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Selective Constraint on Human Pre-mRNA Splicing by Protein Structural Properties

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Abstract

Alternative splicing (AS) is a major mechanism of increasing proteome diversity in complex organisms. Different AS transcript isoforms may be translated into peptide sequences of significantly different lengths and amino acid compositions. One important question, then, is how AS is constrained by protein structural requirements while peptide sequences may be significantly changed in AS events. Here, we address this issue by examining whether the intactness of three-dimensional protein structural units (compact units in protein structures, namely protein units [PUs]) tends to be preserved in AS events in human. We show that PUs tend to occur in constitutively spliced exons and to overlap constitutive exon boundaries. Furthermore, when PUs are located at the boundaries between two alternatively spliced exons (ASEs), these neighboring ASEs tend to co-occur in different transcript isoforms. In addition, such PU-spanned ASE pairs tend to have a higher frequency of being included in transcript isoforms. ASE regions that overlap with PUs also have lower nonsynonymous-to-synonymous substitution rate ratios than those that do not overlap with PUs, indicating stronger negative selection pressure in PU-overlapped ASE regions. Of note, we show that PUs have protein domain- and structural orderness-independent effects on messenger RNA (mRNA) splicing. Overall, our results suggest that fine-scale protein structural requirements have significant influences on the splicing patterns of human mRNAs.

Key words: protein unit, alternative splicing, protein structural constraint.

Introduction

Correct folding of a protein into its native three-dimensional (3D) structure is critical for normal protein functions. The molecular mechanism responsible for protein folding is not fully understood and remains one of the most fundamental problems in biological sciences. Nowadays, more than 1,000 different structural domains have been identified and deposited in protein structural databases, for example, SCOP (Structural Classification of Proteins) (Murzin et al. 1995;

Andreeva et al. 2008), DDBASE (DIAL Derived Domain Database) (Vinayagam et al. 2003), PDP (Protein Domain Parser) (Alexandrov and Shindyalov 2003), CATH (Class, Architecture, Topology, and Homologous superfamily) (Orongo et al. 1997; Cuff et al. 2011), or FSSP (Families of Structurally Similar Proteins) (Holm and Sander 1994). Since the beginning of the 1970s, extensive efforts have been made to decompose 3D protein structures into smaller structural units for a better resolution of biologically meaningful elements (Wetlauber

1973; Wetlaufer and Ristow 1973; Rossmann and Liljas 1974). Among these elements, protein structural domains are especially described and studied (Wetlaufer and Ristow 1973; Holland et al. 2006; Xu et al. 2006). Such subdivisions of protein sequences have important implications for evolutionary studies. For example, structurally ordered peptide regions are known to evolve more slowly than disordered regions (Brown et al. 2010), for the former usually contain more functional protein domains (Ponting and Russell 2002) and are supposedly subject to stronger functional constraints. Recently, a novel approach—protein peeling—has been proposed to divide 3D peptide structures into small structural units, termed protein units (PUs) (Gelly, de Brevern, et al. 2006; Gelly and de Brevern 2011). A PU corresponds to a protein sequence fragment with a high number of intraunit contacts between residues. A protein is cut into a series of PUs maximizing these numbers, whereas the number of contacts between PUs is minimized, thus creating highly compact PUs (Gelly and de Brevern 2011).

PUs are composed of consecutive amino acid sequences. Because the consecutiveness of protein sequences may change with protein isoforms that result from alternative splicing (AS) of messenger RNAs (mRNAs), AS may have the potential to drastically change protein structures. To date, only a small number of protein isoform structures (fewer than 10) can be found in Protein Data Bank (PDB; Stetefeld and Ruegg 2005). Researchers have linked some structural properties (e.g., protein termini) to AS events (Birzele et al. 2008). However, the effects of AS on 3D protein structures and the related selective constraints remain underexplored.

One previous study done by Panchenko et al. (1996) compared substructures named “foldons” to exons. The authors showed that on a limited set of 16 proteins, exons correspond with foldons. Foldons are isolated from protein structures using an energetic criterion. These structural units differ from PUs in terms of size and frequency of occurrence along protein sequences, although they do share some similar properties with PUs. The small number of proteins examined, however, cannot support the general applicability of their findings. Tress et al. (2007) suggested that the spectrum of conventional enzymatic or structural functions is unlikely to be substantially extended through AS events. In addition, previous analyses have shown that AS rarely changes protein domains but can significantly modify protein structures (Birzele et al. 2008; Menon et al. 2011). Therefore, the commonly used protein domains may not provide clear signals in view of selective constraint on AS, possibly because they are generally of huge size. Meanwhile, PUs, which are intermediates between protein domains and local protein conformations, could be better adjusted to AS than domains because of their smaller sizes and are thus more appropriate for studying the correlation between AS and protein structure. For example, when a PU overlaps an exon–exon boundary, it may

occasionally be disrupted when the exon–exon junction is altered by AS. We reason that if PUs are biologically important, such disruptions should be avoided. In other words, the building blocks of 3D structural units (i.e., PUs) should be arranged at the one-dimensional level (exon–exon junctions) in such a pattern that maintains the intactness of the structural units. Accordingly, we generated the following hypotheses: 1) PUs tend to occur in constitutively spliced exons (CSEs; i.e., exons that are always included in different transcript isoforms), so that AS may not cause the exclusion of these structural units; 2) when PUs cross exon boundaries, these boundaries tend to always occur in different transcript isoforms (in other words, these boundaries tend to be “constitutive boundaries”); 3) when PUs cross the exon boundaries flanked by pairs of alternatively spliced exons (ASEs; i.e., exons that are occasionally excluded from some transcript isoforms), these ASE pairs tend to co-occur in transcript isoforms; 4) PU-spanned ASE–ASE pairs tend to have a higher frequency of being included in different transcript isoforms; and 5) PU-spanned ASE regions tend to evolve more slowly than non-PU-spanned ASE regions.

To examine these hypotheses, we decomposed the available human 3D protein structures into PUs, and mapped these PUs onto the corresponding transcripts. Our results show that PUs have significant influences on the pattern of AS and the evolution of exons in human. These observations suggest that the selective constraints on fine-scale structural units (i.e., PUs) and regulations of mRNA splicing may be concordant with each other.

Materials and Methods

General Principle

This study analyzes the correlation between human transcript structure (in the context of AS) and fine-scale protein structural units (PUs) (fig. 1). These two sets of information were retrieved from different databases and mapped onto each other using in-house PERL scripts (available upon request), so that the boundaries between exons (nucleotide sequence) and the boundaries of PUs (structure) can be compared. If a PU is entirely included in an exon, the intactness of this PU is considered as undisturbed. Meanwhile, a PU may also span an exon–exon boundary. In this case, we need to consider whether this exon pair consists of two CSEs or it includes one or two ASEs. In the case of a CSE–CSE exon pair, the intactness of the PU may still be preserved because the exon pair always occurs in different transcript isoforms. However, in the case of CSE–ASE or ASE–ASE, the PU may occasionally be disrupted when the ASE is not present in the transcript. The exon–exon boundaries that remain unchanged in all the transcript isoforms of a gene are termed “constitutive boundaries,” whereas those that differ between isoforms are designated as “non-constitutive boundaries.” Constitutive boundaries occur only in CSE–CSE exon pairs. Nonconstitutive

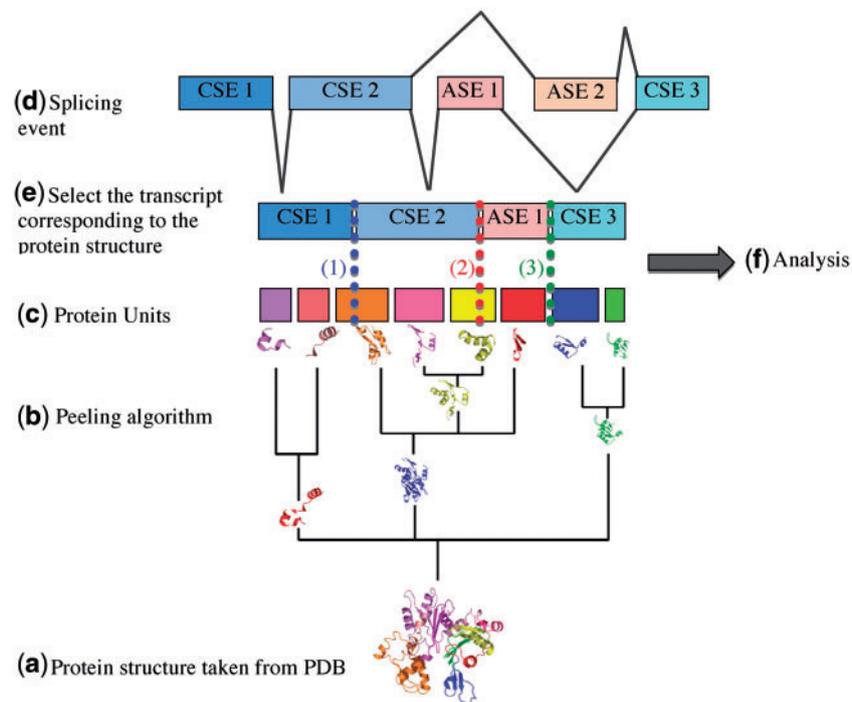


FIG. 1.—The general principle of this study.

boundaries occur mostly in CSE–ASE and ASE–ASE exon pairs, but in rare cases, they may also occur in CSE–CSE exon pairs (when one or both of the CSEs have alternative 5′- or 3′-exon boundaries).

Protein Structures and the Definition of PUs

The 3D structures of human proteins were downloaded from the PDB (<http://www.pdb.org>, last accessed Sept. 9, 2012) (PDB Release of Tuesday, April 12, 2011) (Bernstein et al. 1977). We then filtered the structures to keep only those obtained from X-ray experiments and those that share no more than 95% of sequence identity with each other (to avoid redundancy) using the PICSES webserver (Wang and Dunbrack 2005). In the end, we obtained 5,563 protein structures. The PUs were generated using a local Protein Peeling 3D server (www.dsimb.inserm.fr/dsimb_tools/peeling3/, last accessed Sept. 9, 2012) (Gelly and de Brevern 2011). For the algorithm, the protein structures are described as a succession of α carbon atom of each residue. The distances between C_{α} are translated into contact probabilities using a logistic function. Protein Peeling only uses this contact probability matrix. An optimization procedure, based on the Matthews' coefficient of correlation between contact probability submatrices, defines optimal cutting points that separate the examined region into two or three PUs. The process is iterated until the compactness of the resulting PUs reaches a given limit. Default parameters of Protein Peeling (Gelly, Etchebest, et al. 2006) were used in this study.

Mapping Exons to PUs

The retrieved PDB peptide chains were BLASTP aligned against the human known proteins annotated in the Ensembl database (Release 61; www.ensembl.org, last accessed Sept. 9, 2012) to identify the corresponding Ensembl peptide sequences. To ensure the accuracy of this cross-database mapping, we required that the alignable length be $\geq 95\%$ of the Ensembl sequence, and the query and target sequences be at least 95% identical. The Ensembl transcripts that correspond to the identified Ensembl peptides were retrieved for the analysis of transcript structure. We required that the Ensembl transcript sequences contain a start codon at the 5′-end and a stop codon at the 3′-end of the coding sequence to ensure that the sequences are complete. In the end, we obtained 2,946 human transcripts (genes), which include 34,949 coding exons. To analyze AS events, we also retrieved the 9,342 known transcript isoforms (with known protein products and the start and stop codons) encoded by the 2,946 genes. Among the analyzed genes, 690 encode only one known transcript. On average, each gene in this data set has ~ 3.2 (9,342/2,946) transcript isoforms. The distribution of the number of transcript isoforms per gene is illustrated in [supplementary figure S1, Supplementary Material](#) online. To control for the effects of protein domains on transcript structure, we also retrieved the Pfam domain information from the Ensembl database (Release 61). An in-house PERL script was used to analyze the retrieved Ensembl known transcripts to classify exons into CSEs and ASEs and to calculate the

Table 1

The Numbers (Percentages) of CSEs and ASEs That Contain Complete PUs

	No. Analyzed Exons	No. Observed ^a	No. Expected ^b	O/E ^c
CSE	11,033 (31.6%)	3,674	2,885	1.27
ASE	23,916 (68.4%)	5,456	6,245	0.87

^aObserved number of exons that contain complete PUs.^bExpected number of exons that contain complete PUs. For CSEs: $(3,674 + 5,456) \times 0.316 = 2,885$; for ASEs: $(3,674 + 5,456) \times 0.684 = 6,245$.^cNo. observed/No. expected.

weighted exon frequency (WEF, explained in the next section). The identified Ensembl peptide sequences were aligned with their PDB sequence partners using MUSCLE 3.7 (Edgar 2004) with default parameters. The corresponding exon boundaries were then mapped onto the protein structures (and the PUs within) according to the alignment files.

Definition of WEF

WEF is the length-weighted average of the frequency an exon occurs in alternatively spliced transcript isoforms (supplementary fig. S2, Supplementary Material online). Briefly, the frequency of an exon was defined as the proportion of transcript isoforms that include this exon. Therefore, by definition, CSEs should have an exon frequency of 100%. As CSEs appear to be important for the structures and normal functions of the proteins where they belong, we reason that exons with a high frequency may be biologically important, which is actually supported by our recent study (Chen, Liao, et al. 2012). However, because exons from different transcript isoforms usually partially overlap with each other (supplementary fig. S2, Supplementary Material online), the “frequency” of an exon may be difficult to define. Therefore, we divided each exon into several subregions according to how it overlaps with exons from different transcript isoforms. The WEF was defined as the length-weighted average of the frequencies of such subregions.

Computation of Observed/Expected (O/E) Ratio of PU-Containing Exons and PU-Spanned Exon Boundaries

To examine whether the intactness of PUs tends to be preserved, we calculated the O/E ratios of exons that contain complete PUs (PU-containing exons) and the O/E ratios of exon boundaries that overlap with a PU (PU-spanned exon boundaries). The expected numbers of PU-containing exons were calculated with reference to the percentages of CSEs (31.6%) and ASEs (68.4%) observed in our data set (table 1). Specifically, the total number of PU-containing exons is 9,130 (3,674 CSEs + 5,456 ASEs). The expected number of CSEs that contain PUs is $9,130 \times 31.6\% = 2,885$. Similarly, the observed number of ASEs that contain PUs is $9,130 \times 68.4\% = 6,245$. The O/E ratio is simply the observed number divided by the expected number of CSEs (or ASEs). The O/E ratios for PU-spanned exon boundaries were

computed in a similar way. An O/E ratio larger than one indicates that the event of interest occurs more frequently than expected.

Estimation of Evolutionary Rates and Prediction of Intrinsically Disordered Amino Acid Residues

The nucleotide sequences, peptide sequences, and orthology information of human–mouse one-to-one orthologous genes were downloaded from the Ensembl database (Release 61). The human peptide sequences analyzed in this study were aligned against the peptide isoforms encoded by the mouse orthologous genes using MUSCLE 3.7 (Edgar 2004) with default parameters. For each human peptide, the longest alignable mouse peptide was selected. The peptide sequence alignments were back translated to nucleotide sequences, and the exon boundaries were delineated with reference to the human transcript annotations. The “orthologous exonic regions” thus obtained were then submitted to the Codeml package of PAML 4 (Yang 2007) for estimations of nonsynonymous substitution rate (d_N), synonymous substitution rate (d_S), and the d_N/d_S ratio. Of note, to ensure data quality, we required that the alignable exonic sequence length be $\geq 90\%$ of the human exon. Intrinsically disordered amino acid residues were predicted by using DISOPRED 2.4 (Ward et al. 2004) with default parameters. The statistical tests (χ^2 and Wilcoxon rank sum tests) were done by using the R package (R Core Team 2012). The χ^2 tests were conducted with default parameters (with continuity correction [“correct = TRUE”]), and the *P* values were exact *P* values (“simulate.p.value = FALSE”). The Wilcoxon rank sum tests were also conducted using default parameters (with continuity correction; *P* values were calculated according to a normal approximation).

The same procedure was then performed on the basis of the known human genes (according to the human genome version hg 19) of the UCSC (University of California Santa Cruz) Genome Browser (<http://genome.ucsc.edu>, last accessed Sept. 9, 2012).

Analysis of Covariance

To disentangle the effects of PU overlapping and structural disorderness (or Pfam domain overlapping) on the evolutionary rates of protein subregions, we applied the analysis of

covariance (ANCOVA) (McDonald 2009) with the following equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \varepsilon \quad (1)$$

Where Y is the evolutionary measurement of interest (d_N/d_S , d_{Nv} , or d_S); X_1 indicates whether the region of interest overlaps with a PU ($X_1 = 1$ if it does, otherwise $X_1 = 0$); X_2 is the proportion of structurally disordered region predicted by DISOPRED 2.4 (or the proportion of Pfam domain as annotated by Ensembl); and $X_1 X_2$ is the interaction term between the two variables.

Therefore, for PU-overlapped regions,

$$(Y|X_1 = 1) = (\beta_0 + \beta_1) + (\beta_2 + \beta_{12})X_2 + \varepsilon \quad (2)$$

Whereas for non-PU-overlapped regions,

$$(Y|X_1 = 0) = \beta_0 + \beta_2 X_2 + \varepsilon \quad (3)$$

If $\beta_{12} \neq 0$, the regression slopes for PU-overlapped regions and non-PU-overlapped regions would be considered as different. Alternatively, if $\beta_{12} \sim 0$ but $\beta_1 \neq 0$, the intercepts of the two regression lines would be considered as different. In either case, the factor of PU overlapping and the proportion of structurally disordered regions (or Pfam domain) would be regarded as having independent effects on the evolutionary measurement of interest (McDonald 2009; Chen, Pan, et al. 2012). ANCOVA was conducted by using the R package with default parameters.

Results

PUs Tend to Occur in CSEs

According to the cross-database comparison of Ensembl and human protein structures from PDB, we retrieved 34,949 exons that can be mapped to PU-containing peptides. Approximately two-thirds of these exons are ASEs and one-third are CSEs (table 1). The distribution of CSEs is fairly even across the examined peptides and so is the distribution of PUs except that PUs seem to occur less frequently at both termini of a peptide (supplementary fig. S3, Supplementary Material online). We first examined whether PUs tend to fall completely within CSEs (so that they can always be included in the translated peptide sequences). Indeed, as presented in table 1, the observed-to-expected (O/E) ratio of PU-containing CSEs (1.27) is larger than unity, whereas the O/E ratio of ASEs is smaller than 1 (0.87). The proportions of CSEs and ASEs that contain PUs differ significantly from expected ($P < 2.2E-16$, by χ^2 test). Of note, CSEs may occasionally change their boundaries, which may also disrupt PUs. However, only a small percentage ($3.7\% = 135/3,674$) of the examined CSEs have such a “boundary effect” on the PUs within. The difference between CSEs and ASEs in table 1 remains highly significant even if we remove these 135 CSEs. Meanwhile, CSEs are more likely to correspond to structurally ordered protein

regions than ASEs. This preference may potentially bias our results because PUs may be more readily identifiable in structurally ordered protein regions. We thus conducted the above analysis for CSEs and ASEs that correspond to structurally ordered protein regions. We actually obtained a similar result (supplementary table S1, Supplementary Material online). This result supports our hypothesis that PUs are biologically important, so that they have a higher-than-expected probability of always occurring in mRNAs (and thus the protein products).

Next, we compared the weighted exon frequencies (WEFs; see Materials and Methods) between ASEs that contain PUs and those that do not. Following the logic described earlier, if PUs are biologically important, ASEs that contain PUs may be more frequently included in transcript isoforms (with a higher WEF) than those that do not. Indeed, our analysis indicates that PU-containing ASEs have a significantly higher WEF (median = 0.54) than non-PU-containing ASEs (median = 0.50) ($P < 2.2E-16$, by the Wilcoxon rank sum test).

The Intactness of PUs Tends to Be Preserved Even When They Cross Exon Boundaries

Because PUs usually cross exon boundaries, we analyzed whether the PU-spanned exon boundaries also tend to be “fixed” in different AS isoforms, so that the disruption of cross-exon boundary PUs can be avoided. To this end, we examined the O/E ratios of “constitutive exon boundaries” and “non-constitutive exon boundaries” that overlap with PUs. A constitutive exon boundary is defined as an exon-exon junction that does not shift its position and always occurs in transcript isoforms. If either of the flanking exons changes its border at the junction, or becomes absent in any of the isoforms, the exon boundary is considered as nonconstitutive (see Materials and Methods). Of note, in the previous section, we examined whether PUs tend to be 100% included in CSEs (table 1). In that analysis, PUs that partially overlap exons were not considered. By contrast, for the current analysis, we examine whether PUs tend to be located at constitutive boundaries. In other words, only PUs that partially overlap exons are examined here. Biologically, these two analyses also differ from each other. AS may lead to complete loss of a PU if it is included entirely in an ASE. In comparison, splicing events may delete only part of a PU if it is located at a nonconstitutive boundary. In the latter case, we do not know whether the residual PU fragment is still important for the structure of the resulting peptide.

Interestingly, as presented in table 2, the O/E ratio of PU-spanned constitutive exon boundary is larger than 1 (1.16), whereas the ratio of PU-spanned nonconstitutive exon boundary is smaller than 1 (0.94). PUs are significantly enriched at constitutive boundaries (P value $< 2.2E-16$, by χ^2 test). Therefore, PUs not only occur more frequently within CSEs but also tend to occur at constitutive exon

Table 2

The Numbers (Percentages) of PU-Spanned Exon Boundaries

	No. Analyzed	No. PU Spanned	No. Expected ^a	O/E ^b
Constitutive boundary	8,437 (26.4%)	3,822	3,282	1.16
Nonconstitutive boundary	23,566 (73.6%)	8,610	9,150	0.94

^aExpected number of PU-spanned exon pairs. For constitutive boundary: $(3,822 + 8,610) \times 0.264 = 3,282$; for nonconstitutive boundary: $(3,822 + 8,610) \times 0.736 = 9,150$.

^bNo. PU spanned/no. expected.

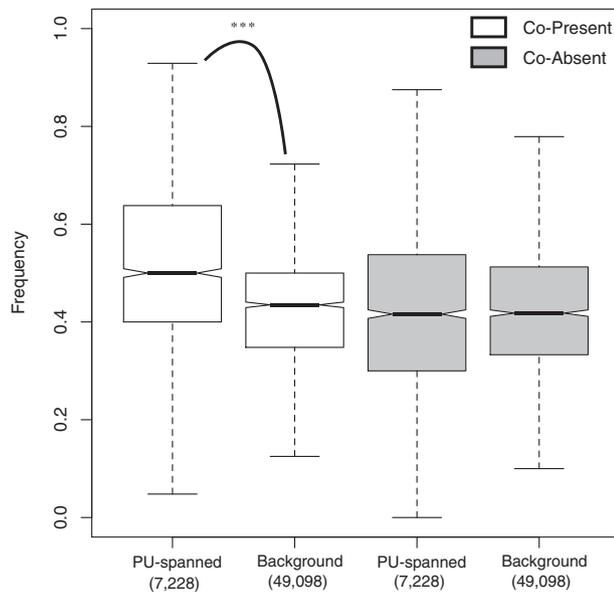


Fig. 2.—The proportion of PU-spanned ASE–ASE pairs that are either copresent (white) or coabsent (gray) in the same transcripts, when compared with the background ratios. The curve with stars indicates statistically significant difference ($P < 2.2E-16$ by the Wilcoxon rank sum test). The number of exon pairs analyzed for each category is given in the parenthesis. The total number of analyzed genes is 1,796.

boundaries and to avoid nonconstitutive exon boundaries. These observations suggest that the intactness of PUs tends to be preserved in AS events, lending further support for the biological importance of these structural units.

We then focus on the PU-spanned nonconstitutive exon boundaries, especially those flanked by ASE–ASE pairs. They are of interest because the inclusion/exclusion of such ASEs in transcript isoforms may cause disruptions of PUs. To prevent disruption of PUs, these PU-spanned ASE–ASE pairs should tend to co-occur in the same transcripts. We thus calculated the proportions of PU-spanned ASE–ASE pairs that are either copresent or coabsent in the same transcripts and compared these proportions with the background values (derived from all the ASE–ASE exon pairs in our data set). These proportions were computed in a way similar to the calculation of exon frequency (i.e., the proportion of transcript isoforms that contain both [copresent] or neither [coabsent] of the two neighboring ASEs). As shown in figure 2, the proportion of PU-spanned ASE–ASE pairs that co-occur in transcripts is

significantly larger than expected ($P < 2.2E-16$; all the statistical tests in figures 2–4 were done by using the Wilcoxon rank sum test). Meanwhile, the proportion of coabsent PU-spanned ASE–ASE pairs is not larger than the background value (fig. 2). These results indicate that AS tends to maintain the intactness of PUs by including both PU-spanned ASEs in the same transcripts.

PU-Spanned ASEs Have a Protein Domain-Independent Effect on AS

One concern in the above analysis is that PUs may tend to overlap with functional protein domains. This may confound our result that PU-spanned ASE pairs tend to co-occur in transcripts because such copresence may have reflected the requirement to prevent disruptions of protein domains. To examine this possibility, we repeated the previous analysis by controlling for whether the ASE–ASE boundary overlaps a Pfam domain. Our result indicates that PU-spanned ASE–ASE pairs have only a slightly higher frequency of copresence (0.375) than non-PU-spanned pairs (0.364) when both overlap with Pfam domains (the difference is statistically insignificant, $P = 0.068$; fig. 3). Interestingly, the difference is highly significant ($P < 2.2E-16$) when neither PU-spanned nor non-PU-spanned ASE pairs overlap Pfam domains at the exon boundary (fig. 3). These observations suggest that the requirement to preserve functional protein domains may not fully explain the higher-than-expected probability of copresence of PU-spanned ASE pairs. In other words, PUs may have a Pfam domain-independent effect on the copresence of ASE–ASE pairs. Of note, the domain-overlapping ASE pairs have reduced sample sizes when compared with non-domain-overlapping ASE pairs (fig. 3). Therefore, it is also likely that the decreased statistical significance in the former group is associated with the reduction in sample size.

PU-Spanned ASEs Tend to Have a Higher Frequency of Exon Usage

The next question is whether the PU-spanned ASE pairs are more frequently used in transcript isoforms than non-PU-spanned ASE pairs. The extreme case of frequently used exons is CSEs, which are always included in different transcript isoforms and appear to be important for the normal functions of the proteins where they belong. Therefore, we speculate that ASEs are more functionally relevant if they occur frequently in transcript isoforms (although a more ideal measurement may be exonic expression level or exonic expression

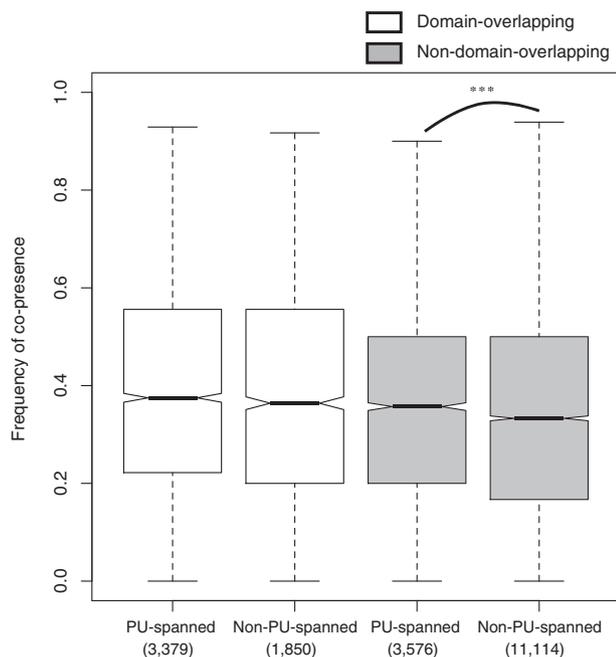


Fig. 3.—The proportion of PU-spanned ASE–ASE pairs that are copresent in the same transcripts when Pfam domain overlapping is controlled. The curve with stars indicates statistically significant difference ($P < 2.2E-16$ by the Wilcoxon rank sum test). The number of exon pairs analyzed for each category is given in the parenthesis.

breadth). To this end, we compared the WEFs of the PU-spanned and non-PU-spanned exon pairs. As shown in figure 4, the WEFs of PU-spanned ASE–ASE pairs are significantly higher than those of non-PU-spanned ASE–ASE pairs ($P < 2.2E-16$). Considering that protein domain and the proportion of structurally disordered regions may also confound this result, we performed the same analysis by separately controlling for Pfam domain overlapping and structural orderliness and obtained similar results (supplementary fig. S4A and B, Supplementary Material online; both $P < 2.2E-16$). These observations indicate that PU-spanned ASEs have higher WEFs regardless of whether the ASEs overlap with Pfam domains/structurally ordered regions or not.

One potential bias in the above analyses is that the definition of CSEs and ASEs may differ with data sources. We thus retrieved the known human transcripts from the UCSC Genome Browser and conducted the analyses again. The results remain similar (supplementary tables S2 and S3 and figs. S5 and S6, Supplementary Material online).

PUs Have Structural Orderliness- and Protein Domain-Independent Effects on the Evolution of ASEs

Finally, we are interested to know whether PU-overlapped exonic regions evolve at the same rate as non-PU-overlapped regions. If PUs are biologically important, PU-overlapped regions are expected to evolve more slowly than non-PU-

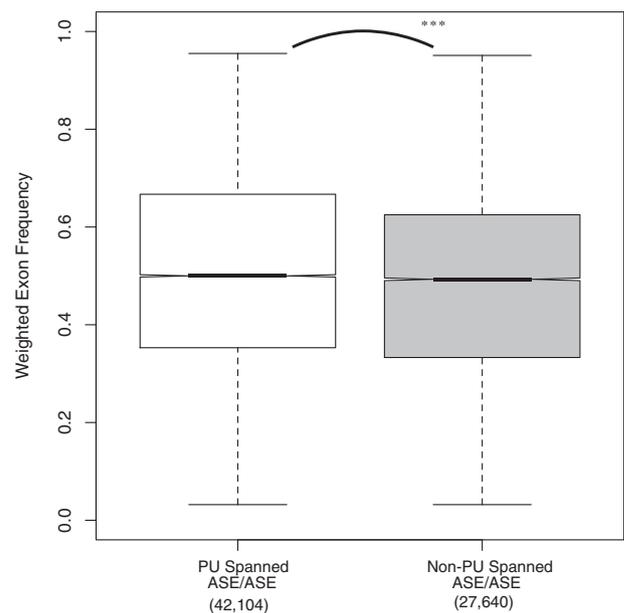


Fig. 4.—The distributions of weighted exon frequency of PU-spanned ASE–ASE and non-PU-spanned ASE–ASE pairs. Note that the WEFs (weighted exon frequencies) were averaged for the two ASEs of each ASE–ASE pair. The curve with stars indicates statistically significant difference ($P < 2.2E-16$ by the Wilcoxon rank sum test). The number of exon pairs analyzed for each category is given in the parenthesis.

overlapped regions. We thus retrieved human–mouse orthologous exons and divided the exons into PU-overlapped and non-PU-overlapped regions. Of note, only ASEs are included in this analysis because CSEs are usually evolutionarily more conserved. Also note that the boundaries of PUs and exons differ from each other in most of the cases. We thus separately concatenated the PU-overlapped and non-PU-overlapped ASE regions (regardless of the exon boundaries) in the same transcripts for calculations of d_N , d_S , and the d_N/d_S ratio. It is worth noting that the number of peptides analyzed here is decreased to 506 because of the requirements for high data quality (the human–mouse alignable sequence length must be $\geq 90\%$ of the human sequence length; see Materials and Methods) and for the simultaneous occurrences of multiple biological features (PU/non-PU, ordered/disordered region, and Pfam domain/non-Pfam domain). Because the factor of structural orderliness may confound the analysis, we employed ANCOVA to clarify whether PU overlapping has a structural orderliness-independent effect on each of the three evolutionary measurements (see Materials and Methods). As presented in table 3, for d_N/d_S and d_N , β_{12} does not deviate significantly from zero (table 3). However, β_1 is significantly smaller than 0 in both of the cases, indicating a structural orderliness-independent effect of PU overlapping in decreasing these two evolutionary measurements. Of note, β_2 in the analysis for d_N does not significantly deviate from 0 possibly because of the reduced sample size. In comparison, for d_S , neither β_{12} nor

Table 3

Estimates of Regression Coefficients (*P* Values) in the Analysis of Covariance for PU Overlapping and Proportion of Structurally Disordered Region^a

	d_N/d_S	d_N	d_S
β_0	-1.83 ^{b***} (<2.2E-16)	-2.27 ^{***} (<2.2E-16)	-0.50 ^{***} (<2.2E-16)
β_1	-0.27* (0.02)	-0.24** (0.01)	-0.03 (0.31)
β_2	0.38* (0.03)	0.22 (0.08)	-0.18 ^{***} (4.76E-05)
β_{12}	0.05 (0.87)	0.09 (0.69)	0.11 (0.13)

^aThe regression model was $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \varepsilon$ (Y : d_N/d_S , d_N , or d_S ; X_1 : PU overlapped=1 and non-PU overlapped=0; X_2 : proportion of structurally disordered region).

^bStatistical significance: * $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$.

Table 4

Estimates of Regression Coefficients and *P* Values in the Analysis of Covariance for PU Overlapping and Proportion of Pfam Domain^a

	d_N/d_S	d_N	d_S
β_0	-1.59 ^{b***} (<2.2E-16)	-2.13 ^{***} (<2.2E-16)	-0.62 ^{***} (<2.2E-16)
β_1	-0.38* (0.02)	-0.28* (0.02)	0.08 (0.05)
β_2	-0.17 (0.28)	-0.10 (0.40)	0.10* (0.01)
β_{12}	0.09 (0.71)	0.04 (0.81)	-0.10 (0.09)

^aThe regression model was $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \varepsilon$ (Y : d_N/d_S , d_N , or d_S ; X_1 : PU overlapped = 1 and non-PU overlapped = 0; X_2 : proportion of Pfam domain).

^bStatistical significance: * $P < 0.05$; *** $P < 0.001$.

β_1 deviates significantly from 0. Therefore, PU overlapping does not appear to have any effect on synonymous substitutions. This implies that PU overlapping may have influenced d_N/d_S by affecting d_N (rather than d_S). We also applied ANCOVA for another potential confounding factor (the proportion of Pfam domain) and obtained similar results (table 4).

Discussions

In this study, by analyzing thousands of protein structures, we demonstrate that fine-scale 3D structural units (PUs) are significantly correlated with mRNA splicing patterns at a genome-wide scale. PUs are meaningful elements in terms of protein structure. They have internal contacts maintaining local structures important for the stability of whole protein architecture. It is therefore plausible that the disruption of a PU has a significant impact on the architecture and the folding of a protein. Thus, any evolutionary event, such as the emergence of a splice site, may have a negative impact when it disrupts a PU.

The observation that PUs tend to occur within CSEs and to cross constitutive exon boundaries suggests that the intactness of PUs is biologically important. In fact, similar trends are also observed in mouse despite the remarkably reduced sample size (supplementary tables S4 and S5, Supplementary Material online). Therefore, natural selection appears to constrain on AS events to avoid disruptions of PUs in mammals.

Also supporting the biological importance of PUs is the finding that PU-spanned ASE-ASE pairs tend to co-occur in alternative transcript isoforms. Interestingly, such copresence of PU-spanned ASEs is particularly significant when the exon

boundaries do not overlap with Pfam domains. This observation suggests that PUs have a protein domain-independent effect on mRNA splicing. Similarly, we also show that PUs have a Pfam domain- and structural orderness-independent effect on WEF. ASEs with high WEFs may be more biologically relevant because such ASEs are frequently included in different transcript isoforms. The observation that PU-spanned ASEs have higher WEFs than non-PU-spanned ASEs thus lends further support for the biological importance of PUs. The biological relevance of PUs is also reflected in the reduced d_N/d_S ratio in PU-spanned ASE regions when compared with non-PU-spanned ASE regions. Overall, our results suggest that PUs, as a new concept of protein structure decomposition, have significant influences on the regulation of AS and the evolution of mammalian exons.

However, one noteworthy observation in our study is that a considerable number of PUs may actually be disrupted in AS events (table 2). Because there is only a limited number of 3D structures for protein isoforms, it is difficult to systematically estimate the structural effects of such disruptions. We speculate that different PUs may contribute differentially to protein structural stability. In other words, the disruptions of certain PUs are less deleterious, and such PUs can be more easily found to be located at nonconstitutive boundaries. The mixture of “more important” and “less important” PUs in our data set could have brought noises and decreased the effect sizes in our analyses. That said, until we could confidently measure the effects of PU disruptions on protein structures and/or functions, the reason why only some PUs are disrupted remains unclear.

Also important for this study is the definition of CSEs and ASEs. In fact, the proportion of ASEs in the human

transcriptome increases while that of CSEs decreases with the accumulation of large-scale RNA-sequencing (RNA-seq) data. This is because an increasing number of transcript isoforms are being discovered, thus changing many of the previously recognized “CSEs” to ASEs. Although some of the changes in the definition of the CSE/ASE exon type are biologically sensible, such RNA-seq-based definitions may have a number of drawbacks. First, RNA-seq data may include functionally irrelevant transcriptional noises or noncoding RNAs (Lu et al. 2009; McIntyre et al. 2011; Tarazona et al. 2011). Second, de novo assembly of the human transcriptome remains a difficult and error-prone task (Qu et al. 2009; Kircher and Kelso 2010). Assembly errors may add to the noises in determining transcript structures. Third, some transcript isoforms may be expressed at a very low level, or only in a very specific condition or a short time span. It remains unclear whether such transcripts are biologically important or not. Given the potential caveats of RNA-seq data, caution must be taken in defining “biologically meaningful” transcript isoforms. An alternative approach is to use the average exonic expression level or the specificity of exonic expression (or exonic expression breadth) across multiple tissues, which are continuous variables and can be compared both within and between genes. It will be interesting to investigate how PU and exonic expression patterns are correlated with each other.

Supplementary Material

Supplementary figures S1–S6 and tables S1–S5 are available at *Genome Biology and Evolution* online (<http://www.gbe.oxfordjournals.org/>).

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