\ell)}} (\mathbf{x}_{2j}^{(\ell)} - \widehat{\Delta}_{21}^{(\ell)} \mathbf{x}_{1j}^{(\ell)} - \widehat{\boldsymbol{\eta}}_2^{(\ell)}) (\mathbf{x}_{2j}^{(\ell)} - \widehat{\Delta}_{21}^{(\ell)} \mathbf{x}_{1j}^{(\ell)} - \widehat{\boldsymbol{\eta}}_2^{(\ell)})', \quad \mathbf{V}_{p_2} = \sum_{\ell=1}^m \mathbf{V}_{p_2}^{(\ell)},$$

$$\mathbf{B}_{p_2} = \sum_{\ell=1}^m (N_1^{(\ell)} + N_2^{(\ell)}) (\widehat{\boldsymbol{\eta}}_2^{(\ell)} - \widetilde{\boldsymbol{\eta}}_2) (\widehat{\boldsymbol{\eta}}_2^{(\ell)} - \widetilde{\boldsymbol{\eta}}_2)'.$$

Because ξ_2^\dagger is of the form of LR for H_{01} in the case of complete data, the modified LRT statistic $-2\rho_{\xi_2} \log \xi_2^\dagger$ is given, where

$$\rho_{\xi_2} = 1 - \frac{2p_2^2 + 9p_2 + 11}{6(N_1 + N_2)(p_2 + 3)(m - 1)} \left(\sum_{\ell=1}^m \frac{N_1 + N_2}{N_1^{(\ell)} + N_2^{(\ell)}} - 1 \right).$$

Similarly, ξ_3 can be decomposed as $\xi_3 = \xi_3^\dagger \xi_3^\ddagger$, where

$$\xi_3^\dagger = \frac{\prod_{\ell=1}^m \left| \widehat{\Delta}_{33}^{(\ell)} \right|^{\frac{N_1^{(\ell)}}{2}}}{\left| \frac{1}{N_1} (\mathbf{V}_{p_3} + \mathbf{B}_{p_3}) \right|^{\frac{N_1}{2}}}, \quad \xi_3^\ddagger = \frac{\left| \frac{1}{N_1} (\mathbf{V}_{p_3} + \mathbf{B}_{p_3}) \right|^{\frac{N_1}{2}}}{\left| \widetilde{\Delta}_{33} \right|^{\frac{N_1}{2}}},$$

and

$$\mathbf{V}_{p_3}^{(\ell)} = \sum_{j=1}^{N_1^{(\ell)}} (\mathbf{x}_{3j}^{(\ell)} - \widehat{\Delta}_{3(12)}^{(\ell)} \mathbf{x}_{(12)j}^{(\ell)} - \widehat{\boldsymbol{\eta}}_3^{(\ell)}) (\mathbf{x}_{3j}^{(\ell)} - \widehat{\Delta}_{3(12)}^{(\ell)} \mathbf{x}_{(12)j}^{(\ell)} - \widehat{\boldsymbol{\eta}}_3^{(\ell)})', \quad \mathbf{V}_{p_3} = \sum_{\ell=1}^m \mathbf{V}_{p_3}^{(\ell)},$$

$$\mathbf{B}_{p_3} = \sum_{\ell=1}^m N_1^{(\ell)} (\widehat{\boldsymbol{\eta}}_3^{(\ell)} - \widetilde{\boldsymbol{\eta}}_3) (\widehat{\boldsymbol{\eta}}_3^{(\ell)} - \widetilde{\boldsymbol{\eta}}_3)'.$$

Because ξ_3^\dagger is of the form of LR for H_{01} in the case of complete data, the modified LRT statistic $-2\rho_{\xi_3} \log \xi_3^\dagger$ is given, where

$$\rho_{\xi_3} = 1 - \frac{2p_3^2 + 9p_3 + 11}{6N_1(p_3 + 3)(m - 1)} \left(\sum_{\ell=1}^m \frac{N_1}{N_1^{(\ell)}} - 1 \right).$$

Therefore, the decomposed form of $\lambda_m = \xi_1 \xi_2 \xi_3$ is $\lambda_m = \xi_1 \xi_2^\dagger \xi_2^\dagger \xi_3^\dagger \xi_3^\dagger$. We give a correction only for ξ_1, ξ_2^\dagger , and ξ_3^\dagger . Thus, we give the test statistic $-2 \log \tau_m$ for improving the accuracy of the χ^2 approximation, where

$$\tau_m = (\xi_1)^{\rho_{\xi_1}} (\xi_2^\dagger)^{\rho_{\xi_2^\dagger}} (\xi_3^\dagger)^{\rho_{\xi_3^\dagger}}.$$

Next, using LR of the covariance test with complete data from the previous section, we propose a test statistic by decomposing the LR λ_m with three-step monotone missing data. Let

$$\xi_{11}^* = \frac{\prod_{\ell=1}^m \left| \frac{1}{n^{(\ell)}} \mathbf{V}_{p_1}^{(\ell)} \right|^{\frac{n^{(\ell)}}{2}}}{\left| \frac{1}{n} \mathbf{V}_{p_1} \right|^{\frac{n}{2}}}, \quad \xi_{21}^* = \frac{\prod_{\ell=1}^m \left| \frac{1}{n_1^{(\ell)} + n_2^{(\ell)}} \mathbf{V}_{p_2}^{(\ell)} \right|^{\frac{n_1^{(\ell)} + n_2^{(\ell)}}{2}}}{\left| \frac{1}{n_1 + n_2} \mathbf{V}_{p_2} \right|^{\frac{n_1 + n_2}{2}}}, \quad \xi_{31}^* = \frac{\prod_{\ell=1}^m \left| \frac{1}{n_1^{(\ell)}} \mathbf{V}_{p_3}^{(\ell)} \right|^{\frac{n_1^{(\ell)}}{2}}}{\left| \frac{1}{n_1} \mathbf{V}_{p_3} \right|^{\frac{n_1}{2}}},$$

where

$$\begin{aligned} \mathbf{V}_{p_1}^{(\ell)} &= \sum_{j=1}^{N^{(\ell)}} (\mathbf{x}_{1j}^{(\ell)} - \widehat{\boldsymbol{\eta}}_1^{(\ell)}) (\mathbf{x}_{1j}^{(\ell)} - \widehat{\boldsymbol{\eta}}_1^{(\ell)})', \quad \mathbf{V}_{p_1} = \sum_{\ell=1}^m \mathbf{V}_{p_1}^{(\ell)}, \\ n_1^{(\ell)} &= N_1^{(\ell)} - (p_1 + p_2) - 1, \quad n_1 = \sum_{\ell=1}^m n_1^{(\ell)}, \\ n_1^{(\ell)} + n_2^{(\ell)} &= N_1^{(\ell)} + N_2^{(\ell)} - p_1 - 1, \quad n_1 + n_2 = \sum_{\ell=1}^m (n_1^{(\ell)} + n_2^{(\ell)}). \end{aligned}$$

Because ξ_{11}^*, ξ_{21}^* , and ξ_{31}^* are of the form of LR for H_{02} in the case of complete data, the modified LRT statistics $-2\rho_{\xi_{11}^*} \log \xi_{11}^*, -2\rho_{\xi_{21}^*} \log \xi_{21}^*$, and $-2\rho_{\xi_{31}^*} \log \xi_{31}^*$ are given, where

$$\begin{aligned} \rho_{\xi_{11}^*} &= 1 - \frac{2p_1^2 + 3p_1 - 1}{6(p_1 + 1)(m - 1)} \left(\sum_{\ell=1}^m \frac{1}{n^{(\ell)}} - \frac{1}{n} \right), \\ \rho_{\xi_{21}^*} &= 1 - \frac{2p_2^2 + 3p_2 - 1}{6(p_2 + 1)(m - 1)} \left(\sum_{\ell=1}^m \frac{1}{n_1^{(\ell)} + n_2^{(\ell)}} - \frac{1}{n_1 + n_2} \right), \\ \rho_{\xi_{31}^*} &= 1 - \frac{2p_3^2 + 3p_3 - 1}{6(p_3 + 1)(m - 1)} \left(\sum_{\ell=1}^m \frac{1}{n_1^{(\ell)}} - \frac{1}{n_1} \right). \end{aligned}$$

Therefore, we propose the test statistic $-2 \log \phi_m$ for improving the accuracy of the χ^2 approximation, where

$$\phi_m = (\xi_{11}^*)^{\rho_{\xi_{11}^*}} (\xi_{21}^*)^{\rho_{\xi_{21}^*}} (\xi_{31}^*)^{\rho_{\xi_{31}^*}} \frac{\lambda}{\xi_{11} \xi_{21} \xi_{31}},$$

and

$$\xi_{11} = \frac{\prod_{\ell=1}^m \left| \frac{1}{N^{(\ell)}} \mathbf{V}_{p_1}^{(\ell)} \right|^{\frac{N^{(\ell)}}{2}}}{\left| \frac{1}{N} \mathbf{V}_{p_1} \right|^{\frac{N}{2}}}, \quad \xi_{21} = \frac{\prod_{\ell=1}^m \left| \frac{1}{N_1^{(\ell)} + N_2^{(\ell)}} \mathbf{V}_{p_2}^{(\ell)} \right|^{\frac{N_1^{(\ell)} + N_2^{(\ell)}}{2}}}{\left| \frac{1}{N_1 + N_2} \mathbf{V}_{p_2} \right|^{\frac{N_1 + N_2}{2}}}, \quad \xi_{31} = \frac{\prod_{\ell=1}^m \left| \frac{1}{N_1^{(\ell)}} \mathbf{V}_{p_3}^{(\ell)} \right|^{\frac{N_1^{(\ell)}}{2}}}{\left| \frac{1}{N_1} \mathbf{V}_{p_3} \right|^{\frac{N_1}{2}}}.$$

Next, we propose the test statistic $-2\rho_{L_m} \log \lambda_m$ via linear interpolation, where

$$\rho_{L_m} = \left\{ 1 - \frac{(p_1 + p_2)N_2 + p_1N_3}{p(N_2 + N_3)} \right\} \rho_{N_1, m} + \frac{(p_1 + p_2)N_2 + p_1N_3}{p(N_2 + N_3)} \rho_{N, m}$$

and

$$\rho_{N, m} = 1 - \frac{2p^2 + 9p + 11}{6N(p + 3)(m - 1)} \left(\sum_{\ell=1}^m \frac{N}{N^{(\ell)}} - 1 \right), \quad \rho_{N_1, m} = 1 - \frac{2p^2 + 9p + 11}{6N_1(p + 3)(m - 1)} \left(\sum_{\ell=1}^m \frac{N_1}{N_1^{(\ell)}} - 1 \right).$$

5 Asymptotic expansion approximation

In this section, we give an approximate upper 100α percentile of $-2 \log \lambda_m$ with three-step monotone missing data. The upper 100α percentile of $-2 \log \lambda_{S_m}$ can be expanded as

$$\begin{aligned} q_{c_m}^*(\alpha) &= \chi_{f_m}^2(\alpha) + \frac{\nu}{N} \left(\sum_{\ell=1}^m \frac{1}{k_1^{(\ell)}} - 1 \right) \chi_{f_m}^2(\alpha) \\ &\quad + \frac{1}{N^2} \chi_{f_m}^2(\alpha) \left\{ \nu^2 \left(\sum_{\ell=1}^m \frac{1}{k_1^{(\ell)}} - 1 \right)^2 + \frac{2\gamma_1}{f_m} + \frac{2\gamma_1}{f_m(f_m + 2)} \chi_{f_m}^2(\alpha) \right\} + O(N^{-3}), \end{aligned}$$

where

$$\begin{aligned} \nu &= \frac{2p^2 + 9p + 11}{6(p + 3)(m - 1)}, \quad k_1^{(\ell)} = \frac{N^{(\ell)}}{N}, \\ \gamma_1 &= \frac{1}{288} \left[6p(p + 1)(p + 2)(p + 3) \left(\sum_{\ell=1}^m \frac{1}{\{k_1^{(\ell)}\}^2} - 1 \right) - \frac{(2p^2 + 9p + 11)^2(2p - 1)}{p(p + 3)(m - 1)} \left(\sum_{\ell=1}^m \frac{1}{k_1^{(\ell)}} - 1 \right)^2 \right], \end{aligned}$$

where $\chi_{f_m}^2(\alpha)$ is the upper 100α percentile of the χ^2 distribution with f_m degrees of freedom (Hosoya and Seo (2016)). Based on linear interpolation and letting $q_m^*(\alpha)$ be the upper 100α percentile of $-2 \log \lambda_m$, the following can be obtained:

$$q_m^*(\alpha) = \left\{ 1 - \frac{(p_1 + p_2)N_2 + p_1N_3}{p(N_2 + N_3)} \right\} q_{N_1, m}(\alpha) + \frac{(p_1 + p_2)N_2 + p_1N_3}{p(N_2 + N_3)} q_{N, m}(\alpha)$$

where

$$\begin{aligned} q_{N, m}(\alpha) &= \chi_{f_m}^2(\alpha) + \frac{\nu}{N} \left(\sum_{\ell=1}^m \frac{1}{k_1^{(\ell)}} - 1 \right) \chi_{f_m}^2(\alpha) + \frac{1}{N^2} \chi_{f_m}^2(\alpha) \left\{ \nu^2 \left(\sum_{\ell=1}^m \frac{1}{k_1^{(\ell)}} - 1 \right)^2 + \frac{2\gamma_1}{f_m} + \frac{2\gamma_1}{f_m(f_m + 2)} \chi_{f_m}^2(\alpha) \right\}, \\ q_{N_1, m}(\alpha) &= \chi_{f_m}^2(\alpha) + \frac{\nu}{N_1} \left(\sum_{\ell=1}^m \frac{1}{k_2^{(\ell)}} - 1 \right) \chi_{f_m}^2(\alpha) + \frac{1}{N_1^2} \chi_{f_m}^2(\alpha) \left\{ \nu^2 \left(\sum_{\ell=1}^m \frac{1}{k_2^{(\ell)}} - 1 \right)^2 + \frac{2\gamma_2}{f_m} + \frac{2\gamma_2}{f_m(f_m + 2)} \chi_{f_m}^2(\alpha) \right\}, \end{aligned}$$

$$k_2^{(\ell)} = \frac{N_1^{(\ell)}}{N_1},$$

$$\gamma_2 = \frac{1}{288} \left[6p(p + 1)(p + 2)(p + 3) \left(\sum_{\ell=1}^m \frac{1}{\{k_2^{(\ell)}\}^2} - 1 \right) - \frac{(2p^2 + 9p + 11)^2(2p - 1)}{p(p + 3)(m - 1)} \left(\sum_{\ell=1}^m \frac{1}{k_2^{(\ell)}} - 1 \right)^2 \right].$$

6 Simulation studies

We evaluate the accuracy and the asymptotic behavior of the χ^2 approximation via Monte Carlo simulation (10^6 runs). Now let

$$\begin{aligned}\alpha_m &= \Pr\{-2 \log \lambda_m > \chi_{f_m}^2(\alpha)\}, \\ \alpha_{\rho_{L_m}} &= \Pr\{-2\rho_{L_m} \log \lambda_m > \chi_{f_m}^2(\alpha)\}, \\ \alpha_{\tau_m} &= \Pr\{-2 \log \tau_m > \chi_{f_m}^2(\alpha)\}, \\ \alpha_{\phi_m} &= \Pr\{-2 \log \phi_m > \chi_{f_m}^2(\alpha)\}, \\ \alpha_{q_m^*} &= \Pr\{-2 \log \lambda_m > q_m^*(\alpha)\}.\end{aligned}$$

In Tables 1-9, we provide the simulated upper 100α percentiles of $-2 \log \lambda_m$, $-2\rho_{L_m} \log \lambda_m$, $-2 \log \tau_m$, and $-2 \log \phi_m$ and the approximate upper percentiles of $-2 \log \lambda_m(q_m^*(\alpha))$ and the actual type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, and $\alpha_{q_m^*}$; $\alpha = 0.05, 0.01$;

$$(N_1^{(\ell)}, N_2^{(\ell)}, N_3^{(\ell)}) = \begin{cases} (t, t, t), \\ (t, t/2, t/2), & t = 20, 40, 80, 160, 320, \\ (t, 2t, 2t), \end{cases}$$

where (p_1, p_2, p_3) in Tables 1-3, 4-6, and 7-9 are $(8, 4, 2), (4, 4, 4), (2, 4, 8)$, respectively.

The simulated values are closer to the upper percentile of the χ^2 distribution when the sample size increases. However, compared with one sample case (Sakai, Yagi, and Seo (2021)), the accuracy of the simulated values is not very good, even if the sample size is quite large. In addition, by comparing the Type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, the accuracy of the approximate percentile ($q_m^*(\alpha)$) is the best.

Table 1: Simulated values for $-2 \log \lambda_m$, $-2\rho_{L_m} \log \lambda_m$, $-2 \log \tau_m$, and $-2 \log \phi_m$ and the approximate values for $-2 \log \lambda_m$ and the actual type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, and $\alpha_{q_m^*}$ for $(p_1, p_2, p_3) = (8, 4, 2), m = 2$

Sample Size		Upper Percentile					Type I Error				
$N_1^{(\ell)}$	$N_2^{(\ell)} = N_3^{(\ell)}$	$-2 \log \lambda_m$	$-2\rho_{L_m} \log \lambda_m$	$-2 \log \tau_m$	$-2 \log \phi_m$	$q_m^*(\alpha)$	α_m	$\alpha_{\rho_{L_m}}$	α_{τ_m}	α_{ϕ_m}	$\alpha_{q_m^*}$
$\alpha = 0.05$											
20	20	216.28	172.21	205.92	198.27	192.15	.890	.347	.814	.735	.222
40	40	168.46	151.29	164.94	162.51	164.54	.318	.092	.261	.224	.073
80	80	155.45	147.53	153.83	152.80	153.94	.135	.063	.118	.107	.059
160	160	150.15	146.32	149.36	148.86	149.43	.083	.055	.077	.073	.054
320	320	147.74	145.86	147.36	147.12	147.38	.065	.052	.062	.060	.052
20	10	226.15	169.60	212.16	203.56	203.51	.942	.314	.869	.795	.199
40	20	172.28	150.74	167.29	164.52	169.07	.383	.088	.299	.254	.068
80	40	157.18	147.35	154.88	153.68	155.91	.156	.062	.129	.116	.057
160	80	151.01	146.29	149.89	149.32	150.35	.090	.055	.081	.077	.054
320	160	148.13	145.81	147.58	147.31	147.82	.067	.052	.063	.062	.052
20	40	208.35	173.62	200.62	193.78	184.39	.826	.364	.754	.675	.228
40	80	165.04	151.29	162.71	160.63	161.25	.263	.093	.228	.198	.073
80	160	153.91	147.49	152.86	151.98	152.44	.118	.063	.107	.099	.059
160	320	149.40	146.29	148.90	148.48	148.72	.077	.055	.073	.070	.054
320	640	147.37	145.83	147.11	146.91	147.03	.062	.052	.060	.059	.052
$\alpha = 0.01$											
20	20	236.59	188.39	225.14	216.80	208.90	.746	.161	.624	.518	.083
40	40	182.90	164.27	179.09	176.45	178.61	.132	.023	.099	.080	.017
80	80	168.61	160.02	166.87	165.71	167.02	.038	.014	.032	.028	.012
160	160	163.05	158.90	162.21	161.66	162.11	.020	.012	.018	.017	.011
320	320	160.38	158.34	159.97	159.71	159.88	.014	.011	.013	.013	.011
20	10	247.21	185.39	231.92	222.51	221.35	.842	.137	.708	.596	.069
40	20	187.03	163.65	181.65	178.60	183.55	.174	.022	.120	.095	.015
80	40	170.51	159.85	168.02	166.73	169.17	.047	.013	.036	.031	.012
160	80	163.84	158.72	162.62	162.01	163.11	.022	.011	.019	.018	.011
320	160	160.66	158.15	160.07	159.77	160.36	.015	.011	.014	.013	.010
20	40	228.21	190.17	219.54	211.89	200.42	.644	.174	.545	.448	.088
40	80	179.16	164.23	176.64	174.36	175.03	.100	.023	.081	.067	.016
80	160	167.00	160.04	165.86	164.88	165.40	.032	.014	.028	.025	.012
160	320	162.15	158.77	161.60	161.14	161.34	.018	.011	.017	.016	.011
320	640	159.86	158.20	159.59	159.37	159.51	.013	.011	.013	.013	.011

Note: The closest value to α from among $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$ and $\alpha_{q_m^*}$ of each row is in bold.
 $\chi_{f_m}^2(0.05) = 145.46$, $\chi_{f_m}^2(0.01) = 157.80$, $f_m = 119$.

Table 2: Simulated values for $-2 \log \lambda_m$, $-2\rho_{L_m} \log \lambda_m$, $-2 \log \tau_m$, and $-2 \log \phi_m$ and the approximate values for $-2 \log \lambda_m$ and the actual type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, and $\alpha_{q_m^*}$ for $(p_1, p_2, p_3) = (8, 4, 2), m = 3$

Sample Size		Upper Percentile					Type I Error				
$N_1^{(\ell)}$	$N_2^{(\ell)} = N_3^{(\ell)}$	$-2 \log \lambda_m$	$-2\rho_{L_m} \log \lambda_m$	$-2 \log \tau_m$	$-2 \log \phi_m$	$q_m^*(\alpha)$	α_m	$\alpha_{\rho_{L_m}}$	α_{τ_m}	α_{ϕ_m}	$\alpha_{q_m^*}$
$\alpha = 0.05$											
20	20	386.37	316.39	369.89	353.72	350.57	.966	.428	.920	.835	.266
40	40	312.64	284.33	306.77	301.86	306.33	.415	.103	.337	.274	.079
80	80	291.58	278.38	288.88	286.76	289.05	.163	.066	.139	.121	.061
160	160	282.93	276.53	281.62	280.65	281.62	.094	.057	.085	.079	.056
320	320	278.88	275.72	278.23	277.75	278.20	.069	.053	.065	.063	.053
20	10	402.83	313.29	380.34	361.95	368.90	.988	.394	.956	.887	.238
40	20	319.14	283.67	310.81	305.06	313.75	.503	.098	.389	.314	.073
80	40	294.54	278.17	290.68	288.21	292.32	.192	.065	.155	.133	.059
160	80	284.25	276.35	282.39	281.24	283.14	.103	.056	.090	.082	.055
320	160	279.45	275.56	278.53	277.97	278.94	.072	.053	.067	.064	.052
20	40	373.02	317.75	360.99	346.78	337.93	.928	.441	.875	.778	.269
40	80	307.05	284.30	303.17	298.99	300.91	.339	.102	.289	.239	.078
80	160	289.08	278.37	287.31	285.51	286.56	.141	.066	.126	.112	.061
160	320	281.56	276.34	280.70	279.87	280.43	.085	.056	.079	.074	.055
320	640	278.30	275.72	277.88	277.47	277.62	.066	.053	.063	.061	.053
$\alpha = 0.01$											
20	20	411.79	337.21	394.14	376.70	372.32	.893	.215	.792	.645	.105
40	40	331.74	301.70	325.55	320.27	325.04	.194	.026	.141	.105	.018
80	80	309.18	295.18	306.31	304.07	306.62	.050	.014	.040	.033	.013
160	160	300.07	293.28	298.68	297.66	298.71	.023	.012	.020	.018	.012
320	320	295.59	292.24	294.91	294.40	295.09	.015	.011	.014	.013	.011
20	10	429.17	333.78	405.32	385.45	391.89	.954	.188	.867	.731	.088
40	20	338.64	301.01	329.83	323.77	332.94	.262	.025	.177	.128	.017
80	40	312.52	295.15	308.43	305.81	310.09	.062	.014	.046	.038	.013
160	80	301.40	293.02	299.42	298.23	300.33	.026	.012	.022	.019	.011
320	160	296.42	292.30	295.44	294.85	295.87	.016	.011	.015	.014	.011
20	40	397.83	338.88	384.80	369.44	358.85	.809	.226	.712	.566	.108
40	80	325.97	301.82	321.85	317.41	319.27	.143	.026	.113	.086	.018
80	160	306.52	295.17	304.66	302.77	303.98	.040	.014	.034	.029	.013
160	320	298.65	293.12	297.77	296.88	297.45	.020	.012	.018	.017	.011
320	640	295.08	292.35	294.64	294.19	294.47	.014	.011	.014	.013	.011

Note: The closest value to α from among $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$ and $\alpha_{q_m^*}$ of each row is in bold.
 $\chi_{f_m}^2(0.05) = 274.99$, $\chi_{f_m}^2(0.01) = 291.68$, $f_m = 238$.

Table 3: Simulated values for $-2 \log \lambda_m$, $-2\rho_{L_m} \log \lambda_m$, $-2 \log \tau_m$, and $-2 \log \phi_m$ and the approximate values for $-2 \log \lambda_m$ and the actual type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, and $\alpha_{q_m^*}$ for $(p_1, p_2, p_3) = (8, 4, 2), m = 4$

Sample Size		Upper Percentile					Type I Error				
$N_1^{(\ell)}$	$N_2^{(\ell)} = N_3^{(\ell)}$	$-2 \log \lambda_m$	$-2\rho_{L_m} \log \lambda_m$	$-2 \log \tau_m$	$-2 \log \phi_m$	$q_m^*(\alpha)$	α_m	$\alpha_{\rho_{L_m}}$	α_{τ_m}	α_{ϕ_m}	$\alpha_{q_m^*}$
$\alpha = 0.05$											
20	20	551.12	457.54	529.02	504.47	503.92	.989	.500	.965	.894	.308
40	40	453.34	414.86	445.38	437.94	444.59	.491	.112	.398	.314	.084
80	80	424.69	406.66	420.98	417.79	421.22	.187	.069	.156	.133	.063
160	160	412.83	404.07	411.03	409.54	411.12	.100	.057	.090	.082	.056
320	320	407.35	403.03	406.46	405.74	406.46	.072	.054	.068	.064	.053
20	10	573.44	453.95	543.20	515.07	528.56	.997	.467	.984	.935	.277
40	20	462.11	413.97	450.73	442.04	454.63	.592	.107	.462	.361	.078
80	40	428.70	406.36	423.44	419.74	425.67	.223	.067	.176	.146	.061
160	80	414.75	403.95	412.20	410.46	413.20	.112	.057	.097	.087	.056
320	160	408.26	402.95	407.01	406.15	407.46	.076	.053	.070	.066	.053
20	40	533.12	459.06	517.10	495.51	486.83	.969	.512	.935	.846	.311
40	80	445.59	414.64	440.30	433.98	437.22	.401	.111	.341	.273	.083
80	160	421.29	406.66	418.87	416.18	417.83	.158	.069	.140	.121	.063
160	320	411.20	404.06	410.03	408.77	409.49	.091	.058	.085	.078	.056
320	640	406.47	402.94	405.89	405.28	405.66	.068	.053	.065	.062	.053
$\alpha = 0.01$											
20	20	580.70	482.10	557.39	531.05	529.52	.955	.270	.887	.739	.129
40	40	476.28	435.85	467.89	459.97	466.86	.251	.030	.181	.127	.020
80	80	446.06	427.12	442.17	438.80	442.24	.059	.015	.046	.037	.014
160	160	433.53	424.33	431.65	430.07	431.60	.025	.012	.022	.020	.012
320	320	427.68	423.14	426.76	425.97	426.71	.016	.011	.015	.014	.011
20	10	604.22	478.32	572.34	542.27	555.52	.986	.241	.940	.818	.109
40	20	485.14	434.59	473.26	464.13	477.43	.340	.028	.227	.156	.018
80	40	450.12	426.67	444.61	440.75	446.92	.077	.015	.055	.042	.013
160	80	435.41	424.07	432.73	430.91	433.79	.030	.012	.024	.021	.011
320	160	428.58	423.00	427.26	426.38	427.76	.017	.011	.016	.014	.011
20	40	562.28	484.17	545.13	521.88	511.51	.899	.282	.821	.659	.132
40	80	468.11	435.60	462.52	455.79	459.10	.183	.030	.143	.103	.020
80	160	442.23	426.88	439.71	436.90	438.67	.047	.015	.040	.033	.014
160	320	431.91	424.41	430.69	429.34	429.90	.022	.012	.020	.018	.012
320	640	426.72	423.02	426.10	425.48	425.87	.015	.011	.014	.013	.011

Note: The closest value to α from among $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$ and $\alpha_{q_m^*}$ of each row is in bold.
 $\chi_{f_m}^2(0.05) = 402.06$, $\chi_{f_m}^2(0.01) = 422.09$, $f_m = 357$.

Table 4: Simulated values for $-2 \log \lambda_m$, $-2\rho_{L_m} \log \lambda_m$, $-2 \log \tau_m$, and $-2 \log \phi_m$ and the approximate values for $-2 \log \lambda_m$ and the actual type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, and $\alpha_{q_m^*}$ for $(p_1, p_2, p_3) = (4, 4, 4), m = 2$

Sample Size		Upper Percentile					Type I Error				
$N_1^{(\ell)}$	$N_2^{(\ell)} = N_3^{(\ell)}$	$-2 \log \lambda_m$	$-2\rho_{L_m} \log \lambda_m$	$-2 \log \tau_m$	$-2 \log \phi_m$	$q_m^*(\alpha)$	α_m	$\alpha_{\rho_{L_m}}$	α_{τ_m}	α_{ϕ_m}	$\alpha_{q_m^*}$
$\alpha = 0.05$											
20	20	169.48	131.16	159.56	149.79	153.97	.842	.260	.740	.591	.162
40	40	133.02	117.98	129.97	126.58	129.75	.304	.090	.252	.197	.072
80	80	121.89	115.00	120.59	119.10	120.49	.133	.063	.117	.101	.059
160	160	117.27	113.95	116.66	115.96	116.58	.082	.055	.077	.071	.054
320	320	115.19	113.56	114.89	114.54	114.80	.065	.053	.062	.060	.052
20	10	172.43	128.56	161.33	151.16	159.08	.868	.220	.765	.617	.138
40	20	134.31	117.22	130.76	127.22	131.82	.329	.082	.266	.208	.066
80	40	122.47	114.68	120.96	119.42	121.41	.140	.061	.121	.104	.057
160	80	117.60	113.86	116.88	116.14	117.01	.085	.055	.079	.072	.054
320	160	115.29	113.46	114.94	114.57	115.01	.066	.052	.063	.060	.052
20	40	166.93	132.96	157.96	148.44	150.44	.815	.288	.716	.567	.174
40	80	131.87	118.45	129.21	125.94	128.22	.284	.093	.239	.188	.074
80	160	121.37	115.20	120.28	118.85	119.79	.126	.065	.113	.098	.060
160	320	117.06	114.08	116.55	115.87	116.25	.080	.057	.076	.070	.055
320	640	114.94	113.48	114.70	114.37	114.64	.063	.052	.061	.058	.052
$\alpha = 0.01$											
20	20	186.80	144.56	175.63	164.85	169.37	.663	.103	.520	.355	.050
40	40	145.97	129.46	142.58	138.91	142.45	.125	.022	.095	.067	.016
80	80	133.76	126.20	132.33	130.70	132.21	.038	.014	.032	.026	.013
160	160	128.55	124.92	127.89	127.11	127.89	.020	.011	.018	.016	.011
320	320	126.42	124.63	126.10	125.73	125.94	.014	.011	.013	.013	.011
20	10	189.82	141.53	177.37	166.47	175.03	.705	.080	.552	.381	.040
40	20	147.47	128.71	143.57	139.72	144.74	.140	.020	.102	.071	.014
80	40	134.30	125.75	132.63	130.93	133.22	.041	.013	.034	.027	.012
160	80	128.97	124.86	128.18	127.37	128.37	.021	.011	.019	.017	.011
320	160	126.38	124.37	125.99	125.61	126.17	.014	.010	.014	.013	.010
20	40	183.96	146.53	173.80	163.41	165.47	.623	.120	.490	.332	.057
40	80	144.67	129.95	141.74	138.18	140.77	.112	.024	.087	.062	.017
80	160	133.14	126.37	131.92	130.37	131.44	.035	.014	.031	.025	.013
160	320	128.46	125.19	127.90	127.16	127.52	.019	.012	.018	.016	.011
320	640	126.08	124.47	125.81	125.45	125.76	.014	.011	.013	.012	.010

Note: The closest value to α from among $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$ and $\alpha_{q_m^*}$ of each row is in bold.
 $\chi_{f_m}^2(0.05) = 113.15$, $\chi_{f_m}^2(0.01) = 124.12$, $f_m = 90$.

Table 5: Simulated values for $-2 \log \lambda_m$, $-2\rho_{L_m} \log \lambda_m$, $-2 \log \tau_m$, and $-2 \log \phi_m$ and the approximate values for $-2 \log \lambda_m$ and the actual type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, and $\alpha_{q_m^*}$ for $(p_1, p_2, p_3) = (4, 4, 4), m = 3$

Sample Size		Upper Percentile					Type I Error				
$N_1^{(\ell)}$	$N_2^{(\ell)} = N_3^{(\ell)}$	$-2 \log \lambda_m$	$-2\rho_{L_m} \log \lambda_m$	$-2 \log \tau_m$	$-2 \log \phi_m$	$q_m^*(\alpha)$	α_m	$\alpha_{\rho_{L_m}}$	α_{τ_m}	α_{ϕ_m}	$\alpha_{q_m^*}$
$\alpha = 0.05$											
20	20	301.38	240.80	285.82	265.97	277.83	.941	.325	.869	.684	.192
40	40	244.74	220.15	239.73	233.05	239.35	.397	.099	.324	.233	.077
80	80	226.75	215.36	224.60	221.67	224.40	.160	.066	.139	.112	.062
160	160	219.18	213.67	218.17	216.79	217.99	.092	.057	.085	.075	.056
320	320	215.62	212.91	215.13	214.46	215.06	.068	.053	.065	.061	.053
20	10	306.27	237.02	288.81	268.26	286.03	.957	.275	.890	.712	.161
40	20	246.91	219.00	241.11	234.07	242.74	.429	.090	.343	.245	.070
80	40	227.78	214.90	225.26	222.16	225.91	.171	.064	.145	.116	.059
160	80	219.62	213.42	218.44	216.98	218.71	.096	.056	.087	.077	.055
320	160	215.88	212.82	215.30	214.59	215.40	.070	.053	.066	.062	.052
20	40	297.14	243.39	283.18	264.08	272.10	.923	.358	.848	.657	.207
40	80	242.78	220.82	238.46	232.08	236.85	.367	.105	.306	.221	.081
80	160	225.76	215.55	223.94	221.16	223.24	.151	.068	.133	.108	.063
160	320	218.69	213.75	217.84	216.53	217.44	.088	.057	.082	.074	.056
320	640	215.41	212.98	215.00	214.36	214.79	.067	.053	.064	.061	.053
$\alpha = 0.01$											
20	20	323.22	258.25	306.29	284.86	297.63	.834	.139	.698	.445	.064
40	40	261.93	235.61	256.52	249.31	256.11	.182	.025	.134	.083	.018
80	80	242.55	230.36	240.26	237.09	240.02	.049	.015	.040	.030	.013
160	160	234.42	228.53	233.36	231.86	233.15	.023	.012	.020	.017	.012
320	320	230.61	227.71	230.09	229.37	230.01	.015	.011	.014	.013	.011
20	10	328.35	254.10	309.37	287.38	306.45	.870	.109	.734	.477	.049
40	20	264.16	234.30	257.95	250.46	259.74	.205	.022	.146	.089	.016
80	40	243.51	229.75	240.82	237.54	241.64	.053	.014	.042	.031	.012
160	80	234.91	228.27	233.63	232.06	233.91	.024	.012	.021	.018	.011
320	160	230.84	227.58	230.22	229.46	230.37	.016	.011	.014	.013	.011
20	40	318.91	261.22	303.60	283.02	291.47	.798	.161	.664	.415	.072
40	80	259.67	236.19	255.06	248.35	253.43	.163	.027	.123	.077	.019
80	160	241.46	230.54	239.52	236.61	238.78	.044	.015	.037	.028	.014
160	320	233.96	228.67	233.04	231.63	232.55	.021	.012	.020	.017	.012
320	640	230.35	227.75	229.92	229.26	229.71	.015	.011	.014	.013	.011

Note: The closest value to α from among $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$ and $\alpha_{q_m^*}$ of each row is in bold.
 $\chi_{f_m}^2(0.05) = 212.30$, $\chi_{f_m}^2(0.01) = 227.06$, $f_m = 180$.

Table 6: Simulated values for $-2 \log \lambda_m$, $-2\rho_{L_m} \log \lambda_m$, $-2 \log \tau_m$, and $-2 \log \phi_m$ and the approximate values for $-2 \log \lambda_m$ and the actual type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, and $\alpha_{q_m^*}$ for $(p_1, p_2, p_3) = (4, 4, 4), m = 4$

Sample Size		Upper Percentile					Type I Error				
$N_1^{(\ell)}$	$N_2^{(\ell)} = N_3^{(\ell)}$	$-2 \log \lambda_m$	$-2\rho_{L_m} \log \lambda_m$	$-2 \log \tau_m$	$-2 \log \phi_m$	$q_m^*(\alpha)$	α_m	$\alpha_{\rho_{L_m}}$	α_{τ_m}	α_{ϕ_m}	$\alpha_{q_m^*}$
$\alpha = 0.05$											
20	20	428.72	347.94	408.06	378.36	397.27	.977	.384	.933	.750	.222
40	40	353.35	320.06	346.59	336.56	345.88	.471	.108	.384	.261	.083
80	80	329.04	313.54	326.12	321.74	325.75	.183	.069	.156	.121	.064
160	160	318.65	311.14	317.27	315.20	317.07	.099	.058	.091	.078	.056
320	320	313.89	310.19	313.22	312.20	313.08	.071	.054	.068	.063	.053
20	10	435.55	343.22	412.30	381.39	408.27	.985	.329	.947	.777	.186
40	20	356.23	318.48	348.37	337.85	350.45	.508	.098	.407	.276	.074
80	40	330.33	312.83	326.91	322.27	327.80	.196	.066	.163	.125	.060
160	80	319.30	310.84	317.68	315.50	318.04	.104	.056	.093	.080	.055
320	160	314.26	310.10	313.47	312.41	313.55	.073	.053	.069	.064	.053
20	40	422.86	351.15	404.36	375.76	389.55	.967	.422	.918	.724	.241
40	80	350.62	320.89	344.80	335.29	342.50	.436	.114	.362	.248	.086
80	160	327.62	313.73	325.17	321.02	324.18	.170	.070	.148	.115	.065
160	320	317.98	311.24	316.83	314.88	316.32	.095	.058	.088	.077	.057
320	640	313.58	310.26	313.03	312.08	312.71	.070	.054	.067	.062	.053
$\alpha = 0.01$											
20	20	454.38	368.76	432.11	400.68	420.46	.919	.177	.813	.520	.078
40	40	373.57	338.38	366.37	355.78	365.75	.235	.028	.172	.097	.019
80	80	347.92	331.53	344.82	340.20	344.38	.058	.015	.047	.033	.014
160	160	336.89	328.95	335.41	333.21	335.18	.025	.012	.022	.018	.012
320	320	331.74	327.83	331.03	329.95	330.96	.016	.011	.015	.014	.011
20	10	461.56	363.72	436.65	403.75	432.15	.943	.140	.843	.556	.060
40	20	376.70	336.77	368.39	357.35	370.60	.266	.025	.187	.105	.017
80	40	349.20	330.69	345.57	340.70	346.55	.064	.014	.050	.034	.013
160	80	337.52	328.57	335.80	333.51	336.21	.027	.012	.023	.019	.011
320	160	332.14	327.74	331.31	330.19	331.45	.017	.011	.015	.014	.011
20	40	448.33	372.30	428.28	397.83	412.26	.893	.205	.782	.487	.088
40	80	370.77	339.33	364.55	354.47	362.16	.209	.031	.157	.090	.021
80	160	346.48	331.79	343.85	339.51	342.71	.053	.016	.043	.031	.014
160	320	336.06	328.93	334.83	332.79	334.38	.024	.012	.021	.017	.012
320	640	331.41	327.89	330.80	329.79	330.56	.016	.011	.015	.013	.011

Note: The closest value to α from among $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$ and $\alpha_{q_m^*}$ of each row is in bold.
 $\chi_{f_m}^2(0.05) = 309.33$, $\chi_{f_m}^2(0.01) = 326.98$, $f_m = 270$.

Table 7: Simulated values for $-2 \log \lambda_m$, $-2\rho_{L_m} \log \lambda_m$, $-2 \log \tau_m$, and $-2 \log \phi_m$ and the approximate values for $-2 \log \lambda_m$ and the actual type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, and $\alpha_{q_m^*}$ for $(p_1, p_2, p_3) = (2, 4, 8), m = 2$

Sample Size		Upper Percentile					Type I Error				
$N_1^{(\ell)}$	$N_2^{(\ell)} = N_3^{(\ell)}$	$-2 \log \lambda_m$	$-2\rho_{L_m} \log \lambda_m$	$-2 \log \tau_m$	$-2 \log \phi_m$	$q_m^*(\alpha)$	α_m	$\alpha_{\rho_{L_m}}$	α_{τ_m}	α_{ϕ_m}	$\alpha_{q_m^*}$
$\alpha = 0.05$											
20	20	254.40	174.29	219.28	192.99	226.10	.992	.393	.926	.697	.229
40	40	180.69	152.24	170.58	162.66	177.07	.527	.101	.355	.227	.069
80	80	160.66	148.01	156.47	153.06	159.09	.200	.067	.146	.109	.059
160	160	152.50	146.49	150.57	148.97	151.73	.104	.056	.087	.074	.054
320	320	148.89	145.96	147.95	147.18	148.46	.073	.053	.066	.061	.052
20	10	255.63	170.40	219.86	193.61	230.65	.993	.332	.930	.705	.197
40	20	181.17	150.97	170.71	162.73	178.88	.537	.090	.360	.230	.062
80	40	160.90	147.49	156.59	153.17	159.88	.204	.063	.148	.110	.056
160	80	152.65	146.28	150.66	149.04	152.10	.106	.055	.088	.075	.053
320	160	148.97	145.86	148.00	147.22	148.64	.074	.052	.066	.061	.052
20	40	253.18	177.21	218.69	192.51	223.00	.991	.442	.922	.690	.251
40	80	180.07	153.05	170.17	162.28	175.76	.517	.109	.349	.222	.074
80	160	160.36	148.33	156.29	152.91	158.49	.197	.069	.145	.108	.061
160	320	152.41	146.70	150.54	148.95	151.45	.103	.058	.086	.074	.056
320	640	148.85	146.06	147.95	147.19	148.32	.073	.054	.066	.061	.053
$\alpha = 0.01$											
20	20	236.59	188.39	225.14	216.80	208.90	.746	.161	.624	.518	.083
40	40	182.90	164.27	179.09	176.45	178.61	.132	.023	.099	.080	.017
80	80	168.61	160.02	166.87	165.71	167.02	.038	.014	.032	.028	.012
160	160	163.05	158.90	162.21	161.66	162.11	.020	.012	.018	.017	.011
320	320	160.38	158.34	159.97	159.71	159.88	.014	.011	.013	.013	.011
20	10	278.87	185.90	239.23	210.79	251.19	.971	.146	.813	.474	.066
40	20	196.61	163.83	185.22	176.58	194.30	.296	.022	.158	.082	.013
80	40	174.62	160.07	169.90	166.19	173.50	.069	.014	.044	.029	.012
160	80	165.60	158.70	163.43	161.69	165.01	.027	.011	.021	.017	.011
320	160	161.51	158.14	160.48	159.63	161.25	.017	.011	.015	.013	.010
20	40	276.16	193.29	237.93	209.48	242.81	.965	.225	.799	.457	.093
40	80	195.40	166.08	184.61	176.08	190.89	.279	.029	.151	.078	.017
80	160	173.96	160.91	169.56	165.91	171.99	.065	.015	.042	.028	.013
160	320	165.38	159.18	163.39	161.67	164.31	.027	.012	.021	.017	.012
320	640	161.47	158.44	160.50	159.67	160.91	.017	.011	.015	.013	.011

Note: The closest value to α from among $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$ and $\alpha_{q_m^*}$ of each row is in bold.
 $\chi_{f_m}^2(0.05) = 145.46$, $\chi_{f_m}^2(0.01) = 157.80$, $f_m = 119$.

Table 8: Simulated values for $-2 \log \lambda_m$, $-2\rho_{L_m} \log \lambda_m$, $-2 \log \tau_m$, and $-2 \log \phi_m$ and the approximate values for $-2 \log \lambda_m$ and the actual type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, and $\alpha_{q_m^*}$ for $(p_1, p_2, p_3) = (2, 4, 8), m = 3$

Sample Size		Upper Percentile					Type I Error				
$N_1^{(\ell)}$	$N_2^{(\ell)} = N_3^{(\ell)}$	$-2 \log \lambda_m$	$-2\rho_{L_m} \log \lambda_m$	$-2 \log \tau_m$	$-2 \log \phi_m$	$q_m^*(\alpha)$	α_m	$\alpha_{\rho_{L_m}}$	α_{τ_m}	α_{ϕ_m}	$\alpha_{q_m^*}$
$\alpha = 0.05$											
20	20	386.37	316.39	369.89	353.72	350.57	.966	.428	.920	.835	.266
40	40	312.64	284.33	306.77	301.86	306.33	.415	.103	.337	.274	.079
80	80	291.58	278.38	288.88	286.76	289.05	.163	.066	.139	.121	.061
160	160	282.93	276.53	281.62	280.65	281.62	.094	.057	.085	.079	.056
320	320	278.88	275.72	278.23	277.75	278.20	.069	.053	.065	.063	.053
20	10	449.95	316.60	394.06	342.83	411.98	1.000	.440	.984	.768	.240
40	20	333.77	284.31	316.64	300.88	329.61	.688	.103	.472	.263	.067
80	40	300.73	278.45	293.54	286.73	298.83	.261	.067	.182	.121	.058
160	80	287.14	276.50	283.81	280.64	286.04	.124	.057	.099	.079	.055
320	160	280.91	275.71	279.30	277.77	280.30	.080	.053	.071	.063	.053
20	40	445.60	326.75	391.88	341.07	399.59	.999	.569	.981	.751	.313
40	80	331.94	287.67	315.70	300.14	324.47	.666	.128	.458	.254	.083
80	160	299.75	279.76	292.98	286.33	296.53	.250	.074	.177	.118	.064
160	320	286.62	277.07	283.51	280.39	284.96	.120	.059	.097	.077	.057
320	640	280.67	275.99	279.15	277.64	279.77	.079	.054	.070	.062	.054
$\alpha = 0.01$											
20	20	411.79	337.21	394.14	376.70	372.32	.893	.215	.792	.645	.105
40	40	331.74	301.70	325.55	320.27	325.04	.194	.026	.141	.105	.018
80	80	309.18	295.18	306.31	304.07	306.62	.050	.014	.040	.033	.013
160	160	300.07	293.28	298.68	297.66	298.71	.023	.012	.020	.018	.012
320	320	295.59	292.24	294.91	294.40	295.09	.015	.011	.014	.013	.011
20	10	479.07	337.10	418.85	364.41	438.00	.997	.220	.939	.544	.087
40	20	354.14	301.66	335.84	319.15	349.87	.443	.027	.236	.098	.014
80	40	319.12	295.48	311.46	304.29	317.03	.097	.015	.058	.033	.012
160	80	304.57	293.28	301.04	297.66	303.42	.034	.012	.025	.018	.011
320	160	297.90	292.38	296.20	294.55	297.31	.019	.011	.016	.014	.011
20	40	474.55	347.98	416.58	362.35	424.78	.996	.330	.932	.523	.128
40	80	352.26	305.29	334.99	318.57	344.40	.418	.036	.225	.093	.019
80	160	318.02	296.81	310.79	303.75	314.58	.091	.017	.055	.032	.014
160	320	304.05	293.91	300.72	297.42	302.26	.032	.012	.024	.018	.012
320	640	297.70	292.74	296.09	294.48	296.75	.018	.011	.016	.013	.011

Note: The closest value to α from among $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$ and $\alpha_{q_m^*}$ of each row is in bold.
 $\chi_{f_m}^2(0.05) = 274.99$, $\chi_{f_m}^2(0.01) = 291.68$, $f_m = 238$.

Table 9: Simulated values for $-2 \log \lambda_m$, $-2\rho_{L_m} \log \lambda_m$, $-2 \log \tau_m$, and $-2 \log \phi_m$ and the approximate values for $-2 \log \lambda_m$ and the actual type I error rates $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$, and $\alpha_{q_m^*}$ for $(p_1, p_2, p_3) = (2, 4, 8), m = 4$

Sample Size		Upper Percentile					Type I Error				
$N_1^{(\ell)}$	$N_2^{(\ell)} = N_3^{(\ell)}$	$-2 \log \lambda_m$	$-2\rho_{L_m} \log \lambda_m$	$-2 \log \tau_m$	$-2 \log \phi_m$	$q_m^*(\alpha)$	α_m	$\alpha_{\rho_{L_m}}$	α_{τ_m}	α_{ϕ_m}	$\alpha_{q_m^*}$
$\alpha = 0.05$											
20	20	551.12	457.54	529.02	504.47	503.92	.989	.500	.965	.894	.308
40	40	453.34	414.86	445.38	437.94	444.59	.491	.112	.398	.314	.084
80	80	424.69	406.66	420.98	417.79	421.22	.187	.069	.156	.133	.063
160	160	412.83	404.07	411.03	409.54	411.12	.100	.057	.090	.082	.056
320	320	407.35	403.03	406.46	405.74	406.46	.072	.054	.068	.064	.053
20	10	636.66	459.77	562.66	487.33	586.06	1.000	.534	.996	.813	.284
40	20	481.98	415.02	458.76	435.23	475.99	.784	.113	.558	.287	.070
80	40	437.08	406.72	427.28	417.15	434.50	.309	.069	.210	.128	.059
160	80	418.51	403.98	413.94	409.21	417.15	.137	.057	.107	.081	.055
320	160	410.02	402.90	407.81	405.52	409.32	.085	.053	.074	.064	.052
20	40	630.73	473.01	559.58	485.05	569.37	1.000	.671	.995	.798	.374
40	80	479.47	419.52	457.49	434.28	469.02	.763	.144	.542	.277	.090
80	160	435.92	408.67	426.70	416.76	431.37	.295	.078	.203	.125	.067
160	320	417.95	404.89	413.67	409.03	415.67	.134	.061	.106	.080	.058
320	640	409.85	403.44	407.79	405.54	408.60	.084	.055	.074	.063	.054
$\alpha = 0.01$											
20	20	580.70	482.10	557.39	531.05	529.52	.955	.270	.887	.739	.129
40	40	476.28	435.85	467.89	459.97	466.86	.251	.030	.181	.127	.020
80	80	446.06	427.12	442.17	438.80	442.24	.059	.015	.046	.037	.014
160	160	433.53	424.33	431.65	430.07	431.60	.025	.012	.022	.020	.012
320	320	427.68	423.14	426.76	425.97	426.71	.016	.011	.015	.014	.011
20	10	670.19	483.99	591.51	512.03	616.33	1.000	.296	.981	.604	.111
40	20	506.09	435.79	481.65	456.91	499.97	.559	.030	.307	.111	.016
80	40	458.83	426.96	448.54	437.94	456.21	.123	.015	.070	.035	.012
160	80	439.34	424.08	434.51	429.51	437.95	.039	.012	.028	.019	.011
320	160	430.54	423.06	428.23	425.82	429.72	.020	.011	.017	.014	.011
20	40	664.17	498.09	588.50	509.64	598.73	1.000	.431	.977	.582	.167
40	80	503.28	440.36	480.13	455.79	492.63	.530	.042	.293	.105	.021
80	160	457.65	429.04	447.95	437.51	452.92	.115	.018	.067	.034	.015
160	320	438.56	424.85	434.07	429.17	436.39	.037	.013	.027	.018	.012
320	640	430.26	423.53	428.10	425.74	428.96	.020	.011	.017	.014	.011

Note: The closest value to α from among $\alpha_m, \alpha_{\rho_{L_m}}, \alpha_{\tau_m}, \alpha_{\phi_m}$ and $\alpha_{q_m^*}$ of each row is in bold.
 $\chi_{f_m}^2(0.05) = 402.06$, $\chi_{f_m}^2(0.01) = 422.09$, $f_m = 357$.

7 Numerical example

In this section, we give an example for test statistics and approximate upper percentiles proposed in this paper. The data consisted of cholesterol values measured during treatment at five time points (baseline, 6 months, 12 months, 20 months and 24 months) of a placebo group and a high dose group (Wei and Lachin (1984)). To construct the three-step monotone missing data, we used data with values available for up to 24 months, data with values available for up to 20 months, and data with values available for up to 12 months. That is $m = 2, p_1 = 3, p_2 = 1, p_3 = 1$. For the placebo group ($\ell = 1$), $N_1^{(1)} = 31, N_2^{(1)} = 4, N_3^{(1)} = 3$, and for the high dose group ($\ell = 2$), $N_1^{(2)} = 36, N_2^{(2)} = 7, N_3^{(2)} = 12$. Then, LRT statistic and test statistics are

$$\begin{aligned} -2 \log \lambda_m &= 82.201, & -2\rho_{L_m} \log \lambda_m &= 75.425, \\ -2 \log \tau_m &= 66.542, & -2 \log \phi_m &= 80.527. \end{aligned}$$

And, approximate upper percentile is

$$q_m^*(0.05) = 34.422, \quad q_m^*(0.01) = 41.196,$$

and $\chi_{20}^2(0.05) = 31.410, \chi_{20}^2(0.01) = 37.566$. Thus, the null hypothesis is rejected for all test statistics and approximate upper percentile.

8 Conclusions

We discussed simultaneous tests for mean vectors and covariance matrices with three-step monotone missing data for a multi-sample problem. We proposed two test statistics ($-2 \log \tau_m, -2 \log \phi_m$) by decomposing the LR and correcting it by extracting the LR of the simultaneous test and the test of the variance in the case of complete data. We also proposed a test statistic ($-2\rho_{L_m} \log \lambda_m$) via linear interpolation. In addition, we provided an approximate upper 100α percentile ($q_m^*(\alpha)$). Further, based on the simulation results, an approximate upper 100α percentile $q_m^*(\alpha)$ is the most accurate. Finally, we gave an example of the proposed test statistics. The results of this paper can be extended to the k -step monotone missing data. We are currently investigating this problem.

Acknowledgments

The second author's research is partly supported by a Grant-in-Aid for Early-Career Scientists (19K20225).

References

- [1] Hao, J. and Krishnamoorthy, K. (2001). Inferences on a normal covariance matrix and generalized variance with monotone missing data, *Journal of Multivariate Analysis*, **78**, 62–82.
- [2] Hosoya, M. and Seo, T. (2015). Simultaneous testing of the mean vector and the covariance matrix with two-step monotone missing data, *SUT Journal of Mathematics*, **51**, 83–98.
- [3] Hosoya, M. and Seo, T. (2016). On the likelihood ratio test for the equality of multivariate normal populations with two-step monotone missing data, *Journal of Statistical Theory and Practice*, **10**, 673–692.
- [4] Jinadasa, K. G. and Tracy, D. S. (1992). Maximum likelihood estimation for multivariate normal distribution with monotone sample, *Communications in Statistics – Theory and Methods*, **21**, 41–50.
- [5] Kanda, T. and Fujikoshi, Y. (1998). Some basic properties of the MLE’s for a multivariate normal distribution with monotone missing data, *American Journal of Mathematical and Management Sciences*, **18**, 161–190.
- [6] Muirhead, R. J. (2005). *Aspects of Multivariate Statistical Theory*, John Wiley & Sons, Inc., Hoboken, New Jersey.
- [7] Sakai, R., Yagi, A., and Seo, T. (2021). Simultaneous testing of mean vector and covariance matrix with three-step monotone missing data, *Technical Report No.21-04*, Statistical Research Group, Hiroshima University, Hiroshima, Japan.
- [8] Srivastava, M. S. (2002). *Methods of Multivariate Statistics*, John Wiley & Sons, Inc., New York.
- [9] Wei, L. J. and Lachin, J. M. (1984). Two-sample asymptotically distribution-free tests for incomplete multivariate observations, *Journal of the American Statistical Association*, **79**, 653–661.
- [10] Yagi, A., Yamaguchi, R., and Seo, T. (2016). Simultaneous testing of mean vectors and covariance matrices with monotone missing data, *Technical Report No.16-02*, Statistical Research Group, Hiroshima University, Hiroshima, Japan.