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Comparison between Conventional and Adjusted Mean Probability of Correct Classification for Two Groups Problem: A Preliminary Study

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Abstract

This paper describes a new approach to determine classification performance based on the computation and application of margin of error. This procedure revealed that as the proportion of contamination increases, the misclassification rate and the margin of error also increases. On the other hand, if the mean probability of correct classification is approaching the mean of the optimal probability, the margin of error tends to reduce maximally. The upper and lower classification limits enable us to determine the performance of the technique of interest. If the computed mean probability exceed the upper classification limit this indicates that the rate of misclassification is high. In a general note, we are $(1-\alpha)\%$ confident of the classification result based on this approach. This new technique was applied to investigate the performance of the Fisher linear classification analysis, Fisher's approach based on the minimum covariance determinant and the probability based classification technique. In general, the performance analysis revealed that as the proportion of contamination increases, the misclassification rate increases thereby producing large margin of error. The implication of large margin of error to classification rule is that the adjusted mean probability based on the margin of error will overshot the upper classification limit which indicates high misclassification rate or possibly highly contaminated data set.

Keywords: Classification, Robust, Mean probability, Margin of error

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1. Introduction

The Fisher linear classification analysis (FLCA) [1] was introduced when it was applied to study the Iris data set. Conventionally, the FLCA procedure was proposed for two groups. The FLCA assist in gaining information regarding the separation between the two groups with regards to the within group mean and the contribution of the profile variables[2, 3]. It is a dimension reduction technique and belongs to the class of supervised learning technique[4], though nonparametric[5]. The basic assumptions of the FLCA are homoscedasticity of the covariance matrices. The coefficient of the FLCA is computed based on the difference between the within group mean vectors and the pooled covariance matrix. These sample statistics are the building blocks of the FLCA but are sensitive to influential observations [6-14]. The sample mean vectors and covariance matrices computed based on data set generated from a multivariate normal distribution enhances the performance of the FLCA maximally [15, 16]. On the other hand, if the data set is not drawn from a multivariate normal distribution, the sample statistics computed are influenced by influential observations hence when these sample statistics are applied to develop the FLCA; the misclassification rate for the FLCA tends to increase maximally.

It has been suggested that when the data set are not normally distributed the mean vectors and covariance matrices are influenced by outliers, hence various propositions have been proposed to robustfiy these parameters to enhance maximum classification performance (robust). The maximum likelihood estimator (*M* estimator)[17], generalized maximum likelihood estimator (*GM* estimators)[18], Smooth estimator (*S* estimator)[19], minimum volume ellipsoid (*MVE*) [20] and the minimum covariance determinant estimator (*MCD*) [21] were proposed to robustify the mean vectors and covariance matrices. The robustified mean vectors and covariance matrices are substituted into the conventional FLCA technique to obtain robust FLCA. The MCD procedure has been applied to robustify the Fisher linear discriminant analysis and the quadratic discriminant analysis[22]. The MCD procedure strictly depends on information glean from the half set. Detail of this robust high breakdown method and its application to classification is contain in Rousseeuw (1999).

Probabilistic extension of the Fisher linear classification analysis was also proposed based on the homoscedasticity assumption by [23, 24]. Robust and flexible Fisher linear discriminant analysis based on probabilistic concepts that "relax" the equal covariance matrix assumption has been investigated[25]. The conventional and robust Fisher's techniques assumed that the prior probabilities for the respective groups are equal [5]. In this paper, the Fisher's technique is modified by introducing the within group probabilities to the separation parameter. This procedure violates the equal prior probability assumption and adheres strictly to the equal covariance matrices. The comparative classification performance of these techniques is investigated for contaminated normal data set using the margin of error to determine robustness.

The reminder of this paper is organized as follow. Section Two describes the Fisher linear classification analysis. The robust Fisher's approach based on the minimum covariance determinant is contained in Section Three. Section Four described the probability base classification technique. The computation of the margin of error is described in Section Five. Simulations and conclusion are contained in Sections Six and Seven respectively.

2. Fisher linear classification analysis (FLCA)

Fisher linear classification analysis (FLCA) was developed for two groups problem. We assumed that the two independent sample observations are drawn from multivariate normal distribution. It is equally assumed that the variance covariance matrices are homoscedastic with unknown mean vectors for the respective groups. The Fisher's technique is a linear combination of the observed variables that best describes the maximum separation between the groups[4]. Since the population mean vectors and covariance matrices are unknown, the sample estimates is used to estimate the population mean vectors and covariance matrices respectively. The estimate of the population covariance matrix is unbiased and the evaluation of the Fisher's linear classification scores based on the group mean vectors and the difference between the mean of the Fisher's linear classification score is approximately the Mahalonobis distance[5]. The Fisher linear classification analysis [1] for two groups problem is defined mathematically as follows,

$$h\_pv = u^T x, \qquad (2.1)$$

where u denote the Fisher linear coefficient, x is the sample observation and h_pv denote the Fisher's classification sore, a scalar. The following equation in comparison with the classification score allows an observation to be assigned to the correct group, say,

$$mean\_cut = \frac{\sum_{i=1}^{2} \bar{x}_i}{2} u^T. \qquad (2.2)$$

Where $mean\_cut$ denote the midpoint and $\bar{x}_i$ is the within group mean vectors. The computation of the Fisher linear coefficient is possible if the group means are unequal. This condition is vital to enable separation, classification and discrimination feasible. To design the allocation rule for the two groups based on the multivariate sample observations, let $\beta_i (i = 1, 2)$ denote the prior probabilities for the two groups and we assumed that $\beta_1 = \beta_2$ with the basic understanding that $\sum_{i=1}^{2} \beta_i = 1$. Define $\eta_{c1} = \varpi(2/1)$ to be the cost of misallocating an observation in group two into group one and let $\eta_{c2} = \varpi(1/2)$ be the cost of misallocating an observation from group one into group two, respectively. The total probability of misallocation is given as $\Omega = \beta_1\eta_{c1} + \beta_2\eta_{c2}$. The total probability of correct allocation is obtained by taking the sum of the diagonal of the confusion matrix divided by the total sample size and the misallocation probability otherwise. In practice, the cost of misallocation is not known; hence Fisher's allocation rule is based on the assumption that the prior probabilities and misallocation cost for both groups are equal. The comparison between the classification score and the midpoint defines the linear classification rule. The Fisher linear classification rule is obtained by comparing the classification score with the classification midpoint. The allocation rule is based on Equations (2.1-2.2). An observation is assigned to group one if the classification score is greater than or equal to the midpoint otherwise the observation is assigned to group two if the classification score is less than the midpoint.

3. Fisher Linear Classification Analysis Based on Minimum Covariance Determinant (FMCD)

The minimum covariance determinant procedure search for the subset h_i (out of n_i) of the data set whose covariance matrix has the minimum determinant[22]. The sample observations based on the half set are chosen from the multivariate data set to obtain the *MCD* estimates of mean vectors and covariance matrices. These robust estimates are computed based on the clean data set selected by the half set. The *MCD* estimates are substituted into the conventional Fisher's equations, say Equations (2.1-2.2) to obtain the robust Fisher linear classification rule. Detail description of this method is contained in Hubert and Van Driessen (2004). The *MCD* approach requires the correction factor to obtain unbiased and consistent estimates if the data set comes from a multivariate normal distribution. The correction factor is used for the *FAST-MCD* algorithm to compute the *MCD* estimates. Detail description and theorem to compute the concentration steps based on the half set of the *MCD* technique is contain in [26], respectively. The allocation procedure for this method is the same as that of the Fisher linear classification analysis.

4. Probability Base Classification Technique (PCT)

This procedure[27] requires the computation of the within group mean difference, say, $h\_gd = \bar{x}_1 - \bar{x}_2$, and the sum of the within group mean vectors is given as $s\_+ = \bar{x}_1 + \bar{x}_2$, respectively. To formulate the coefficient of the new procedure, the absolute value of h_gd is computed, then the following are obtained;

$$\begin{aligned} \tilde{d}t\_v &= 1 + \sqrt{|s\_+|}, \\ w\_pc &= h\_gd^2 / \tilde{d}t\_v, \\ s\_h &= 1 - \left|w\_pc^2\right|. \end{aligned} \quad (4.1)$$

Based on the definitions in Equation (4.1), the following is obtained

$$w\_pt = e^{r\beta} + e^{r\beta^2/s\_+} + p_i, r = 1, \quad (4.2)$$

where $p_i = n_i / \sum_{i=1}^{2} n_i$, is the within group probabilities, n_i is the sample size for each group, n is the total sample size for the two groups and $p = \sum_{i=2}^{2} p_i$, is the total probability. The coefficient of this technique is given as

$$\begin{aligned} h\_ku &= \left(\frac{w\_pt}{S_{pooled}^{-1}} \right)' x = f\_u'x, \\ f\_u &= \frac{w\_pt}{S_{pooled}^{-1}}, \end{aligned} \quad (4.3)$$

Where S_{pooled} denote the pooled covariance matrix. The classification cutoff point is given as follows,

$$mean\_p = \frac{s\_+}{2} f\_u', \tag{4.4}$$

The classification rule is defined as

$$h\_ku < mean\_p, \tag{4.5}$$

in this regard, an observation is assigned to group one if Equation (4.5) is satisfied otherwise the observation is classified to group two if the following equation hold,

$$h\_ku \geq mean\_p. \tag{4.6}$$

5. Margin of error

Relying on confidence interval technique, we compare the performance of the above classification techniques by computing the margin of error based on the proportion of data contamination. In this respect, the t- test is used. The computation of the standard deviation is described as follow.

$$S^2 = \frac{\sum_{j=1}^{k}(x_j - \bar{\mathbf{x}})(x_j - \bar{\mathbf{x}})}{n-1}, j = 1, 2, ..., k,$$

$$w = \frac{(\bar{\mathbf{x}} - \bar{\bar{\mathbf{x}}})^2}{\sum_{j=1}^{k}(x_j - \bar{\mathbf{x}})^2},$$

Where $\bar{\bar{\mathbf{x}}}$ denote the mean of the optimal probability, $\bar{\mathbf{x}}$ is the mean probability of correct classification, x is the mean for each replication assumed as the sample observations and k is the number of replications. The new sample variance is obtained as follows;

$$S_w^2 = S^2 \left[1 / \sum_{i=1}^{2} n_i + w \right],$$

$$q_t = \sqrt{S_w^2}. \tag{5.1}$$

Where q_t denotes the standard deviation and the lower and upper classification limit is determine based on $\bar{\mathbf{x}} \pm t_{\alpha/2} q_t$. Where $(1-\alpha)$ is the confidence coefficient and $t_{\alpha/2}$ is based on $t-$distribution with $n-2$ degree of freedom[28]. The margin of error used for the mean of the optimal probability is defined as $t_{\alpha/2}\sqrt{p}/M$, where p is the sample dimension and M Monte Carlo sample size. In this regard, the margin of error of the optimal probability is a constant whereas the margin of error of the mean probability of correct classification for each technique depends on the information from the method. The idea is to estimate the upper and lower classification benchmark and to determine robustness. In this regard, the classification technique with small margin of error is robust while the reverse is possible.

6. Simulation study

The simulation is designed based on the contaminated normal model $\varepsilon N_p(0,I_p)+(1-\varepsilon)N_p(\mu_p,\Sigma_p)$. The implication of this model is that we draw ε observations from $N_p(0,I_p)$ and $1-\varepsilon$ observations from $N_p(\mu_p,\Sigma_p)$ for each group with different sample mean vectors, variance and percentage of contamination $\varepsilon = 10, 20, 30, 40$. The Monte Carlo simulation is performed for various dimensions p (2,3,4) and sample sizes $n_i = 20, 30, 60, i = 1, 2, n = \sum_{i=1}^{2} n_i$. The simulation setup is based on the normal contaminated model;

A: $$\begin{aligned}\tau_1 &: \varepsilon N_2(0,1)+(1-\varepsilon)N_2(0,9)\\ \tau_2 &: \varepsilon N_2(0,1)+(1-\varepsilon)N_2(1,9)\end{aligned}$$

A1: $$\begin{aligned}\tau_1 &: \varepsilon N_3(0,1)+(1-\varepsilon)N_3(0,0.625)\\ \tau_2 &: \varepsilon N_3(0,1)+(1-\varepsilon)N_3(5,0.625)\end{aligned}$$

A2: $$\begin{aligned}\tau_1 &: \varepsilon N_4(0,1)+(1-\varepsilon)N_4(1,16)\\ \tau_2 &: \varepsilon N_4(0,1)+(1-\varepsilon)N_4(8,16)\end{aligned}$$

For each group, the data set are drawn and reshuffled based on the value of ε. The data set is divided into training sample (60%) and validation sample (40%), respectively. The mean probability of correct classification and standard deviation are based on 1000 replications. The margin of error based on equation (5.1) is added/subtracted from the computed mean probability of correct classification to determine robustness (within upper classification limit) and breakdown (above upper classification limit). The mean probability of correct classification and the adjusted mean probability of correct classification are compared to investigate the effect of contamination. We observed that as the sample size increases the margin of error become smaller and otherwise. The tables below reveal the performance of these techniques. Table 1 contains the performance of the various linear classification techniques based on the simulation setup A. Figure 1 compares the conventional mean probability with the adjusted mean probability of correct classification. The analysis revealed that as the proportion of contamination increases, the misclassification rate increases for FLCA, FMCD and PCT as shown. Due to the high misclassification rate the margin of error is large and thereby presenting the MFLCA, MFMCD and MPCT to be robust for increasing proportion of contamination, respectively. In other worlds, based on the results reported in Table 1, the robust technique has the smallest margin of error whereas the method that underperformed has large margin of error. The explanation is self evident in Figure 1.

Table 1.Mean probability of correct classification based on margin of error (Optimal mean=0.6480 for FLCA, FMCD, PCT, maximum benchmark = 0.6558, minimum benchmark =0.6402 for MFLCA, MFMCD, MPCT $p=3$)

% of cont.	n_i	**FLCA**	**FMCD**	**PCT**	**MFLCA**	**MFMCD**	**MPCT**
10	30	0.6292 (0.0200)	0.6283 (0.0199)	0.6275 (0.0199)	0.6543 (0.0032)	0.6542 (0.0032)	0.6542 (0.0032)
20	30	0.6108 (0.0194)	0.6079 (0.0193)	0.6106 (0.0194)	0.6544 (0.0032)	0.6544 (0.0033)	0.6444 (0.0032)
30	30	0.5738 (0.0182)	0.5482 (0.0174)	0.5732 (0.0182)	0.6552 (0.0037)	0.6562 (0.0041)	0.6553 (0.0037)
40	30	0.5444 (0.0172)	0.5118 (0.0162)	0.5472 (0.0173)	0.6563 (0.0042)	0.6578 (0.0050)	0.6562 (0.0041)

Cont.: contamination
OMPC: optimal mean probability of classification for the margin of error
M_MPC: lower limit of OMPC

FLCA: conventional mean probability based on FLCA
FMCD: conventional mean probability based on FMCD
PCT: conventional mean probability based on PCT
MFLCA: mean probability based on margin of error for FLCA
MFMCD: mean probability based on margin of error for FMCD
MPCT: mean probability based on margin of error for PCT

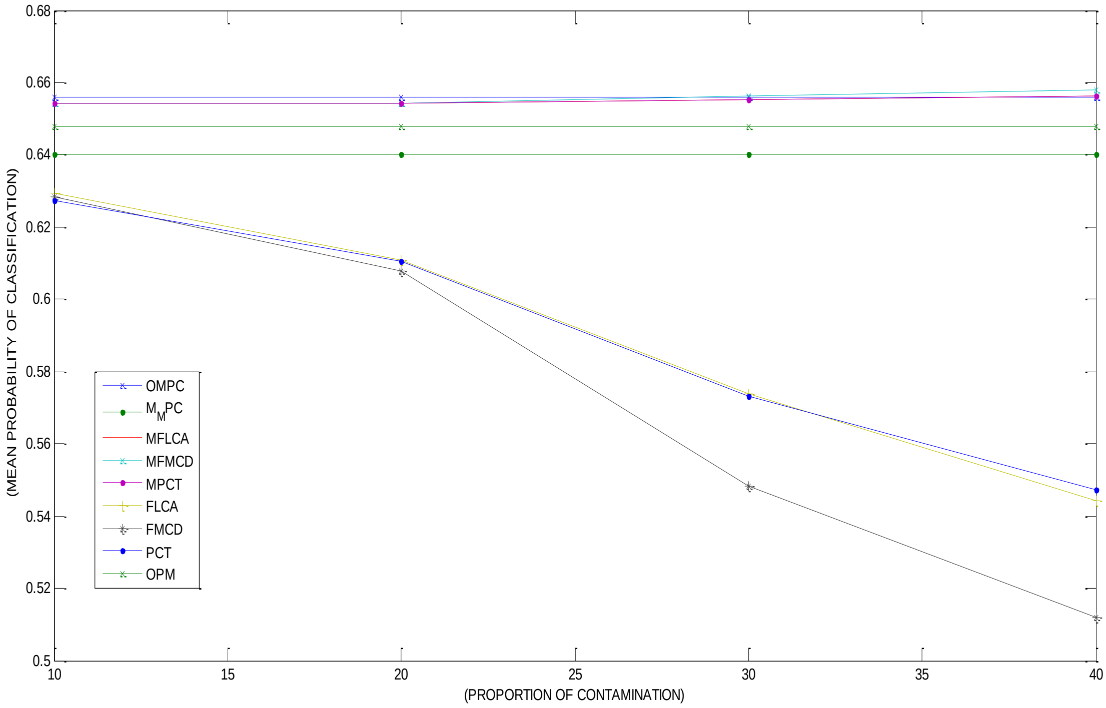

Figure 1. Comparison of performance based on conventional and adjusted mean probability of classification

The overshot is due to the high misclassification rate for the MFMCD technique which implies that as the misclassification rate increases the margin of error become large. Table 2 and Figure 2 contain the simulation results for setup A1.

Table 2.Mean probability of correct classification based on margin of error (Optimal mean = 0.9251 for FLCA, FMCD, PCT, maximum benchmark=0.9427, minimum benchmark=0.9074 for MFLCA, MFMCD, MPCT, $p = 2$)

% of cont.	n_i	FLCA	FMCD	PCT	MFLCA	MFMCD	MPCT
10	20	0.8179 (0.0260)	0.8069 (0.0256)	0.8163 (0.0259)	0.9344 (0.0047)	0.9348 (0.0049)	0.9345 (0.0048)
20	20	0.8082 (0.0257)	0.7953 (0.0253)	0.7992 (0.0254)	0.9348 (0.0049)	0.9354 (0.0052)	0.9352 (0.0051)
30	20	0.7700 (0.0245)	0.7854 (0.0250)	0.7726 0.0246)	0.9365 (0.0058)	0.9358 (0.0054)	0.9364 (0.0058)
40	20	0.7231 (0.0231)	0.7512 (0.0239)	0.7274 (0.0232)	0.9390 (0.0071)	0.9375 (0.0063)	0.9387 (0.0069)

Cont.: contamination
OMPC: optimal mean probability of classification for the margin of error
M_MPC: lower limit of OMPC
FLCA: conventional mean probability based on FLCA
FMCD: conventional mean probability based on FMCD
PCT: conventional mean probability based on PCT
MFLCA: mean probability based on margin of error for FLCA
MFMCD: mean probability based on margin of error for FMCD
MPCT: mean probability based on margin of error for PCT
OPM: optimal mean probability

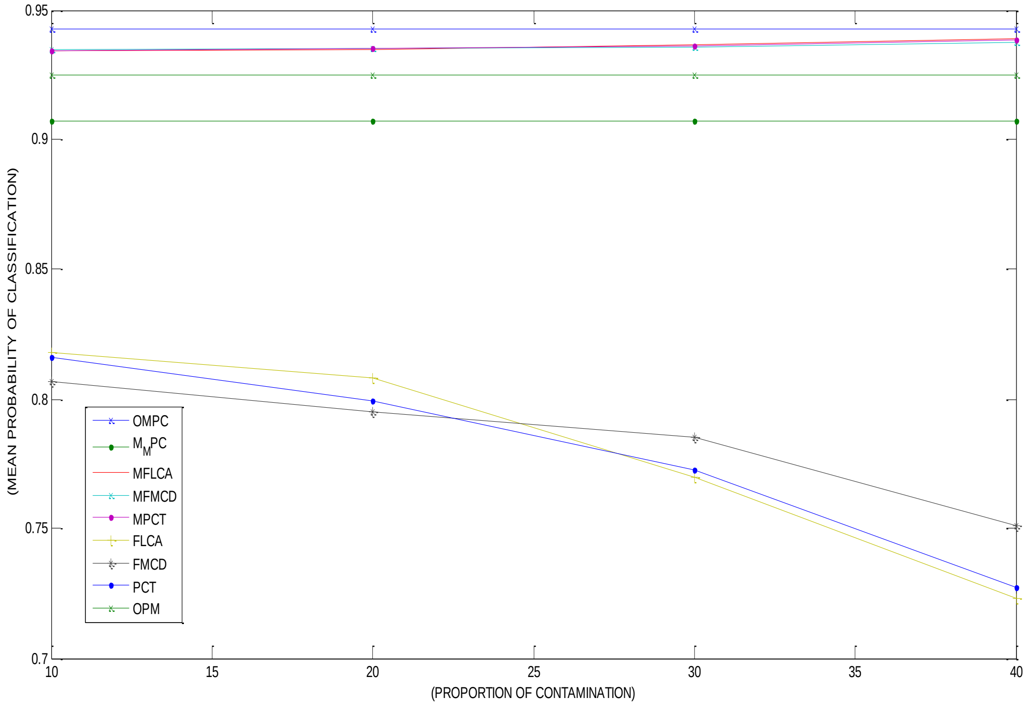

Figure 2. Comparison of performance based on conventional and adjusted mean probability of classification

Table 3 and Figure 3 contain the simulation results for setup A2.

Table 3.Mean probability of correct classification based on margin of error (Optimal mean = 0.9671 for FLCA, FMCD, PCT, maximum benchmark=0.9984, minimum benchmark=0.9357, for MFLCA, MFMCD, MPCT $p = 4$)

% of cont.	n_i	**FLCA**	**FMCD**	**PCT**	**MFLCA**	**MFMCD**	**MPCT**
10	60	0.9291 (0.0294)	0.9305 (0.0294)	0.9291 (0.0294)	0.9728 (0.0029)	0.9728 (0.0029)	0.9728 (0.0029)
20	60	0.8642 (0.0273)	0.9012 (0.0285)	0.8565 (0.0271)	0.9751 (0.0040)	0.9736 (0.0042)	0.9754 (0.0042)
30	60	0.7613 (0.0241)	0.8599 (0.0272)	0.7720 (0.0245)	0.9805 (0.0068)	0.9753 (0.0042)	0.9800 (0.0065)
40	60	0.6145 (0.0196)	0.7948 (0.0252)	0.6455 (0.0206)	0.9894 (0.0113)	0.9787 (0.0059)	0.9875 (0.0104)

Cont.: contamination
OMPC: optimal mean probability of classification for the margin of error
M_MPC: lower limit of OMPC
FLCA: conventional mean probability based on FLCA
FMCD: conventional mean probability based on FMCD
PCT: conventional mean probability based on PCT
MFLCA: mean probability based on margin of error for FLCA
MFMCD: mean probability based on margin of error for FMCD
MPCT: mean probability based on margin of error for PCT
OPM: optimal mean probability

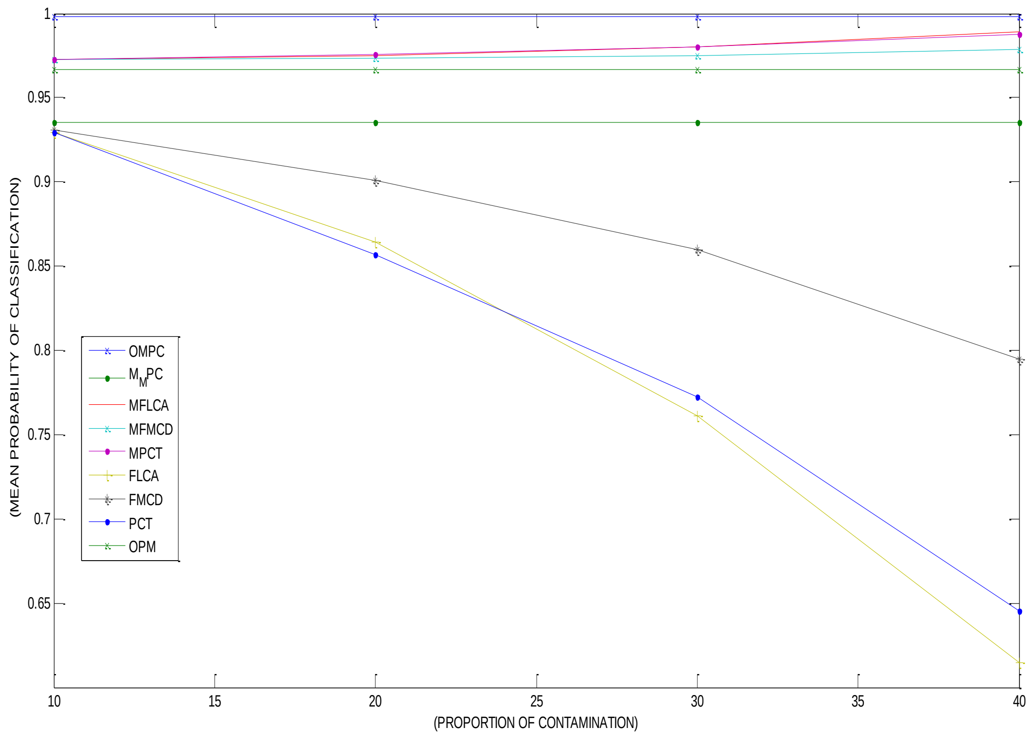

Figure 3. Comparison of performance based on conventional and adjusted mean probability of classification

7. Conclusion

Conventionally, the Fisher linear classification analysis and the probability based classification technique performed very well for large sample sizes which implies that the central limit theorem is evident. Generally, as the rate of contamination increases, the mean probability of correct classification decreases. In this study, the Fisher technique based on the minimum covariance determinant is robust than the other techniques. In the same vain, the probability based classification method is robust than the Fisher's procedure. The new analytic procedure revealed that as the misclassification rate increases the margin of error increases due to increase in contamination. It also indicates that as the misclassification rate decreases the margin of error decreases. In this case, care must be taken to analyze the performance. The new analytic procedure revealed that if the mean probability based on the margin of error exceeds the upper limit, corrective action should be taken because it shows that that technique is not robust and hence the high misclassification rate has given rise to large margin of error. On a general note, this approach also determine upper and lower performance limit and we are certain that if the performance level is not within this limits corrective action is required. This simulation has revealed that as the misclassification rate increases the margin of error also increases the revise is also applicable. This analytic procedure is useful for practical applications. In either case, we are 95% confident of the classification results. Conclusively, based on classification analysis, the performance of the two groups linear classification performance can be investigated based on the information obtained from the margin of error. If the margin of error is very small this implies that that classification method is robust the contrary is evidently possible.

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