

NormqPCR: Functions for normalisation of RT-qPCR data

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Contents

1	Introduction	1
2	Combining technical replicates	2
3	Dealing with undetermined values	3
4	Selection of most stable reference/housekeeping genes	5
4.1	geNorm	5
4.2	NormFinder	11
5	Normalization by means of reference/housekeeping genes	14
5.1	ΔCq method using a single housekeeper	14
5.2	ΔCq method using a combination of housekeeping genes	15
5.3	$2^{-\Delta\Delta Cq}$ method using a single housekeeper	16
5.4	$2^{\Delta\Delta Cq}$ method using a combination of housekeeping genes	19

1 Introduction

The package "NormqPCR" provides methods for the normalization of real-time quantitative RT-PCR data. In this vignette we describe and demonstrate the available functions. Firstly we show how the user may combine technical replicates, deal with undetermined values and deal with values above a user-chosen threshold. The rest of the vignette is split into two distinct sections, the first giving details of different methods to select the best housekeeping gene/genes for normalisation, and the second showing how to use the selected housekeeping gene(s) to produce $2^{-\Delta Cq}$ normalised estimators and $2^{-\Delta\Delta Cq}$ estimators of differential expression.

2 Combining technical replicates

When a raw data file read in using `read.qPCR` contains technical replicates, they are dealt with by concatenating the suffix `_TechRep.n` to the detector name, where `n` in 1, 2...`N` is the number of the replication in the total number of replicates, `N`, based on order of appearance in the qPCR data file.

So if we read in a file with technical replicates, we can see that the detector/feature names are thus suffixed:

```
> library(ReadqPCR) # load the ReadqPCR library
> library(NormqPCR)
> path <- system.file("exData", package = "NormqPCR")
> qPCR.example.techReps <- file.path(path, "qPCR.techReps.txt")
> qPCRBatch.qPCR.techReps <- read.qPCR(qPCR.example.techReps)
> rownames(exprs(qPCRBatch.qPCR.techReps))[1:8]

[1] "gene_aj_TechReps.1" "gene_aj_TechReps.2" "gene_al_TechReps.1"
[4] "gene_al_TechReps.2" "gene_ax_TechReps.1" "gene_ax_TechReps.2"
[7] "gene_bo_TechReps.1" "gene_bo_TechReps.2"
```

It is likely that before continuing with the analysis, the user would wish to average the technical replicates by using the arithmetic mean of the raw Cq values. This can be achieved using the `combineTechReps` function, which will produce a new `qPCRBatch` object, with all tech reps reduced to one reading:

```
> combinedTechReps <- combineTechReps(qPCRBatch.qPCR.techReps)
> combinedTechReps
```

```
qPCRBatch (storageMode: lockedEnvironment)
assayData: 8 features, 3 samples
  element names: exprs
protocolData: none
phenoData
  sampleNames: one three two
  varLabels: sample
  varMetadata: labelDescription
featureData: none
experimentData: use 'experimentData(object)'
Annotation:
```

3 Dealing with undetermined values

When an RT-qPCR experiment does not produce a reading after a certain number of cycles (the cycle threshold), the reading is given as undetermined. These are represented in `qPCRBatch` objects as `NA`. Different users may have different ideas about how many cycles they wish to allow before declaring a detector as not present in the sample. There are two methods for the user to decide what to do with numbers above a given cycle threshold:

First the user might decide that anything above 38 cycles means there is nothing present in their sample, instead of the standard 40 used by the `taqman` software. They can replace the value of all readings above 38 as `NA` using the following:

Firstly read in the `taqman` example file which has 96 detectors, with 4 replicates for `mia` (case) and 4 non-`mia` (control):

```
> path <- system.file("exData", package = "NormqPCR")
> taqman.example <- file.path(path, "/example.txt")
> qPCRBatch.taqman <- read.taqman(taqman.example)
```

We can see that for the detector: `Cc120.Rn00570287_m1` we have these readings for the different samples:

```
> exprs(qPCRBatch.taqman)["Cc120.Rn00570287_m1",]

      fp1.day3.v      fp2.day3.v      fp5.day3.mia      fp6.day3.mia      fp.3.day.3.v
              NA              NA      35.74190      34.05922      35.02052
fp.4.day.3.v fp.7.day.3.mia fp.8.day.3.mia
              NA      35.93689      36.57921
```

We can now use the `replaceAboveCutOff` method in order to replace anything above 35 with `NA`:

```
> qPCRBatch.taqman.replaced <- replaceAboveCutOff(qPCRBatch.taqman, newVal = NA,
+ cutOff = 35)
> exprs(qPCRBatch.taqman.replaced)["Cc120.Rn00570287_m1",]
```

```
      fp1.day3.v      fp2.day3.v      fp5.day3.mia      fp6.day3.mia      fp.3.day.3.v
              NA              NA              NA      34.05922              NA
fp.4.day.3.v fp.7.day.3.mia fp.8.day.3.mia
              NA              NA              NA
```

It may also be the case that the user wants to get rid of all `NA` values, and replace them with an arbitrary number. This can be done using the `replaceNAs` method. So if the user wanted to replace all `NAs` with 40, it can be done as follows:

```
> qPCRBatch.taqman.replaced <- replaceNAs(qPCRBatch.taqman, newNA = 40)
> exprs(qPCRBatch.taqman.replaced)["Cc120.Rn00570287_m1",]

      fp1.day3.v    fp2.day3.v    fp5.day3.mia    fp6.day3.mia    fp.3.day.3.v
      40.00000      40.00000      35.74190      34.05922      35.02052
fp.4.day.3.v fp.7.day.3.mia fp.8.day.3.mia
      40.00000      35.93689      36.57921
```

In addition, the situation sometimes arises where some readings for a given detector are above a given cycle threshold, but some others are not. The user may decide for example that if a given number of readings are NAs, then all of the readings for this detector should be NAs. This is important because otherwise an unusual reading for one detector might lead to an inaccurate estimate for the expression of a given gene.

This process will necessarily be separate for the different sample types, since you might expect a given gene to show expression in one sample type compared to another. Therefore it is necessary to designate the replicates per sample type using a contrast matrix. It is also necessary to make a sampleMaxMatrix which gives a maximum number of NAs allowed for each sample type.

So in the example file above we two sample types, with 4 biological replicates for each, the contrastMatrix and sampleMaxMatrix might be constructed like this:

```
> sampleNames(qPCRBatch.taqman)

[1] "fp1.day3.v"      "fp2.day3.v"      "fp5.day3.mia"    "fp6.day3.mia"
[5] "fp.3.day.3.v"    "fp.4.day.3.v"    "fp.7.day.3.mia"  "fp.8.day.3.mia"

> a <- c(0,0,1,1,0,0,1,1) # one for each sample type, with 1 representing
> b <- c(1,1,0,0,1,1,0,0) # position of sample type in the sampleNames vector
> contM <- cbind(a,b)
> colnames(contM) <- c("case","control") # then give the names of each sample type
> rownames(contM) <- sampleNames(qPCRBatch.taqman) # and the rows of the matrix
> contM

      case control
fp1.day3.v      0      1
fp2.day3.v      0      1
fp5.day3.mia    1      0
fp6.day3.mia    1      0
fp.3.day.3.v    0      1
fp.4.day.3.v    0      1
fp.7.day.3.mia  1      0
fp.8.day.3.mia  1      0
```

```
> sMaxM <- t(as.matrix(c(3,3))) # now make the contrast matrix
> colnames(sMaxM) <- c("case","control") # make sure these line up with samples
> sMaxM
```

```
      case control
[1,]      3      3
```

More details on contrast matrices can be found in the limma manual, which requires a similar matrix when testing for differential expression between samples.

For example, if the user decides that if at least 3 out of 4 readings are NAs for a given detector, then all readings should be NA, they can do the following, using the `makeAllNewVal` method:

```
> qPCRBatch.taqman.replaced <- makeAllNewVal(qPCRBatch.taqman, contM, sMaxM, newVal=NA)
```

Here you can see for the Ccl20.Rn00570287_m1 detector, the control values have been made all NA, whereas before 3 were NA and one was 35. However the case values have been kept, since they were all below the NA threshold. It is important to filter the data in this way to ensure the correct calculations are made downstream when calculating variation and other parameters.

```
> exprs(qPCRBatch.taqman.replaced)["Ccl20.Rn00570287_m1",]
```

fp1.day3.v	fp2.day3.v	fp5.day3.mia	fp6.day3.mia	fp.3.day.3.v
NA	NA	35.74190	34.05922	NA
fp.4.day.3.v	fp.7.day.3.mia	fp.8.day.3.mia		
NA	35.93689	36.57921		

4 Selection of most stable reference/housekeeping genes

This section contains two subsections containing different methods for the selection of appropriate housekeeping genes.

4.1 geNorm

We describe the selection of the best (most stable) reference/housekeeping genes using the method of Vandesompele et al (2002) [3] (in the sequel: Vand02) which is called *geNorm*. We first load the package and the data

```
> options(width = 68)
> data(geNorm)
> str(exprs(geNorm.qPCRBatch))
```

```

num [1:10, 1:85] 0.0425 0.0576 0.1547 0.1096 0.118 ...
- attr(*, "dimnames")=List of 2
..$ : chr [1:10] "ACTB" "B2M" "GAPD" "HMBS" ...
..$ : chr [1:85] "BM1" "BM2" "BM3" "BM4" ...

```

We start by ranking the selected reference/housekeeping genes. The geNorm algorithm implemented in function `selectHKs` proceeds stepwise; confer Section “Materials and methods” in Vand02. That is, the gene stability measure M of all candidate genes is computed and the gene with the highest M value is excluded. Then, the gene stability measure M for the remaining gene is calculated and so on. This procedure is repeated until two respectively, `minNrHK` genes remain.

```

> tissue <- as.factor(c(rep("BM", 9), rep("FIB", 20), rep("LEU", 13),
+                       rep("NB", 34), rep("POOL", 9)))
> res.BM <- selectHKs(geNorm.qPCRBatch[,tissue == "BM"], method = "geNorm",
+                     Symbols = featureNames(geNorm.qPCRBatch), minNrHK = 2, log = FALSE)

```

HPRT1	YWHAZ	RPL13A	UBC	GAPD	SDHA
0.5160313	0.5314564	0.5335963	0.5700961	0.6064919	0.6201470
TBP	HMBS	B2M	ACTB		
0.6397969	0.7206013	0.7747634	0.8498739		
HPRT1	RPL13A	YWHAZ	UBC	GAPD	SDHA
0.4705664	0.5141375	0.5271169	0.5554718	0.5575295	0.5738460
TBP	HMBS	B2M			
0.6042110	0.6759176	0.7671985			
HPRT1	RPL13A	SDHA	YWHAZ	UBC	GAPD
0.4391222	0.4733732	0.5243665	0.5253471	0.5403137	0.5560120
TBP	HMBS				
0.5622094	0.6210820				
HPRT1	RPL13A	YWHAZ	UBC	SDHA	GAPD
0.4389069	0.4696398	0.4879728	0.5043292	0.5178634	0.5245346
TBP					
0.5563591					
HPRT1	RPL13A	UBC	YWHAZ	GAPD	SDHA
0.4292808	0.4447874	0.4594181	0.4728920	0.5012107	0.5566762
UBC	RPL13A	HPRT1	YWHAZ	GAPD	
0.4195958	0.4204997	0.4219179	0.4424631	0.4841646	
RPL13A	UBC	YWHAZ	HPRT1		
0.3699163	0.3978736	0.4173706	0.4419220		
UBC	RPL13A	YWHAZ			
0.3559286	0.3761358	0.3827933			

```

RPL13A      UBC
0.3492712 0.3492712

```

```

> res.POOL <- selectHKs(geNorm.qPCRBatch[,tissue == "POOL"], method = "geNorm",
+                       Symbols = featureNames(geNorm.qPCRBatch), minNrHK = 2,
+                       trace = FALSE, log = FALSE)
> res.FIB <- selectHKs(geNorm.qPCRBatch[,tissue == "FIB"], method = "geNorm",
+                      Symbols = featureNames(geNorm.qPCRBatch), minNrHK = 2,
+                      trace = FALSE, log = FALSE)
> res.LEU <- selectHKs(geNorm.qPCRBatch[,tissue == "LEU"], method = "geNorm",
+                      Symbols = featureNames(geNorm.qPCRBatch), minNrHK = 2,
+                      trace = FALSE, log = FALSE)
> res.NB <- selectHKs(geNorm.qPCRBatch[,tissue == "NB"], method = "geNorm",
+                     Symbols = featureNames(geNorm.qPCRBatch), minNrHK = 2,
+                     trace = FALSE, log = FALSE)

```

We obtain the following ranking of genes (cf. Table 3 in Vand02)

```

> ranks <- data.frame(c(1, 1:9), res.BM$ranking, res.POOL$ranking,
+                     res.FIB$ranking, res.LEU$ranking,
+                     res.NB$ranking)
> names(ranks) <- c("rank", "BM", "POOL", "FIB", "LEU", "NB")
> ranks

```

	rank	BM	POOL	FIB	LEU	NB
1	1	RPL13A	GAPD	GAPD	UBC	GAPD
2	1	UBC	SDHA	HPRT1	YWHAZ	HPRT1
3	2	YWHAZ	HMBS	YWHAZ	B2M	SDHA
4	3	HPRT1	HPRT1	UBC	GAPD	UBC
5	4	GAPD	TBP	ACTB	RPL13A	HMBS
6	5	SDHA	UBC	TBP	TBP	YWHAZ
7	6	TBP	RPL13A	SDHA	SDHA	TBP
8	7	HMBS	YWHAZ	RPL13A	HPRT1	ACTB
9	8	B2M	ACTB	B2M	HMBS	RPL13A
10	9	ACTB	B2M	HMBS	ACTB	B2M

Remark 1:

Since the computation is based on gene ratios, the two most stable control genes in each cell type cannot be ranked.

We plot the average expression stability M for each cell type (cf. Figure 2 in Vand02).

```

> library(RColorBrewer)
> mypalette <- brewer.pal(5, "Set1")

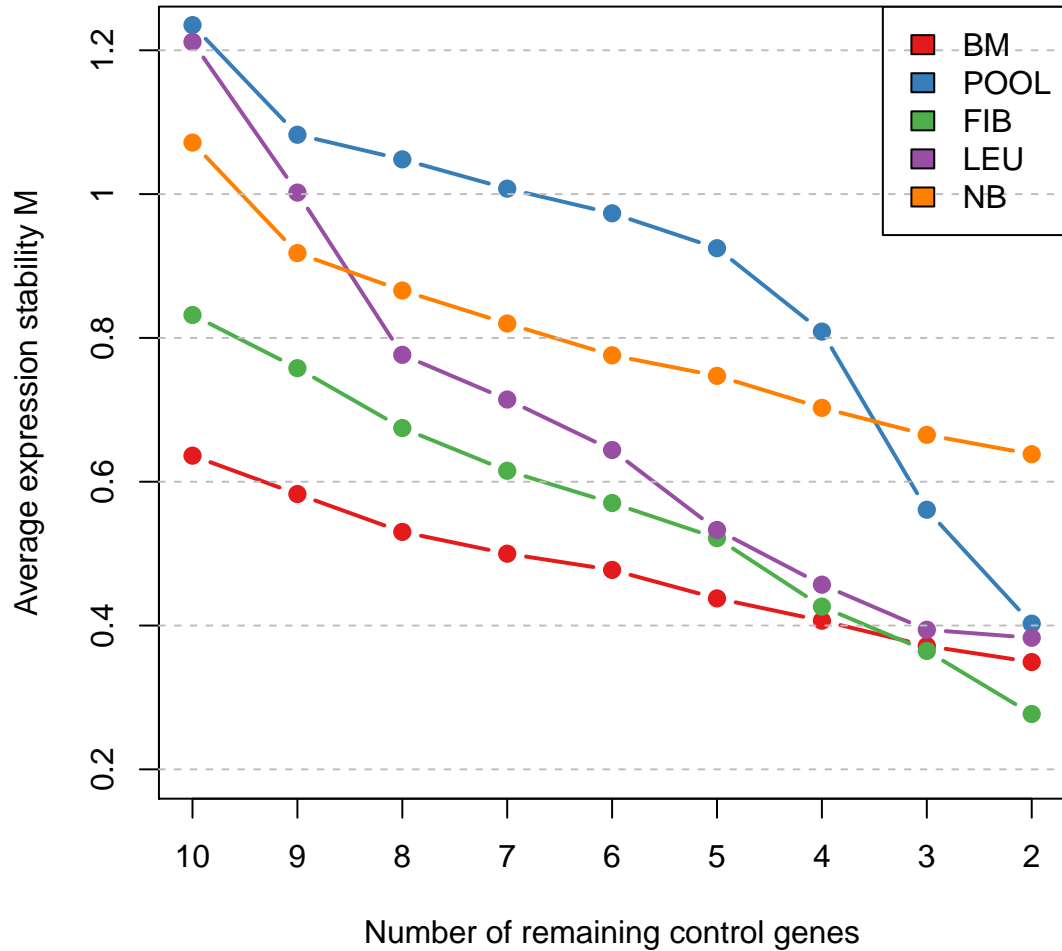
```

```

> matplot(cbind(res.BM$meanM, res.POOL$meanM, res.FIB$meanM,
+               res.LEU$meanM, res.NB$meanM), type = "b",
+         ylab = "Average expression stability M",
+         xlab = "Number of remaining control genes",
+         axes = FALSE, pch = 19, col = mypalette,
+         ylim = c(0.2, 1.22), lty = 1, lwd = 2,
+         main = "Figure 2 in Vandesompele et al. (2002)")
> axis(1, at = 1:9, labels = as.character(10:2))
> axis(2, at = seq(0.2, 1.2, by = 0.2), labels = seq(0.2, 1.2, by = 0.2))
> box()
> abline(h = seq(0.2, 1.2, by = 0.2), lty = 2, lwd = 1, col = "grey")
> legend("topright", legend = c("BM", "POOL", "FIB", "LEU", "NB"),
+       fill = mypalette)

```


Figure 2 in Vandesompele et al. (2002)



Second, we plot the pairwise variation for each cell type (cf. Figure 3 (a) in Vand02)

```
> mypalette <- brewer.pal(8, "YlGnBu")
> barplot(cbind(res.POOL$variation, res.LEU$variation, res.NB$variation,
+             res.FIB$variation, res.BM$variation), beside = TRUE,
+         col = mypalette, space = c(0, 2),
+         names.arg = c("POOL", "LEU", "NB", "FIB", "BM"),
+         ylab = "Pairwise variation V",
+         main = "Figure 3(a) in Vandesompele et al. (2002)")
```

```

> legend("topright", legend = c("V9/10", "V8/9", "V7/8", "V6/7",
+                               "V5/6", "V4/5", "V3/4", "V2/3"),
+       fill = mypalette, ncol = 2)
> abline(h = seq(0.05, 0.25, by = 0.05), lty = 2, col = "grey")
> abline(h = 0.15, lty = 1, col = "black")

```

Figure 3(a) in Vandesompele et al. (2002)



Remark 2:

Vand02 recommend a cut-off value of 0.15 for the pairwise variation. Below this bound the inclusion of an additional housekeeping gene is not required.

4.2 NormFinder

The second method for selection reference/housekeeping genes implemented in package is the method derived by [1] (in the sequel: And04) called *NormFinder*.

The ranking contained in Table 3 of And04 can be obtained via

```
> data(Colon)
> str(exprs(Colon.qPCRBatch))

num [1:13, 1:40] 922 1167 920 818 1409 ...
- attr(*, "dimnames")=List of 2
..$ : chr [1:13] "ACTB" "CFL1" "CLTC" "FLJ20030" ...
..$ : chr [1:40] "C.C108T" "C.C215T" "C.C242T" "C.C415T" ...

> group <- pData(Colon.qPCRBatch)[,"Group"]
> res.Colon <- stabMeasureRho(Colon.qPCRBatch, group = group,
+                             log = FALSE)
> sort(res.Colon) # cf. Table 3 in Andersen et al (2004)

      TPT1      UBC      SUI1      GAPD      CFL1      TUBA6
0.1414763 0.1610925 0.1730781 0.1767370 0.1771489 0.1775287
      RPS13      UBB      NACA      CLTC      RPS23      ACTB
0.1869378 0.1885640 0.1919831 0.2029681 0.2201116 0.2329093
      FLJ20030
0.2568652

> data(Bladder)
> str(exprs(Bladder.qPCRBatch))

num [1:14, 1:28] 3041 4453 2465 1329 6102 ...
- attr(*, "dimnames")=List of 2
..$ : chr [1:14] "ACTB" "ATP5B" "CFL1" "FLJ20030" ...
..$ : chr [1:28] "X1014.1" "X1131.1" "X1164.1" "X1206.1" ...

> group <- pData(Bladder.qPCRBatch)[,"Group"]
> cat("test1")

test1

> res.Bladder <- stabMeasureRho(Bladder.qPCRBatch, group = group,
+                               log = FALSE)
> cat("test test")

test test
```

```
> sort(res.Bladder)
```

HSPCB	ATP5B	RPS23	CFL1	UBC	TEGT
0.08078175	0.10094343	0.12881495	0.13119714	0.13363952	0.14265863
RPS13	TPT1	FLJ20030	GAPD	UBB	FLOT2
0.15495774	0.16566827	0.17352074	0.18887425	0.19256415	0.20147640
ACTB	S100A6				
0.22197915	0.24452110				

Of course, we can also reproduce the geNorm ranking also included in Table 3 of And04.

```
> selectHKs(Colon.qPCRBatch, log = FALSE, trace = FALSE,
+           Symbols = featureNames(Colon.qPCRBatch))$ranking
```

1	1	3	4	5	6
"RPS23"	"TPT1"	"RPS13"	"SUI1"	"UBC"	"GAPD"
7	8	9	10	11	12
"TUBA6"	"UBB"	"NACA"	"CFL1"	"CLTC"	"ACTB"
13					
"FLJ20030"					

```
> selectHKs(Bladder.qPCRBatch, log = FALSE, trace = FALSE,
+           Symbols = featureNames(Bladder.qPCRBatch))$ranking
```

1	1	3	4	5	6
"CFL1"	"UBC"	"ATP5B"	"HSPCB"	"GAPD"	"TEGT"
7	8	9	10	11	12
"RPS23"	"RPS13"	"TPT1"	"FLJ20030"	"FLOT2"	"UBB"
13	14				
"ACTB"	"S100A6"				

As we are often interested in more than one reference/housekeeping gene we also implemented a step-wise procedure of the NormFinder algorithm explained in Section “Average control gene” in the supplementary information of And04. This procedure is available via function `selectHKs`.

```
> group <- pData(Colon.qPCRBatch)[,"Group"]
> selectHKs(Colon.qPCRBatch,
+           log = FALSE, trace = TRUE, group = group,
+           Symbols = featureNames(Colon.qPCRBatch), minNrHKs = 12,
+           method = "NormFinder")$ranking
```

TPT1	UBC	SUI1	GAPD	CFL1	TUBA6
0.1414763	0.1610925	0.1730781	0.1767370	0.1771489	0.1775287
RPS13	UBB	NACA	CLTC	RPS23	ACTB
0.1869378	0.1885640	0.1919831	0.2029681	0.2201116	0.2329093
FLJ20030					
0.2568652					
UBC	TUBA6	GAPD	SUI1	CFL1	RPS13
0.1031043	0.1114774	0.1142132	0.1152734	0.1185269	0.1200290
CLTC	NACA	UBB	ACTB	RPS23	FLJ20030
0.1232217	0.1297298	0.1301249	0.1384574	0.1445223	0.1471372
NACA	CFL1	SUI1	GAPD	UBB	TUBA6
0.08888919	0.09117470	0.09249714	0.09290098	0.09697394	0.09763415
RPS13	CLTC	RPS23	FLJ20030	ACTB	
0.09769254	0.10351175	0.10424815	0.11516759	0.11855899	
TUBA6	GAPD	CLTC	CFL1	SUI1	RPS13
0.07604126	0.07857074	0.08012378	0.08118840	0.08124209	0.08381455
ACTB	FLJ20030	UBB	RPS23		
0.08704531	0.09214267	0.09281511	0.09926029		
GAPD	CFL1	SUI1	CLTC	RPS13	UBB
0.07052455	0.07075470	0.07199446	0.07486103	0.07540652	0.07649412
FLJ20030	RPS23	ACTB			
0.08378769	0.08455423	0.08599148			
SUI1	RPS13	CFL1	UBB	CLTC	FLJ20030
0.06745408	0.06754705	0.06822068	0.06887908	0.07101164	0.07230004
RPS23	ACTB				
0.08041376	0.08261883				
RPS13	CFL1	UBB	CLTC	FLJ20030	RPS23
0.06496047	0.06559937	0.06648983	0.06742791	0.06847696	0.07708310
ACTB					
0.07803569					
CFL1	CLTC	UBB	FLJ20030	ACTB	RPS23
0.06270147	0.06274136	0.06632289	0.06830593	0.07273986	0.07379364
CLTC	UBB	FLJ20030	ACTB	RPS23	
0.06142205	0.06258837	0.06323820	0.07119490	0.07415997	
UBB	RPS23	FLJ20030	ACTB		
0.04975140	0.06153268	0.06260266	0.07634498		
FLJ20030	RPS23	ACTB			
0.05658949	0.06211800	0.06395867			
RPS23	ACTB				
0.06731095	0.07412848				
1	2	3	4	5	6

```

      "TPT1"      "UBC"      "NACA"      "TUBA6"      "GAPD"      "SUI1"
        7         8         9         10         11         12
"RPS13"      "CFL1"      "CLTC"      "UBB" "FLJ20030"      "RPS23"

> group <- pData(Bladder.qPCRBatch)[,"Group"]
> selectHKs(Bladder.qPCRBatch, group = group,
+           log = FALSE, trace = FALSE,
+           Symbols = featureNames(Bladder.qPCRBatch), minNrHKs = 13,
+           method = "NormFinder")$ranking

      1         2         3         4         5         6
"HSPCB"      "ATP5B"      "RPS23"      "CFL1"      "UBC"      "TEGT"
      7         8         9         10         11         12
"RPS13"      "TPT1"      "GAPD"      "UBB" "FLJ20030"      "FLOT2"
     13
"S100A6"

```

5 Normalization by means of reference/housekeeping genes

5.1 ΔC_q method using a single housekeeper

The ΔC_q method normalises detectors within a sample by subtracting the cycle time value of the housekeeper gene from the other genes. This can be done in NormqPCR as follows:

for the example dataset from "ReadqPCR" we must first read in the data:

```

> path <- system.file("exData", package = "NormqPCR")
> taqman.example <- file.path(path, "example.txt")
> qPCR.example <- file.path(path, "qPCR.example.txt")
> qPCRBatch.taqman <- read.taqman(taqman.example)

```

We then need to supply a housekeeper gene to be subtracted:

```

> hkgs<-"Actb-Rn00667869_m1"
> qPCRBatch.norm <- deltaCq(qPCRBatch = qPCRBatch.taqman, hkgs = hkgs, calc="arith")
> head(exprs(qPCRBatch.norm))

```

	fp1.day3.v	fp2.day3.v	fp5.day3.mia
Actb.Rn00667869_m1	0.000000	0.000000	0.000000
Adipoq.Rn00595250_m1	0.016052	-0.116520	2.933523
Adrbk1.Rn00562822_m1	NA	NA	6.566628
Agtrl1.Rn00580252_s1	4.899380	5.035841	6.397364
Alpl.Rn00564931_m1	12.531942	11.808657	13.035166

B2m.Rn00560865_m1	0.741558	0.890717	2.040470
	fp6.day3.mia	fp.3.day.3.v	fp.4.day.3.v
Actb.Rn00667869_m1	0.000000	0.000000	0.000000
Adipoq.Rn00595250_m1	2.540987	-0.178971	-0.563263
Adrbk1.Rn00562822_m1	6.642561	NA	NA
Agtrl1.Rn00580252_s1	5.680837	5.220796	4.425364
Alpl.Rn00564931_m1	12.239549	12.394802	11.772896
B2m.Rn00560865_m1	2.234605	0.505516	0.877598
	fp.7.day.3.mia	fp.8.day.3.mia	
Actb.Rn00667869_m1	0.000000	0.000000	
Adipoq.Rn00595250_m1	2.458509	2.736475	
Adrbk1.Rn00562822_m1	3.737100	6.873568	
Agtrl1.Rn00580252_s1	4.794776	5.345202	
Alpl.Rn00564931_m1	12.110000	12.255186	
B2m.Rn00560865_m1	1.927563	1.903269	

This returns a new `qPCRBatch`, with new values in the `exprs` slot. This will be compatible with many other bioconductor and R packages, such as `heatmap`.

Note these numbers might be negative. For further analysis requiring positive values only, 2^{\cdot} can be used to transform the data into $2^{\Delta CT}$ values.

5.2 ΔCq method using a combination of housekeeping genes

If the user wishes to normalise by more than one housekeeping gene, for example if they have found a more than one housekeeping gene using the `NormFinder/geNorm` algorithms described above, they can. This is implemented by calculating the average of these values to form a "pseudo-housekeeper" which is subtracted from the other values. So using the same dataset as above, using housekeeping genes `GAPDH`, `Beta-2-microglobulin` and `Beta-actin`, the following steps would be taken:

```
> hkg<-c("Actb-Rn00667869_m1", "B2m-Rn00560865_m1", "Gapdh-Rn99999916_s1")
> qPCRBatch.norm <- deltaCq(qPCRBatch = qPCRBatch.taqman, hkg = hkg, calc="arith")
> head(exprs(qPCRBatch.norm))
```

	fp1.day3.v	fp2.day3.v	fp5.day3.mia
Actb.Rn00667869_m1	-1.2998917	-1.2816963	-1.380296
Adipoq.Rn00595250_m1	-1.2838397	-1.3982163	1.553227
Adrbk1.Rn00562822_m1	NA	NA	5.186332
Agtrl1.Rn00580252_s1	3.5994883	3.7541447	5.017068
Alpl.Rn00564931_m1	11.2320503	10.5269607	11.654870
B2m.Rn00560865_m1	-0.5583337	-0.3909793	0.660174
	fp6.day3.mia	fp.3.day.3.v	fp.4.day.3.v

Actb.Rn00667869_m1	-1.5106197	-1.1644617	-1.1714227
Adipoq.Rn00595250_m1	1.0303673	-1.3434327	-1.7346857
Adrbk1.Rn00562822_m1	5.1319413	NA	NA
Agtrl1.Rn00580252_s1	4.1702173	4.0563343	3.2539413
Alpl.Rn00564931_m1	10.7289293	11.2303403	10.6014733
B2m.Rn00560865_m1	0.7239853	-0.6589457	-0.2938247
	fp.7.day.3.mia	fp.8.day.3.mia	
Actb.Rn00667869_m1	-1.323712	-1.286277	
Adipoq.Rn00595250_m1	1.134797	1.450198	
Adrbk1.Rn00562822_m1	2.413388	5.587291	
Agtrl1.Rn00580252_s1	3.471064	4.058925	
Alpl.Rn00564931_m1	10.786288	10.968909	
B2m.Rn00560865_m1	0.603851	0.616992	

5.3 $2^{-\Delta\Delta C_q}$ method using a single housekeeper

It is possible to use the $2^{-\Delta\Delta C_q}$ method for calculating relative gene expression between two sample types. Both the same well and the separate well methods as detailed in [2] can be used for this purpose, and will produce the same answers, but with different levels of variation. By default detectors in the same sample will be paired with the housekeeper, and the standard deviation used will be that of the differences between detectors and the housekeepers. However, if the argument `paired=FALSE` is added, standard deviation between case and control will be calculated as $s = \sqrt{s_1^2 + s_2^2}$, where s_1 is the standard deviation for the detector readings and s_2 is the standard deviation the housekeeper gene readings. The latter approach is not recommended when the housekeeper and genes to be compared are from the same sample, as is the case when using the taqman cards, but is included for completeness and for situations where readings for the housekeeper might be taken from a separate biological replicate (for example in a *post hoc* manner due to the originally designated housekeeping genes not performing well), or for when NormqPCR is used for more traditional qPCR where the products undergo amplifications from separate wells.

for the example dataset from "ReadqPCR" we must first read in the data:

```
> path <- system.file("exData", package = "NormqPCR")
> taqman.example <- file.path(path, "example.txt")
> qPCR.example <- file.path(path, "qPCR.example.txt")
> qPCRBatch.taqman <- read.taqman(taqman.example)
```

`deltaDeltaCq` also requires a contrast matrix. This is to contain columns which will be used to specify the samples representing `case` and `control` which are to be compared, in a similar way to the "limma" package. these columns should contain 1s or 0s which refer to the samples in either category:


```
> contM <- cbind(c(0,0,1,1,0,0,1,1),c(1,1,0,0,1,1,0,0))
> colnames(contM) <- c("interestingPhenotype","wildTypePhenotype")
> rownames(contM) <- sampleNames(qPCRBatch.taqman)
> contM
```

	interestingPhenotype	wildTypePhenotype
fp1.day3.v	0	1
fp2.day3.v	0	1
fp5.day3.mia	1	0
fp6.day3.mia	1	0
fp.3.day.3.v	0	1
fp.4.day.3.v	0	1
fp.7.day.3.mia	1	0
fp.8.day.3.mia	1	0

We can now normalise each sample by a given housekeeping gene and then look at the ratio of expression between the case and control samples. Results show (by column): 1) Name of gene represented by detector. 2) Case ΔCq for the detector: the average cycle time for this detector in the samples denoted as "case" - the housekeeper cycle time. 3) the standard deviation for the cycle times used to calculate the value in column 2). 4) Control ΔCq for the detector: the average cycle time for this detector in the samples denoted as "controller", or the "callibrator" samples - the housekeeper cycle time. 5) The standard deviation for the cycle times used to calculate the value in column 4). 6) $2^{-\Delta\Delta Cq}$ - The difference between the ΔCq values for case and control. We then find 2^{-} of this value. 7) and 8) correspond to 1 s.d. either side of the mean value, as detailed in [2].

```
> hkg <- "Actb-Rn00667869_m1"
> ddCq.taqman <- deltaDeltaCq(qPCRBatch = qPCRBatch.taqman, maxNACase=1, maxNAControl=1, hkg=hkg)
> head(ddCq.taqman)
```

	ID	$2^{-dCt.interestingPhenotype}$
1	Actb.Rn00667869_m1	1.000e+00
2	Adipoq.Rn00595250_m1	1.587e-01
3	Adrbk1.Rn00562822_m1	2.602e-02
4	Agtrl1.Rn00580252_s1	2.300e-02
5	Alpl.Rn00564931_m1	1.892e-04
6	B2m.Rn00560865_m1	2.464e-01

	interestingPhenotype.sd	$2^{-dCt.wildTypePhenotype}$
1	0.000e+00	1.000e+00
2	2.280e-02	1.171e+00
3	3.266e-02	NA
4	1.014e-02	3.434e-02

5	4.770e-05	2.298e-04	
6	2.498e-02	5.965e-01	
	wildTypePhenotype.sd	2 ⁻ ddCt	2 ⁻ ddCt.min 2 ⁻ ddCt.max
1	0.000e+00 1		NA NA
2	2.131e-01 0.135541545192243		NA NA
3	NA +		NA NA
4	8.584e-03 0.669721905042939		NA NA
5	6.107e-05 0.823327272466571		NA NA
6	7.668e-02 0.413128242070071		NA NA

We can also average the taqman data using the separate samples/wells method . Here standard deviation is calculated separately and then combined, as described above. Therefore the pairing of housekeeper with the detector value within the same sample is lost. This can potentially increase variance.

```
> hkg <- "Actb-Rn00667869_m1"
> ddCqAvg.taqman <- deltaDeltaCq(qPCRBatch = qPCRBatch.taqman, maxNACase=1, maxNAControl=1,
> head(ddCqAvg.taqman)
```

	ID	2 ⁻ dCt.interestingPhenotype	
1	Actb.Rn00667869_m1	1.000e+00	
2	Adipoq.Rn00595250_m1	1.587e-01	
3	Adrbk1.Rn00562822_m1	2.602e-02	
4	Agtrl1.Rn00580252_s1	2.300e-02	
5	Alpl.Rn00564931_m1	1.892e-04	
6	B2m.Rn00560865_m1	2.464e-01	
	interestingPhenotype.sd	2 ⁻ dCt.wildTypePhenotype	
1	0.000e+00	1.000e+00	
2	2.280e-02	1.171e+00	
3	3.266e-02	NA	
4	1.014e-02	3.434e-02	
5	4.770e-05	2.298e-04	
6	2.498e-02	5.965e-01	
	wildTypePhenotype.sd	2 ⁻ ddCt	2 ⁻ ddCt.min 2 ⁻ ddCt.max
1	0.000e+00 1		NA NA
2	2.131e-01 0.135541545192243		NA NA
3	NA +		NA NA
4	8.584e-03 0.669721905042939		NA NA
5	6.107e-05 0.823327272466571		NA NA
6	7.668e-02 0.413128242070071		NA NA

5.4 $2^{\Delta\Delta Cq}$ method using a combination of housekeeping genes

If the user wishes to normalise by more than one housekeeping gene, for example if they have found a more than one housekeeping gene using the NormFinder/geNorm algorithms described above, they can. This is implemented by calculating the average of these values using the geometric mean to form a "pseudo-housekeeper" which is subtracted from the other values. For the dataset above, using housekeeping genes GAPDH, Beta-2-microglobulin and Beta-actin:

```
> qPCRBatch.taqman <- read.taqman(taqman.example)
> contM <- cbind(c(0,0,1,1,0,0,1,1),c(1,1,0,0,1,1,0,0))
> colnames(contM) <- c("interestingPhenotype","wildTypePhenotype")
> rownames(contM) <- sampleNames(qPCRBatch.taqman)
> hkg<-c("Actb-Rn00667869_m1", "B2m-Rn00560865_m1", "Gapdh-Rn99999916_s1")
> ddCq.gM.taqman <- deltaDeltaCq(qPCRBatch = qPCRBatch.taqman, maxNACase=1, maxNAControl=1,
> head(ddCq.gM.taqman)
```

	ID	2 ⁻ dCt.interestingPhenotype			
1	Actb.Rn00667869_m1	2.594e+00			
2	Adipoq.Rn00595250_m1	4.083e-01			
3	Adrbk1.Rn00562822_m1	4.182e-02			
4	Agtrl1.Rn00580252_s1	5.520e-02			
5	Alpl.Rn00564931_m1	4.767e-04			
6	B2m.Rn00560865_m1	6.367e-01			
	interestingPhenotype.sd	2 ⁻ dCt.wildTypePhenotype			
1	0.09819	2.345e+00			
2	0.24929	2.713e+00			
3	1.45844	NA			
4	0.63719	7.878e-02			
5	0.42589	5.242e-04			
6	0.05413	1.390e+00			
	wildTypePhenotype.sd	2 ⁻ -ddCt	2 ⁻ -ddCt.min	2 ⁻ -ddCt.max	
1	0.071373	1.10638851325547	1.034e+00	1.184310	
2	0.201905	0.150497255530234	1.266e-01	0.178884	
3	NA	+	NA	NA	
4	0.333840	0.700597907024805	4.505e-01	1.089636	
5	0.386280	0.909381199520663	6.769e-01	1.221662	
6	0.163975	0.457939394245865	4.411e-01	0.475448	

There is also the option of using the mean housekeeper method using shared variance between the samples being compared, similar to the second `deltaDeltaCq` method shown above.

```

> qPCRBatch.taqman <- read.taqman(taqman.example)
> contM <- cbind(c(0,0,1,1,0,0,1,1),c(1,1,0,0,1,1,0,0))
> colnames(contM) <- c("interestingPhenotype","wildTypePhenotype")
> rownames(contM) <- sampleNames(qPCRBatch.taqman)
> hkg<-c("Actb-Rn00667869_m1", "B2m-Rn00560865_m1", "Gapdh-Rn99999916_s1")
> ddAvgCq.gM.taqman <-deltaDeltaCq(qPCRBatch = qPCRBatch.taqman, maxNACase=1, maxNAControl=
> head(ddAvgCq.gM.taqman)

```

	ID	2 ⁻ dCt.interestingPhenotype
1	Actb.Rn00667869_m1	2.594e+00
2	Adipoq.Rn00595250_m1	4.083e-01
3	Adrbk1.Rn00562822_m1	4.182e-02
4	Agtrl1.Rn00580252_s1	5.520e-02
5	Alpl.Rn00564931_m1	4.767e-04
6	B2m.Rn00560865_m1	6.367e-01

	interestingPhenotype.sd	2 ⁻ dCt.wildTypePhenotype
1	0.3849	2.345e+00
2	0.4822	2.713e+00
3	1.4545	NA
4	0.6905	7.878e-02
5	0.5846	5.242e-04
6	0.2777	1.390e+00

	wildTypePhenotype.sd	2 ⁻ ddCt	2 ⁻ ddCt.min	2 ⁻ ddCt.max
1	0.3574	1.10638851325547	8.473e-01	1.444684
2	0.2495	0.150497255530234	1.077e-01	0.210221
3	NA	+	NA	NA
4	0.2813	0.700597907024805	4.341e-01	1.130625
5	0.3689	0.909381199520663	6.064e-01	1.363762
6	0.4576	0.457939394245865	3.778e-01	0.555126

TO SHOW EXAMPLE USING GENORM/NORMFINDER DATA

References

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11

- [2] Kenneth Livak, Thomase Schmittgen (2001). Analysis of Relative Gene Expression Data Using Real-Time Quantitative PCR and the $2^{\Delta\Delta C_t}$ Method. *Methods* 25, 402-408, 2001 <http://www.ncbi.nlm.nih.gov/pubmed/11846609> 16, 17
- [3] Jo Vandesompele, Katleen De Preter, Filip Pattyn, Bruce Poppe, Nadine Van Roy, Anne De Paepe and Frank Speleman (2002). Accurate normalization of real-time quantitative RT-PCR data by geometric averaging of multiple internal control genes. *Genome Biology* 2002, 3(7):research0034.1-0034.11 <http://genomebiology.com/2002/3/7/research/0034/> 5