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Background:

High-resolution, long-read sequencing technologies, such as PacBio HiFi and Oxford Nanopore (ONT) sequencing, have enabled the generation of long, accurate reads, which have revolutionized the field of genomics in the past few years [1].

Methods:

We used 455 (7.4%) HiFi reads and 13 (288C) ONT reads for de novo assembly. The assembly was performed using the PacBio HiFi and ONT (QAC), Bionano Genomics (BIO) and Oxford Nanopore (ON) technologies. The assembly was evaluated using the QUAST tool.

Results:

We successfully assembled a high-quality, long-read genome. The assembly was evaluated using the QUAST tool. The assembly was compared to the reference genome using the QUAST tool. The assembly was evaluated using the QUAST tool. The assembly was compared to the reference genome using the QUAST tool.

The high-resolution and long-read sequencing technologies enabled the generation of long, accurate reads, which have revolutionized the field of genomics in the past few years [1]. The high-resolution and long-read sequencing (TGS), Pacific Bioscience (PacBio) and Oxford Nanopore Technology (ONT) are real-time, long-read sequencing technologies, which can sequence the whole genome of a single cell [2].

Launched by PacBio's HiFi read, high-fidelity (HiFi) reads, obtained by PacBio's HiFi sequencing method, have a high accuracy (>99.9%). Unlike SGS and PacBio's HiFi reads, which are based on DNA sequencing, ONT's long-read sequencing identifies DNA base modifications by measuring the change in electrical current during DNA sequencing. The HiFi reads have a high accuracy and a high read length. The HiFi reads have a high accuracy and a high read length. The HiFi reads have a high accuracy and a high read length.

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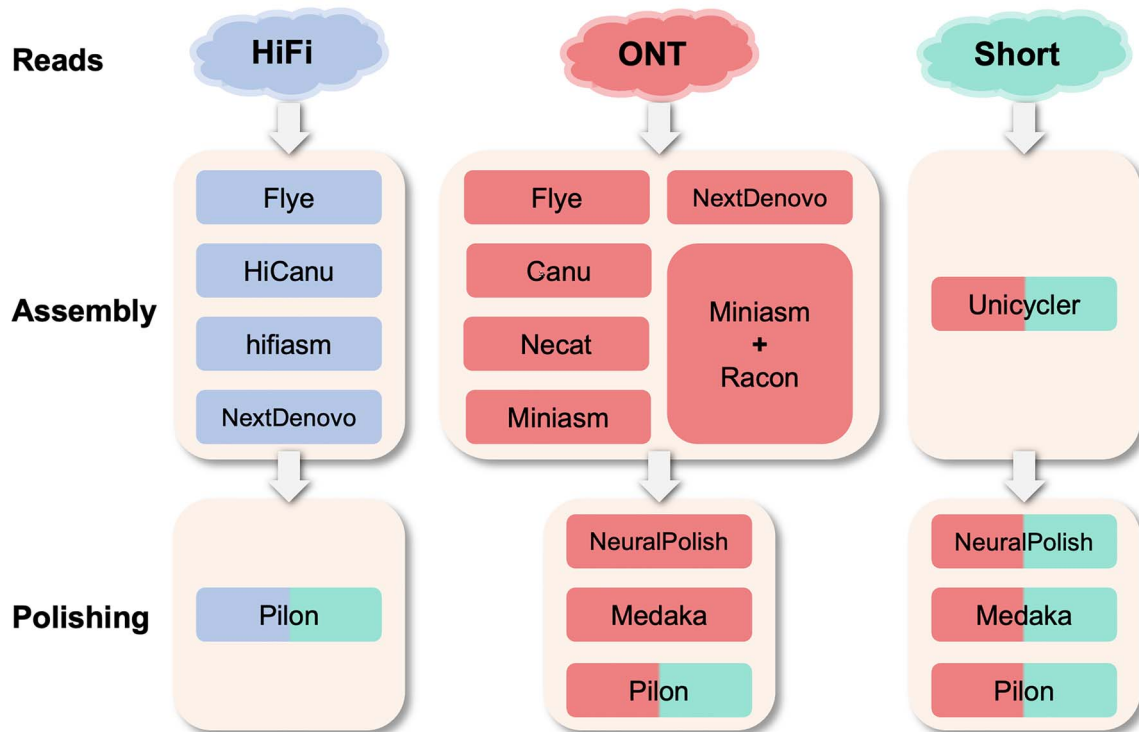


Figure 2. De novo assembly and polishing pipeline benchmarking. The data are listed in each pipeline in the legend: Blue, HiFi; Red, ONT; Green, short reads from BGISEQ.

The effectiveness of assembly, polishing, evaluation and annotation are provided in Supplemental file.

De novo assemblers showed significant differences in assembly quality on ONT datasets

We used the reference strain of *S. cerevisiae*, S288C, to compare the capabilities of the advanced assembly pipeline, Canu, Flye, Neca, Miniasm, MiniRacn, NeDen and Unicycler. The assembly pipeline showed significant difference in assembly quality. Genome accuracy especially the Indel > 100 kb is highly variable (Figure 2A). Unicycler has the most outstanding performance in Indel > 100 kb, which is a feature, followed by MiniRacn, Neca and Flye. In addition, Miniasm, Canu has the most Indel < 100 bp. The assembly quality of Miniasm, hifiasm, Flye and Neca is similar to MiniRacn, hifiasm and Neca are used to help MiniRacn and hifiasm to improve the accuracy in different read depth (Figure 2B). A few cases in Neca and NeDen showed that the assembly had a significant number of contigs that the chromosome number of the reference genome (16 chromosomes and 2 plasmids) and Flye has the best N50 (Figure 2C and D). According to the BUSCO (Figure 2E and Supplemental file S2, see Supplemental

file S2, available online at <https://academic.oup.com/bib>), Unicycler has the most complete gene number, followed by MiniRacn, Flye and Neca.

Canu has the least contig number, which is fewer contigs than the other assemblers. Canu is a de novo assembler that is designed to handle long reads (480X and 480X) (Figure 2). Unicycler is a hybrid assembler that can handle both long and short reads. Miniasm is a hybrid assembler that can handle both long and short reads. Unicycler does not include the basic core genes and contigs. BUSCO evaluation, which has 211 complete genes, is a standard for 0.1–0.5% (Supplemental file S2, see Supplemental file S2, available online at <https://academic.oup.com/bib>), which indicates the lack of core genes and contigs. This suggests that the influence of the assembler on the assembly quality is significant.

As the read depth of the reference genome is 10X–800X, the computing time is reduced by all assemblers (Figure 2F). Miniasm and NeDen consumed the least CPU time, followed by MiniRacn and Neca. Unicycler consumed the most main memory and took 1536 CPU hours in 800X reads, followed by Canu, while NeDen is a low-memory assembler and ended memory (Supplemental file S3, see Supplemental file S3, available online at <https://academic.oup.com/bib>).

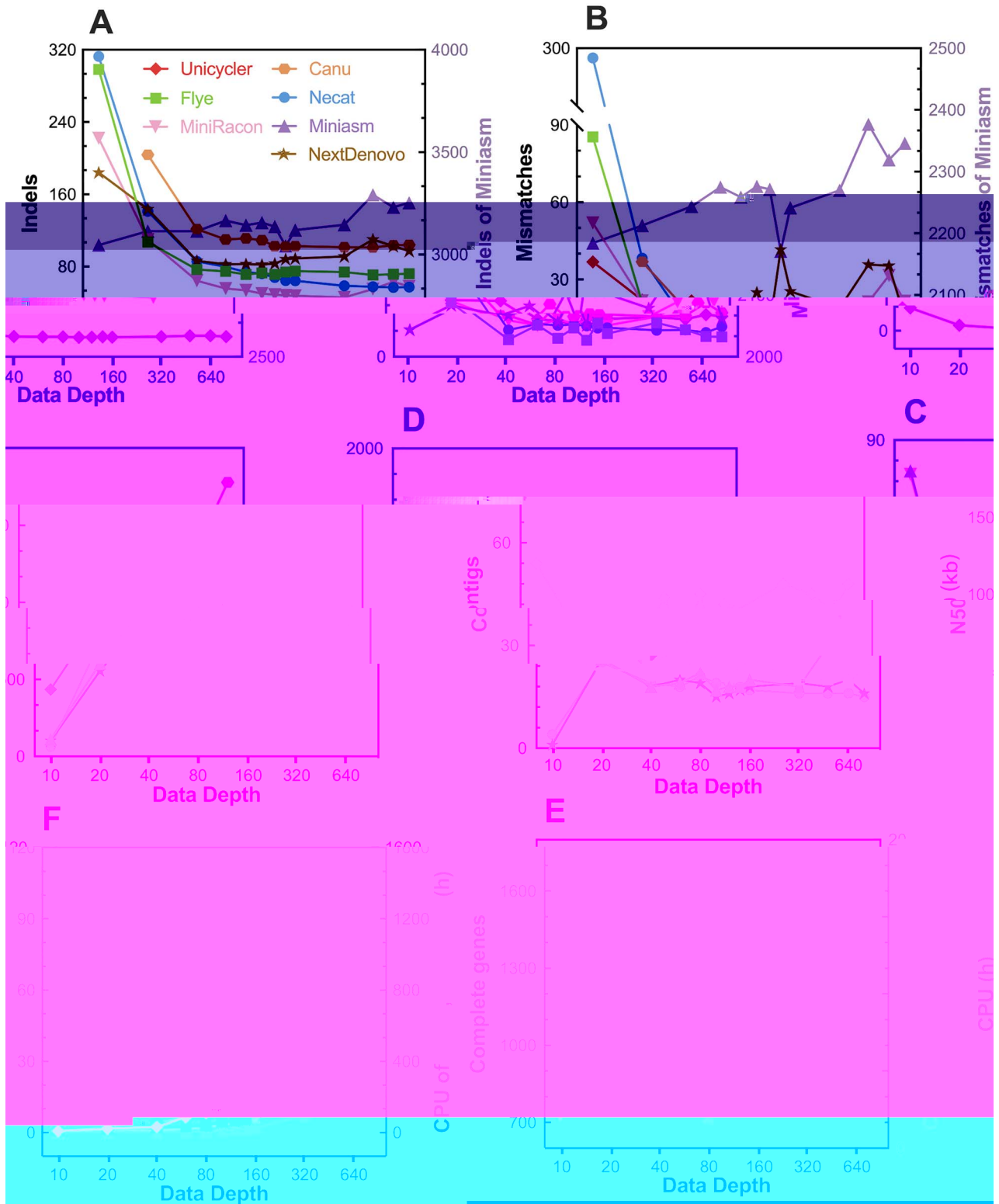


Figure 1. Main metrics for assembly on 13 ONT datasets with different data depths. Number of Indel (A) and Mismatches (B) in 100 kb, contig number (C), length of N50 (D), complete genes' number by BUSCO (E) and cumulative time for different assemblers (F).

C_score evaluation of assemblers

Here, we evaluate the performance of each assembler in terms of the number of indels, mismatches, contig number, N50, complete genes, and CPU time. For each metric, we calculate a score between 0 and 1, where 0 represents the best performance and 1 represents the worst. The scores are calculated as follows: $C_{indel} = \frac{Indel_{assembler} - Indel_{best}}{Indel_{worst} - Indel_{best}}$, $C_{mismatch} = \frac{Mismatch_{assembler} - Mismatch_{best}}{Mismatch_{worst} - Mismatch_{best}}$, $C_{cnfig} = \frac{Cnfig_{assembler} - Cnfig_{best}}{Cnfig_{worst} - Cnfig_{best}}$, $C_{N50} = \frac{N50_{assembler} - N50_{best}}{N50_{worst} - N50_{best}}$, $C_{complete_genes} = \frac{Complete_genes_{assembler} - Complete_genes_{best}}{Complete_genes_{worst} - Complete_genes_{best}}$, and $C_{CPU} = \frac{CPU_{assembler} - CPU_{best}}{CPU_{worst} - CPU_{best}}$.

length in kb and hence the number of complete genes is also a good metric to evaluate the performance of each assembler. For each metric, we calculate a score between [0, 1] by Min-Max normalization. A score of 0 indicates the best performance and a score of 1 indicates the worst. The overall C_score is calculated as the average of the scores for each metric. The C_score is calculated as follows: $C_score = \frac{C_{indel} + C_{mismatch} + C_{cnfig} + C_{N50} + C_{complete_genes} + C_{CPU}}{6}$.

Table 1. The mean metrics (M) and completeness (C_{score}) of different assemblers on ONT data.

	Contigs	N50 (kb)	Mismatches	Indels	Completeness	C _{score}
Fl e	25.0	942.4	16.3	93.1	1506.7	0.904
Neca	17.2	825.4	33.3	91.8	1419.2	0.824
Ne Den	17.2	798.2	22.3	101.8	1446.2	0.795
MiniRac n	26.5	788.1	19.7	70.9	1512.5	0.713
Can	35.8	834.9	18.4	114.4	1458.1	0.678
Unic cle	40.3	836.6	17.6	4.4	1697.6	0.677
Minia m	26.9	770.8	2265.1	3150.6	5.9	0.116

*E_{min} = 10⁻³, E_{max} = 10⁻¹, 13 ONT reads (M) = 10⁶, 800...

metric (M_i). The M_{min} and M_{max} mean the minimum and maximum of the metric. The M_{min} and M_{max} have been used.

$$M = \frac{M_{max} - M_{min}}{M_{max} + M_{min}} \quad (3)$$

For high-quality assembly, the metrics N50 and the number of contigs should be high and the metrics contig, mismatch, indel should be low and complete. The effective definition of C_{score} in E_{main} (4) by combining five SM, the efficiency of the assembly is reflected by the positive and negative numbers in the metric. Then, we calculate the C_{score} [0, 1] as Min-Max normalization and obtained the C_{score} in E_{main} (5), where the C_{score} and C_{score} mean the minimum and maximum of the metric of the C_{score}, which is -3 and 2, respectively.

$$C_{score} = \frac{M_{N50} + M_{C_{score}} - M_{C_{score}} - M_{M_{score}} - M_{I_{score}}}{M_{N50} + M_{C_{score}} - M_{C_{score}} - M_{M_{score}} - M_{I_{score}}} \quad (4)$$

$$C_{score} = \frac{C_{score} - (-3)}{2 - (-3)} \quad (5)$$

The metric mean of the 13 sub-items calculated the C_{score} of 7 assemblers (Table 1). Fl e has the best completeness performance, followed by Neca. Besides, Unic cle has the excellent accuracy performance and long CPU hours.

Influence of polishing process on assembly quality

For each obtained draft assembly of ONT reads, we obtained a polished assembly by using each of the five polishing pipelines (Neural Polish, Medaka, Pilon, Medaka_Pilon) and then analyzed its performance through QUAST (Selenen et al., 2015) (Selenen et al., 2015) (Data available online at <http://academic.ccm/bib>) and calculated the main metrics IR of each polishing process (Figure 3).

Medaka can reduce the contig number, average degree and Neural Polish can improve the N50 metric since the overlapping read improves the contig. Pilon has a better effect on the improvement of the contig because it is the head of the SGS for

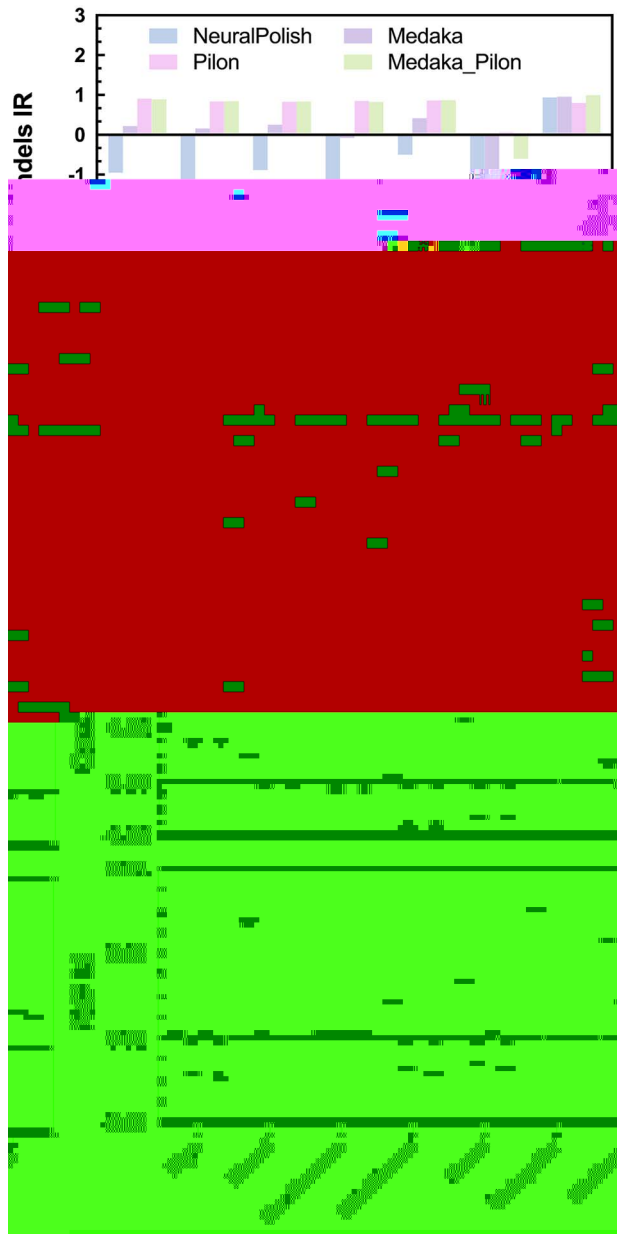


Figure 3. Metrics IR of assemblies after polishing.

fine polishing. However, in terms of accuracy, Pilon is the best polishing method for mismatch and indel among the five pipelines, followed by Medaka. Medaka can reduce the mismatch frequency, especially for Unic cle. After Unic cle's assembly and Medaka's polishing, we obtained the

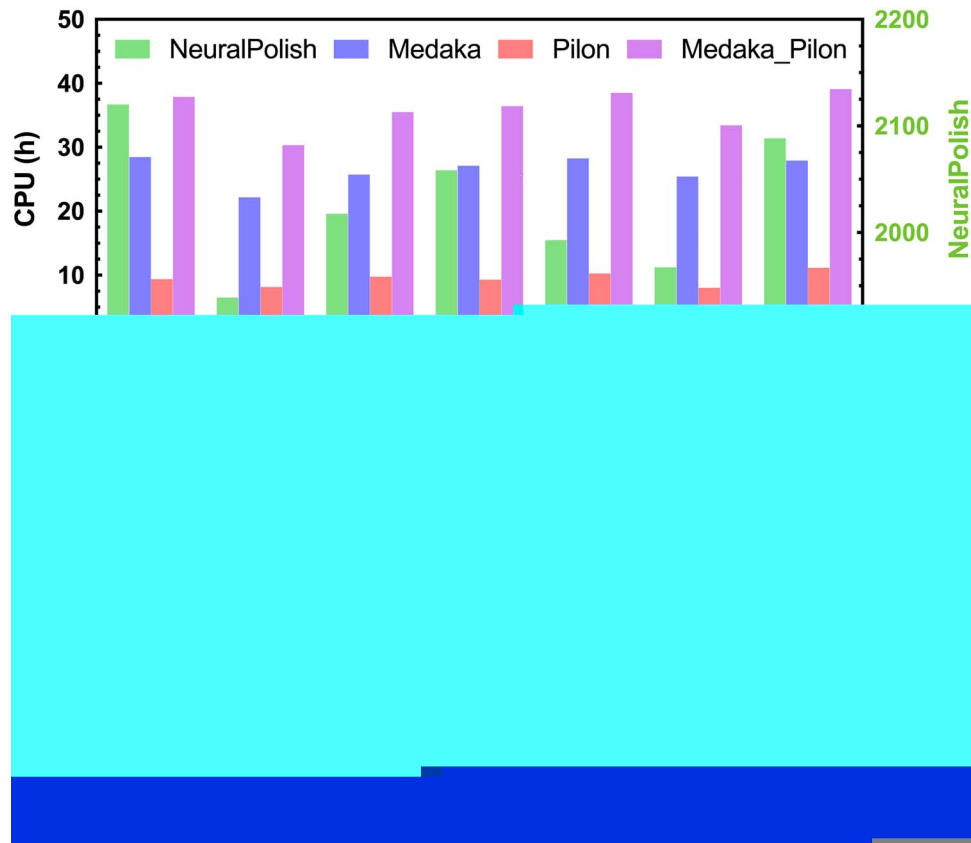


Figure 4. Comparison of CPU time for the different methods. The color of the bars indicates the method used for each sample.

leaving a small amount of time (See Supplemental Figure S4, <https://academic.oup.com/bib>). NeuralPolish had a better performance in accuracy. On the other hand, it can reduce the amount of time for Miniasm, and on the other hand, it can reduce the amount of time for Canu, which is the most expensive method. NeuralPolish had a better performance in accuracy (See Supplemental Figure S5, <https://academic.oup.com/bib>). It is expected that the combination of NeuralPolish, in addition to the other methods, will be a good choice for genome assembly.

The main result of this study is that the combination of Pilon and Medaka is the most effective for increasing the accuracy of the assembly, and Pilon is the most effective in reducing the amount of time for Miniasm. Combined with the other methods, the combination of Medaka_Pilon is the most effective in reducing the amount of time for Miniasm (Figure 3).

In terms of main performance, we calculated the amount of CPU time and memory used for 13 samples (Figure 4). Pilon took the least time and memory for all of the samples. Medaka took the most time and memory for all of the samples. However, the combination of Medaka and Pilon is the most effective in reducing the amount of time for Miniasm. The combination of Medaka_Pilon is the most effective in reducing the amount of time for Miniasm.

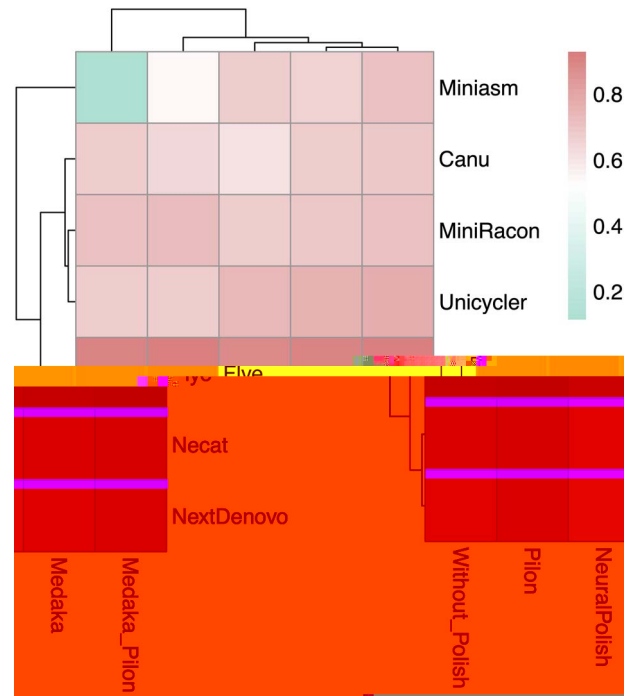


Figure 5. The correlation between different methods. The color of the heatmap indicates the correlation between the methods.

in the next section, we will discuss the results of the benchmarking. The combination of Medaka and Pilon is the most effective in reducing the amount of time for Miniasm (See Supplemental Figure S6, <https://academic.oup.com/bib>), which is about 160 CPU hours for each

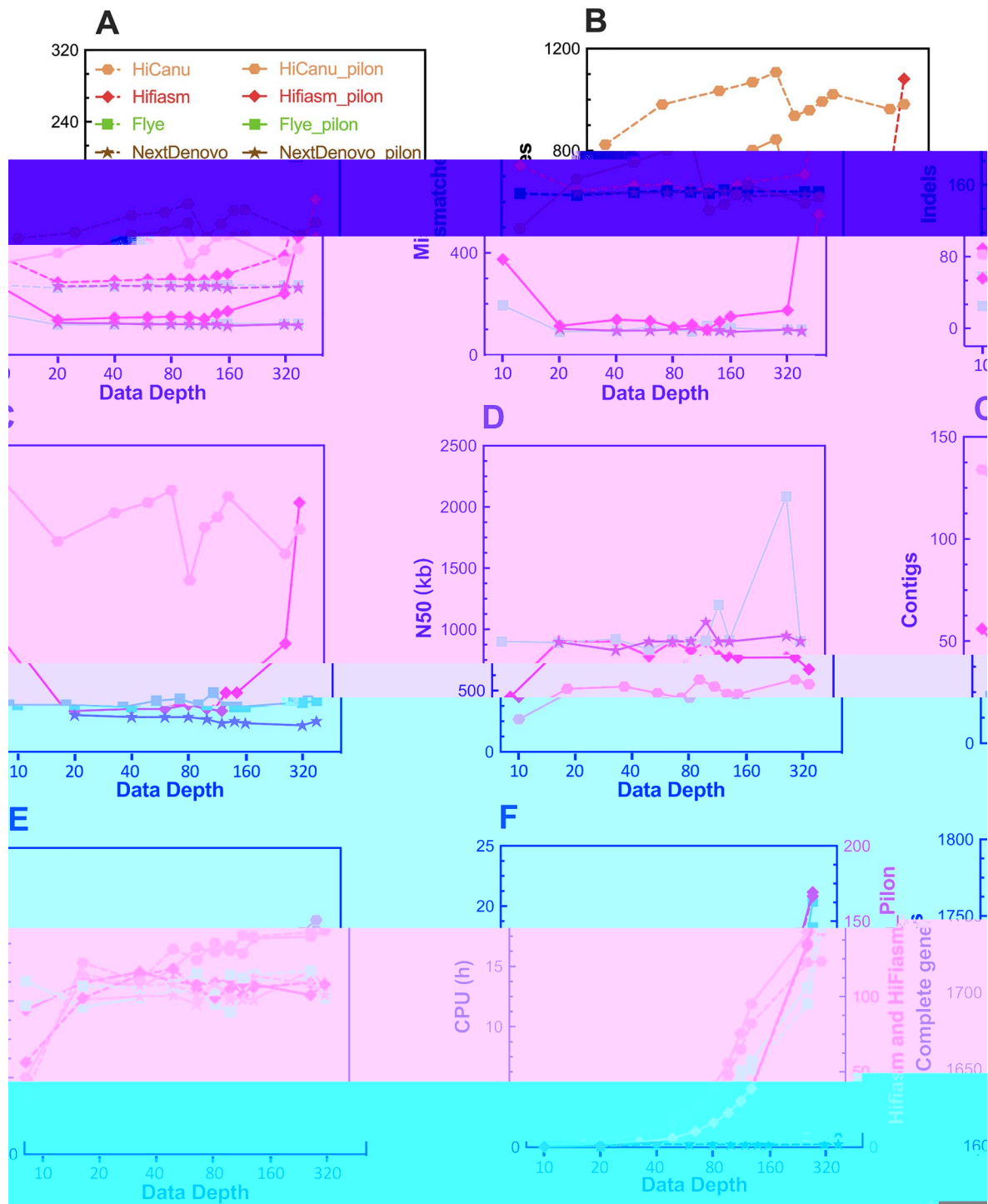


Figure 5. Performance evaluation of polishing pipelines. The figure shows the number of indels (A) and misassemblies (B) per 100 kb, contig number (C), length of N50 (D), complete gene number from BUSCO (E) and computational time (F).

assembly, in which the performance of the assembly is evaluated.

C_score evaluation of polishing pipelines after ONT dataset assembly

We also calculated the C_score for all pipelines for ONT data and displayed the heatmap in Figure 5. The results showed that the Medaka_Pilon pipeline

performed well in the assembly. Medaka has the best performance and is closely followed by the next best branch in the Medaka_pipeline, followed by the next best alternative. Pilon also has a good performance compared to Minimap. In terms of assembly, the pipeline using Pilon and HiFiasm performed better than the other pipelines. Finally, the pipeline using Pilon achieved the highest C_score

Table 2. The mean genomic alignment (M) and completeness (C_score) of different assemblers on HiFi datasets.

	Contigs	N50 (kb)	Mismatches	Indels	Completeness	C_score
Flye_Pilon	24.0	1034.4	108.8	15.5	1704.6	0.778
NeDen_Pilon	15.6	914.5	97.4	14.1	1705.0	0.760
hifiasm_Pilon	37.7	787.8	190.3	36.1	1709.6	0.649
Flye	24.0	1034.6	637.8	57.2	1711.3	0.647
NeDen	15.6	914.6	634.7	56.2	1709.0	0.602
hifiasm	37.7	787.9	707.6	77.4	1705.6	0.424
HiCanu_Pilon	113.1	495.3	659.4	101.9	1723.5	0.292
HiCanu	113.1	495.3	988.3	128.3	1726.6	0.200

*Eukaryote genome assembly benchmark, 11 HiFi datasets (M), 10,000, 380,000.

Table 3. Overall alignment of C_score > 0.9 between main assemblers on ONT and HiFi datasets.

Pipelines	Flye_Pilon_HiFi	ND_Pilon_HiFi	Flye_HiFi	Flye_Pilon_ONT	Flye_MP_ONT
C_score	0.971	0.942	0.922	0.921	0.919

*A. C. score > 0.9 between main assemblers on ONT and HiFi datasets. D: Datasets used for evaluation.

in the case of Pilon, Medaka_Pilon and Medaka. Minimap2 alignment of the reference genome for each dataset.

Evaluation of assemblers on HiFi datasets

We compared the assemblers designed for long reads. The overall performance of HiFi reads, HiCanu, hifiasm, Flye and NeDen (Figure 6). HiCanu showed significant difference in assembly quality. Assembly of HiCanu has the lowest quality in both contig and accuracy, in terms of N50 and the highest mismatch and indel rates, especially for 380. However, HiCanu is significantly more accurate in BUSCO evaluation and in terms of the number of complete genes (Figure 6E).

The overall performance of the assemblers on HiFi datasets is summarized in Table 2. The quality of the genome assembly of hifiasm decreased as the length (>300) of the contigs, mismatch and indel rates increased dramatically at 320 and 380.

The effectiveness of the assemblers on HiFi datasets is evaluated. Each assembler obtained from HiFi datasets is aligned to Pilon. Pilon coverage is significantly improved in accuracy and genome integrity of the assembly. The effectiveness of the assemblers in terms of accuracy and genome quality in terms of alignment to the ONT datasets is also evaluated for HiFi datasets.

C_score of the eight assemblers (flye, hifiasm, Pilon, NeDen, hifiasm, Flye, Pilon, NeDen) is shown in Table 2. The C_score of 0.778 and 0.760 (Table 2

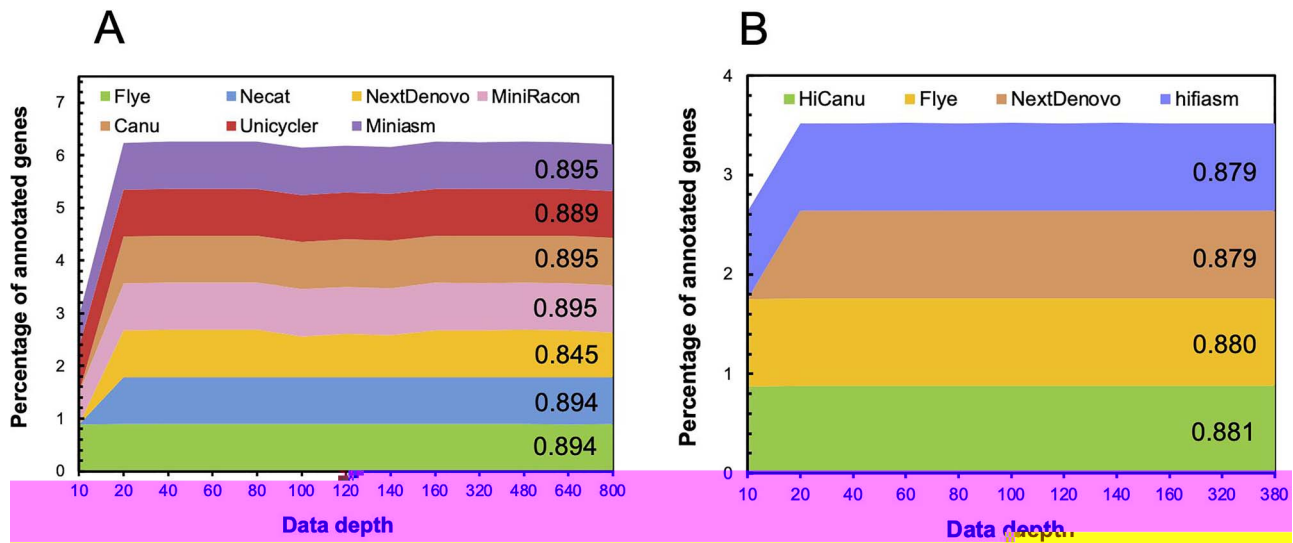


Figure 7. The percentage of annotated genes built by assemblers (A) and polishers (B) on ONT (A) and HiFi (B) data at a range of data depths. The percentage of annotated genes at 800X (A) and 380X (B).

The CPU time and memory usage of HiFi data are smaller than those of ONT data at the same depth (Figure 2F and 6F).

Notably, when the data depth is equal to 10X, Flye performs best in both HiFi and ONT data. However, the characteristics of different tools should be considered. For example, the error rate of hifiasm will increase if the data depth is less than 10X.

The effect of data depth on assemblers and polishers

The assembly quality is highly variable across different assemblers and polishers (10X, 20X, 40X in Figure 2 and 10X in Figure 6) and keeps relatively high-depth. Different methods have different characteristics in terms of data depth (Suleman et al., Figure S4, see Suleman et al., Data available online at <https://academic.oup.com/bib>). Notably, in this case, the best performance is achieved by the high coverage of the high-quality data. On the other hand, the best performance is achieved by the high-quality data. On the other hand, the high-quality data, the memory usage will be reduced, and the high-depth data may encounter the assembly problem. The effect is necessary to determine the quality of the data. In detail, the data at 20X can build more genes, but the high-quality data is necessary. For high-quality genes, the coverage of the data should be less than 80X for ONT (Figure 2) and 20X for HiFi data (Figure 6), but it is recommended to exceed 320X if assembled by Canu and Miniasm on ONT data.

Yeast genome annotation

The percentage of genes has been built by ONT and HiFi data in the Medaka_Pil and Pil in the high-quality data in Figure 7. For the full ONT and HiFi data, the genome built by the line can contain 87% genes. Flye has the best performance in terms of identifying genes and data depth is 10X. The percentage of the annotated genes in the assembly is high, such as Necat and Canu on ONT data and NextDenovo on HiFi data. The main reason for this is that the data depth is especially 10X.

The difference in the quality of genome annotation between different methods, especially the gene identification from the initial line at 320X. More than 5259 genes can be successfully identified by all methods and there are 79 and 6 genes that cannot be built by ONT and HiFi data, respectively (Suleman et al., Figure S9, see Suleman et al., Data available online at <https://academic.oup.com/bib>), which indicates that the high-quality data has an effect on genome annotation.

Case study

According to the main results, the initial line is selected, Flye_Pil and Flye_MP for ONT data and Flye_Pil and NextDenovo_Pil for HiFi data, build the draft genome for the industrial yeast strains of different genes, *S. pombe* FLO-DUT (SP) and *S. cerevisiae* CICC-1445 (SC). Although the accuracy of the assembly such as MiMaChe and Indel cannot be achieved since the reference is not available for the yeast, the results are compared with the metrics in SP and SC assemblies and demonstrated in Table 4 and 5.

Table 4. Summary of main *de novo* assembly methods for the *S. pombe* FLO-DUT (SP)

Assembly		SP			
		Flye_Pilon_ONT	Flye_MP_ONT	ND_Pilon_HiFi	Flye_Pilon_HiFi
Number of contigs		8	6	6	4
Largest contig (Mb)		5.554	5.555	5.624	5.595
Total length (Mb)		12.73	12.73	12.81	12.65
GC (%)		36.05	36.05	36.05	36.05
N50 (Mb)		4.495	4.495	4.555	4.554
BUSCO	Complete	811	797	804	801
	Fragmented	110	108	111	111

Table 5. Summary of main *de novo* assembly methods for the *S. cerevisiae* CICC-1445 (SC)

Assembly		SC			
		Flye_Pilon_ONT	Flye_MP_ONT	ND_Pilon_HiFi	Flye_Pilon_HiFi
Number of contigs		31	32	15	61
Largest contig (Mb)		1.475	1.479	2.417	0.978
Total length (Mb)		11.84	11.87	12.05	12.21
GC (%)		38.37	38.38	38.40	38.27
N50 (Mb)		0.811	0.818	0.946	0.580
BUSCO	Complete	1622	1613	1712	1683
	Fragmented	149	148	144	149

Both assemblies can build the high-contig genome with N50 above 4500 kb in SP and 800 kb in SC. Neither Pilon pipeline in HiFi data obtained genome with the highest N50 in both. And both HiFi pipeline have significant high completeness in SC assembly than HiFi pipeline.

The completeness of SC assembly BUSCO is more than HiFi SP, highlighting the difference in assembly quality between the difference annotation datasets. The completeness data of SC is almost equal to db10 (classical) while HiFi SP is almost equal to db10 (high-multiplex), highlighting the high accuracy of the specific gene.

For the evaluation of the sequencing strategy, the factors should be considered such as price, throughput and convenience. Unlike Flye, which can effectively measure the length of the mid-coverage in multiplexing, neither Denovo has the same number of reads as the high-depth data, suggesting that the error rate is relatively low.

Among all the assemblies, the Uniclust assembly has the best assembly and efficiency in contig quality and accuracy. On the other hand, the addition of the read coverage of the fragments in the assembly, while on the other hand, it will reduce the depth of the high-coverage in the read [26]

In this study, we performed 455 and 88 *de novo* assemblies of *S. cerevisiae* S288C using high-coverage ONT and HiFi data, respectively, to compare the influence of assembly method, library and sequencing depth on the accuracy of the genome. According to the C_census, the assembly based on Flye assembly method is better than ONT and HiFi data, and neither is the recommended choice for HiFi data. The library choice is not a major factor for assembly and Medaka_Pilon method is better than ONT data. In the case of accuracy, neither SP and SC, the genome based on HiFi data are more accurate and complete than HiFi ONT

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Key Points

C m ehen i e benchma king n he la e a embl and li hing l f ad anced TGS da a e (ONT and HiFi) f eka ic m del gani m.
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Fl ei hem b a emble n b h ONT and HiFi da a e and Ne Den al e f m andingl n HiFi da a e .
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The c m a i n in hi a e e e n n he π 2.0 cl e ed b he Cen e f High-Pe f mance C m ing a Shanghai Jia T ng Uni e i . We al hank he C e Facili and Se ice Cen e (CFSC) in Sch l f Life Science and Bi echn lg , SJTU f ain cl e and DNA am le e a a i n.

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