

In silico chromosome staining: Reconstruction of Giemsa bands from the whole human genome sequence

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Giemsa staining has been used for identifying individual human chromosomes. Giemsa-dark and -light bands generally are thought to correspond to GC-poor and GC-rich regions; however, several experiments showed that the correspondence is quite poor. To elucidate the precise relationship between GC content and Giemsa banding patterns, we developed an “*in silico* chromosome staining” method for reconstructing Giemsa bands computationally from the whole human genome sequence. Here we show that 850-level Giemsa bands are best correlated with the difference in GC content between a local window of 2.5 megabases and a regional window of 9.3 megabases along a chromosome. The correlations are of strong statistical significance for almost all 43 chromosomal arms. Our results clearly show that Giemsa-dark bands are *locally* GC-poor regions compared with the flanking regions. These findings are consistent with the model that matrix-associated regions, which are known to be AT-rich, are present more densely in Giemsa-dark bands than in -light bands.

Distinct patterns of Giemsa-dark (G) and -light (R) bands observed on mitotic chromosomes reflect regional differences in chromatin higher-order structures and functions at various levels. Giemsa bands are related to functional nuclear processes such as replication or transcription in the following points. First, DNA replication timing during the cell cycle differs; R bands are early-replicating, whereas G bands are late-replicating (1, 2). Second, R bands are gene-rich and contain most housekeeping genes as well as a large number of CpG islands, whereas G bands are gene-poor and preferentially contain tissue-specific genes (3, 4). Giemsa bands are related also to chromatin structures; the chromatins in G bands are more condensed than those in R bands during both metaphase and interphase (5, 6). Recently, G- and R-band DNAs were demonstrated to form discrete domains in the interphase cell nucleus, and they are differently located in the nucleus; G-band DNA is localized at the nuclear periphery, whereas R-band DNA is in the interior of the nucleus (7).

Bernardi *et al.* (8, 9) proposed that the human genome is composed of isochores, long DNA segments (>>300 kb) that are homogeneous in GC content. G and R bands generally were thought to correspond to GC-poor and -rich isochores, respectively. Recently, 338 clones were mapped to 850-level bands of varying staining intensity, and the sequence analysis of the regions surrounding these clones confirmed that G bands are more AT-rich than R bands with statistical significance (10). However, the general correspondence between isochores and cytogenetic bands is only an approximation. Compositional maps of human chromosomes revealed that (i) G bands are homogeneous in GC content and essentially consist of GC-poor isochores, and in contrast, (ii) R bands are heterogeneous and contain both GC-rich and -poor isochores (11, 12). These results indicate that Giemsa banding patterns cannot be explained only by the difference in base composition. Thus, the relationship between the nucleotide sequence and cytogenetic bands still has remained elusive. The purpose of this study is to elucidate the

precise relationship between Giemsa bands and genome sequences by using the draft sequence of the whole human genome (13). In this article, we show that G bands are the regions in which the GC content is relatively lower than that of the surrounding regions.

Materials and Methods

Data. DNA sequences of the draft human genome (the version of October 7, 2000) were downloaded from the web site genome.ucsc.edu/(13). The relative position of each boundary between neighboring Giemsa bands in relation to the total euchromatic portion of each chromosomal arm was obtained from Francke (14).

Calculation of the Similarity Score. The basic idea to calculate the similarity score S between Giemsa bands and *in silico* bands is to determine the optimal “alignment” of G bands by using dynamic programming (15). Let the i -th G band in a Giemsa banding pattern (pattern A) and the j -th G band in an *in silico* banding pattern (pattern B) be G_i^A and G_j^B , respectively (Fig. 2A). The local score $s(G_i^A, G_j^B)$ between G_i^A and G_j^B is calculated by the expression $s(G_i^A, G_j^B) = 1 - (|C_i^A - C_j^B| + |T_i^A - T_j^B| + |L_i^A - L_j^B|)/2L$, where $C_i^A(C_j^B)$, $T_i^A(T_j^B)$ and $L_i^A(L_j^B)$ stand for the position of the centromeric end of $G_i^A(G_j^B)$, the position of the telomeric end of $G_i^A(G_j^B)$, and the length of $G_i^A(G_j^B)$, respectively. L stands for the average length of G bands at an 850-band level among all chromosomes. Based on the experimental data of relative band sizes (14) and the DNA length of each chromosomal arm, L is calculated as ≈ 4.0 megabases (Mb). We calculate the local score $s(G_i^A, G_j^B)$ for all the combinations of G_i^A and G_j^B . The optimal alignment of two banding patterns is found by dynamic programming (15). Gap penalties $g(G_i^A)$ and $g(G_j^B)$ are defined as L_i^A/L and L_j^B/L , respectively. We constructed a matrix F by the following recurrence equation: $F_{i,j} = \max[F_{i-1,j-1} + s(G_i^A, G_j^B), F_{i-1,j} - g(G_i^A), F_{i,j-1} - g(G_j^B)]$. The initial conditions were as follows: $F_{0,0} = 0$, $F_{i,0} = -\sum_{k=1}^i g(G_k^A)$, $F_{0,j} = -\sum_{k=1}^j g(G_k^B)$. $F_{m,n}$ gives the score of the optimal alignment, where m and n are the numbers of G bands in the patterns A and B. $F_{m,n}$ is defined as the similarity score S between banding patterns A and B.

Statistical Test. The sequence of each chromosomal arm was split into 10-kb fragments, and these fragments were shuffled randomly, yielding a shuffled sequence with the same length and average GC content as the whole sequence of the chromosome. For each shuffled sequence, *in silico* staining was conducted by

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Abbreviations: G, Giemsa-dark; R, Giemsa-light; Mb, megabase(s); MAR, matrix-associated region.

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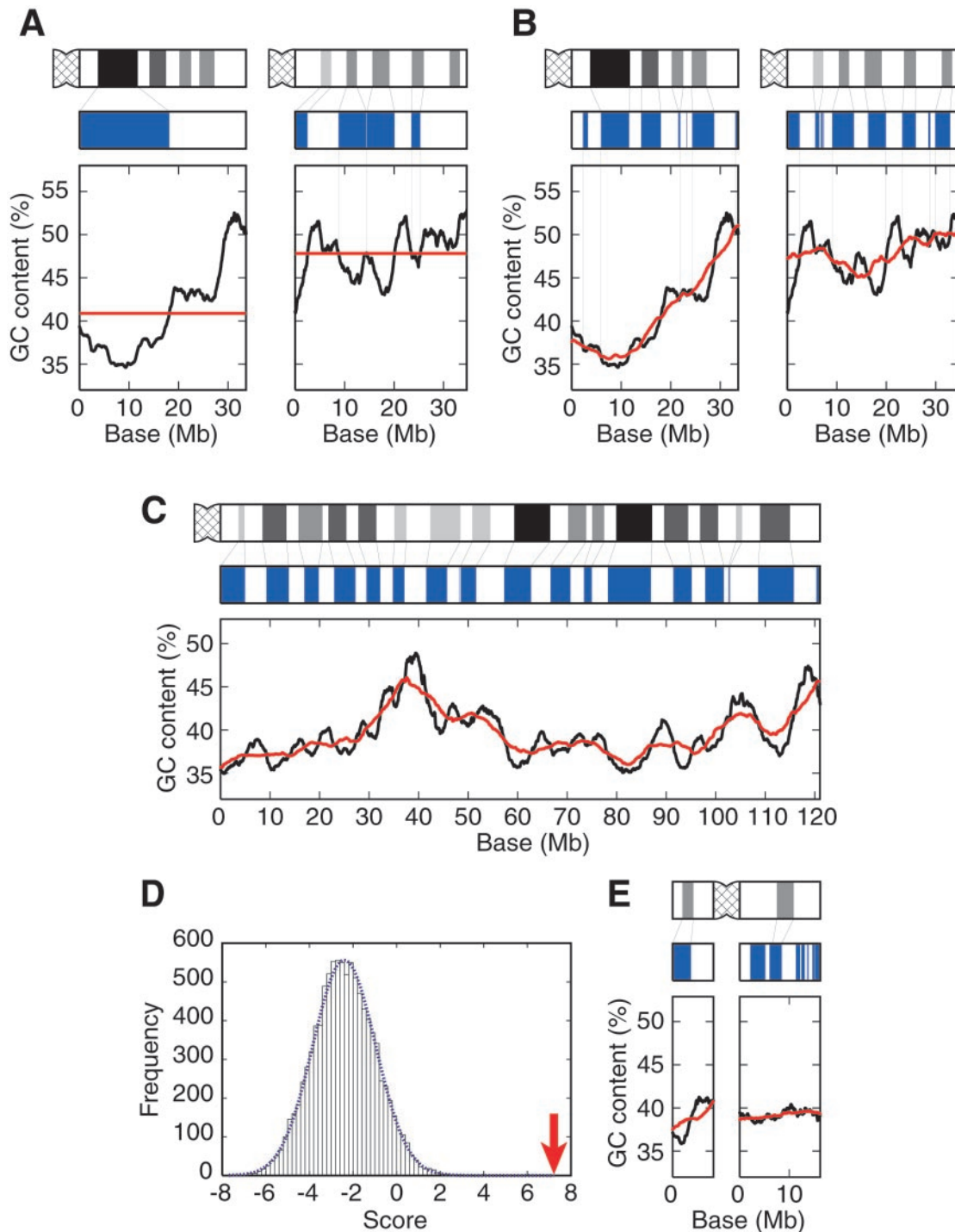


Fig. 1. Reconstruction of Giemsa bands *in silico*. (A) No correspondence between G bands and GC-poor regions or R bands and GC-rich regions in chromosomes 21 (Left) and 22 (Right). The Giemsa banding pattern shown in black (Top) was obtained from Francke (14). The diagram in blue (Middle) was obtained by computationally staining the regions in which the GC content for a 2.5-Mb window is lower than the average GC content over the chromosome. The graph at Bottom shows the variation in GC content for a 2.5-Mb window sliding in 10-kb steps across the chromosome (black line) and the average GC content (red line)—40.9% (Left) and 47.8% (Right). The number of nucleotides used for the calculation of the GC content becomes smaller than 2.5 Mb when the window contains chromosomal ends or strings of Ns (ambiguous nucleotides or sequence gaps). (B) Correlation between Giemsa bands and *in silico* bands in chromosomes 21 (Left) and 22 (Right). Giemsa bands are shown in black (Top). The diagram in blue (Middle) shows *in silico* bands obtained by computationally staining the regions in which the GC content for a 2.5-Mb window is lower than that for a 9.3-Mb window. The graph at Bottom shows the variation in GC content for a 2.5-Mb local window (black line) and a 9.3-Mb regional window (red line) sliding in 10-kb steps across the chromosome. The thin lines between Giemsa and *in silico* bands denote aligned G bands. (C) The best correlation between Giemsa bands and *in silico* bands observed for chromosome 3q. Giemsa bands are shown in black (Top) and *in silico* bands are shown in blue (Middle). The black and red lines in the graph at Bottom show the variation in GC content for 2.5- and 9.3-Mb windows, respectively. The thin lines between Giemsa and *in silico* bands denote aligned G bands. (D) Distribution of the similarity scores in a simulation for chromosome 3q. The dotted blue line represents a normal distribution having the values of the mean and the standard deviation calculated from 10,000 random samples. The arrow shows the observed similarity score between *in silico* and Giemsa bands ($P = 9 \times 10^{-12}$). (E) A poor correspondence between Giemsa and *in silico* bands for chromosome Y. The representation is the same as that described for C.

using a local window of 2.5 Mb and a regional window of 9.3 Mb. The similarity score S_{exp} between Giemsa bands and the banding pattern constructed from the shuffled sequence was calculated. The simulation scheme was iterated 10,000 times. By using a normal distribution, the probability P for the observed similarity score S_{obs} was calculated for each chromosomal arm.

Results

Fig. 1A shows the variation in GC content for human chromosomes 21 and 22, the complete DNA sequences of which are known (16, 17). We computationally stained the genomic regions in which the GC content in a window is lower than the average GC content over the chromosome, obtaining completely different patterns from the Giemsa bands experimentally observed. Therefore, the simple correspondence between GC-poor regions and G bands or that between GC-rich regions and R bands is not precise. Fig. 1A rather implies a possible correspondence between G bands and *locally* GC-poor regions compared with the flanking regions. Therefore, we invented a “two-window analysis” in which two windows with different sizes are used for detecting the regions in which the GC content is lower than that of the flanking regions (Fig. 1B). The diagrams in blue were obtained by computationally staining the regions in which the GC content for a local window (2.5-Mb) is lower than that for a regional window (9.3-Mb). The sizes of the two windows were chosen to optimize the correspondence between *in silico* bands and Giemsa bands (see below). We refer to the method of two windows for computationally producing such patterns as “*in silico* staining,” and the patterns obtained by *in silico* staining as “*in silico* bands.” *In silico* bands are very similar to Giemsa bands in both chromosomes with the exception of the centromeric or telomeric regions (Fig. 1B).

We quantified the similarity between Giemsa bands and *in silico* bands by defining a similarity score S . The basic idea to calculate S is to find out the best alignment of G bands by using dynamic programming (15). The aligned G bands of a perfect match contribute by one to the score S (Fig. 2B, Upper Left). Therefore, the score S has a meaning of the total number of aligned G bands. More similarity gives a higher score. For example, the similarity scores between Giemsa and *in silico* bands are 1.93 and 2.63 for chromosomes 21 and 22, respectively (see Fig. 1B); in contrast, the similarity scores between Giemsa bands and the blue diagrams shown in Fig. 1A are -3.70 and 0.59 for chromosomes 21 and 22, respectively. Therefore, the score S is an informative measure for detecting the similarity between two banding patterns. To optimize the sizes of local and regional windows, we calculated the sum of the scores for all 43 chromosomal arms by using all the combinations of local and regional window sizes. These window sizes were changed independently by 0.1-Mb steps. We then found that the total score reaches the maximum when the local and regional window sizes are 2.5 and 9.3 Mb, respectively (Fig. 2C). Fig. 3 shows the comparisons between Giemsa and *in silico* bands obtained by using windows of 2.5 and 9.3 Mb for all chromosomes.

To evaluate the statistical significance of the similarities between Giemsa and *in silico* bands, we performed computer simulations for each of 43 chromosomal arms. Table 1 shows the result of the statistical test. Of 43 chromosomal arms, 33 are significant at a 5% level, and 30 are significant at a 1% level. The best correspondence between Giemsa and *in silico* bands is observed for chromosome 3q ($P \approx 10^{-11}$; Fig. 1C and D). We can see almost perfect one-to-one correspondence of G bands throughout the chromosomal arm, although it is more than 120 Mb long. Of 10 chromosomal arms that do not show significant correlation, three arms are very short (<20 Mb). Note that our method does not work well for regions so close to the chromosomal end that a regional window cannot be taken. Thus, it is reasonable that a very short chromosomal arm such as chromo-

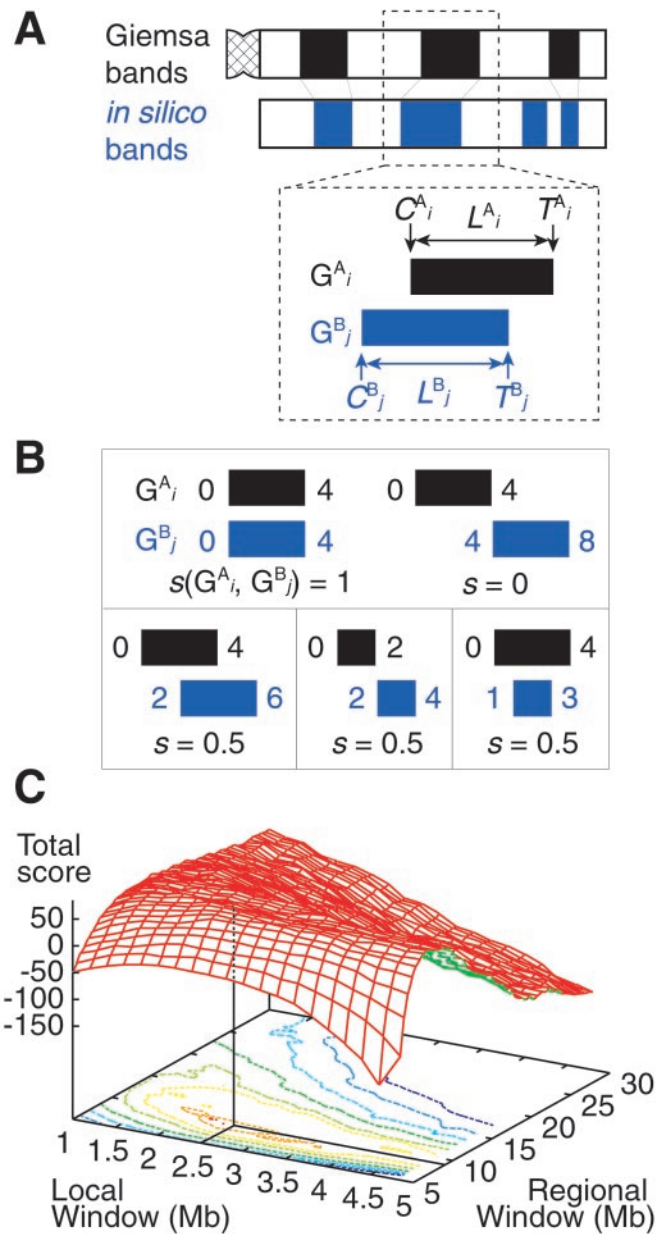


Fig. 2. (A) Calculation of the similarity score S between Giemsa and *in silico* bands (see *Materials and Methods*). (B) Examples of the calculation of $s(G_i^A, G_j^B)$. The coordinates of the centromeric and the telomeric ends of $G_i^A(G_j^B)$ are shown in Mb at the ends of $G_i^A(G_j^B)$. In the case of a perfect match, the expression of $s(G_i^A, G_j^B)$ gives one (Upper Left). When the positions of G_i^A and G_j^B are different by $L = 4$ Mb, $s(G_i^A, G_j^B)$ is equal to zero (Upper Right). Depicted are three examples of “half matches,” i.e., $s(G_i^A, G_j^B) = 0.5$ (Lower). (C) The sum of the similarity scores for all 43 chromosomal arms. The total scores were calculated for all the combinations of local and regional window sizes. These window sizes were changed independently by 0.1-Mb steps from 1 to 5 Mb for a local window and 5 to 30 Mb for a regional window. The local and regional window sizes that maximize the total score are 2.5 and 9.3 Mb, respectively. Contours are plotted at $-50, -25, 0, 25, 50, 62.5, 75,$ and 80 (from blue to red).

somes Yp or Yq shows a poor correlation (Fig. 1E). It also explains the observation that the correlation is relatively weak in the regions close to the chromosomal ends. Therefore, we conclude that Giemsa banding patterns are reconstructed successfully by *in silico* staining for almost all the chromosomal arms.

It is known that the staining intensity is not uniform among G bands. G bands in Fig. 3 are depicted by four different degrees

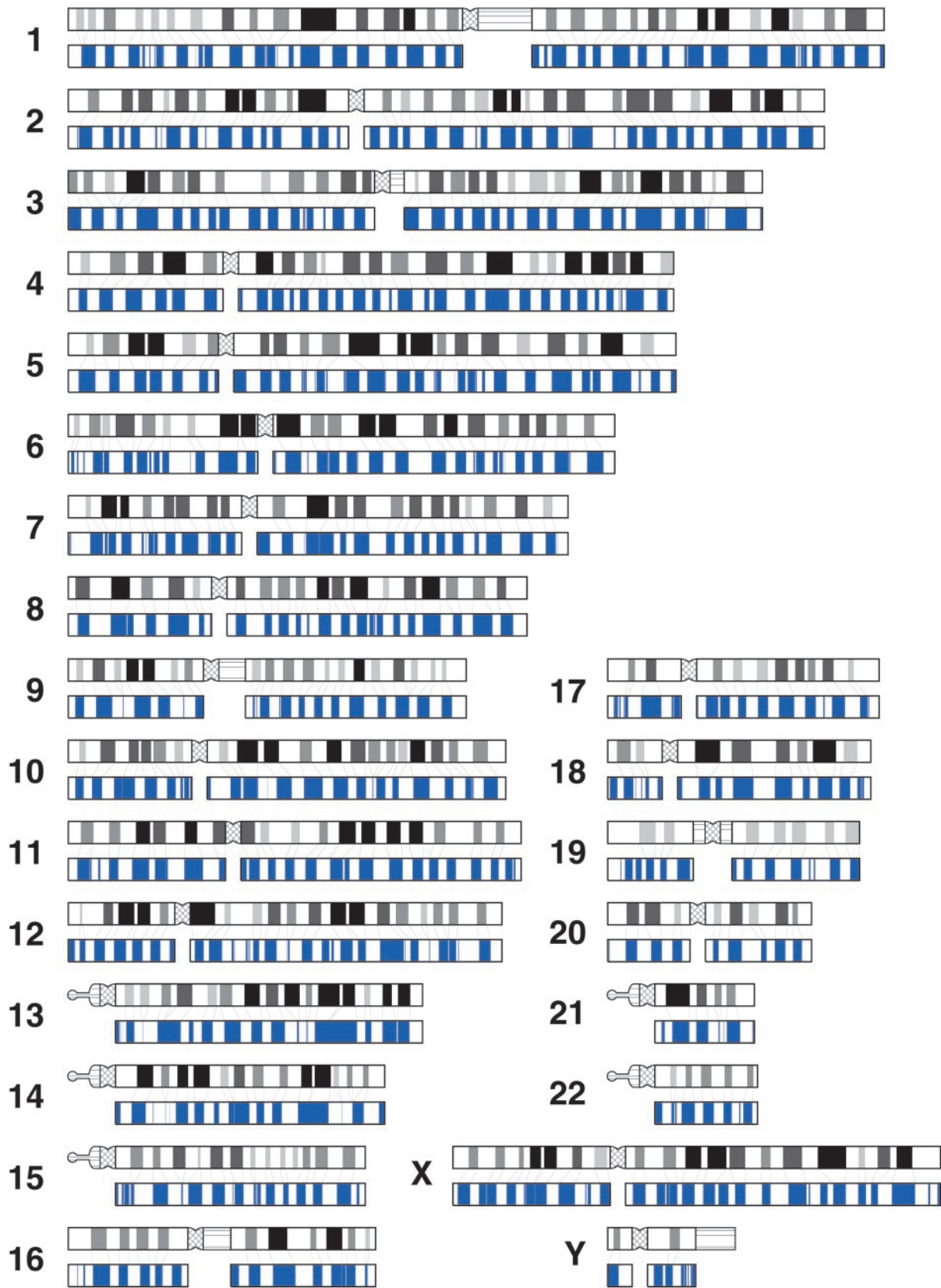


Fig. 3. Giemsa and *in silico* bands for all chromosomes. Short (p) and long (q) arms are positioned left and right, respectively. Giemsa bands obtained from Francke (14) are shown in black ideograms. The bands depicted in black, gray, and white represent euchromatins, and the darkness of each band reflects the shading. Pericentromeric heterochromatin and heteromorphic regions of chromosomes 1, 3, 9, 16, 19, and Y are depicted by crosshatched and horizontal lines, respectively. *In silico* bands constructed by using windows of 2.5 and 9.3 Mb are shown in blue. The thin lines between Giemsa and *in silico* bands denote aligned G bands. The coordinates of *in silico* bands for each chromosomal arm are available at the web site www.cib.nig.ac.jp/dda/home.html.

Table 1. Statistics of *in silico* staining

Chromosome	S_{obs}	S_{exp}	P	Length, Mb
1p	2.50	-3.49 ± 1.48	$3 \times 10^{-5*}$	133
1q	-0.23	-3.85 ± 1.42	$5 \times 10^{-3*}$	118
2p	-0.18	-3.07 ± 1.21	$9 \times 10^{-3*}$	94
2q	3.84	-5.25 ± 1.61	$7 \times 10^{-9*}$	155
3p	1.10	-1.68 ± 1.36	$2 \times 10^{-2†}$	103
3q	7.22	-2.40 ± 1.43	$9 \times 10^{-12*}$	121
4p	0.51	-3.08 ± 0.96	$9 \times 10^{-5*}$	52
4q	2.69	-6.39 ± 1.63	$1 \times 10^{-8*}$	147
5p	1.47	-1.70 ± 0.97	$5 \times 10^{-4*}$	50
5q	-1.02	-8.31 ± 1.54	$1 \times 10^{-6*}$	149
6p	4.00	-0.68 ± 1.02	$2 \times 10^{-6*}$	64
6q	2.50	-4.45 ± 1.46	$1 \times 10^{-6*}$	115
7p	2.86	-0.01 ± 0.99	$2 \times 10^{-3*}$	58
7q	2.51	-2.95 ± 1.32	$2 \times 10^{-5*}$	105
8p	2.40	-2.11 ± 0.93	$7 \times 10^{-7*}$	48
8q	6.35	-1.36 ± 1.36	$6 \times 10^{-9*}$	101
9p	1.16	0.95 ± 0.87	4×10^{-1}	45
9q	4.68	2.37 ± 1.05	$1 \times 10^{-2†}$	74
10p	0.63	0.19 ± 0.84	3×10^{-1}	41
10q	1.08	-2.25 ± 1.34	$7 \times 10^{-3*}$	100
11p	3.60	-1.53 ± 1.00	$1 \times 10^{-7*}$	53
11q	2.24	-2.09 ± 1.28	$4 \times 10^{-4*}$	94
12p	0.80	-0.06 ± 0.77	1×10^{-1}	35
12q	2.23	-1.40 ± 1.36	$4 \times 10^{-3*}$	105
13q	4.73	-0.25 ± 1.40	$2 \times 10^{-4*}$	103
14q	4.78	0.26 ± 1.20	$8 \times 10^{-5*}$	90
15q	3.89	1.63 ± 1.14	$2 \times 10^{-2†}$	84
16p	1.58	-1.54 ± 0.79	$4 \times 10^{-5*}$	40
16q	2.65	-0.92 ± 0.85	$1 \times 10^{-5*}$	48
17p	-0.53	-1.07 ± 0.51	1×10^{-1}	24
17q	0.94	-0.05 ± 0.96	2×10^{-1}	61
18p	-0.47	-0.51 ± 0.54	5×10^{-1}	18
18q	1.12	-4.79 ± 1.01	$2 \times 10^{-9*}$	65
19p	-1.62	-1.97 ± 0.59	3×10^{-1}	28
19q	1.59	-1.10 ± 0.89	$1 \times 10^{-3*}$	43
20p	1.99	-0.86 ± 0.67	$1 \times 10^{-5*}$	27
20q	2.98	0.21 ± 0.78	$2 \times 10^{-4*}$	35
21q	1.93	-1.10 ± 0.70	$7 \times 10^{-6*}$	33
22q	2.63	0.81 ± 0.70	$4 \times 10^{-3*}$	34
Xp	0.21	-0.05 ± 0.95	4×10^{-1}	53
Xq	1.60	-5.57 ± 1.33	$3 \times 10^{-8*}$	106
Yp	0.47	0.02 ± 0.34	9×10^{-2}	8
Yq	-1.31	-1.04 ± 0.42	7×10^{-1}	16

The observed similarity score, S_{obs} , is calculated using Giemsa and *in silico* bands. The expected similarity score, S_{exp} , is calculated using Giemsa bands and a pattern generated from a random sequence. S_{exp} is given as mean \pm s.d. *, $P < 0.01$. †, $P < 0.05$.

of darkness: solid black, light black, dark gray, and light gray. To understand the relationship between the degree of darkness and the GC content, we calculated the average GC content over all the *in silico* G bands that correspond to a particular degree of darkness of G bands. The GC contents for the four different degrees of darkness are calculated as 36.5, 38.0, 40.3, and 41.8% for solid black, light black, dark gray, and light gray, respectively. Thus, we support the idea that the difference in the staining intensity of G bands is related to the difference in the GC content (18).

Discussion

The successful reconstruction of Giemsa bands by *in silico* staining could be explained from the viewpoint of chromatin structures. Chromatin DNA is composed of loops and matrix-associated regions (MARs), the regions of DNA attaching to

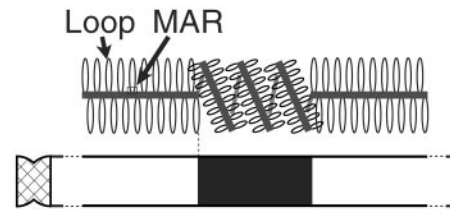


Fig. 4. Model of a metaphase chromatin structure adapted from Saitoh and Laemmli (5).

nuclear scaffolds. Saitoh and Laemmli (5) experimentally detected a lineup of MARs named AT-queue using specific dye. They proposed a model of a metaphase chromatin structure in which G bands are the regions where AT-queue is tightly folded, whereas R bands are the regions where AT-queue is unfolded and located along a longitudinal axis of a chromatin (Fig. 4). According to Saitoh and Laemmli's model, MARs are present densely in G bands and sparsely in R bands. MARs are known to be AT-rich ($\approx 70\%$) but lack any clear consensus motifs (19), although some patterns common to MARs have been reported (20). Our finding of the correlation between G bands and the regions in which the GC content is lower than that of the flanking regions would be explained in the following way. Suppose that a genomic region is under a functional constraint to have a compact chromatin structure. A decrease in GC content would be selectively advantageous in the region or an increase in GC content would be disadvantageous in the region, because many different sites can function as MARs in an AT-rich region. Note that MARs are AT-rich but do not have any clear consensus motifs. Therefore, the regions under the constraint of compact chromatin structures would be subject to a selective pressure for reducing the GC content or against increasing the GC content. That is, structural constraint would keep the region in a G band more AT-rich than the flanking R-band regions.

The optimal sizes of local and regional windows, 2.5 and 9.3 Mb, respectively, are reasonable because of the following reasons. The average length of Giemsa bands among all chromosomes is ≈ 4 Mb (see *Materials and Methods*). Because a 9.3-Mb regional window generally contains both a G band and its flanking R band, this size of a regional window can reflect properly the GC content of the surrounding region of a local window. On the other hand, the entire region of a 2.5-Mb local window generally can be contained in either a G or an R band, because almost all bands are larger than 2.5 Mb. Because a local window with a size smaller than 2.5 Mb tends to yield larger degrees of statistical fluctuation, 2.5 Mb is considered to be an appropriate size for a local window to detect sensitively the difference in GC content between a G band and the flanking R band. It implies that the performance of our method may not be good for fine bands that are smaller than the local window size. For example, the correspondences of *in silico* bands to two G bands at the positions of ≈ 4 and 105 Mb in chromosome 3q (Fig. 1C) are relatively poor, because those bands are experimentally shown very small, approximately only 1.2-Mb long for both.

The correlation between Giemsa and *in silico* bands is expected to improve further by using the data of genome-wide fluorescence *in situ* hybridization mapping (10). This expectation is made because, first, we assume that the terminus of a DNA sequence of each chromosomal arm exactly corresponds to a boundary between a C band (constitutive heterochromatin) and the first euchromatic band. However, the DNA sequences used for the analyses would contain constitutive heterochromatin regions as well as euchromatin regions. For chromosome 22q, for example, the *in silico* G band at the centromeric end does not correspond to any G bands experimentally observed (Fig. 1B).

This observation is explained well by the idea that the available DNA sequence of chromosome 22q contains the pericentromeric heterochromatin region, because constitutive heterochromatins are highly AT-rich. Such extra *in silico* G bands at the centromeric ends are observed also in chromosomes 1q, 5q, 7q, 10q, 12p, 14q, 16q, and 19q (Fig. 3). Second, *in silico* bands predicted from a DNA sequence is aligned to cytogenetic bands without considering the difference of DNA density. In other words, a compaction ratio between G and R bands is assumed to be one, although it is known that G bands are more condensed than R bands (5, 6). Therefore, the performance would improve by taking into account the difference of a compaction ratio. The improvement of the performance may not be expected much, because the ratio of the G-band length to the length of an R band containing the same amount of DNA would be on the order of only the cube root of the compaction ratio. Although these assumptions may cause a limited number of poorly corresponding *in silico* bands, the correspondence would improve by incorporating the fluorescence *in situ* hybridization mapping data into our analysis.

The origin of isochores is in a longstanding controversy. Bernardi *et al.* (8, 9) proposed that isochores arose from adaptive evolution. They argue that an increase in GC content is advantageous in warm-blooded organisms, because G–C bonds contribute to greater thermodynamic stability of RNA, DNA, and proteins. The opposing view is that isochores arose from mutational biases (21–23). Our results imply the relationship between isochores and chromatin structures, inferring a different mechanism of isochore formation. We propose that the functional constraint for retaining compact chromatin would be one contributor to forming isochores. Note that our method of two-window analysis for identifying Giemsa bands implies the presence of another factor that determines the regional trend in GC content. The mechanism of determining the regional trend in GC content, however, remains an open question.

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