

Data manipulation with Rcell (Version 1.1-5)

Alan Bush

October 27, 2011

1 Introduction

Once you have your data loaded into **R**, you can filter it and plot it as shown in “Getting Started with Rcell”. To read that document type in the console

```
> vignette("Rcell")
```

But many times we want to do some manipulation or transformations on the data before plotting it. In this document you’ll see how this can be done using **Rcell**.

2 Transforming variables

The easiest way to modify your dataset is to create new variables from existing ones. For example, its desirable to correct the fluorescence measure of a cell by the background fluorescence. To do this for the YFP channel we can use the `f.bg.y` variable, that contains the most common value (mode) for pixels not associated with any cell. If a cell has no fluorophores, we expect it to have a total fluorescence equivalent to `f.bg.y` times the number of pixels of the cell, `a.tot`. So the background corrected fluorescence can be calculated as `f.tot.y - f.bg.y*a.tot`. To create a new variable called `f.total.y` with the corrected value for fluorescence we can use the `transform` function. As all other **Rcell** functions, the first argument is the `cell.data` object to transform.

```
> X <- transform(X, f.total.y = f.tot.y - f.bg.y * a.tot)
```

Once created, you can use the new variable as any other variable of the dataset. You can create several variables in a single call to `transform`, as shown next for the fluorescence density variables.

```
> X <- transform(X, f.density.y = f.tot.y/a.tot, f.density.c = f.tot.c/a.tot)
```

You can keep track of the variables you’ve created with the `summary` function, that will display among other things the “transformed” variables with their definition.

```
> summary(X)
```

3 Merging variables

Sometimes there is no formula to specify the new variable you want to create. For example, you might want to create a variable that describes the treatment each position received. In the example dataset (`help(ACL394)`) each position received a different dose of alpha-factor pheromone, according to the Table 1.

You can create this table in Excel for example, and save it as a tab delimited text file. If you name it “mytable.txt”, then you can load it into **R** with `read.table`. The best option is to save the file in your working directory, or to change your working directory to where you saved the file (see `?setwd`).

pos	alpha.factor
1	1.25
2	1.25
3	1.25
8	2.50
9	2.50
10	2.50
15	5.00
16	5.00
17	5.00
22	10.00
23	10.00
24	10.00
29	20.00
30	20.00
31	20.00

Table 1: example data.frame to merge

```
> mytable <- read.table("mytable.txt", head = TRUE)
```

If the first row of your text file contains the column names (recommended), you have to set *head* to `TRUE` in `read.table`. Once loaded you can add the new data to your dataset using the `merge` function. This function looks for common variables between your cell.data and the data.frame you loaded and, if it finds them, it merges the dataset according to those common variables. In this case it will merge by *pos*. You can also specify the variable to merge by with the *by* argument.

```
> X <- merge(X, mytable)
```

```
merging by pos
```

```
merged vars:
```

```
alpha.factor: numeric w/values 1.25, 2.5, 5, 10, 20
```

4 Transform By

A common transformation is normalization, i.e. dividing the value of a variable by the “basal” level. For example, we might be interest in the fold increase of YFP fluorescence through time. So we need to divide the measured value at each time by the value at time zero, and we need to this for every cell. How can we do this? The steps we should follow are the following:

1. Divide the dataset by cell, creating a table for each cell.
2. Indentify the value of fluorescence for time zero.
3. Create a new variable by dividing the fluorescence at each time by the value at time zero.
4. Join the cells datasets back together to retrieve the original dataset with the new variable.

All these steps are done by the function `transform.by`, but it requires information on how each step should be done. For the first step, it needs to know how to partition the dataset. This is specified by passing a quoted list of variable, whos combination of levels specify a group. For example, if you want to divide the dataset by position, the second argument of `transform.by` should be `.(pos)`. If you want to divide

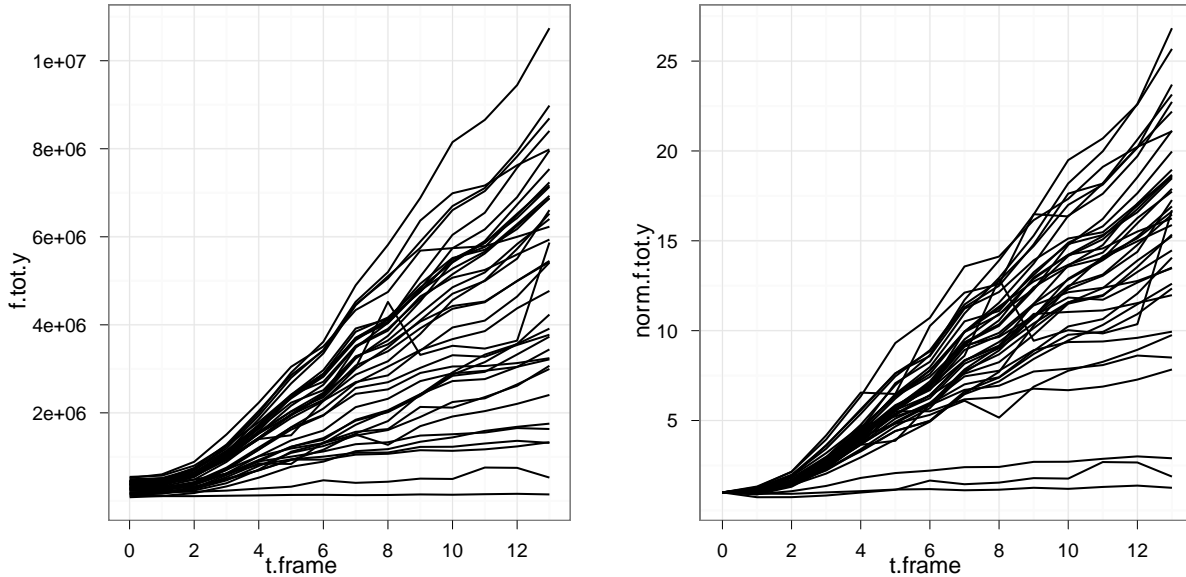


Figure 1: Left: raw single cell time course for YFP fluorescence. Right: Same data normalized to each cells value at time zero.

your dataset by cell use `.(pos, cellID)`. Note that cells in different position can have the same `cellID`, so the combination of `pos` and `cellID` uniquely identifies a cell. The variable `ucid` (for Unique Cell ID) is another way to uniquely identify a cell. Next we need to specify the name of the new variable to be created (`norm.f.tot.y` for example), and the definition for this variable, `f.tot.y/f.tot.y[t.frame==0]`. With the square brackets we are selecting the value of `f.tot.y` when `t.frame` is zero. Remember to use the logical operator `==` and not the assignation operator `=` within the brackets.

```
> X <- transform.by(X, .(pos, cellID), norm.f.tot.y = f.tot.y/f.tot.y[t.frame ==
+ 0])
```

An other way to normalize the data, is dividing by the mean of the first three values.

```
> X <- transform.by(X, .(pos, cellID), norm2.f.tot.y = f.tot.y/mean(f.tot.y[t.frame <=
+ 2]))
```

For more details on plotting read

```
> vignette("cplot")
```

5 Aggregating your data

To calculate summary statistics you can use the `aggregate` function, that returns an aggregated data.frame. That means that the value of each cell of this data.frame was calculated from more than one cell of the original dataset. For example you might be intereset in getting the mean YFP fluorescence for each pheromone dose. `aggregate` accepts two notations that give equivalent results.

```
> aggregate(X, .(alpha.factor), select = "f.total.y")
> aggregate(X, f.total.y ~ alpha.factor)
```

	alpha.factor	f.total.y
1	1.25	1071898
2	2.50	1622198
3	5.00	2234246
4	10.00	2393427
5	20.00	2377602

You can calculate other statistics using the *FUN* argument, and you can include more than one variable. Here we calculate the median for *f.tot.y*, *f.tot.c* and *a.tot*. Note the use of the wildcard in the *select* argument.

```
> aggregate(X, .(alpha.factor), select = c("f.tot.*", "a.tot"), FUN = median)
```

	alpha.factor	f.tot.c	f.tot.y	a.tot
1	1.25	1047808.5	1212391	415.5
2	2.50	1055751.0	1564543	415.0
3	5.00	1037465.0	2032817	407.0
4	10.00	1001638.5	2224172	398.0
5	20.00	961167.5	2083660	380.0

The partition of the dataset can be done by more than one variable, for example by dose and time. Using the function *funstofun* from the **reshape** package, you can calculate more than one statistic at once.

```
> aggregate(X, f.density.y ~ t.frame + alpha.factor, FUN = funstofun(median, sd),
+ subset = t.frame%%3 == 0)
```

	t.frame	alpha.factor	f.density.y.median	f.density.y.sd
1	0	1.25	1037.6060	162.4781
2	3	1.25	2103.6828	420.8901
3	6	1.25	3646.6715	892.4902
4	9	1.25	3916.8426	1112.6042
5	12	1.25	4081.6656	1295.7236
6	0	2.50	1043.6030	141.9683
7	3	2.50	2283.6054	577.7679
8	6	2.50	4663.5886	1387.7653
9	9	2.50	5809.6937	1895.5383
10	12	2.50	6715.9285	2200.4825
11	0	5.00	1057.4033	163.5038
12	3	5.00	2519.7817	662.3112
13	6	5.00	5619.7677	1633.4406
14	9	5.00	8206.8911	2418.8710
15	12	5.00	9600.1285	2859.8918
16	0	10.00	1009.4154	131.5840
17	3	10.00	2686.9785	508.3823
18	6	10.00	5883.8167	1218.5057
19	9	10.00	9131.4531	2018.9390
20	12	10.00	10792.7466	2478.7091
21	0	20.00	1022.5990	120.6829
22	3	20.00	2730.6114	571.0274
23	6	20.00	6440.7103	1645.1310
24	9	20.00	9512.2292	2497.7941
25	12	20.00	11746.9381	3383.9809

6 Evaluating expression in your dataset

Using the `with` function, you can evaluate a expression in a enviroment created from your dataset. That means that you can use the names of your variables. For example to calculate the mean of `f.tot.y` from position 1

```
> with(X, mean(f.tot.y), subset = pos == 1)
[1] 1372297
```

If you don't use the `with` function, **R** won't know what the variable `f.tot.y` means, as it is not in the search path.

7 Exporting your data

Although you can do much of your analysis using **Rcell** functions, you might need to export the data to some other application or use another package within **R**. To retrieve the entire dataset in a `data.frame`, use the double square brackets notation. This returns the registers that pass the `QC.filter`.

```
> df <- X[[ ]]
```

This dataset is usually big, and has many variables or registers you are not interested in. You can subset the dataset as you would a `data.frame` (but using double brackets)

```
> df <- X[[pos == 1, c("cellID", "f.tot.y", "a.tot")]]
```

You can then save the `data.frame` to a file with `write.table`, or use it in another **R** package.

For some kinds of data analysis you need your data in a different for than the one **Rcell** uses. You can use the `reshape` function to reshape your data. For instance, a common restructuring is to display time as different columns, and individual cells as different rows. You can obtain this sort of `data.frames` with the following command.

```
> reshape(X, pos + cellID ~ variable + t.frame, select = "f.tot.y", subset = pos <=
+ 2 & cellID <= 10 & t.frame%%2 == 0)

  pos cellID f.tot.y_0 f.tot.y_2 f.tot.y_4 f.tot.y_6 f.tot.y_8 f.tot.y_10 f.tot.y_12
1    1      1   378752   748712  1350707  2028179  2155404  2072739  2214004
2    1      2   176429   300842   448582   535334   549019   562208   512430
3    1      3   384393   665472  1234888  1913377  2036718  2217148  2071306
4    1      4   245876   510412   887509  1493615  1692185  1987466  2137951
5    1      6   347597   629056  1000791  1533244  1788453  2188437  2381668
6    1      7   325715   558893   998972  1740997  2080686  2575011  2845928
7    1      8   276242   481790   842095  1310683  1464268  1735160  1826068
8    1     10   314574   559742  1050029  1832519  2166170  2765528  2981627
9    2      2   387551   620656  1049458  1327046  1317000  1409672  1742833
10   2      3   428014   655421  1239405  1616264  1942105  2268256  2583064
11   2      4   452047   718126  1381880  1808801  2260311  2624726  3127893
12   2      5   330852   228660   285463   294746   357041   354951   308372
13   2      6   166711   139176   173661   184098   201449   202782   223541
14   2      7   453124   665657  1288083  1847586  2532047  2676930  2793809
15   2      8   137043   232664   448551   652693   830410   957173  1094667
16   2      9   504990   632012   961822  1340065  1640487  1769006  1929912
17   2     10   317594   440622   763946  1221629  1711411  1788251  1834715
```

see `help(reshape.cell.data)` for more details.

References

- Pau, Fuchs et al. (2010). EBImage: an R package for image processing with applications to cellular phenotypes. *Bioinformatics*, 26(7):979-981.
- Colman-Lerner, Gordon et al. (2005). Regulated cell-to-cell variation in a cell-fate decision system. *Nature*, 437(7059):699-706.
- Chernomoretz, Bush et al. (2008). Using Cell-ID 1.4 with R for Microscope-Based Cytometry. *Curr Protoc Mol Biol.*, Chapter 14:Unit 14.18.