CpG Island Definition and Methylation Mapping of the T2T-YAO Genome

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Abstract

Precisely defining and mapping all cytosine positions and their clusters, known as CpG islands (CGIs), as well as their methylation status are pivotal for genome-wide epigenetic studies, especially when population-centric reference genomes are ready for timely application. Here we first align the two high-quality reference genomes, T2T-YAO and T2T-CHM13, from different ethnic backgrounds in a base-by-base fashion and compute their genome-wide density-defined and position-defined CGIs. Second, mapping some representative genome-wide methylation data from selected organs onto the two genomes, we find that there are about 4.7–5.8% sequence divergency of variable categories depending on quality cutoffs. Genes among the divergent sequences are mostly associated with neurological functions. Moreover, CGIs associated with the divergent sequences are significantly different with respect to CpG density and observed CpG/expected CpG (O/E) ratio between the two genomes. Finally, we find that the T2T-YAO genome not only has a greater CpG site coverage than that of the T2T-CHM13 genome when whole-genome bisulfite sequencing (WGBS) data from the European and American populations are mapped to each reference, but also show more hyper-methylated CpG sites as compared to the T2T-CHM13 genome. Our study suggests that future genome-wide epigenetic studies of the Chinese populations rely on both acquisition of high-quality methylation data and subsequent precision CGI mapping based on the Chinese T2T reference.

Keywords: T2T-YAO; Position-defined CpG island; Density-defined CpG Island; DNA methylation; Genome analysis

Introduction

Position-sensitive and co-methylated CpG islands (CGIs) represent one of the several key epigenetic mechanisms for chromosome integrity and gene expression regulation [1, 2]. To define highly variable CGIs based on both position and density genome-wide

and to map their methylation status under different physiological conditions and in different cell types are prerequisite in most epigenomic studies [3–7]. Human reference genomes, especially those tailored to specific populations, provide single-base-resolution coordinates for genome-wide genetic and epigenetic mapping with ultimate precision [8]. The release of the telomere-to-telomere CHM13 (T2T-CHM13) genome in 2022 has provided such a benchmark by filling-up sequence gaps that contribute nearly 8% increase of the previous human genome assembly [9]. Therefore, it is of essence to compare it to the more recent human genome assembly of the Chinese population, the T2T-YAO genome [10], and to annotate all CGIs for both assemblies. Here, we simply raise three basic questions. First, are there significant differences in CGIs and their methylation between the two reference genomes? And if so, what are the relevant genes and their functions diverged between them? Second, does the T2T-YAO genome provide additional information or serve more appropriately as one of the reference genomes for the Chinese population? Both are of importance for subsequent genome-wide epigenetic studies and building methylation databases specifically for the Chinese populations under complex physiological and pathological conditions. We, therefore, chose to accurately predict genome-wide CGIs for both reference genomes and validate their applications in methylation studies by testing them on a limited number of datasets due to data availability and quality.

A genome-wide comparison of two reference genomes has been done recently between the classical GRCH38 and T2T-CHM13 genomes and the authors discovered nearly 200 million base pairs (Mbp) unique to the T2T-CHM13 genome[9]. This result supports our effort in mapping the T2T-YAO and T2T-CHM13 genomes to explore their divergent sequences, and determining whether the divergent sequences are associated with specific biological functions became our first scientific question. We have described previously a genome-wide inclusive CGI definition, *i.e.*, a distance-based clustering method yielding short CpG cluster, known as position-defined CGIs show potential gene regulatory functions and are closely correlated with gene expression

specificity [2, 11, 12]. Therefore, whether there was any specificity between T2T-YAO

and T2T-CHM13 according to CGI features, became our second scientific question. It

becomes feasible now to carry out a comparative analysis on the T2T-YAO and T2T-

CHM13 genomes on CGI methylation profiles using public WGBS data [2, 8, 11, 12],

and this is what we address as the third scientific question.

To this end, we align the two genomes, compute both density-defined and position-

defined CGIs, separately, and map some genome-wide methylation WGBS data from

representative organs to analyze differentially methylated CGIs between the two

genomes. Our major findings are as follows: (1) There is an approximately 4.7–5.8%

difference between the two genomes, which is composed of divergent sequence-

associated genes correlated closely with neurological functions based on GO

enrichment analysis [13–18]. (2) CGIs associated with the divergent sequences are

significantly different with respect to CpG density and O/E ratio [11, 19]. (3) Not only

do WGBS data mapped to the T2T-YAO genome have a greater CpG site coverage than

those of the T2T-CHM13 genome, but also the T2T-YAO genome shows more hyper-

methylated CpG sites than T2T-CHM13 does. Our study demonstrates statistically

significant differences between T2T-YAO and T2T-CHM13 in genome sequence and

epigenetic landmarks[20–22], such as CGI and methylation patterns, suggesting that

the establishment of CGI and methylation profiles based on the Chinese T2T reference

genome is crucial for subsequent genome-wide epigenetic studies based on Chinese

populations.

Results

In order to address the three scientific questions (**Figure 1)**, we analyzed the two

genomic references, their CGI distribution, and genome-wide CGI-associated

methylation.

Comparative sequence analysis

To address our first question, we aligned the T2T-YAO-hp and T2T-CHM13

genomes and functionally categorized the divergently enriched genes from the T2T-

YAO-hp genome (*-hp* stands for the haploid sequence from the offspring of the triad

family T2T-YAO assemblies; T2T-YAO-hp and T2T-YAO used here are equivalent

unless otherwise specified).

Sequence differences between T2T-YAO-hp and T2T-CHM13

First, from the sequence alignment (the alignment results are detailed in

Supplementary **Table S1 and S2**), as shown in **Table 1**, the T2T-CHM13 genome has

approximately 54.6 Mbp more sequence as compared to the T2T-YAO-hp genome. The

uniquely divergent sequences account for 5.751% and 4.665% of the full length T2T-

CHM13 and T2T-YAO-hp genomes, respectively. Therefore, the difference between the

two genomes is approximately 4.7%–5.8%. Second, using NGenomeSyn [23], we

created a collinearity map of the two genomes and observed that the two sequences are

very similar both in identity and chromosome length (**Figure 2)** in general [24]. The

divergent sequences between the two genomes are mainly concentrated in specific

regions of each chromosome (Figure 2B). For instance, some of the divergent

sequences of chromosomes 15 and 22 are enriched at the their left telomeric ends,

whereas others, such as chromosome 9, have those located near the centromeres. The

examples of some longest diverge sequence segments include 3.31×10^7 bp *vs*. $1.69 \times$

10^7 bp of chromosome 9 and 2.15×10^7 bp *vs*. 1.31×10^7 bp of chromosome Y; both

are longer in the T2T-CHM13 genome (Figure 2C).

Divergent-sequence-associated genes

We categorized the divergent-sequence-associated genes of the two genomes

(**Figure 3A** and Supplementary **Table S3)** and show that most of them are protein-

coding genes, accounted for 44.26%, and the rest include lncRNAs that are 25.93% of

the total gene count. Our GO enrichment analysis for the protein-coding genes shows

that the most significant terms are "homophilic cell adhesion via plasma membrane

adhesion molecules", "ion channel complex", and "gated channel activity" in the

biological process (BP), cellular component (CC), and molecular function (MF)

categories [25], respectively, and that most of these GO terms are associated with

certain functions of the nervous system (**Figure 3B**).

CGI prediction and analysis

CGI prediction results

We employed the rule-based method [12, 19] and distance-based clustering

method [12, 19] to predict the number of CGIs and the average CGI length for the two

genomes (**Table 2** and Supplementary **Table S4)**, and show the distribution of CGIs on

each of the T2T-YAO-hp and T2T-CHM13 chromosomes (Supplementary **Figure S1**

compares). On one hand, the number of density-defined CGIs and the average length

predicted for the T2T-YAO-hp genome are slightly smaller (84,471 bp *vs.* 87,788 bp

and shorter (391 bp *vs.* 407 bp) than those of the T2T-CHM13 genome, respectively.

On the other, the number of position-defined CGIs predicted for the T2T-YAO-hp

genome is greater than those of the T2T-CHM13 genome under the default parameter

d=50 bp (222,421 bp *vs.* 220,736 bp). In addition, the CGI number predicted for the

T2T-YAO-hp genome is less than those of the T2T-CHM13 genome regardless if their

density-defined CGIs or position-defined CGIs, but the average length of the position-

defined CGIs predicted by the T2T-YAO-hp genome is collectively longer than those

of the T2T-CHM13 genome (*e.g.*, 60 bp *vs.* 58 bp with d = 25 bp) under the parameters

d = 25 bp and 12 bp. We also predicted all CGIs related to divergent sequences of the

two genomes (Supplementary **Table S5)**.

To study the relationship between position-defined CGIs and density-defined

CGIs for the same genome, we investigated sequences that intersect the two groups (for

the position-defined CGIs, d = 25 bp) for both genomes **(Figure 4)**. First, the total

length of density-defined CGIs is much longer, approximately three times that of

position-defined CGIs for each genome *(e.g.*, (24,991,625 + 8,062,542)/

(8,062,542 + 1,735,619) = 3.37 for the T2T-YAO-hp genome). Second, although

most of the position-defined CGIs overlap with the density-defined CGIs, there is still

a fraction (16.5% and 17.7%, respectively) that is not predicted by the rule-based CGI

predicting method.

CGI feature comparison

First, to compare the differences in CGIs between the two genomes, we calculated

four commonly used CGI features, *i.e.*, CGI length, GC content, CpG density, and CGI

O/E ratio [2, 26] (**Figure 5**) and show the feature distribution of genome-wide and

divergent-sequence-associated position-defined CGIs, including d = 12 bp, 50 bp

(Supplementary **Figure S2)**. Other than the grouping of density-defined or position-

defined CGIs, there is no obvious difference among the four commonly used CGI

features between the two genomes based on all CGI counts (Figure 5A–5D). For

example, in both genomes, the peak lengths of the density-defined CGIs and the

position-defined CGIs are approximately 210 bp and 30–50 bp, respectively (Figure

5A).

Second, there is a greater difference in the four commonly used CGI features of

the divergent sequence CGIs between the two genomes than those of all CGI counts

(Figure 5E–5H). For instance, the density-defined CGIs of the T2T-CHM13 genome

have two peaks in high GC content regions (from 50% to 60%), whereas the density-

defined CGIs of the T2T-YAO-hp genome have a single peak in the same regions. In

addition, the position-defined CGIs in the divergent sequences, except for a small

difference in the distribution of CGI lengths, have significantly different distributions

for GC content, O/E ratio, and CpG density (Figure 5E–5H, Supplementary **Figure S2**,

and Supplementary **Table S6**).

Third, for all CGIs or divergent-sequence-associated CGIs, the distance-based

clustering method is more likely to identify CGIs with shorter lengths and greater GC

content, O/E ratio, and CpG density than the rule-based CGI predicting method (Figure

5).

Methylation analysis and comparison

194   To address our third question, we compared not only the number of cytosine sites

195 (C sites, Supplementary **Figure S3**) and methylation levels of all CpG sites, but also

196 methylation levels of genome-wide CGIs for the two genomes.

197 *CpG methylation levels*

198   We classified CpG methylation levels of similar (Supplementary **Figure S4**) and

199 divergent sequences between the two genomes (**Figure 6**). In addition, based on the

200 WGBS data of two germline tissues, the ovary and testis, we also determined

201 methylation profiles of whole genomes and divergent sequences for the two genomes

202 (Supplementary **Figure S5**). The number of CpG sites of the divergent sequences failed

203 to be mapped based on the same WGBS methylation data is much lower in the T2T-

204 YAO-hp genome than in the T2T-CHM13 genome in both germline tissues. For

205 example, the number of CpG sites in the divergent sequences of the ovary failed to be

206 mapped to T2T-YAO-hp is 2.16×10^6 bp, whereas that in the T2T-CHM13 genome is

207 3.49×10^6 bp. Inversely, the number of CpG sites in the divergent sequences mapped

208 for T2T-YAO-hp is greater than that for T2T-CHM13 at all three methylation levels. In

209 terms of quantity, the most notable difference is what found in the hypermethylated

210 sequences (2.8×10^5 *vs*. 2.2×10^5 for ovary; 3.1×10^5 *vs*. 2.5×10^5 for testis).

211 *CGI methylation levels*

212   We used Equation 6 to calculate the methylation level of all density-defined and

213 position-defined CGIs for the two reference genomes (**Figure 7** and Supplementary

214 **Figure S6**). First, after both definitions, the proportions of CGI-invalid data (WGBS

215 data failed to be mapped to any CGIs) are higher in the T2T-CHM13 than in T2T-YAO-

216 hp genomes (Figure 7); there are 10.46% *vs*. 7.27% for the density-defined CGIs and

217 23.63% *vs*. 14.87% for position-defined CGIs not mapped in the ovary for the two

218 genomes (Figure 7A). Second, the proportions of hyper-methylated, intermediate

219 methylated, and hypo-methylated of CGIs, predicted by both definitions, are slightly

220 greater for the T2T-YAO-hp genome than those of the T2T-CHM13 genome; the

proportions of hyper-methylated, intermediate methylated, and hypo-methylated for the

T2T-YAO-hp genome predicted as position-defined CGIs are 19.73%, 13.29%, and

53%, respectively, as opposed to those of the T2T-CHM13 genome, 17.32%, 11.77%,

and 48.02% (Figure 7B). Third, the density-defined CGIs appear to have the greatest

proportion of hypermethylation for both genomes, whereas position-defined CGIs have

a greater proportion of hypomethylation (Figure 7). The density-defined CGIs of both

genomes have higher proportions of hyper-methylated CGIs (50.02% *vs.* 48.40% for

the T2T-YAO and T2T-CHM13 genomes, respectively) than those of intermediate

methylated and hypo-methylated CGIs, whereas the position-defined CGIs have the

greatest proportion of hypomethylation (53.65% *vs.* 48.57% for the T2T-YAO and T2T-

CHM13 genomes, respectively).

Discussion and conclusion

The aim of this study is to emphasize merits and specific applications of a

population-centric reference genome by comparing the sequence divergence, as well as

various epigenetic parameters, between the T2T-YAO and T2T-CHM genomes. We

have further provided the evidence suggesting the necessity of using T2T-YAO as a

reference genome for future genome-wide genetic and epigenetic studies in Chinese

populations. We have started with the two high-quality genome sequences to compute

the genome-wide cytosine and CpG sites and further categorized them into two groups

of CGIs, position-defined and density-defined. After the three-round stratification, we

have presented the divergent-sequence-associated genes and concluded that these genes

are mostly neurological in function. In addition, we have mapped the methylation levels

of CpGs and CGIs for the two reference genomes using selected public WGBS data.

The overall sequence divergence between the two reference genomes are

significant and interesting, albeit only 4.7–5.8% (minimal alignment length of 5,000bp

and identity cutoff of 90%). Such a loosely-defined difference, generally speaking, is

mostly population-associated variations between the northern Chinese and European

populations [9, 10]. Future studies will have to expand empirical data into within-
population variations based on big data for their detailed categorization of functional
relevance. The current divergent sequences appear to non-uniformly spread out into
certain chromosomal regions within a few chromosomes and their specific regions,
such as the cases involving chromosomes 9 and Y; such a distribution also suggests
population-associated selection and recombination. Furthermore, the GO enrichment of
divergent-sequence-associated genes specific to the T2T-YAO genome indicates a
strong preference for specific molecular mechanisms related to neuronal cells and
synapses, providing clues for future in-depth investigation.

Our genome-wide CGI study between the two genomes indicates that two-fold
CGI stratifications are necessary for precision methylation mapping. It is important to
start methylation mapping from all potential methylation sites that are ensured only by
T2T population-specific genomes. The two CGI definitions and their grouping schemes,
such as the distance (12 bp, 25 bp, and 50 bp) and the density (high, moderate, and low),
provide matrices for pattern and rule recognitions, which are used to identify genes and
other genomic elements and features for further functional scrutinization. In addition,
after the application of the two CGI definitions, there is still a significant fraction of the
C and CpG sites to be further annotated, leveraging on the complete genomes, as some
of these sites are actually methylated.

From the methylation mapping of the two datasets representing the two germline
tissues, we have learnt several lessons. First, we expected more CpG sites to be mapped
in the T2T-CHM13 reference from the methylation data of the European origins since
its DNA is from a single homozygous complete hydatidiform mole (46, XX) and the Y
sequence is from another assembly of similar origin. However, to our surprise, the
number of CpG methylation sites to the divergent sequence associated to the T2T-YAO
genome is greater than that of the T2T-CHM13 reference. Second, the CpG sites that
failed to be mapped by the gender-specific methylation data are also biased toward the
same direction, *i.e.*, there are more to be mapped in the T2T-YAO reference. These

subjective mapping results lead to an across-the-board conclusion that methylation
patterns are reference sensitive regardless the methylation levels. Third, we have also
shown apparent differences of CGI methylation between the two CGI definitions and
the rate varies among different methylation levels.

After all, there are still several questions that need further exploration. First, the
success of large-scale genome-wide epigenomic studies rely on hign-quality and
population-specific reference genomes and there are more much more references to be
constructed for human methylation atlas of different populations. Second, novel and
more thorough CpG and CGI definitions are needed for understanding the relatedness
of data to be mapped and their references. Since artificial intelligence (AI) has been
gradually used in genome-wide methylation-associated studies [27, 28], determining
how to use AI techniques [29–32] such as neural networks to investigate the
relationship between sequence features, CGI, methylation, and expression specificity
of the human genome has become a future research direction. Finally, genome-wide
CGI prediction and methylation analysis are not only data intensive but also time-
consuming. However, there is currently no such web service that collects and manages
CGI and methylation annotation data for the Chinese T2T genome. Therefore, we will
build a web service for online computation, data sharing and visualization based on
high-performance computing[33, 34], such as GPU acceleration and distributed
computing, to provide a data foundation and an online platform for further study.

Materials and methods

Data source

We downloaded the human GRCh38 and T2T-CHM13 (v2.0) genome sequences
from the NCBI databases [35] and the Chinese T2T-YAO-hp genome sequence from
the BIGD (BIG Data Center, Beijing) databases [10]. We used CGI data of the T2T-
CHM13 genome, which were predicted based on the Gardiner-Garden and Frommer
(GGF) [36] standard in UCSC [37]. We downloaded the WGBS data for two

representative tissues from the ENCODE database [38], which are ovary

(ENCSR417YFD) from a European donor and testis (ENCSR806NNG) from an

American individual.

Methods

The workflow of this study in three main aspects is described in Figure 1, and

our key algorithms used are described as follows.

Comparative sequence analysis

<u>Statistics of all cytosine C sites</u>

We counted and compared the number and distribution of cytosine sites (C sites)

that can be methylated among the T2T-YAO-hp, T2T-CHM13, and GRCh38 genomes.

Since most DNA methylation sites found in mammals involve CpG dinucleotides [39],

we categorized C sites into three different contexts: CpG, CHG, and CHH, where H

represents A, C or T.

<u>Genome alignment and analysis</u>

We used nucmer, a sequence alignment algorithm of the MUMmer system [40], to

carry out genome-wide alignment and analysis for the T2T-YAO-hp and T2T-CHM13

genomes (**Figure S7**). We set the key parameters for nucmer to calculate similar and

divergent sequences as follows: minimum alignment length is 5,000 bp, minimum

alignment similarity is 90%. The similar sequences are those regions identified by

nucmer as aligning between the two genomes. Conversely, divergent sequences are

those regions that do not meet these above-mentioned alignment criteria, thus

representing unique sequences present in each genome. The GO enrichment of

divergent-sequence-associated genes were analyzed by using the clusterProfiler

algorithm [41].

CGI definition and analysis

Our previous studies denoted the CGIs predicted by the classical rule-based

method [36] as density-defined CGIs, and the CGIs predicted by the distance-based

clustering method [26] as position-defined CGIs, which are able to localize more short

CGIs of potential gene regulatory functions and are closely correlated with gene

expression specificity [2, 11, 12] in the human genome. Therefore, in order to

comprehensively compare CGI features of the two reference genomes, we calculated

not only all the density-defined and position-defined CGIs for the T2T-YAO-hp and

T2T-CHM13 genomes but also the density-defined and position-defined CGIs related

to divergent sequences of the two genomes (Supplementary **Figure S8**).

<u>Density-defined CGI</u>

Based on the GGF standard of CGIs [36], we computed the sequence segments

that meet Equations. 1–3 as density-defined CGIs by the CpGPlot algorithm [42].

$$\text{length} \geq 200\text{bp} \tag{1}$$

$$\text{GC content} \geq 50\% \tag{2}$$

$$O/E\ ratio = \frac{Number\ of\ CpG}{Number\ of\ C\ \times\ Number\ of\ G} \times \text{length} \geq 0.6 \tag{3}$$

where length is the nucleotide number of the analysed gene sequence region, GC

content is the proportion of G+C in the analysed gene sequence region, and O/E ratio

represents the ratio of observed CpG to expected CpG.

<u>Position-defined CGI</u>

We first calculated the CpG clusters in the genome by Equation 4, and then

considered these CpG clusters with small p values [26] (Equation 5) as position-defined

CGIs.

$$d_i = x_{i+1} - x_i - 1 \tag{4}$$

$$P(d) = (1 - p)^{d-1}p \tag{5}$$

where x represents the coordinates of CpG and i represents the index of CpG.

P(d) represents the probability of finding a distance d between neighboring CpGs. p

corresponds to the probability of CpGs in the sequence. Since the default value of d in

the CpGcluster algorithm is 50 and our previous study found that LAUPs (lineage-

associated underrepresented permutations) are strongly associated with CGIs, the

length of the shortest LAUPs of multiple species ranges from 10 to 14 [19], and the

length of 25 bp is the statistical proportionality demarcation point for all CpGs and

core-promoter-associated CpG regions in the human genome [2], we computed CGIs

with d = 50 bp, 25 bp, and 12 bp (the average of 10 and 14).

Genome-wide methylation analysis

<u>WGBS data mapping</u>

We applied gemBS [43], a large-scale WGBS data analysis method, to carry out

methylation analysis for the two representative tissues (ovary and testis) by setting T2T-

YAO-hp and T2T-CHM13 as references. The details of the procedure are described in

Supplementary **Figure S9**.

<u>CGI methylation ratio computing</u>

After obtaining the CGI prediction for the reference genome and the methylation

rate for each CpG site, Equation 6 calculates the methylation ratio for each CGI.

372
$$\text{mean\_methylation}(cgi) = \frac{\sum_{cpg \in cgi} reads \times \text{ methylation\_ratio}(cpg)}{\sum_{cpg \in cgi} reads} \quad (6)$$

where *reads* represent the sequencing depth of WGBS for each CpG site in the CGI,

and methylation_ratio(*cpg*) represents the methylation ratio of each CpG site derived

from the gemBS parallelization algorithm.

<u>Methylation level classification</u>

According to the previous studies [2, 44], Equation 7 was used to classify the

methylation ratio for each CpG site and CGI into three methylation levels, "hyper-

methylated", "hypo-methylated", and "intermediate methylated".

380
$$\text{Methylation level}(chr, p) = \begin{cases} -1, \text{ invalid} & \text{no reads map to this cpg or cgi} \\ 1, \text{ hyper-methylated} & \text{methylation}_{\text{ratio}(chr,p)} > 0.75 \\ 2, \text{ hypo-methylated} & \text{methylation}_{\text{ratio}(chr,p)} < 0.1 \\ 3, \text{ intermediate methylated} & \text{otherwise} \end{cases} \quad (7)$$

381 where chr and p represent the chromosome and the coordinates of the CpG site,

382 respectively.

CRediT author statement

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Competing interests

The authors have declared no competing interests.

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References

[1] Pongor CI, Bianco P, Ferenczy G, Kellermayer R, Kellermayer M. Optical trapping nanometry of hypermethylated CPG-Island DNA. Biophys. J 2017;112:512.

[2] Xiao M, Yin R, Gao P, Yu J, Ma F, Dai Z, et al. Position-defined CpG islands provide complete co-methylation indexing for human genes. International Conference on Intelligent Computing (2022).2022:319-33.

[3] Dor Y, Cedar H. Principles of DNA methylation and their implications for biology and medicine. Lancet 2018;392:777-86.

[4] Wu H, Zhang Y. Reversing DNA methylation: mechanisms, genomics, and biological functions. Cell 2014;156:45-68.

[5] Acton R, Yuan W, Gao F, Xia Y, Bourne E, Wozniak E, et al. The genomic loci of specific human tRNA genes exhibit ageing-related DNA hypermethylation. Nat. Commun 2021;12:2655.

[6] Liu B, Du Q, Chen L, Fu G, Li S, Fu L, et al. CpG methylation patterns of human mitochondrial DNA. Sci. Rep 2016;6:23421.

[7] El-Maarri O, Olek A, Balaban B, Montag M, van der Ven H, Urman B, et al. Methylation levels at selected CpG sites in the factor VIII and FGFR3 Genes, in mature female and male germ cells: implications for male-driven evolution. Am. J. Hum. Genet 1998;63:1001-8.

[8] Gershman A, Sauria MEG, Guitart X, Vollger MR, Hook PW, Hoyt SJ, et al. Epigenetic patterns in a complete human genome. Science 2022;376:eabj5089.

[9] Aganezov S, Yan SM, Soto DC, Kirsche M, Zarate S, Avdeyev P, et al. A complete reference genome improves analysis of human genetic variation. Science 2022;376:eabl3533.

[10] He Y, Chu Y, Guo S, Hu J, Li R, Zheng Y, et al. T2T-YAO: a telomere-to-telomere assembled diploid reference genome for Han Chinese. Genomics Proteomics Bioinformatics 2023;S1672-0229(23)00100-6.

[11] Zhang L, Dai Z, Yu J, Xiao M. CpG-island-based annotation and analysis of human
housekeeping genes. Brief. Bioinformatics 2021;22:515-25.

[12] Xiao M, Yang X, Yu J, Zhang L. CGIDLA：developing the web server for CpG
island related density and LAUPs (Lineage-associated Underrepresented Permutations)
Study. IEEE/ACM Trans Comput Biol Bioinform 2019;17:2148-54.

[13] Lai X, Zhou J, Wessely A, Heppt M, Maier A, Berking C, et al. A disease network-
based deep learning approach for characterizing melanoma. Int J Cancer
2022;150:1029-44.

[14] Zhang L, Liu G, Kong M, Li T, Wu D, Zhou X, et al. Revealing dynamic
regulations and the related key proteins of myeloma-initiating cells by integrating
experimental data into a systems biological model. Bioinformatics 2021;37:1554-61.

[15] Zhao J, Cao Y, Zhang L. Exploring the computational methods for protein-ligand
binding site prediction. Comput Struct Biotechnol J 2020;18:417-26.

[16] Zhang L, Zheng C, Li T, Xing L, Zeng H, Li T, et al. Building up a robust risk
mathematical platform to predict Colorectal Cancer. Complexity 2017;2017:1-14.

[17] Zhang L, Liu Y, Wang M, Wu Z, Li N, Zhang J, et al. EZH2-, CHD4-, and IDH-
linked epigenetic perturbation and its association with survival in glioma patients. J
Mol Cell Biol 2017;9:477-88.

[18] Xia Y, Yang C, Hu N, Yang Z, He X, Li T, et al. Exploring the key genes and
signaling transduction pathways related to the survival time of glioblastoma multiforme
patients by a novel survival analysis model. BMC Genom 2017;18:950.

[19] Zhang L, Xiao M, Zhou J, Yu J. Lineage-associated underrepresented permutations
(LAUPs) of mammalian genomic sequences based on a Jellyfish-based LAUPs analysis
application (JBLA). Bioinformatics 2018;34:3624-30.

[20] Zhang L, Zhao J, Bi H, Yang X, Zhang Z, Su Y, et al. Bioinformatic analysis of
chromatin organization and biased expression of duplicated genes between two poplars
with a common whole-genome duplication. Hortic Res 2021;8:62.

[21] Zhang L, Bai W, Yuan N, Du Z. Comprehensively benchmarking applications for
detecting copy number variation. PLoS Comput Biol 2019;15:e1007069.

[22] Zhang Q, Zhang H, Zhou K, Zhang L. Developing a physiological signal-based,
mean threshold and Decision-Level Fusion Algorithm (PMD) for emotion recognition.
Tsinghua Sci Technol 2023;28:673-85.

[23] He W, Yang J, Jing Y, xu L, Yu K, Fang X. NGenomeSyn: an easy-to-use and
flexible tool for publication-ready visualization of syntenic relationships across
multiple genomes. Bioinformatics (Oxford, England) 2023;39.

[24] Guarracino A, Buonaiuto S, de Lima LG, Potapova T, Rhie A, Koren S, et al.
Recombination between heterologous human acrocentric chromosomes. Nature
2023;617:335-43.

[25] Huntley RP, Tony S, Prudence MM, Aleksandra S, Carlos B, Martin MJ, et al. The
GOA database: gene ontology annotation updates for 2015. Nucleic Acids Res
2015;43:1057-63.

[26] Hackenberg M, Previti C, Luque-Escamilla PL, Carpena P, Martínez-Aroza J,
Oliver JL. CpGcluster: a distance-based algorithm for CpG-island detection. BMC
Bioinform 2006;7:446.

[27] You Y, Lai X, Pan Y, Zheng H, Vera J, Liu S, et al. Artificial intelligence in cancer
target identification and drug discovery. Signal Transduct Target Ther 2022;7:156.

[28] Tian H, He Y, Xue Y, Gao YQ. Expression regulation of genes is linked to their
CpG density distributions around transcription start sites. Life Science Alliance
2022;5:e202101302.

[29] Zhang L, Fan S, Vera J, Lai X. A network medicine approach for identifying
diagnostic and prognostic biomarkers and exploring drug repurposing in human cancer.
Comput Struct Biotechnol J 2023;21:34-45.

[30] You Y, Zhang L, Tao P, Liu S, Chen L. Spatiotemporal transformer neural network
for time-series forecasting. Entropy (Basel) 2022;24:1651.

[31] Song H, Chen L, Cui Y, Li Q, Wang Q, Fan J, et al. Denoising of MR and CT
images using cascaded multi-supervision convolutional neural networks with
progressive training. Neurocomputing 2022;469:354-65.

[32] Liu G-D, Li Y-C, Zhang W, Zhang L. A brief review of artificial intelligence
applications and algorithms for psychiatric disorders. Engineering 2020;6:462-7.

[33] Zhang L, Badai J, Wang G, Ru X, Song W, You Y, et al. Discovering hematoma-
stimulated circuits for secondary brain injury after intraventricular hemorrhage by
spatial transcriptome analysis. Front Immunol 2023;14:1123652.

[34] Zhang L, Zhang L, Guo Y, Xiao M, Feng L, Yang C, et al. MCDB: A
comprehensive curated mitotic catastrophe database for retrieval, protein sequence
alignment, and target prediction. Acta Pharm Sin B 2021;11:3092-104.

[35] Pruitt KD, Tatusova T, Maglott DR. NCBI Reference Sequence (RefSeq): a curated
non-redundant sequence database of genomes, transcripts and proteins. Nucleic Acids
Res 2005;33:D501-4.

[36] Gardiner-Garden M, Frommer M. CpG islands in vertebrate genomes. J Mol Biol
1987;196:261-82.

[37] Lee BT, Barber GP, Benet-Pagès A, Casper J, Clawson H, Diekhans M, et al. The
UCSC genome browser database: 2022 update. Nucleic Acids Res 2022;50:D1115-d22.

[38] Luo Y, Hitz BC, Gabdank I, Hilton JA, Kagda MS, Lam B, et al. New
developments on the encyclopedia of DNA elements (ENCODE) data portal. Nucleic
Acids Res 2020;48:D882-d9.

[39] He X-J, Chen T, Zhu J-K. Regulation and function of DNA methylation in plants
and animals. Cell Res 2011;21:442-65.

[40] Marçais G, Delcher AL, Phillippy AM, Coston R, Salzberg SL, Zimin A.
MUMmer4: A fast and versatile genome alignment system. PLoS Comput Biol
2018;14:e1005944.

[41] Yu G, Wang LG, Han Y, He QY. clusterProfiler: an R package for comparing
biological themes among gene clusters. Omics-a Journal of Integrative Biology
2012;16:284-7.

[42] Rice P, Longden I, Bleasby A. EMBOSS: the European molecular biology open
software suite. Trends Genet 2000;16:276-7.

[43] Merkel A, Fernández-Callejo M, Casals E, Marco-Sola S, Schuyler R, Gut IG, et
al. gemBS: high throughput processing for DNA methylation data from bisulfite
sequencing. Bioinformatics 2019;35:737-42.

[44] Ziller MJ, Gu H, Muller F, Donaghey J, Tsai LT, Kohlbacher O, et al. Charting a
dynamic DNA methylation landscape of the human genome. Nature 2013;500:477-81.

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Figure legends

Figure 1   Workflow of the study

GO, Gene Ontology; T2T, telomere-to-telomere; WGBS, whole-genome bisulfite sequencing; CGI, CpG island.

Figure 2   Sequence alignment between the T2T-CHM13 and T2T-YAO-hp genomes.

A. A collinearity map of the genome alignment. Colored lines link the high-identity or collinear sequence segments of the two compared genomes and the line thickness as a similarity measure. **B.** Visualization of sequence comparison across chromosomes. Blue and orange highlight similar sequences as vertical bars of the T2T-CHM13 and T2T-YAO-hp genomes, respectively. Blank bars represent divergent sequences of the two genomes. **C.** Divergent sequence length statistics of the two genomes. Blue and orange bars represent the divergent sequence lengths of the T2T-CHM13 and T2T-YAO-hp genomes in different chromosomes, respectively. Chr, chromosome.

Figure 3   GO enrichment of divergent-sequence-associated genes

A. Proportion of the types of divergent-sequence-associated genes in these two reference genomes. **B.** GO enrichment analysis of divergent sequence related protein-coding genes. Size and color of the circle represent the number of enriched genes and the statistical significance value (adjusted *P* value) [22, 41] of the current GO term, respectively. ncRNA, non-coding RNA; lncRNA, long non-coding RNA; BP, biological process; MF, molecular function; CC, cellular component.

Figure 4   The sequence intersecting the density-defined and position-defined CGIs (d = 25 bp)

The white part represents the sequence length intersecting position-defined and density-defined CGIs. The orange and blue parts represent the sequence length unique to the density-defined and position-defined CGIs, respectively.

Figure 5   Comparison of CGI features between the T2T-CHM13 and T2T-YAO-hp genomes

A. Length of all CGIs; **B.** GC content of all CGIs; **C.** O/E ratio of all CGIs; **D.** CpG density of all CGIs; **E.** Length of divergent-sequence-associated CGIs; **F.** GC content of divergent-sequence-associated CGIs; **G.** O/E ratio of divergent-sequence-associated CGIs; **H.** CpG density of divergent-sequence-associated CGIs. O/E, observed CpG/expected CpG.

Figure 6   CpG methylation level of divergent sequences between the T2T-CHM13 and T2T-YAO-hp genomes

Green, blue, and orange highlight the number of hyper-methylated, intermediate methylated, and hypo-methylated, respectively. Gray highlights the number of CpG sites that failed in mapping with WGBS data. Dark and light colors are used to distinguish the T2T-YAO-hp and T2T-CHM13 genomes, respectively.

Figure 7   CGI methylation levels of the two genomes

A. CGI methylation levels annotated by using the ovary data. **B.** CGI methylation levels annotated by using the testis data. Green, blue, and orange highlight the proportion of CGIs that are hyper-methylated, intermediate methylated, and hypo-methylated, respectively. Gray highlights the proportion that failed from all CGIs mapping, denoted as *invalid*. Darker and lighter colors are used to distinguish the T2T-YAO-hp and T2T-

589 CHM13 genome, respectively.

Tables

Table 1   Sequence differences between the T2T-CHM13 and T2T-YAO-hp genomes

Table 2   CGIs Statistics of the T2T-CHM13 and T2T-YAO-hp genomes

A

B

T2T-CHM13

T2T-YAO-hp

27,333,743
(76.5%)　8,394,427　1,664,339
(16.5%)

Position-defined
CGI (d = 25 bp)

Density-defined
CGI

24,991,625
(75.6%)　8,062,542　1,735,619
(17.7%)

Position-defined
CGI (d = 25 bp)

Density-defined
CGI

A

B

Table 1   Sequence differences between the T2T-CHM13 and T2T-YAO-hp genomes

	Total length (bp)	Divergent sequence length (bp)	Divergent sequence proportion	Similar sequence length (bp)
T2T-CHM13	3,117,275,501	179,281,068	5.751%	2,937,994,433
T2T-YAO-hp	3,062,707,975	142,866,485	4.665%	2,919,841,490

Note: We use nucmer to compute similar sequences between the two reference genomes and call other remaining sequences as divergent sequences.

Table 2   CGIs Statistics of the T2T-CHM13 and T2T-YAO-hp genomes

Category		Density-defined CGI	Position-defined CGI		
			d = 50 bp	d = 25 bp	d = 12 bp
T2T-CHM13	CGI count	87,788	220,736	174,594	101,972
	Average CGI length (bp)	407	258	58	23
T2T-YAO-hp	CGI count	84,471	222,421	161,997	96,449
	Average CGI length (bp)	391	261	60	24

Note: d denotes the maximum distance between neighboring CpGs in the position-defined CGIs.