Hybrid correction of highly noisy long reads using a variable-order de Bruijn graph

SUPPLEMENTARY MATERIAL

Pierre Morisse¹, Thierry Lecroq¹ and Arnaud Lefebvre¹ ¹Normandie Univ, UNIROUEN, LITIS, 76000 Rouen, France

Input : s string, k integer, b boolean, K integer Output : E, the edges of the node representing the k-mer s in the de Brujin graph of order k. If b = 0, the graph is traversed forward, otherwise, it is traversed backward. Auxiliary: occs (integer, integer) set, i integer, id integer, pos integer 1 begin $E \leftarrow \emptyset$ $\mathbf{2}$ $occs \leftarrow \emptyset$ 3 if b = 0 then 4 $occs \leftarrow qetOccurrencesPositions(s[1..k-1])$ 5 else 6 $occs \leftarrow getOccurrencesPositions(s[0..k-2])$ 7 $i \leftarrow 0$ 8 while i < size(occs) and size(E) < 4 do 9 $(id, pos) \leftarrow occs[i]$ $\mathbf{10}$ if b = 0 and $pos + k \le K$ then 11 $E \leftarrow E \cup \{(s, \text{getKmer}(id)[pos..pos + k - 1])\}$ 12else if b = 1 and pos > 0 then $\mathbf{13}$ $E \leftarrow E \cup \{(s, \text{getKmer}(id)[pos - 1..pos + k - 2])\}$ $\mathbf{14}$ $i \leftarrow i + 1$ $\mathbf{15}$ return : E

Algorithm S1: Retrieve the edges of a given node. getOccurrencesPositions and getKmer are PgSA functions that allow respectively to retrieve the occurrences positions of the given string in the set of K-mers, and to retrieve the sequence corresponding to the K-mer of identifier *id*. Line 2: Start with an empty set of edges. Lines 3-7: If traversing the graph forward, get the occurrences positions of the suffix of s in the set of Kmers, if traversing it backward, get the occurrences positions of its prefix. Lines 8-15: Process the list of occurrences positions. The processing stops when all the occurrences have been processed or when 4 edges have been found, as we work with the DNA alphabet and cannot find more than 4 edges per node. Lines 11-12: If traversing forward and if the position component does not represent the suffix of length k-1 of the K- mer of identifier id, add an edge to the k-mer starting at position pos in this Kmer. Lines 13-14: If traversing backward and if the position component does not represent the prefix of length k-1 of the K-mer of identifier *id*, add an edge to the k-mer starting at position pos - 1 in this K-mer.

```
: S (string, integer, integer, integer, string) array,
   Input
                   minOverlap integer
   Output : The set of seeds, after merging overlapping seeds
   Auxiliary: i integer, j integer, s1 string, s2 string, suffLen integer,
                   suffSeq string, suffScore integer
1 begin
        sortByPosition(S)
 \mathbf{2}
        i \leftarrow 0
 3
        i \leftarrow 1
 4
        while i < size(S) - 1 and j < size(S) do
 \mathbf{5}
            if S[j].pos \leq S[i].pos + S[i].len then
 6
                 s1 \leftarrow S[i].seq[S[j].pos - S[i].pos..S[i].len - 1]
 \mathbf{7}
                 s2 \leftarrow S[j].seq[0..len(s1) - 1]
 8
                if S[j].pos + S[j].len > S[i].pos + S[i].len and
 9
                  length(s1) \ge minOverlap and s1 = s2 then
                     suffLen \leftarrow S[j].pos + S[j].len - S[i].pos - S[i].len
\mathbf{10}
                     suffSeq \leftarrow S[j].seq[S[j].len-suffLen..S[j].len-1]
11
                     suffScore \leftarrow (S[j].score/S[j].len) \times suffLen
\mathbf{12}
                     S[i].seq \leftarrow S[i].seq + suffSeq
\mathbf{13}
                     S[i].len \leftarrow S[i].len + suffLen
\mathbf{14}
                     S[i].score \leftarrow S[i].score + suffScore
15
                     delete(S[j])
16
                else if S[i].score < S[j].score then
17
                     delete(S[j])
\mathbf{18}
                 else
19
                    delete(S[i])
\mathbf{20}
            else
\mathbf{21}
                i \leftarrow j
\mathbf{22}
                j \leftarrow j + 1
\mathbf{23}
```

Algorithm S2: Merge seeds with overlapping alignment positions.

```
Input
                 : S (string, integer, integer, integer, string) array,
                   maxDistance integer, minOverlap integer
   Output : The set of seeds, after merging overlapping seeds
   Auxiliary: i integer, j integer, overlap integer, suffLen integer
1 begin
 \mathbf{2}
        sortByPosition(S)
        i \leftarrow 0
 3
       j \leftarrow 1
 \mathbf{4}
        while i < size(S) - 1 and j < size(S) do
 \mathbf{5}
            if S[i].pos - S[i].pos - S[i].len < maxDistance then
 6
                 overlap \leftarrow overlapLength(S[i].seq, S[j].seq)
 7
                if overlap \geq minOverlap then
 8
                     suffLen \leftarrow S[j].len - overlap
 9
                     suffSeq S[j].seq[overlap..S[j].len - 1]
\mathbf{10}
                     suffScore \leftarrow (S[j].score/S[j].len) \times suffLen
11
                     S[i].seq \leftarrow S[i].seq + suffSeq
12
                     S[i].len \leftarrow S[i].len + suffLen
13
                     S[i].score \leftarrow S[i].score + suffScore
\mathbf{14}
                     delete(S[j])
\mathbf{15}
                 else
16
                     i \leftarrow j
17
                    j \leftarrow j + 1
\mathbf{18}
            else
19
                i \leftarrow j
\mathbf{20}
               j \leftarrow j + 1
\mathbf{21}
```

Algorithm S3: Merge consecutive seeds with close alignment positions that overlap.

Description of Algorithm S2

Line 2: Sort the seeds in ascending order of their alignment start position. Lines 3-4: Begin with the two first seeds. Line 5-23: Keep processing while some seeds remain. Line 6-20: The seeds have overlapping alignment positions, attempt to merge them. Lines 7-8: Retrieve the overlapping sequences from the seeds that should coincide. Line 9-16: If the j^{th} seed can extend the i^{th} seed, if the seeds overlap over a sufficient length and if their overlapping sequences do coincide, merge the seeds. Line 10-12: Get the length, sequence and score of the non-overlapping suffix of the j^{th} seed. We define the suffix score as the average score of a base times the length of suffix. Lines 13-15: Actually merge the seeds. Append the non-overlapping sequence of the j^{th} seed to the sequence of the i^{th} seed, and update the alignment length and score of the i^{th} seed accordingly. Line 16: The i^{th} and j^{th} seeds have been merged, remove the j^{th} seed from the array. Lines 17-20: The seeds cannot be merged, only keep the one with the best alignment score. Lines 21-23: The seeds do not have overlapping alignment positions, move on to the next ones.

Description of Algorithm S3

Line 2: Sort the seeds in ascending order of their alignment start position. Lines 3-4: Begin with the two first seeds. Line 5-21: Keep processing while some seeds remain. Line 6-18: The seeds have close alignment positions, attempt to merge them. Line 7: Compute then length of the prefix-suffix overlap between the seeds. Lines 8-15: The overlap between the seeds is long enough, merge them. Line 9-11: Get the length, sequence and score of the non-overlapping suffix of the j^{th} seed. Again, we define the suffix score as the average score of a base times the length of suffix. Lines 12-14: Actually merge the seeds. Append the non-overlapping sequence of the j^{th} seed to the sequence of the i^{th} seed, and update the alignment length and score of the i^{th} seed accordingly. Line 15: The i^{th} and j^{th} seeds have been merged, remove the j^{th} seed from the array. Lines 16-18: The overlap between the seeds is too short, and the seeds cannot be merged. Move on to the next seeds. Lines 19-21: The seeds do not have close alignment positions, move on to the next ones.



Figure S1: Illustration of the process of skipping a seed. Hatched lines represent the long read and segments represent the seeds. Top: No path allowing to link *source* and *target* together has been found. *target* is thus considered as erroneous and is ignored. Bottom: *target* is redefined as $seed_k$, whereas *source* remains unchanged. A new linking iteration is then performed between these two seeds.

Dataset	A. baylyi	E. coli	S. cerevisiae	C. elegans	
Reference organis	sm				
Strain	ADP1	K-12 substr. MG1655	W303	Bristol N2	
Reference sequence	CR543861	NC_000913	$scf718000000{084-13}$	GCA_000002985.3	
Genome size	3.6 Mbp	4.6 Mbp	12.2 Mbp	$100 { m Mbp}$	
Simulated Pacific	Biosciences dat	a			
Number of reads	8,765	11,306	30,132	_	
Average length	8,202	8,226	8,204	_	
Number of bases	$72 \mathrm{Mbp}$	93 Mbp	247 Mbp	_	
Coverage	20x	20x	20x	_	
Real Oxford Nan	opore data				
Accession number	ERR77685{1-5}	$Genoscope^2$	$Genoscope^3$	FDD18020614	
	$Genoscope^1$	Sequences from Loman Lab	Sequences from Schatz Lab	ERR1002001	
Number of reads	89,011	22,270	205,923	363,500	
Average length	4,284	5,999	5,698	5,524	
Number of bases	381 Mbp	134 Mbp	1,173 Mbp	2,008 Mbp	
Coverage	106x	29x	95x	20x	
Illumina data					
Accession number	FDD7880124	$Genoscope^5$	$Genoscope^{6}$	A DT	
Accession number	ERR/00915	Sequences from Loman Lab	Sequences from Schatz Lab	AnI	
Number of reads	900,000	775,500	2,500,000	20,057,100	
Read length	250	300	250	250	
Number of bases	224 Mbp	232 Mbp	625 Mbp	$5,000 { m Mbp}$	
Coverage	50x	50x	50x	50x	

Table S1: Description of the data used in the experiments.

 $^{1}\rm http://www.genoscope.cns.fr/externe/nas/datasets/MinION/acineto/, reads from run6.$

 $^{2} http://www.genoscope.cns.fr/externe/nas/datasets/MinION/ecoli/$

 $^{3}\rm http://www.genoscope.cns.fr/externe/nas/datasets/MinION/yeast/ <math display="inline">^{4}\rm Only$ a subset of the data was used.

 $^{5} http://www.genoscope.cns.fr/externe/nas/datasets/Illumina/ecoli/$

 $^{6} http://www.genoscope.cns.fr/externe/nas/datasets/Illumina/yeast/$

LoRMA		41.1934	1.6	3.4136	23.6213	16.3801	60.59	20min
Daccord		8.1599	23.8	0.8551	4.9015	3.5049	1.30	1h15min
Canu		15.3633	21.9	2.1142	10.3363	4.1568	0	30min
NaS		8.9441	17.8	0.8403	5.5993	3.7016	0	217h20min
Nanocorr		8.3165	23.6	0.8595	4.9694	3.5894	0	39h52min
LoRDEC		10.5821	23.2	1.0236	6.1702	4.6795	68.53	28min
Jabba		8.3748	20.1	0.8094	4.8851	3.7767	13.66	5min
HG-CoLoR		8.1013	23.4	0.8130	4.7537	3.6307	3.67	4h32min
HALC		8.3101	23.1	0.8479	4.811	3.7514	18.20	1h19min
CoLoRMap		8.2290	22.2	0.8258	4.7652	3.7327	13.31	4h42min
Original		66.6190	247.2	3.8998	13.990	57.9724	N/A	N/A
Method	S. cerevisiae	Error rate $(\%)$	Throughput (Mbp)	Deletions $(\%)$	Insertions $(\%)$	Substitutions $(\%)$	Split reads $(\%)$	Runtime

on the S. cerevisiae daset. The best result for each statistic is highlighted. These results are however Table S2: Statistics of the long reads after correction with the different methods, as reported by LRCStats, erroneous, as LRCStats reported an error rate of 66%, whereas parsing the files generated by SimLord reported an error rate of 18.6%, comparable to that of the other simulated datasets.

Method	Original	Nanocorr	CoLoRMap	LoRDEC	HALC	LoRMA
A. baylyi						
Number of reads	89,011	24,105	$17,\!380$	22,288	35,099	17,984
Split reads $(\%)$	N/A	0	43.63	45.08	13.70	89.38
Average length	4,284	7,205	3,883	3,449	4,498	229
Number of bases (Mbp)	381	174	141	175	190	76
Average identity (%)	70.09	91.95	99.32	99.80	96.62	99.58
Genome coverage $(\%)$	100	100	100	100	100	66.52
Runtime	N/A	22h28min	3h41min	16min	47h41min	29min
E. coli						
Number of reads	22,270	21,764	20,161	21,983	22,215	14,569
Split reads $(\%)$	N/A	0	19.28	26.60	7.97	84.78
Average length	5,999	5,899	4,475	4,135	8,409	165
Number of bases (Mbp)	134	128	115	125	131	18
Average identity (%)	79.46	95.80	99.30	99.83	99.36	99.61
Genome coverage (%)	100	100	100	100	100	25.07
Runtime	N/A	5h48min	2h01min	$13 \min$	2h14min	12min
S. cerevisiae	`					
Number of reads	205,923	66,953	39,088	59,075	89,860	14,856
Split reads $(\%)$	N/A	0	45.02	75.03	28.04	55.34
Average length	$5,\!698$	$3,\!455$	2,294	1,126	1,893	230
Number of bases (Mbp)	$1,\!173$	231	165	221	256	11
Average identity (%)	55.49	87.10	99.45	98.45	98.45	95.93
Genome coverage $(\%)$	99.90	99.59	99.09	98.87	99.13	3.80
Runtime	N/A	158h53min	10h44min	1h09min	2h56min	1h36min
C. elegans	`					
Number of reads	363,500	_	135,544	50,448	_	10,109
Split reads $(\%)$	N/A	_	$20,\!68$	62.99	_	66.87
Average length	5,524	_	2,273	1,322	_	270
Number of bases (Mbp)	2,008	_	419	222		10
Average identity (%)	71.07		98.11	96.63		97.76
Genome coverage (%)	99.99	_	96.37	85.20	_	1.71
Runtime	N/A		91h17min	1h01min	_	1h13min

Table S3: Statistics of the long reads, before and after correction by the different methods excluded from the main comparison.

Similarly to the experiments on simulated data, LoRMA also performed the worst on real data. Its throughput was the smallest among all the tools, the corrected reads it output displayed a size closer to that of short reads, and covered all the reference genomes very poorly. Nanocorr was the slowest among all the tools, behind NaS, except on the A. baylyi dataset, where HALC was the slowest. In addition, Nanocorr did not manage to produce corrected long reads of good quality. Indeed, the lowest error rate it managed to reach was still of more that 4%, on the *E. coli* dataset. On average, the error rate of the output long reads was comparable to, or even worse than what self-correction methods achieved. The long reads, however, covered the reference genomes very well. On the larger C. elegans dataset, Nanocorr was not run due to its large runtimes. On all the datasets but C. elegans, on which it failed to perform correction because of an internal error of LoRDEC, HALC produced the greatest number of corrected long reads. However, its throughput was not proportional to that number, as, despite correcting more long reads, it actually output less bases than HG-CoLoR, up to two times less on the S. cerevisiae dataset. Moreover, its runtimes were quite unpredictable, as it took near to two days to correct the A. baylyi dataset, and less than 3 hours to correct the S. cerevisiae dataset, despite the former being three times smaller than the latter. As observed during the experiments on simulated data, despite being fast, LoRDEC did once again split an important proportion of long reads, as high a 75% on the S. cerevisiae dataset. As a result, even though they aligned with a high identity, except on C. elegans to which LoRDEC did not scale, the long reads corrected with LoRDEC displayed the shortest average length among all the other long reads but those corrected with LoRMA, reaching less than 20% of the length of the original long reads on S. cerevisiae. Finally, CoLoRMap did also split a lot of long reads, and thus output corrected long reads of much shorter length that the original long reads. The throughput of CoLoRMap was also smaller than that of all the other methods, except for LoRDEC on the *C. elegans* dataset. Compared to HG-CoLoR, which has a bit shorter, but comparable runtimes, CoLoRMap performed worse on every studied statistic.

Method	Nanocorr	CoLoRMap	LoRDEC	HALC	LoRMA
A. baylyi					
Long reads coverage	48x	39x	49x	53x	21x
Number of contigs	1	2	1	1	7
NG50	$3,\!571,\!959$	$3,\!627,\!107$	$3,\!620,\!390$	$3,\!598,\!721$	_
Genome coverage $(\%)$	98.59	100	100	99.92	0.56
Identity (%)	99.98	99.99	99.99	99.98	97.81
E. coli					
Long reads coverage	28x	25x	27x	28x	4x
Number of contigs	13	1	1	2	1
NG50	$824,\!971$	$4,\!642,\!509$	$4,\!649,\!617$	$4,\!650,\!960$	_
Genome coverage $(\%)$	98.61	100	100	99.99	0.59
Identity (%)	99.98	99.99	99.98	99.97	97.96
S. cerevisiae					
Long reads coverage	19x	13x	18x	21x	1x
Number of contigs	111	89	398	108	1
NG50	$181,\!605$	$224,\!554$	14,761	$130,\!894$	_
Genome coverage $(\%)$	96.53	97.71	68.85	96.60	1.07
Identity (%)	99.81	99.94	99.86	99.89	96.33
C. elegans					
Long reads coverage	_	4x	2x	_	0x
Number of contigs	_	2,164	832	_	9
NG50	_	$16,\!610$	_	_	_
Genome coverage $(\%)$	_	63.54	15.71	_	0.15
Identity (%)	_	99.42	99.81	_	98.00

Table S4: Statistics of the assemblies generated from the long reads corrected with the different methods excluded from the main comparison.

In agreement with the results observed in Supplementary Table S3, the long reads corrected with LoRMA could not be assembled at all. The long reads corrected with Nanocorr, despite covering the reference genomes well, only assembled into a satisfying number of contigs for the A. baylyi dataset. The assembly results on the S. cerevisiae dataset were however comparable to those of the other methods. Moreover, for all the assemblies generated from long reads corrected with Nanocorr, a few regions of the reference genomes were not resolved, likely because of the relatively high error rate of the long reads. The long reads corrected with CoLoRMap, despite the small throughput of the tool, surprisingly assembled quite well. A single contig was obtained for *E. coli*, and two contigs, including one of the size of the actual reference genome, were obtained for A. baylyi. On the S. cerevisiae dataset, these corrected long reads assembled into a smaller number of contigs, covering the reference genome better than those corrected with NaS. The genome coverage was also slightly higher than that of the assembly obtained with long reads corrected with HG-CoLoR, but the number of contigs and NG50 size were less satisfying. However, on the C. elegans dataset, the obtained assembly was highly unsatisfying, because of the weak coverage of the corrected long reads, underlining the fact that the method does not scale to larger datasets. The long reads corrected with LoRDEC also assembled into a single contig for both the A. baylyi and the E. coli datasets, despite being highly split. However, on the two larger datasets, the obtained assemblies were composed of a lot of contigs, and failed to resolve large regions of the reference genomes. Indeed, close to a third of S. cerevisiae was not resolved, and only a bit more than 15% of *C. elegans* was covered by contigs. Finally, the long reads corrected with HALC assembled quite well for the first two datasets. A single contig was obtained for A. baylyi, and two contigs, including one of the size of the actual reference genome, were obtained for *E. coli*. On the S. cerevisiae dataset, the corrected long reads yielded an assembly comparable to Nanocorr in terms of number of contigs, and to NaS in terms of NG50 size.

Pre-processing	QuorUM	Karect
A. baylyi		
Number of reads	$16,\!618$	$16,\!618$
Split reads $(\%)$	4.90	4.86
Average length	10,260	10,260
Number of bases (Mbp)	179	179
Average identity $(\%)$	99.40	99.40
Genome coverage $(\%)$	99.82	99.80
E. coli		
Number of reads	$21,\!005$	21,006
Split reads $(\%)$	4.98	4.88
Average length	5,797	5,794
Number of bases (Mbp)	128	128
Average identity $(\%)$	99.81	99.81
Genome coverage $(\%)$	99.43	99.41
S. cerevisiae		
Number of reads	$33,\!484$	$33,\!250$
Split reads $(\%)$	11.47	10.55
Average length	$6,\!455$	$6,\!613$
Number of bases (Mbp)	243	244
Average identity $(\%)$	99.54	99.55
Genome coverage $(\%)$	93.32	93.19

Table S5: Comparison of the long reads corrected with Jabba, when correcting the short reads with QuorUM or with Karect.

Mathad	Original	HG-CoLoR	HG-CoLoR	
method	Offgillar	(125 bp SR)	(250-300 bp SR)	
A. baylyi				
Error rate	0.178534	0.000186	0.000310	
Throughput	71,891,604	64,640,676	64,608,112	
Deletions	2,797,255	6,464	$7,\!802$	
Insertions	$10,\!036,\!447$	$5,\!284$	11,511	
Substitutions	$516,\!638$	$2,\!155$	3,791	
Split reads $(\%)$	N/A	0	0.01	
Runtime	N/A	48min	$47 \mathrm{min}$	
E. coli				
Error rate	0.179267	0.000417	0.000596	
Throughput	$93,\!005,\!258$	$83,\!557,\!763$	83,447,846	
Deletions	$3,\!635,\!647$	$25,\!359$	$23,\!342$	
Insertions	$13,\!038,\!057$	$10,\!436$	28,927	
Substitutions	671,040	$4,\!479$	$5,\!223$	
Split reads $(\%)$	N/A	0.04	0.03	
Runtime	N/A	59min	45min	

Table S6: Statistics of the simulated long reads after correction by HG-CoLoR, with short reads of length 125 bp, as reported by LRCStats. The results on the *S. cerevisiae* dataset are omitted, as LRCStats reported erroneous results.

	0.1.1	HG-CoLoR	HG-CoLoR
Method	Original	(125 bp SR)	(250-300 bp SR)
A. baylyi			
Number of reads	89,011	$26,\!450$	25,278
Split reads $(\%)$	N/A	1.60	1.01
Average length	4,284	$11,\!143$	$11,\!157$
Number of bases (Mbp)	381	299	285
Average identity $(\%)$	70.09	99.90	99.75
Genome coverage $(\%)$	100	99.99	100
Runtime	N/A	1h44min	1h56min
E. coli			
Number of reads	$22,\!270$	$22,\!138$	$21,\!970$
Split reads $(\%)$	N/A	0.29	0.07
Average length	$5,\!999$	6,047	6,093
Number of bases (Mbp)	134	134	134
Average identity $(\%)$	79.46	99.94	99.84
Genome coverage $(\%)$	100	99.99	100
Runtime	N/A	1h15min	1h05min
S. cerevisiae			
Number of reads	$205,\!923$	$73,\!670$	72,228
Split reads $(\%)$	N/A	3.55	5.13
Average length	$5,\!698$	$7,\!484$	6,724
Number of bases (Mbp)	$1,\!173$	572	512
Average identity $(\%)$	55.49	99.50	99.10
Genome coverage $(\%)$	99.90	99.93	99.40
Runtime	N/A	8h50min	8h36min
C. elegans			
Number of reads	$363,\!500$	282,425	$278,\!614$
Split reads $(\%)$	N/A	8.42	8.85
Average length	5,524	5,324	$5,\!127$
Number of bases (Mbp)	2,008	1,641	$1,\!567$
Average identity $(\%)$	71.07	98.90	98.93
Genome coverage $(\%)$	99.99	99.98	99.95
Runtime	N/A	95h17min	80h34min

Table S7: Statistics of the real long reads, before and after correction by HG-CoLoR, with short reads of length 125 bp and of length 250-300 bp.

	HG-CoLoR	HG-CoLoR
Method	(125 bp SR)	(250-300 bp SR)
A. baylyi		
Long reads coverage	83x	79x
Number of contigs	2	1
NG50	$3,\!594,\!329$	$3,\!634,\!461$
Genome coverage $(\%)$	99.97	99.99
Identity (%)	99.98	99.94
E. coli		
Long reads coverage	29x	29x
Number of contigs	1	1
NG50	4,640,101	$4,\!659,\!731$
Genome coverage $(\%)$	99.99	100
Identity (%)	99.99	99.99
S. cerevisiae		
Long reads coverage	46x	41x
Number of contigs	47	67
NG50	$452,\!906$	$297,\!575$
Genome coverage $(\%)$	99.12	97.57
Identity $(\%)$	99.91	99.92
C. elegans		
Long reads coverage	16x	15x
Number of contigs	236	352
NG50	820,836	458,250
Genome coverage $(\%)$	98.95	98.41
Identity $(\%)$	99.86	99.86

Table S8: Statistics of the assemblies generated from the real long reads, after correction by HG-CoLoR, with short reads of length 125 bp and of length 250-300 bp. Reported identities stand for the 1-to-1 alignments.



Figure S2: Impact of the maximum order of the graph on the results, when fixing other parameters. To obtain fair comparisons, the minimum order of the graph was set to half of the maximum order for each experiment. Runtimes are reported for the execution of the whole correction pipeline. We acknowledge that a maximum order of 100 yields more split, and thus slightly shorter reads, that display a lower identity than a maximum order of 90. However, it allows the pipeline to run almost an hour faster, and thus provides a satisfying compromise. Compared to these two values, higher orders tend to display a higher identity, but correct less long reads, and thus output less bases, whereas lower orders tend to correct more long reads, that are however more split, and thus shorter, in addition to display larger runtimes.



Figure S3: Impact of the minimum order of the graph on the results, when fixing other parameters. Runtimes are reported for the execution of the seeds linking and tips extension steps only. The statistics of the number of corrected long reads are not shown, as all the minimum order values corrected the same number of long reads. Apart from genome coverage and average identity of the long reads, all the other statistics displayed a clear peak with a minimum order value of 40.



Figure S4: Impact of the maximum number of branches explorations on the results, when fixing other parameters. Runtimes are reported for the execution of the seeds linking and tips extension steps only. The statistics of the number of corrected long reads are not shown, as all the maximum number of branches explorations values corrected the same number of long reads.