ABSTRACT

Motivation: High-throughput techniques facilitate the simultaneous measurement of DNA copy number at hundreds of thousands of sites on a genome. Older techniques allow measurement only of total copy number, the sum of the copy number contributions from the two parental chromosomes. Single-nucleotide polymorphism (SNP) techniques can in addition enable quantifying parent-specific copy number (PSCN). The raw data from such experiments are two-dimensional, but are unphased. Consequently, inference based on them necessitates development of new analytic methods.

Methods: We have adapted and enhanced the circular binary segmentation (CBS) algorithm for this purpose with focus on paired test and reference samples. The essence of paired parent-specific CBS (Paired PSCBS) is to utilize the original CBS algorithm to identify regions of equal parental copy number and loss of heterozygosity (LOH). PSCN estimates are computed both before and after calling.

Results: The methodology is evaluated by simulation and on glioblastoma data. In the simulation, PSCBS compares favorably to established methods. On the glioblastoma data, PSCBS identifies interesting genomic regions, such as copy-neutral LOH.

Availability: The Paired PSCBS method is implemented in an open-source R package named PSCBS, available on CRAN (http://cran.r-project.org/).

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Supplementary information: Supplementary data are available at Bioinformatics online.

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1 INTRODUCTION

Changes in the number of copies of genomic DNA is an important step in the progression of cancer. Comparative genomic hybridization (CGH) was developed to identify these changes at a resolution of 10–20 Mb (Kallioniemi et al., 1992). Platforms for copy number (CN) analysis that employ microarray technology and that achieve high resolution include array CGH (Pinkel et al., 1998), ROMA (Lucito et al., 2003) and SNP arrays (Hardenbol et al., 2005; Peiffer et al., 2006; Zhao et al., 2004). Current technology has improved the resolution to as low as 1 kb. With custom arrays also available, the resolution in particular neighborhoods can be even higher.

Herefore, CN analysis has consisted primarily of examining total copy number (TCN). TCN is the sum of the CNs from the two parental chromosomes. For normal human cells, total CN is two, one from each parental chromosome. SNP arrays allow separate estimates of CN from the parental chromosomes. This is parent-specific copy number (PSCN).

PSCN may be interesting for two major reasons. First, there may be alleles that differentially undergo CN change (Nagase et al., 2003). Estimating PSCN would help elucidate this situation. Second, when the total CN is C, the PSCNs may be more complicated than (1, C − 1). For instance, diploid (C = 2) CN is maintained when one parental copy is lost and the other is doubled. This type of alteration is called copy-neutral loss of heterozygosity (CN-LOH), and it occurs often in many cancers including glioblastoma (Kuga et al., 2008) and hematologic malignancies (O’Keefe et al., 2010). Such a region would be assumed normal if there was analysis only of total CN.

Direct estimates of PSCN can be made only for SNPs at which a subject is heterozygous. Homozygous SNPs are not directly informative because all the CN signal is in one allele. For example, if both parents contributed G then there would only be a G CN signal, and this would result in no information additional to that contained in total CN. For heterozygous SNPs, however, there are two components to the CN information. If the subject was GT at a SNP, then there would be a CN estimate corresponding to G and one corresponding to T. One of the CNs would be expected to have come from one parent and the other to have come from the other
parent. Additionally, the data are unphased; it is not directly known which measurement is associated with which parental chromosome. CN alterations apply to contiguous regions, and the data on CN derived from microarrays can be noisy. Therefore, methods have been developed to analyze CN data that rely on the underlying spatial correlation. The idea is to split the genome into regions of equal total CN. Methods for this have included direct segmentation (Olshen et al., 2004; Picard et al., 2005; Venkatraman and Olshen, 2007), hidden Markov models (HMMs) (Fridlyand et al., 2004; Guha et al., 2008; Liu et al., 2008) and smoothing (Hsu et al., 2005; Tibshirani and Wang, 2008). When the earlier methods were compared (Lai et al., 2005; Willenbrock and Fridlyand, 2005), direct segmentation methods performed best.

The purpose of the present article is to extend segmentation to allele-specific data. We cannot simply perform two separate segmentations, one for each parental chromosome, because the data are unphased. Therefore, other techniques are needed. As part of our algorithm, we use the circular binary segmentation (CBS) method (Olshen et al., 2004; Venkatraman and Olshen, 2007), although any good segmentation method could replace CBS in our overall procedure. We call our method Paired Parent-Specific CBS (‘Paired PSCBS’) or just ‘PSCBS’, while acknowledging that due to the lack of phase information, we cannot assign segmentation-based estimates to the paternal or maternal chromosomes.

Other approaches to PSCSN segmentation bear some resemblance to PSCBS. Here, we focus on the BAF segmentation method of Staaf et al. (2008), especially since their study provides a comparison to existing methods. It is similar in that it relies on CBS and it adapts to datasets consisting of paired tumor and normal samples. It essentially segments the mirrored B-allele frequency (mirrored BAF), which is the ratio of the higher parental copy number to the total copy number, after removing all homozygotes identified in the normal samples. It differs from PSCBS, as discussed in Section 2, in that it segments only heterozygous SNPs, whereas Paired PSCBS has an advantage in that it utilizes all SNPs as well as any non-poly morphic loci. Another advantage of Paired PSCBS over BAF segmentation is that it uses the normal sample to more accurately quantify the tumor data (Bengtsson et al., 2010).

Another paired method of which we are aware is a hidden Markov method that segments jointly on TCN and mirrored BAF (Lamy et al., 2007). But since it is specific to Affymetrix arrays, and we are interested only in general methods, we did not evaluate it. During the review of this article, Van Loo et al. (2010) published a paired joint segmentation method that was not studied here.

Other methodologies exist that are not based on paired samples. Laframboise et al. (2005) used CBS to segment total CN data, and then estimated parental CN within segments. By not segmenting the allele-specific data, certain events may be missed. Li et al. (2008) developed a similar procedure using an HMM. They referred to the mirrored BAF as the major copy proportion, so their method is called MCP SOMATICS (Assié et al., 2008) uses the BAF, which is the ratio of the B-allele to the total CN, to identify CN abnormalities that are then confirmed by the total CN. QuantiSNP (Coddella et al., 2007) and PennCNV (Wang et al., 2007) are two HMM methods that rely on the same six-state model. Sun et al. (2009) is a ‘2d’ HMM method in the same vein as PennCNV and QuantiSNP, but that has been adopted to cancer studies. Recently, GAP (Popova et al., 2009) segments total CN and allelic ratio independently and then considers the segments defined by the union of the two sets of change-points.

Chen et al. (2011) extended their HMM methodology (Lai et al., 2008) to allele-specific data. An advantage of Chen’s HMM method (PSCN) is that there is no limit on the number of states. In addition, Greenman et al. (2010) developed the PICNIC method, which is also based on an HMM and assigns integer CN states. In the present article, Section 2 covers our methods. Section 3 contains simulations that show the effectiveness of our procedure, as well as an example drawn from glioblastoma data. Finally, Section 4 has discussion.

2 METHODS

The paired parent-specific CBS (Paired PSCBS) algorithm leverages the CBS method (Olshen et al., 2004; Venkatraman and Olshen, 2007) for segmenting total CN data to the 2D unphased data arising from SNP arrays. The algorithm depends on paired test (tumor) and reference (normal) samples that are hybridized to separate arrays.

2.1 Parental-specific data at the locus level

In this subsection, we introduce the locus-level components that go into the segmentation and calling.

2.1.1 Total CNs and allele B fractions

SNP arrays quantify both total and allele-specific signals at the loci of a large number of SNPs. Some platforms also provide total CN estimates (TCNs) at a large number of non-polymorphic loci. For a locus i = 1, 2, . . . , n of either type, on a chromosome, chromosome arm or other region under consideration, let Xi denote the observed total CN ratio for a test sample relative to a reference (here a matched normal sample), where the ratio is multiplied by two for a diploid genome. If the locus is a SNP, we also have allele-specific CNs, which we denote (Ai, Bi), where the TCN is Xi = Ai + Bi (Fig. 1a). If the subject is homozygous at SNP i, then the minimum of Ai and Bi should be zero plus noise, and thus all of the true CN signal is in one of the alleles. If the subject is heterozygous at SNP i, then there should be significantly non-zero CN for both Ai and Bi, and in the case there is balanced heterozygosity, then Ai and Bi should be approximately equal.

A convenient representation for SNPs is (Xi, β), where β = Bi / Xi, which is the ratio of the B-allele CN to the total CN in the test sample (Fig. 1b). This quantity is known as the allelic B fraction (BAF) (Bengtsson et al., 2010). It has also been called the B-allele frequency (Staaf et al., 2008), which may be misleading because it is not a frequency in the strict statistical sense in that it does not involve a count. We note that for a homozygous SNP, β is near zero or one, e.g. for SNPs that are AA and BB as well as AAA and BBB. For a balanced heterozygous SNP, β is near one half, e.g. for SNPs that are AB as well as AABB. Note that by using this representation, we have a total CN signal Xi for any locus, regardless of whether it is a SNP.

2.1.2 Allelic imbalances

The total CN signals do not contain information on allelic imbalances. In addition, homozygous SNPs do not carry information on allelic imbalances, since the two parental components cannot be separated by the array. It is only SNPs that are heterozygous in the germline that provide this information (Assié et al., 2008; Bengtsson et al., 2010; Peiffer et al., 2006; Staaf et al., 2008). Because of this, all information on allelic imbalances is preserved in what we call decrease in heterozygosity (DH) (Bengtsson et al., 2010). DH is defined for heterozygous SNPs as

\[
\alpha = 2\beta - 0.5.
\]

(1)

It provides a measure of how much the allelic composition of the tumor has diverged from the normal (germline) state. It is similar to the mirrored BAF (Staaf et al., 2008).

When there is a parental CN change, true TCN, true DH or both can change. We specify cases where only one of them changes. For instance, in a tumor without normal contamination where PSCNs shift from (0,1) to
Fig. 1. Total CN (a), raw allele B fractions (b), TumorBoost normalized BAFs (c) and DH (d) of chromosome 7 of TCGA sample TCGA-02-0007. Normalized BAFs are less noisy than raw BAFs. As TCN quantifies the difference in total CN between tumor and normal, DH does the same for normalized CNs ratios.

2.1.4 Normalization of DH signals

In order to calculate the DHs, SNPs that are heterozygous in the germline must be identified. Genotypes can be called from the allele-specific signals \((\beta_i, \beta')\) of chromosome 7 of TCGA sample TCGA-02-0007. However, as Bengtsson et al. (2010) showed, a naive genotype caller will miss in the initial round of TCN segmentation, but later be identified by a segmentation of DHs. This also emphasizes an advantage that PSCBS has over, for instance, Staaf’s BAF segmentation and PICNIC, both of which segment based on only one of the two signals available; PSCBS utilizes the signal available in both TCN and DH to detect change-points.

2.2 Segmentation of parent-specific CNs

2.2.1 Identification of change-points in total CNs

CBS is applied to total CNs and DH to detect change-points. This process is repeated recursively for loci \(i = 1, 2, \ldots, m\), where total CNs \((X_i)\) are defined for all loci \(i\) and \(\beta_i\) are defined only for SNPs that are heterozygous in the germline. We next identify segments of constant parent-specific CN using a two-step segmentation in which an initial set of change-points is identified from total CN signals \((X_i)\), which is then updated with additional change-points from the normalized decrease-of-heterozygosity signals \((\bar{\beta}_i)\).

The two-step PSCBS approach is capable of detecting a PSCN change while TCN remains constant. As mentioned in Section 2.1.2, it can detect CNs changed from \((1, 1)\) to \((0, 2)\) in the case of no normal contamination, which would not be recognized by TCN segmentation alone. O’Keefe et al. (2003) provide detailed descriptions on how copy-neutral changes, where a loss in one chromosome is counter-balanced by a perfectly overlapping gain in the other, may occur. Note also that such a copy-neutral change may also be observed instead of a sequence of change-points in regions where the coverage is low, e.g. in the centromere. Likewise, a change from CN-LOH \((0, 2)\) to a deletion \((0, 1)\) would not be detectable from the DHs alone (except when there is normal contamination).

Even in cases where a chromosomal change-point is reflected in both the true TCN and DH, the power to detect a particular change-point differs between TCN and DH as a function of the type of aberration. This is explained in great detail and argued for both theoretically and empirically by Bengtsson et al. (2010), it was shown immediately (Fig. 1d). For convenience, we drop the TB superscript and assume the DH has been TumorBoost-normalized unless stated otherwise.

2.2.2 Identification of additional change-points using DH

In the second round of segmentation, the segments defined by CBS in the first round are...
spli further based on the heterogeneous SNPs. We identify additional change-points from DH $(s)$ using CBS on each such subsegment. Change-points are not pruned; that is, those already identified in the TCN segmentation remain after the DH segmentation. New potential change-points are kept if their associated $P$-values are less than $\alpha_{DB}$. We specify $\alpha_{DB}$ and $\alpha_{LOH}$ so that, due to the Bonferroni inequality, our overall $\alpha \leq \alpha_{DB}+\alpha_{LOH}$ is at a desired level. We choose $\alpha_{DB} \geq \alpha_{LOH}$ because most changes should be found in the first round of segmentation and total CN is available for every locus. The default for PSCBS is $\alpha_{DB}=0.009$ and $\alpha_{LOH}=0.001$ so that $\alpha \leq 0.01$.

2.2.3 Defining boundaries of segments The genomic position of a change-point is formally (Page, 1954) the locus after which the distribution of the data changes. But the actual change in CN can be anywhere in between the change-point locus and the next locus (conditional on having identified the change-point correctly). This was not a major problem when segmenting on TCN, but it is when segmenting on DH since there are TCN loci that do not fall into either DH segment. As a convention, for DH segmentation we average the genomic positions between the change-point and the next heterozygous (DH) locus, and fix the change-point at the TCN locus immediately before this average.

2.2.4 Parent-specific CNs at the (non-called) region level For each segment $s=1, \ldots, 5$ defined by the change-points, the region-level TCN and DH, $(\bar{C}_s, \rho_s)$, are estimated as:

$$\bar{C}_s = \frac{\sum_{x \in I_s} X_x}{|I_s|}, \quad \rho_s = \frac{|\bar{C}_s|}{\bar{C}_s}, \quad (4)$$

where $I_s$ is the set of loci that are located within segment $s$, that is, in region $(\bar{x}_s, \bar{x}_s-x)$ and where non-defined DHCs are excluded when calculating $\rho_s$. The corresponding minor and major CNs, $(\bar{C}_s^{\rho}, \bar{C}_s^{1-\rho})$, are:

$$\bar{C}_s^{\rho} = \frac{1}{2} (1-\rho_s) \bar{C}_s, \quad \bar{C}_s^{1-\rho} = \bar{C}_s - \bar{C}_s^{\rho}, \quad (5)$$

so that $\bar{C}_s = \bar{C}_s^{\rho} + \bar{C}_s^{1-\rho}$, as well as $\rho_s = (\bar{C}_s - \bar{C}_s^{\rho})/\bar{C}_s$ holds.

2.2.5 Bootstrapping We utilize simple percentile bootstrap techniques to estimate standard errors and confidence intervals for the above estimates of CN. Later, we use these estimates in the calling described in Section 2.3. We resample the loci, that is, $(X_x, \rho_x)$ per segment with replacement such that the number of SNPs and the number of non-polymorphic loci, as well as the number of homozygous and heterogeneous SNPs per segment, are preserved in each bootstrap sample. By default, PSCBS draws $B=1000$ bootstrap samples.

2.3 Calling parent-specific CN In this subsection, we detail how to distinguish for every segment among the cases discussed in Section 2.1.1, i.e. equal PSCN, unequal PSCN and LOH. Once calls are made, the PSCN estimates are updated. The segmentation and bootstrapping procedures rely on a minimum of prespecified parameters. Due to technical artifacts, normal contamination and lack of clonality in the tumor, some assumptions or tuning parameters may be necessary. Due to technical artifacts, normal contamination (including normal contamination) and the desired fraction $(\nu)$ of tumor cells to be in LOH. We note that the former component is data driven, while the latter is a predetermined data-independent tuning parameter. We start by distinguishing the case of equal PSCN from the case of unequal PSCN and both parental CNs positive. The former is a case of allelic balance, and the latter is a case of allelic imbalance. Formally, our null hypothesis for allelic balance is $\bar{C}_1 = \bar{C}_2$, or equivalently DH = 0.

As discussed in Section 2.2.5, we estimate confidence intervals for DH, and our tests are based on them. For every region, we take $B$ bootstrap samples and estimate the region-level DH $\bar{C}_1^{\rho_B}, \ldots, \bar{C}_2^{\rho_B}$ as in the original data. We reject the null hypothesis if

$$\bar{C}_2^{\rho_B} - \bar{C}_1^{\rho_B} > \Delta_{DB} \times \alpha_{DB}, \quad (6)$$

where $\bar{C}_2^{\rho_B}$ is the $\rho_B$th percentile of $\bar{C}_2^{\rho_B}, \ldots, \bar{C}_2^{\rho_B}$ and $\Delta_{DB}$ is a bias-correction term. This rejection region corresponds to the one-sided $1-\nu_{DB}$th confidence interval not containing zero. The main reason for $\Delta_{DB}$ is that $\rho$ will always be a biased estimate of the true DH (when near zero), because DH is by definition always non-negative. To summarize, the rejection region corresponds to the one-sided $1-\nu_{DB}$th confidence interval not containing zero.

2.3.2 Calling LOH Analogous to the above, we use a test to call LOH, where the null hypothesis is that a segment is not in LOH, or equivalently, the minor CN is (pointing to the revised version of our tests will be explained below.) Segments already called to be in allelic balance will not be considered. Formally, we reject the null hypothesis if:

$$\bar{C}_1^{\rho_{BLOH}} - \bar{C}_1^{\rho_BLOH} < 0, \quad (7)$$

where $\bar{C}_1^{\rho_BLOH}$ is the $\rho_B$th percentile of $\bar{C}_1^{\rho_BLOH}, \ldots, \bar{C}_1^{\rho_BLOH}$ mean estimates and $\Delta_{LOH} \geq 0$ is a parameter that is derived from data. Choosing $\Delta_{LOH}$ and, more generally, calling LOH requires strong assumptions. Even with these assumptions, there are difficulties. Definition of LOH: LOH is not obviously defined when considering a cell population from a tumor study. The measured CN signals represent the average of a large number of often non-homogeneous cells, so that it is not clear what ‘zero’ minor CN is. This is because the tumor tissue extract will likely consist of some normal cells and possibly a mixture of different tumor cells. Thus, the term LOH can refer to the ‘zero’ minor CN state either of the mixed tumor and normal cells, or of the potentially heterogeneous tumor cells. In either case, we cannot expect all cells to have truly zero minor CNs in segments that we wish to call LOH even when most cells do. Therefore, one option is to consider a segment to be in LOH when the fraction of the cells that has lost the contribution from one parent is $\nu$, where $0 \leq \nu \leq 1$. Exactly which definition of LOH and which value of $\nu$ to use depends on the underlying biological question and needs to be chosen by the investigator.

On background signals including normal contamination: In theory, and as proposed by several (Assié et al., 2008; Lamy et al., 2007; Popova et al., 2009; Staaf et al., 2008; Sun et al., 2009; Van Loo et al., 2010; Yamamoto et al., 2007), it should be possible to estimate the amount of normal contamination from data. Unfortunately, its impacts on the PSCN estimates is confounded by additional sources of background signal, which makes it difficult in practice.

In the Supplementary Materials, we suggest a procedure for setting $\Delta_{LOH}$ that reflects both the amount of background signal (including normal contamination) and the desired fraction $(\nu)$ of tumor cells to be in LOH. We note that the former component is data driven, while the latter is a predetermined data-independent tuning parameter. Stricter calling of LOH would be accomplished by decreasing $\nu$. Unfortunately, it is not unusual to have a tumor with no LOH. In such a case, the above procedure fails to provide a useful $\Delta_{LOH}$. For this reason, as a rough guide, values of $\Delta_{LOH} > 0.75$ should be evaluated further and possibly be replaced by a fixed value. By default, we use $\nu=0.50$ and $\Delta_{LOH}=0.05$. 

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on 05 August 2018
2.3.3 Estimating CN from called regions  If LOH has been found in the tumor, then the called PSCNs are estimated to be $0$ and the total CN, that is $(\hat{C}_1, \hat{C}_2) = (0, \hat{C})$. Otherwise, if the two parental CNs are called equal, then the PSCNs are both estimated to be the total CN divided by 2, that is $(\hat{C}_1, \hat{C}_2) = (\hat{C}, \frac{\hat{C}}{2})$. If they are unequal, the called PSCN estimates are the same as the non-called PSCN estimates, that is, $(\hat{C}_1, \hat{C}_2) = (\hat{C}_1, \hat{C}_2)$. Note that in the first two cases DH is not part of the CN estimates. Also note that for all segments it holds that $\hat{C} = \hat{C}_1 + \hat{C}_2$ and $\bar{C} = (\hat{C}_2 - \hat{C}_1)/\hat{C}$, cf. Section 2.2.4.

2.4 Algorithm and implementation

The paired parent-specific CBS and calling method, referred to as Paired PSCBS, is available in the PSCBS package, which is an open-access and open-source implementation in R. It is available on CRAN (http://cran.r-project.org).

The method is designed and implemented to work with data from any generic SNP microarray technology, e.g. Affymetrix and Illumina. Great efforts have been made to make the implementation robust and straightforward to use. The low-level application programming interface (API) uses standard R data types, making it easy to incorporate PSCBS elsewhere. A high-level API that plugs into the Aroma Project framework (Bengtsson et al., 2008) is planned.

Since PSCBS is a single-pair method, it can be used to process any number of samples in bounded memory. The computational complexity to segment a sample with PSCBS is only slightly more than that for CBS. The reason for this is that the DH segmentation is significantly faster than TCN segmentation, because the regions being segmented are smaller and because homozygotes and non-polymorphic loci are not included.

3 RESULTS

Here, we assess the performance and correctness of Paired PSCBS. First, we assess the performance of PSCBS relative to extant methods on previously simulated data. Second, we show that PSCBS finds interesting genomic regions on glioblastoma data and that its results are similar for Affymetrix and Illumina arrays.

3.1 Simulation results

We compared PSCBS to other known methods using simulated data from Staaf et al. (2008). Specifically, they simulated a normal contamination series for a tumor based on HapMap sample NA06991 hybridized to the Illumina HumanHap550 array. To model a tumor, they added to the original data four regions of loss, three regions of gain and three regions of CN-LOH, as listed in Table 1. The alterations were reflected in the (log base 2) total CN and BAF. The percentage of normal cell contamination ranged from 0% (Supplementary Fig. S1) to 100% in increments of 5%: 10% normal contamination meant 10% normal cells and 90% tumor cells. The 100% normal contamination data was the same as the original sample, except as discussed in what follows. The other methods were ‘Paired BAF’ and ‘Unpaired BAF’ segmentation (Staaf et al., 2008), QuantiSNP (Colella et al., 2007), PennCNV (Wang et al., 2007) and SOMATICs (Assié et al., 2008). The results for all methods but PSCBS were taken from the Staaf analysis. Moreover, in agreement with the original authors, we have identified and corrected for a mistake in the simulated dataset causing the simulated total CNs to be slightly incorrect, cf. Supplementary Materials. The correction was not designed to give us an advantage in this assessment.

3.1.1 Genotyping and PSCBS

We used the 100% normal contamination data as the reference sample for the purpose of genotyping. For segmentation and calling, we treated the test sample as if it already had been TumorBoost adjusted (Bengtsson et al., 2010). The reason is that because the tumor sample derived directly from the normal sample, we would be eliminating all noise in the tumor sample if we adjusted. Other than not doing TumorBoost, we ran PSCBS using all the default parameters.

3.1.2 Calling gains and losses

PSCBS is a segmentation and parent-specific calling algorithm, but it does not call gains and losses; we leave those decisions to the user. For purposes of the simulation assessment, we needed to make these other types of calls. We devised a simple calling algorithm. Regions were called gains or losses based on a sample-specific global threshold. That threshold was an estimated total CN from PSCBS that was more than 0.25 SDs from the median estimated total CN across all SNPS. The SDs were estimated using the residuals between the observed total CNs and the estimated total CNs from the PSCBS segments. Regions were called CN-LOH if they were not called gained or lost and if the parent-specific estimates were unequal. More explanation for this calling of CN-LOH can be found in Section 4.

3.1.3 Assessment

Following Staaf et al. (2008), the sensitivity for each altered region was the fraction of SNPs that were called altered, and the specificity was the fraction of SNPs outside an altered region that were called altered. Overall, as shown in Figure 2, PSCBS was the most sensitive eight times, Paired BAF segmentation was the most sensitive eight times, Paired BAF segmentation was most sensitive once (loss in Region 8), and SOMATICs was the most sensitive once (CN-LOH in Region 10). The sensitivity of SOMATICs was compromised by its low specificity, as can be seen in Figure 3; it is the only method without nearly perfect specificity. PSCBS did relatively least well with the small regions of alteration. This is counter-intuitive because PSCBS, since it incorporates all data rather than just homozygotes like Paired BAF segmentation, should be particularly sensitive to small abnormalities. However, PSCBS is for the purpose of the assessment using a calling algorithm for gains and losses based solely on total

<table>
<thead>
<tr>
<th>Region type</th>
<th>Chrom.</th>
<th>Start</th>
<th>End</th>
<th># Loci</th>
<th># Het.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 CN-LOH</td>
<td>5</td>
<td>1</td>
<td>4770000</td>
<td>9397</td>
<td>2756</td>
</tr>
<tr>
<td>2 Loss</td>
<td>5</td>
<td>111789971</td>
<td>112521346</td>
<td>156</td>
<td>79</td>
</tr>
<tr>
<td>3 Gain</td>
<td>8</td>
<td>1</td>
<td>4520000</td>
<td>12664</td>
<td>3830</td>
</tr>
<tr>
<td>4 Gain</td>
<td>8</td>
<td>128452670</td>
<td>129207869</td>
<td>218</td>
<td>91</td>
</tr>
<tr>
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<td>94825178</td>
<td>1988</td>
<td>648</td>
</tr>
<tr>
<td>7 Gain</td>
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<td>1</td>
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<td>27131</td>
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<tr>
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<tr>
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</tr>
</tbody>
</table>

Here ‘CN-LOH’ stands for copy-neutral loss of heterozygosity. This simulation was originally proposed by Staaf et al. (2008).

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Fig. 2. Sensitivities for PSCBS and five other methods (Unpaired BAF, Paired BAF, QuantiSNP, PennCNV and SOMATICs) as a function of percentage normal contamination for 10 chromosomal aberrations. The performances were quantified using the Staaf et al. (2008) simulated dataset, in which copy-neutral LOH, single-copy gain, single-copy loss (hemizygous loss) and single-copy gain (including whole-chromosome trisomy) have been added to the HapMap sample NA06991 by adjusting the CN mean levels, cf. Table 1. The PSCBS results have been added to those obtained by Staaf et al. (2008).

Fig. 3. Specificities for PSCBS and five other methods (Unpaired BAF, Paired BAF, QuantiSNP, PennCNV and SOMATICs) as a function of normal contamination. The same simulated dataset and annotations as in Figure 2 are used. In this simulation, alterations are more strongly reflected in the allele B fraction than in the total CN, so it does not highlight one of the advantages of PSCBS. Overall, PSCBS compares favorably with other methods. Results for sensitivity can be found in Supplementary Table S1.

3.2 Glioblastoma data results
We examined the performance of the PSCBS algorithm on glioblastoma data from the Cancer Genome Atlas (TCGA). TCGA is a comprehensive effort to improve the understanding of cancer through application of genomic analysis (The Cancer Genome Atlas (TGCA) research Network, 2008). We evaluated the first batch of glioblastoma samples that were part of the TCGA for which there were 23 tumor/normal pairs. We analyzed data from both the Affymetrix GenomeWideSNP_6 array and the Illumina HumanHap550 array. These arrays contained approximately 900k CN. In this simulation, alterations are more strongly reflected in the allele B fraction than in the total CN, so it does not highlight one of the advantages of PSCBS. Overall, PSCBS compares favorably with other methods. Results for sensitivity can be found in Supplementary Table S1.
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Fig. 4. Whole-genome (chromosomes 1-22) PSCBS analysis of TCGA sample TCGA-02-0007. The top is from hybridization to the Affymetrix GenomeWideSNP_6 chip type (1,759,189 loci and 871,166 SNPs of which 234,058 are heterozygous in this sample) and the bottom is from hybridization to the Illumina HumanHap550 chip type (561,466 SNPs of which 175,585 are heterozygous). The black points represent total CN for all loci, and the gray points represent minimum CN for SNPs called heterozygous. The upper (purple) lines are PSCBS estimates of total CN, and the lower (blue) lines are the same for minor CN. Regions called LOH and allelic balance are highlighted at the horizontal axis as black and gray lines, respectively. The Affymetrix and the Illumina technologies show great similarity in their global segmentation patterns, such as finding all the same large regions of LOH.

We also did not call regions with fewer than 10 heterozygotes. We focused here on sample TCGA-02-0007 because it had an interesting pattern of alteration. For this particular sample, the methods for choosing the thresholds for calling segments suggest $\Delta_{AB} = 0.12$ and $\Delta_{LOH} = 0.60$ for the Affymetrix data, and $\Delta_{AB} = 0.077$ and $\Delta_{LOH} = 0.59$ for the Illumina data.

Segmentation results can be found in Figure 4 and in Supplementary Table S2. Large regions of LOH were found on both platforms for chromosomes 6, 7, 10, 11, 13, 14, 19 and 22. Large regions of gain were found on both for chromosomes 7 and 9. While we do not know the true CNs, it is encouraging that PSCBS when applied to both technologies gave similar results, which is consistent with previous studies comparing replicated CN data originating from different sources (Bengtsson et al., 2009b). Figure 5 has a closer look at chromosomes 7, 11 and 19 from the Affymetrix array. In addition to the alterations already mentioned, CN-LOH was found on chromosome 7q. All of 7p and part of 7q near the centromere showed gain in both parental chromosomes.

We show the segmentation of a second sample in Supplementary Figure S2. Note that, as shown in Figure 4, the analysis of the Affymetrix data was more complicated than that of the Illumina data because of the greater variability in the minimum CN. PSCBS, however, worked similarly for either type of data. Finally, to further assert that PSCBS produces valid results, we applied Paired BAF segmentation (Staaf et al., 2008) to the same sample and confirmed that the two methods agree on the major aberrant regions (Supplementary Table S3).

4 DISCUSSION

We developed an extension of CBS to estimate parent-specific CN from SNP data. In a simulation it identified gains and losses accurately and performed favorably compared with some of its competitors. A matched Affymetrix and Illumina real data example showed consistent and visually appealing segmentation results. PSCBS consists of a concatenation of several tests and estimates. In an ideal world we would compute an exact probability that it estimates allele-specific CN correctly. Anyone who sees explicit computation as a target will conclude that at any step of the process, an accurate calculation would be conditional on the outcomes of all previous steps. Such a computation is impossible, no matter the order in which it is attempted. Despite our inability to provide a precise probability, we trust that readers will agree that there are persuasive arguments for use of the algorithm. They include demonstration that it is successful in achieving goals for which it is intended.

As mentioned in Section 3.1, regions in the simulation were called CN-LOH if they were not called gained or lost and the parent-specific estimates were unequal. The first should be uncontroversial,
but the second needs explanation. The simulation consisted of a mixture of tumor and normal cells. In a typical analysis, if there was a high degree of normal contamination, we would not want to call the region LOH. However, if the CN was normal but the parental CNs were imbalanced, we would conclude that there is some degree of LOH. So here we are equating copy-neutral LOH to some degree of copy-neutral LOH. Alternatively, we could have adjusted $\Delta_{\text{LOH}}$ to get the same results, but this seems artificial.

An aspect of our algorithm is that it does not identify CN alterations that are already in the germline. For example, if there was a region with uniparental disomy (Robinson, 2000), where a subject inherits two copies from one parent, Paired PSCBS would not find it because there would be no difference between the tumor and the normal. While some may consider this to be a flaw, we believe it is a feature. Our purpose is to identify changes that come about during tumorigenesis and tumor evolution. A later analysis could be undertaken to find germline abnormalities.

Furthermore, it is important to acknowledge that PSCBS does not generate calibrated PSCNs, which is illustrated by the fact that although Affymetrix and Illumina agree to a great extent on the change-point locations, they differ somewhat in the estimated CN levels (Fig. 4). This means, for instance, that it is not valid to infer the estimated PSCNs as true integer CN levels. This further stresses the importance of PSCN calibration, which is, to the best of our knowledge, still not investigated well enough; it is an important task from which all PSCN methods would gain and which we plan to undertake in a future study.

Contrary to popular belief, we wish to emphasize that for modern Affymetrix arrays, we can hereby produce high-quality PSCN segmentation from a single pair of tumor–normal samples without the need of external references; this brings many advantages (Bengtsson et al., 2010). The reason for this is that the CRMAv2 is a truly single-array method for estimating locus-level TCN and DH signals, and both TumorBoost as well as Paired PSCBS require only a single tumor–normal pair.

On the other hand, the Paired PSCBS algorithm does indeed require paired data. The germline reference sample is used to identify heterozygotes and to improve allele B fraction estimates (Bengtsson et al., 2010). While the latter is a luxury, the former is crucial, even if the genotypes are estimated using an external method. Thus, without germline genotypes it is not possible to perform DH segmentation. In Staaf et al. (2008), a heuristic is proposed for inferring which are the heterozygous SNPs based on the allele B fractions of the tumor. This is doable in segments where the homozygous and heterozygous BAFs are well separated, which may be the case when the DH level is not too large and the noise level of the BAFs is low. In case of pure LOH this would not work, although, as noted by several (Bengtsson et al., 2010; Staaf et al., 2008), normal contamination would to some extent play in our favor. Regardless, this heuristic would break down eventually, and there would be no possibility to distinguish homozygous and heterozygous SNPs from tumor alone. Instead, we are developing an alternative strategy for segmenting the allelic ratios in the setup of unpaired data, which will be the subject of a future publication.

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