Gene expression

MACAT—microarray chromosome analysis tool

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ABSTRACT

Summary: By linking differential gene expression to the chromosomal localization of genes, one can investigate microarray data for characteristic patterns of expression phenomena involving sizeable parts of specific chromosomes. We have implemented a statistical approach for identifying significantly differentially expressed chromosome regions. We demonstrate the applicability of the approach on a publicly available data set on acute lymphocytic leukemia.

Availability: The R-package MACAT can be obtained from http://www.compdiag.molgen.mpg.de/software/macat.shtml

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Supplementary information: http://www.compdiag.molgen.mpg.de/ software/macat.shtml

Microarray data analysts have defined tumor subtypes by specific gene expression profiles, consisting of genes that show differential expression between subtypes (Yeoh et al., 2002). However, tumor subtypes have also been characterized by phenomena involving large chromosomal regions. For instance, Christiansen et al. (2004) report on a subtype of acute myeloid leukemia, showing mutations in the AML1 gene on chromosome 21 along with deletions or loss of chromosome arm 7q. A natural approach to bridging the gap between these two paradigms is to link scoring for differential gene expression to the chromosomal localization of genes. Tumor subtypes can be defined by differential expression patterns affecting sizeable regions of certain chromosomes.

To assist in the identification of significantly differentially expressed chromosome regions, we provide the implementation of a statistical approach. MACAT is written in the R statistical programming language and is part of the developmental branch of the popular Bioconductor package (Gentleman et al., 2004). We assume normalized expression data, which can be provided as a matrix or expression set in R or as a delimited text file. In a preprocessing step the expression data is integrated with gene location data into one common data format. To date, this step has only been implemented for commercial Affymetrix® oligo-nucleotide microarrays.

For each gene, we compute a statistic denoting the degree of differential expression between two groups of samples. This statistic is the regularized t-score introduced in Tusher et al. (2001). In essence, it is Student's t-statistic augmented by a fudge factor s_0 in the denominator, which prevents a high statistic for genes with a low variance.

We set s_0 to the median over all gene standard deviations, analogous to Tibshirani et al. (2002).

The distribution of measured genes is not uniform over the length of the chromosome. Since we want to evaluate differential expression over the whole chromosome, we interpolate the statistic for positions between measured genes. This interpolation, however, does not aim to assign statistics to non-coding regions, but to provide a smooth estimate of differential expression over large chromosomal regions.

The following kernel functions are used for interpolation:

- k-nearest neighbor: For every chromosomal coordinate compute the average of the k nearest genes.
- Radial basis function (rbf): For every coordinate compute the average over all genes weighted by distance from the coordinate.
- Base-pair distance: Similar to the *k*-nearest-neighbors, but the average is taken over all genes within a certain radius of the coordinate.

The free parameters of the kernels determine the degree of smoothing. By default, optimal parameter settings are estimated from the data by cross-validation (for details see the package's vignette).

To judge the significance of differential expression, we investigate random permutations of the class labels. To obtain a reliable simulation of the empirical distribution, we suggest observing at least $B \ge 1000$ permutations. For each permutation, the regularized tstatistic is computed for each gene. Thus, for each gene we obtain Bpermutation statistics and consequently an empirical p-value, denoting the proportion of the permutation statistics being greater or equal than the gene's actual statistic that is based on the true class labels. The permutation statistics also provide upper and lower significance borders, which are smoothed using the same kernel function as for the original statistics.

Optionally, to judge the significance of differential expression over chromosomal regions, one can instead investigate permutations of the ordering of genes on chromosomes.

Meaningful and concise visualization facilitates a better understanding of both the data and the statistical analysis. MACAT includes functions for plotting expression levels and statistical scores versus base-pair coordinate on the chromosome. Regions showing significant differential expression are highlighted in these plots. One can also generate HTML-pages, which contain additional information on genes located within the highlighted chromosomal regions (Fig. 1). For each gene comprehensive annotation, a LocusLink ID,

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Class T , Scores for Chromosome 6



Fig. 1. Excerpt of a generated HTML-page for the *T-versus B-lymphocyte ALL* analysis.

with a hyperlink to the NCBI website, and the empirical *p*-value are provided. In addition, *MACAT* includes functions for writing gene expression levels and statistics into text files, which can be used with other programs for further analyses.

As an example, we present the results of an analysis on *T-versus B-lymphocyte ALL* within the publicly available data set described in Yeoh *et al.* (2002). A region on the p-arm of chromosome 6 could be identified as significantly under-expressed (Fig. 1). Among the genes within that region are the MHC class II genes, which are known to be expressed by B-lymphocytes, but not by T-lymphocytes. Since these genes are distributed over a large part of the p-arm of chromosome 6, it makes sense to assume that all genes in this region are significantly less transcribed in T-lymphocytes compared to B-lymphocytes. This gives an indication that chromosomal regions highlighted by our method are indeed biologically meaningful.

The method which we have described can detect significant differential expression for chromosomal regions. However, the reason for the differential expression, be it a mutation, translocation, hypermethylation, loss of heterozygosity, or another event, remains to be investigated.

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