Self-organizing approach for automated gene identification in whole genomes

Alexander N. Gorban[1,2], Andrey Yu. Zinovyev[1,2,*] and Tatyana G. Popova[1]
[1] *Institute of Computational Modeling RAS, 660036 Krasnoyarsk, Russia and*
[2] *Institut des Hautes Etudes Scientifiques, France*
(Dated: December 12, 2001)

An approach based on using the idea of distinguished coding phase in explicit form for identification of protein-coding regions in whole genome has been proposed. For several genomes an optimal window length for averaging GC-content function and calculating codon frequencies has been found. Self-training procedure based on clustering in multidimensional space of triplet frequencies is proposed.

PACS numbers: 87.15.Cc, 87.10.+e, 87.14.Gg

Most of the computational approaches for identification of coding regions in DNA have following limitations [1]: they need a training set of already known examples of coding and non-coding regions, they work with a comparably short subsequence of DNA rather than whole sequence and they are able to recognize mainly protein-coding regions.

Recently some approaches appeared which promise to be free of these limitations. In the works by Yeramian E. [2, 3] DNA sequence is considered as a linear chain of strong (GC-bond) and weak (AT-bond) hydrogen bonds. Applying a kind of Ising model to the calculation of partition function one can obtain a thermal DNA stability map (a plot of probability of every DNA basepair to be disrupted). With appropriate temperature chosen, the map in some cases shows believable correlation with the arrangement of coding regions in DNA. This fact was exploited with some success to identify coding regions in Plasmodium falsiparum in some non-standard for gene-finders situations.

Another promising approach is to partition the DNA sequence into homogenious in some sense subsequences and to find such a way of partitioning that corresponds to the "coding – non-coding" partition. In the works of Bernaola-Galvan et.al.[4] method of entropic segmentation was formulated that uses difference in codon compositions in coding and non-coding regions. The hypothesis is that codon composition in coding regions is different from junk because of well-known fact of biasing in codon usage.

Methods of gene finding use a variety of numerical characteristics reflecting statistical regularities in some subsequence (window) of DNA. Inphase hexamers seem to be the most effective single measure (see, for example, [5]). Calculation of inphase hexamers based on division of given subsequence into non-overlapping triplets and counting for every triplet dicodon occurences starting from the first, second and third position in the triplet.

In this work we introduce a method for identification of protein-coding regions in DNA that uses notion of distinguished coding phase. We try to explain the reasons for measures which use in a way the idea of coding phase (including such measures as inphase hexamers, assymetry, entropy etc., see [5, 6] for definitions) to be useful in the methods of identification of protein coding regions. Using the idea in the explicit form we formulate procedure for identification of protein-coding regions in a self-organizing manner.

Let's take arbitrary subsequence of DNA (below we

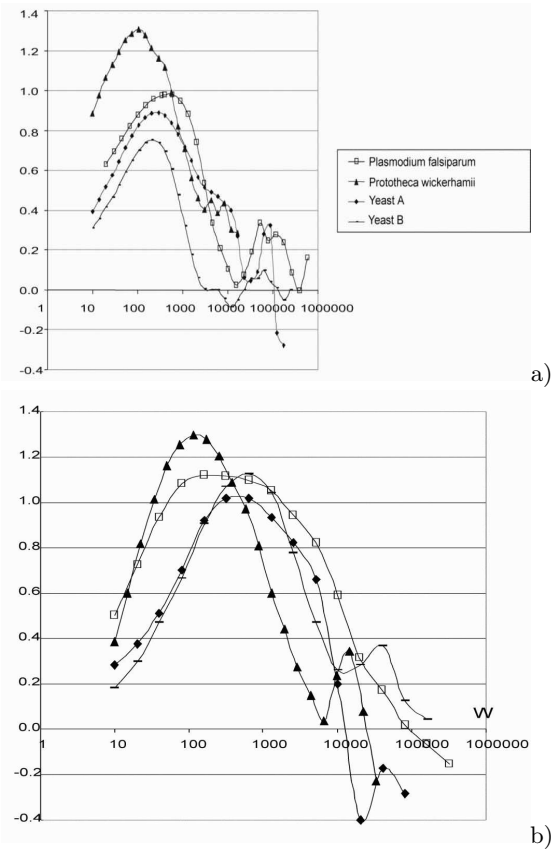

FIG. 1: Effectiveness of two measures (local GC-concentration (a), mixing entropy (b)) for several genomes. Bimodal character of graphs can be explained: first maximum is the difference of coding and non-coding regions themselves, second is statistical difference of long regions (isochores)

*Electronic address: gorban@icm.krasn.ru

think of both DNA strands as of one chain, not touching problem of possible genes overlapping) and divide it into non-overlapping triplets in three different ways, starting from the first, second and third basepair in the window. We get 3 distributions of triplet frequencies $f^{(1)}_{ijk}$, $f^{(2)}_{ijk}$, $f^{(3)}_{ijk}$, $i,j,k \in \{A,C,G,T\}$. Then we can consider mixed distribution $f^{(s)}_{ijk} = \frac{1}{3}(f^{(1)}_{ijk} + f^{(2)}_{ijk} + f^{(3)}_{ijk})$.

If we suppose that given subsequence is protein coding and homogeneous (without introns) then one of the three distributions is the real codon distribution and it defines distinguished coding phase. No matter the distribution is, other two are derivable from it (provided fixed mixed distribution and under several assumptions) and, generally speaking, should be different. This happens due to the fact that the distribution of triplets in coding phase is strictly conserved in the process of evolution.

The situation is fairly opposite in non-coding regions. Due to allowable operations of deleting and inserting a basepair in sequence, all three distributions are expected to be mixed and equal to $f^{(s)}_{ijk}$.

It is worth noticing, that distributions $f^{(1)}_{ijk}$, $f^{(2)}_{ijk}$, $f^{(3)}_{ijk}$ are projections of distribution of pentamers p_{ijklm}, $i,j,k,l,m \in \{A,C,G,T\}$ which counted from every third position starting from the first basepair in a window. It means that information contained in distribution of pentamers seems to be sufficient for prediction of coding regions with the same accuracy as using hexamers (but requires shorter subsequence to evaluate frequencies).

Another interesting note is that GC-concentration in a window is the linear function of the frequencies of triplet distribution in any phase. It means that in the space of triplet (or pentamer, hexamer etc.) frequencies gradient of this functional determines a distinguished direction along what the separation of coding and non-coding windows is good. Really, it is well-known fact that coding regions are GC-rich comparing to non-coding. We will show below that the difference in GC-concentration between coding and non-coding regions is most contrast at the scales comparable to the average gene length in genome.

To implement the simple idea of distinguished phase as a procedure for identification of protein coding regions in DNA, first we investigated dependence of effectiveness of two simple measures on the length of sliding window. It was done on the known genome anotations and it was shown that the dependence has bimodal character and is not very strong in some range of window lengths.

Suppose every nucleotide in one strand of DNA to be "coding" or "non-coding". Then assume that this property depends on some measure calculated over the whole window with length W, centered in the position of the nucleotide. We may evaluate the effectiveness of this measure for separation of coding subset **G** and non-coding subset **J** in the set of all nucleotides. Let $A_W(i)$ be our measure calculated for the i-th position and

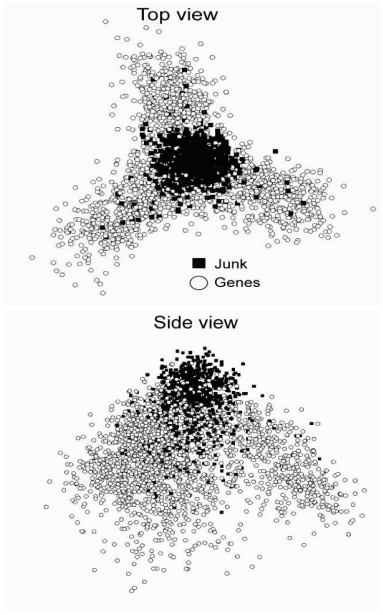

FIG. 2: Distribution of triplet frequencies in the space of first three principal components for P.Wickerhamii

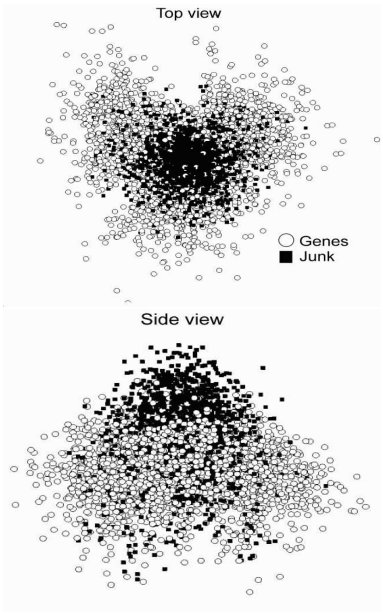

FIG. 3: Distribution of triplet frequencies in the space of first three principal components for S.Cerevisiae III

$$\Delta_W = \frac{\frac{1}{W}(\sum_{i\in\mathbf{G}} A_W(i) - \sum_{i\in\mathbf{J}} A_W(i))}{\sqrt{DA_W(i)}}$$

be a measure of effectiveness, where D is dispersion of $A_W(i)$ over the whole set $\{\mathbf{G},\mathbf{J}\}$. In figures 1(a), 1(b) dependence of Δ_W on W for two measures and several genomes is shown. First (fig.2(a)) is local concentration

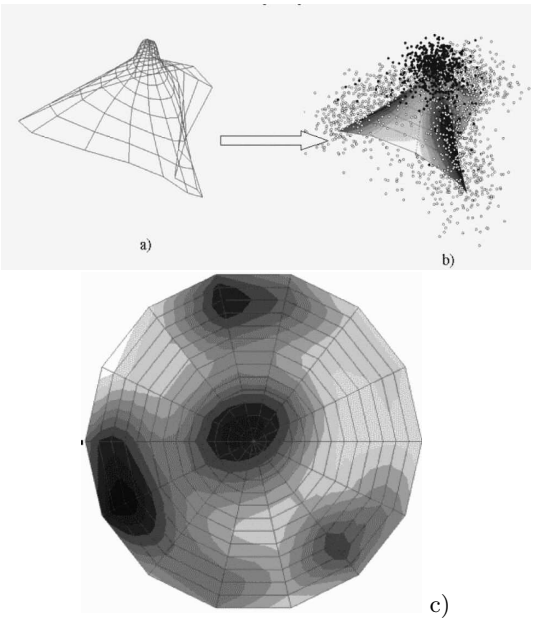

FIG. 4: Two-dimensional visualization of distribution density using method of elastic map: a) form of constructed elastic map; b) position of the map in data space (projection on the first three principal components); c) resulting picture of estimation of density distribution.

of GC-bonds in a window. Second (fig.2(b)) is so called "mixing entropy" $S_M = \frac{1}{3}(3S - S^{(1)} - S^{(2)} - S^{(3)})$, where $S = -\sum_{ijk} f_{ijk}^{(s)} \ln f_{ijk}^{(s)}$, $S^{(m)} = -\sum_{ijk} f_{ijk}^{(m)} \ln f_{ijk}^{(m)}$. It is clear that sets **J** and **G** can be separated with confidence (with enormous number of points we have difference of two mean values more than one standard deviation) and effectiveness of S_M measure seems to be better then GC-average. An optimal window length for calculating the measures is about 400 bp for S.Cerevisiae and P.Falsiparum genomes and about 120 bp in the case of short mitochondrial genome.

Using these values we constructed a finite set of points in 64-dimensional space of triplet frequencies, each point corresponds to the frequencies distribution $f^{(1)}$ of non-overlapping triplets with phase 1 (starts from the first basepair in window). Then coordinates of points in the set $X = \{x_i\}, i = 1...N$ were normalized on unit standard deviation:

$$\tilde{x}_{ij} = \frac{x_{ij} - \bar{x}_j}{\sigma_j},$$

where x_{ij} is the j-th coordinate of the i-th point and $\bar{x}_j$, σ_j are mean value and standard deviation of the j-th coordinate.

The set of normalized vectors $\tilde{x}_i$ was projected into the subspace spanned by the first three principal components of the distribution and visualized with showing known separation for coding and non-coding nucleotides (see fig.2,3). The distribution has bullet-like structure with a kernel corresponding to the non-coding regions (where there is no distinguished phase) and three tails

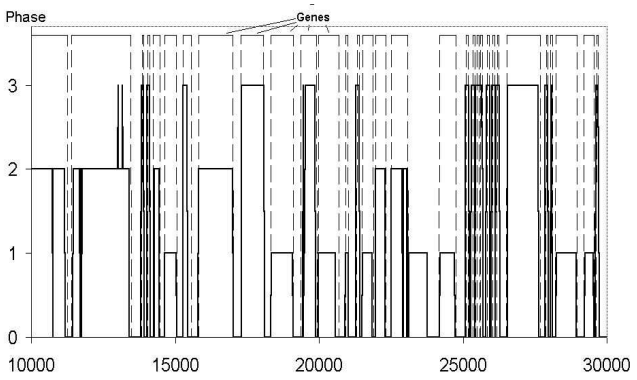

FIG. 5: Prediction of protein-coding regions using clustering in the space of triplet frequencies for P.Wickerhamii. X-axis is basepair position in sequence, Y-axis is number of cluster (coding phase).

which correspond to the three possible shifts of real codon distribution to the phase of test triplets in a window.

To visualize density of the distribution more advanced technology was used named "method of elastic maps"(see [7, 8, 9, 10]). The method of elastic maps just like self-organizing maps [11] constructs point approximation to the non-linear principal 2D-surface using minimization of elastic energy functional that consist of three parts describing "node – data points" attraction and energies of stretching and binding of the net of nodes with appropriate topology. More isometric than in SOM net of nodes allows to construct piece-wise linear 2D-manifold and to project data points in a piece-wise linear fashion onto it, then using the manifold as a 2D screen for visualization purposes. In our case we initialized the net on the 2D-hemisphere put into multidimensional space. After that it was deformed using algorithm of construction elastic net for the optimal approximation and the coloring was used to visualize the resulting density of projections of data points (more precisely, its non-parametric estimation). The distribution of data points has four clusters (fig.4), corresponding to the non-coding regions (central cluster) and protein coding (three peripherial clusters).

Using this fact the procedure for unsupervised prediction of protein coding regions may be formulated. We construct distribution of triplet frequencies just as we did it (using some suboptimal value of window length) and then cluster it for 4 clusters, using appropriate clustering algorithm. It gives separation of all nucleotides into non-coding (0-phase) and protein-coding (1,2,3-phase).

We used simplest method of K-means for clustering and found that separation of nucleotides in investigated genomes relates to the known data with accuracy from 65% up to 85% (calculating accuracy as percentage of correctly predicted nucleotides - coding and non-coding). Though these results are comparable with performance of gene-finders used in real practice [1], more advanced techniques for clustering promise better results. Fragments of the resulting graphs of phase (that is actually

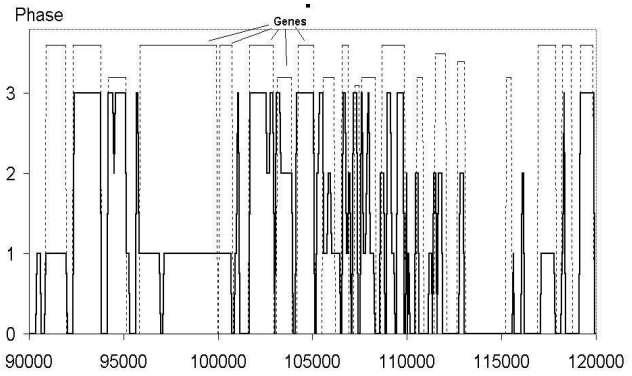

FIG. 6: Prediction of protein-coding regions using clustering in the space of triplet frequencies for S.Cerevisiae III. X-axis is basepair position in sequence, Y-axis is number of cluster (coding phase). Dotted line shows positions of ORFs, the height of bar corresponds to the confidence of gene presence (highest bars are experimentally discovered genes.)

cluster number) of sliding window (calculated through every 3 bp) are shown in fig.5,6.

So, in this paper it was demonstrated that simple notion of distinguished coding phase in three possible distributions of triplets in a window of DNA lays as background in various methods of gene finding. Visualization of the set of sliding windows in the space of triplet frequencies shows symmetric bullet-like structure. Linear dimensions of the structure are determined by amplitudes of two measures: local GC-concentration and mixing entropy.

These two measures have maximum of their effectiveness for separating coding and non-coding regions in the same quite wide range of window lengths (relating to the average length of gene). As average mixing entropy measure is more effective, but it can separate only protein-coding regions, while effectiveness of GC-concentration does not depend on the type of the coding region.

Analysis shows that distribution of windows of DNA in triplet frequencies space forms 4 clusters (central one for junk region, where there is no coding phase, and 3 side ones for three possible phase shifts). Though this clustering is not very compact, it may be used for gene-finding without any learning dataset.

Acknowledgments

Our efforts were inspired by attention of Prof. M.Gromov to the work. We are thankful to Prof. A.Carbone (IHES) for stimulating discussion and help. The paper of A.Carbone and M.Gromov [12] was a good inspiring example for us of how molecular biology can be thought from a mathematical angle.

[1] J.-M. Claverie, Human Molec. Genetics **6**, 1735 (1997).
[2] E. Yeramian, Gene **255**, 139 (2000).
[3] E. Yeramian, Gene **255**, 151 (2000).
[4] P. Bernaola-Galvan, I. Grosse, P. Carpena, and et.al., Phys.Rev.Lett. **85**(6) (2000).
[5] J. Fickett, Computers Chem. **20**(1), 103 (1996).
[6] A. Gorban, A. Zinovyev, and T. Popova, *Statistical approaches to automated gene identification without teacher*, Institut des Hautes Etudes Scientifiques Preprint, IHES/M/01/34 (2001).
[7] A. Gorban and A. Rossiev, Journal of Computer and System Sciences International **38**(5), 825 (1999).
[8] A. Zinovyev, *Visualisaton of Multidimensional Data* (Krasnoyarsk State Technical University Press, Russia, 2000).
[9] A. Gorban, A. Zinovyev, and A. Pitenko, Informatsionnie technologii, Moscow. **6**, 26 (2000).
[10] A. Gorban and A. Zinovyev, *Visualization of data by method of elastic maps and its application in genomics, economics and sociology*, Institut des Hautes Etudes Scientifiques Preprint, IHES/M/01/36 (2001).
[11] T. Kohonen, *Self-Organizing Maps* (Berlin - Heidelberg, 1997).
[12] A. Carbone and M. Gromov, *Mathematical slices of molecular biology*, La Gazette des Mathématiciens, 88:11-80 (2001), numéro Spécial.