A note on the function for the robut control charts (`rcc`) in the `rQCC` package

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Abstract

In this note, we provide a brief summary of variables control charts and a description of how they are constructed using the `rcc` function in the robust quality control chart (`rQCC`) R package. Using `rcc` function, one can construct the traditional Shewhart-type variables control charts. In addition, using various robust location and scale estimates provided by the `rQCC` package, one can easily obtain robust alternatives to the traditional charts.

1 Introduction

Control charts, also known as Shewhart control charts [1, 2, 3], have been widely used to monitor whether a manufacturing process is in a proper state of control or not. The traditional Shewhart-type control charts are made up of the upper control limit (UCL), the center line (CL) and the lower control limit (LCL) and they have the form of $\mathrm{CL} \pm g \cdot \mathrm{SE}$, where the American Standard is based on $g = 3$ with a target false alarm rate of 0.027% and the British Standard is based on $g = 3.09$ with a target false alarm rate of 0.020%. The UCL is given by $\mathrm{CL} + g \cdot \mathrm{SE}$ and the LCL is $\mathrm{CL} - g \cdot \mathrm{SE}$.

In what follows, we provide how to construct the traditional Shewhart-type control charts and robust alternatives to them using various robust location and scale estimates provided by the `rQCC` package. In this note, we assume that we have m samples and that each sample has the same sample size of n. Let X_{ij} be the ith sample (subgroup) from a stable manufacturing process, where $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$. We also assume that X_{ij} are independent and identically distributed as normal with mean μ and variance σ^2. The A, B and D notations here follow the definitions in ASTM (STP 15-C) [4] and ASTM (STP 15-D) [5].

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2 The $\bar{X}$ chart

In order to construct the CL $\pm\, g \cdot$ SE control limits, we consider the relation

$$\frac{\bar{X}_k - E(\bar{X}_k)}{\mathrm{SE}(\bar{X}_k)} = \pm g.$$

Since $E(\bar{X}_k) = \mu$ and $\mathrm{SE}(\bar{X}_k) = \sigma/\sqrt{n_k}$, we have

$$E(\bar{X}_k) \pm g \cdot \mathrm{SE}(\bar{X}_k) = \mu \pm \frac{g}{\sqrt{n_k}}\sigma.$$

Then the control limits for the $\bar{X}$ chart with the sample size n_k are given by

$$\begin{aligned} \mathrm{UCL} &= \mu + A(n_k)\sigma, \\ \mathrm{CL} &= \mu, \\ \mathrm{LCL} &= \mu - A(n_k)\sigma, \end{aligned}$$

where $A(n_k) = g/\sqrt{n_k}$. In practice, the values of the parameters, μ and σ, are not known. Thus, with the estimates $\hat{\mu}$ and $\hat{\sigma}$, we have

$$\begin{aligned} \mathrm{UCL} &= \hat{\mu} + \frac{g}{\sqrt{n_k}}\hat{\sigma}, \\ \mathrm{CL} &= \hat{\mu}, \\ \mathrm{LCL} &= \hat{\mu} - \frac{g}{\sqrt{n_k}}\hat{\sigma}. \end{aligned} \tag{1}$$

Thus, we need to estimate μ and σ by using each sample and then pooling these estimates. Using the ith sample above, the sample mean and variance are given by

$$\bar{X}_i = \frac{1}{n_i}\sum_{j=1}^{n_i} X_{ij} \quad \text{and} \quad S_i^2 = \frac{1}{n_i - 1}\sum_{j=1}^{n_i}(X_{ij} - \bar{X}_i)^2,$$

where $i = 1, 2, \ldots, m$. Then we can estimate μ using all the samples as below:

$$\bar{\bar{X}} = \frac{\bar{X}_1 + \bar{X}_2 + \cdots + \bar{X}_m}{m} = \frac{1}{m}\sum_{i=1}^{m}\bar{X}_i.$$

Note that it is easily seen that $\bar{\bar{X}}$ is unbiased for μ. However, S_i is not unbiased for σ since $E(S_i) = c_4(n_i)\sigma$, where

$$c_4(n_i) = \sqrt{\frac{2}{n_i - 1}} \cdot \frac{\Gamma(n_i/2)}{\Gamma(n_i/2 - 1/2)}.$$

Thus, $S_i/c_4(n_i)$ is unbiased for σ. Then we can easily show that $\bar{S}/c_4(n_k)$ is unbiased for σ, where

$$\bar{S} = \frac{1}{m}\sum_{i=1}^{m} S_i.$$

Thus, by substituting $\hat{\mu} = \bar{\bar{X}}$ and $\hat{\sigma} = \bar{S}/c_4(n)$ into (1), we have the control limits

$$\begin{aligned}
\mathrm{UCL} &= \bar{\bar{X}} + \frac{g}{\sqrt{n}} \frac{\bar{S}}{c_4(n)} = \bar{\bar{X}} + A_3(n)\bar{S}, \\
\mathrm{CL} &= \bar{\bar{X}}, \\
\mathrm{LCL} &= \bar{\bar{X}} - \frac{g}{\sqrt{n}} \frac{\bar{S}}{c_4(n)} = \bar{\bar{X}} - A_3(n)\bar{S},
\end{aligned}$$

where $A_3(n) = A(n)/c_4(n) = g/\{c_4(n)\sqrt{n}\}$.

It is also known that

$$E(R) = d_2(n)\sigma,$$

where R is the sample range from $X_i \sim N(\mu, \sigma^2)$ and

$$d_2(n) = 2\int_0^\infty \Big\{1 - \big[\Phi(z)\big]^n - \big[1 - \Phi(z)\big]^n\Big\} dz.$$

For more details on $d_2(n)$, one can refer to the vignette below.

```
> vignette("factors.cc", package="rQCC")
```

Then, with the ith sample, $R_i/d_2(n)$ is unbiased for σ, where

$$R_i = \max_{1\le j\le n}(X_{ij}) - \min_{1\le j\le n}(X_{ij}).$$

Then, with the m samples, $\bar{R}/d_2(n)$ is unbiased for σ, where

$$\bar{R} = \frac{1}{m}\sum_{i=1}^{m} R_i.$$

Substituting $\hat{\mu} = \bar{\bar{X}}$ and $\hat{\sigma} = \bar{R}/d_2(n)$ into (1), we have the control limits

$$\begin{aligned}
\mathrm{UCL} &= \bar{\bar{X}} + \frac{g}{\sqrt{n}} \frac{\bar{R}}{d_2(n)} = \bar{\bar{X}} + A_2(n)\bar{R}, \\
\mathrm{CL} &= \bar{\bar{X}}, \\
\mathrm{LCL} &= \bar{\bar{X}} - \frac{g}{\sqrt{n}} \frac{\bar{R}}{d_2(n)} = \bar{\bar{X}} - A_2(n)\bar{R},
\end{aligned}$$

where $A_2(n) = A(n)/d_2(n) = g/\{d_2(n)\sqrt{n}\}$.

As alternatives to the above, we can use robust estimates of location and scale. For example, using the median, we can estimate μ

$$\hat{\mu} = \frac{M_1 + M_2 + \cdots + M_m}{m} = \frac{1}{m}\sum_{i=1}^{m} M_i,$$

where

$$M_i = \underset{1\le j\le n}{\text{median}}(X_{ij}).$$

One can also consider estimating σ based on the conventional MAD (median absolute deviation) given by

$$\text{MAD} = \frac{\underset{1\le i\le n}{\text{median}}|X_i - M|}{\Phi^{-1}(3/4)} \approx 1.4826 \cdot \underset{1\le i\le n}{\text{median}}|X_i - M|,$$

where $X_i \sim N(\mu, \sigma^2)$ and $M = \text{median}(X_i)$. Here $\Phi^{-1}(3/4)$ is needed to make this estimator Fisher-consistent [6] for the standard deviation under the normal distribution. For more details, see the references [7, 8]. It should be noted that the above conventional MAD estimator is Fisher-consistent but not unbiased. The "*unbiased* MAD" (uMAD) with a finite sample is developed by Park, Kim and Wang [8] and implemented in the `rQCC` package (see `mad.unbiased` function).

Then, with the m samples, we have the robust unbiased estimate of σ as follows

$$\hat{\sigma} = \frac{\text{uMAD}_1 + \text{uMAD}_2 + \cdots + \text{uMAD}_m}{m} = \frac{1}{m}\sum_{i=1}^{m} \text{uMAD}_i,$$

where

$$\text{uMAD}_i = \underset{1\le j\le n}{\text{uMAD}}(X_{ij}).$$

The `rcc` function constructs the control charts based on various *unbiased* estimates. For example, with the median and uMAD estimates, one can obtain the control limits using the following

```
> rcc(data, loc="median", scale="mad")
```

Another way of constructing the control limits is to use the Hodges-Lehmann [9] for location and Shamos [10] for scale which are respectively given by

$$\text{HL} = \text{median}\left(\frac{X_i + X_j}{2}\right)$$

and

$$\text{Shamos} = \frac{\underset{i<j}{\text{median}}\left(|X_i - X_j|\right)}{\sqrt{2}\,\Phi^{-1}(3/4)} \approx 1.048358 \cdot \underset{i<j}{\text{median}}\left(|X_i - X_j|\right),$$

where $\sqrt{2}\,\Phi^{-1}(3/4)$ is needed to make Shamos estimator Fisher-consistent for the standard deviation under the normal distribution [11]. For the Hodges-Lehmann estimate, the median is obtained by three ways: (i) the pairwise averages with $i < j$ (denoted by HL1), (ii) the pairwise averages with $i \le j$ (HL2), and (iii) all the pairwise averages (HL3). For more details, refer to [8]. It should be noted that the above Shamos is Fisher-consistent but not unbiased. The Hodges-Lehmann and "*unbiased* Shamos" are also developed by [8] and implemented in R (see `HL` and `shamos.unbiased`). For example, with the HL2 and unbiased Shamos estimates, one can obtain the control limits as below.

```
> rcc(data, loc="HL2", scale="shamos")
```

As shown above, by choosing the options for `loc` and `scale`, one can construct various control charts.

3 The S chart

In order to construct the CL $\pm\, g \cdot$ SE control limits, we can consider the relation

$$\frac{S_k - E(S_k)}{\mathrm{SE}(S_k)} = \pm g.$$

Since $E(S_k) = c_4(n)\sigma$ and $\mathrm{SE}(S_k) = \sqrt{1 - c_4(n)^2} \cdot \sigma$, we have

$$E(S_k) \pm g \cdot \mathrm{SE}(S_k) = \left\{c_4(n) \pm g\sqrt{1 - c_4(n)^2}\right\}\sigma.$$

The control limits for the S chart are given by

$$\begin{aligned} \mathrm{UCL} &= B_6(n)\sigma, \\ \mathrm{CL} &= c_4(n)\sigma, \\ \mathrm{LCL} &= B_5(n)\sigma, \end{aligned}$$

where

$$\begin{aligned} B_5(n) &= \max\left\{c_4(n) - g \cdot \sqrt{1 - c_4(n)^2},\ 0\right\}, \\ B_6(n) &= c_4(n) + g \cdot \sqrt{1 - c_4(n)^2}. \end{aligned}$$

Since σ is unknown in practice, we need to choose an appropriate unbiased estimate for σ. One can consider $\hat{\sigma} = \bar{S}/c_4(n)$. Then we have

$$\begin{aligned} \mathrm{UCL} &= B_4(n)\bar{S}, \\ \mathrm{CL} &= \bar{S}, \\ \mathrm{LCL} &= B_3(n)\bar{S}, \end{aligned}$$

where $B_3(n) = B_5(n)/c_4(n)$ and $B_4(n) = B_6(n)/c_4(n)$.

To obtain the robustness property, one can consider a robust estimate of σ. For example, the unbiased MAD or unbiased Shamos estimates of σ can be used as seen before. The limits for the S chart are calculated using the `rcc` function with `type="S"` as below.

```
> rcc(data, scale="mad", type="S")
> rcc(data, scale="shamos", type="S")
```

4 The R chart

We consider the relation
$$\frac{R_k - E(R_k)}{\mathrm{SE}(R_k)} = \pm g.$$
Since $E(R_k) = d_2(n)\sigma$ and $\mathrm{Var}(R_k) = d_3(n)^2\sigma^2$, we have
$$E(R_k) \pm g \cdot \mathrm{SE}(R_k) = \big\{d_2(n) \pm g d_3(n)\big\}\sigma.$$
The control limits for the R chart are given by
$$\begin{aligned}\mathrm{UCL} &= D_2(n)\sigma,\\ \mathrm{CL} &= d_2(n)\sigma,\\ \mathrm{LCL} &= D_1(n)\sigma,\end{aligned}$$
where
$$\begin{aligned}D_1(n) &= \max\left\{d_2(n) - g \cdot d_3(n),\ 0\right\},\\ D_2(n) &= d_2(n) + g \cdot d_3(n),\end{aligned}$$

Since σ is unknown in practice, we need to choose an appropriate unbiased estimate for σ. One can consider $\hat{\sigma} = \bar{R}/d_2(n)$. Then we have
$$\begin{aligned}\mathrm{UCL} &= D_4(n)\bar{R},\\ \mathrm{CL} &= \bar{R},\\ \mathrm{LCL} &= D_3(n)\bar{R},\end{aligned}$$
where $D_3(n) = D_1(n)/d_2(n)$ and $D_4(n) = D_2(n)/d_2(n)$. These limits are easily calculated using the `rcc` function as below.

```
> rcc(data, scale="range", type="R")
```

As afore-mentioned, we can consider a robust estimate of σ. For example, the control limits with the unbiased Shamos are calculated as below.

```
> rcc(data, scale="shamos", type="R")
```

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