ABSTRACT

**Motivation:** Hidden Markov models (HMMs) have proved to be a powerful tool for protein domain identification in newly sequenced organisms. However, numerous domain models may be missed in highly divergent proteins. This is the case for *Plasmodium falciparum* proteins, the main causal agent of human malaria.

**Results:** We propose a method to improve the sensitivity of HMM domain detection by exploiting the tendency of the domains to appear preferentially with a few other favorite domains in a protein. When sequence information alone is not sufficient to warrant the presence of a particular domain, our method enables its detection on the basis of the presence of other Pfam or InterPro domains. Moreover, a shuffling procedure allows us to estimate the false discovery rate associated with the results. Applied to *P.falciparum*, our method identifies 585 new Pfam domains (versus the 363 already known domains in the Pfam database) with an estimated error rate <20%. These new domains provide 387 new Gene Ontology (GO) annotations to the Pfam database. Analogous and congruent results are obtained when applying the method to related *Plasmodium* species (P. vivax and P. yoelli).

**Availability:** Supplementary Material and a database of the new domains and GO predictions achieved on Plasmodium proteins are available at http://www.lirmm.fr/~terrapon/codd/

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**Supplementary information:** Supplementary data are available at Bioinformatics online.

1 INTRODUCTION

Among relevant annotations that can be attached to a protein, domains occupy a key position. Protein domains are sequential and structural motifs that are found independently in different proteins, in different combinations and, as such, seem to be functional subunits of proteins above the raw amino acid sequence level (Richardson, 1981). Several approaches have been developed to define and identify domains. Some are based on observed distinct structural classes of proteins (Murzin et al., 1995). Others are inferred by clustering conserved subsequences (Finn et al., 2008; Mulder et al., 2007). One of the most widely used domain schemata is the Pfam database (Finn et al., 2008). In this database, each domain family is defined with a set of distinct representative protein sequences, manually selected and aligned, and used to learn a hidden Markov model (HMM; Durbin et al., 1998) of the domain. The current release of the Pfam database (version 23.0 of July 2008) offers a large collection of 10,340 HMMs/domains, which account for >73% of all proteins in the Uniprot database (UniProt Consortium, 2009). Some Pfam HMMs have been annotated by the InterPro consortium (Mulder et al., 2007) in the Gene Ontology (GO; Gene Ontology Consortium, 2000). According to the InterPro annotation policy, a domain is annotated with a given GO term if all proteins where this domain is known also share this GO term. This stringent rule allows, when a new domain is detected in a protein, transfer of its annotations to this protein.

When analyzing a new protein sequence, each Pfam HMM is used to compute a score that measures the similarity between the sequence and the domain. If the score is above a given threshold provided by Pfam (score thresholds differ depending on the HMMs), then the presence of the domain can be asserted in the protein. However, when applied to highly divergent proteins, this strategy may miss numerous domains. For example, with *Plasmodium falciparum*, the main causal agent of human malaria, no Pfam domains are detected in nearly 50% of its proteins, while many domain types seem to be missing from the *P.falciparum* library—see Supplementary Table 1 for a comparison of the protein coverage and domain numbers between several eukaryotes. This can be partly explained by the highly atypical genome of *P.falciparum*, which is composed of >80% A+T, and involves low low-complexity insertions of unknown function believed to form non-globular domains (Pizzi and Frontali, 2001). This strongly biases the amino acid composition of *P.falciparum* proteome, in which six amino acids account for >50% of the protein composition (Bastien et al., 2005). In this article, we propose a new method to increase the sensitivity of Pfam domain detection in divergent proteins like those of *P.falciparum*. Our method involves lowering the thresholds provided by Pfam for detecting the domains. This enables more domain detections, but at the expense of numerous false positive predictions. The core of the method is a filter procedure based on domain co-occurrence properties which selects the potential domains that are most likely true.

Several authors have studied domain combinations in proteins (Apic et al., 2001). They showed that numerous domains are frequently found together. As a result, the number of observed...
domain combinations in nature is clearly less than the number of possibilities. The domains tend to appear with a few other favorite domain combinations. For example, when computing the number of distinct Pfam domain pairs observed in Uniprot proteins, only 20,000 out of the ~12.5 million possibilities are observed (a ratio of 1.6‰). This property suggests functional cooperation. Indeed, two-thirds of yeast proteins. Finally, our approach is applied to artificial proteins obtained by simulating evolution events in the shuffling procedure that allows estimation of its false discovery rate.

In this article, we propose to use domain co-occurrence to improve the quality of predictions. Indeed, the presence of domains that cooperate to achieve a given function. To this end, all Uniprot proteins are clustered into groups that are known to be associated with specific GO annotations. Geer et al. (2004) use Bayesian networks of co-occurring motifs to predict subcellular localizations of proteins. McLaughlin et al. (2007) characterize domain assembly (DASSEM) units, i.e., groups of domains that cooperate to achieve a given function. Forshlund and Sonnhammer (2008) propose an approach to predict specific GO annotations from domain groups. Geer et al. (2002) present the CDART tool that allows users to find proteins having a domain composition similar to that of the query protein. In this article, we propose to use domain co-occurrence to improve the quality of Pfam domain detection. In the following, we first describe our approach and present a shuffling procedure that allows estimation of its false discovery rate (FDR). Next, the method is assessed by searching for domains in artificial proteins obtained by simulating evolution events in the yeast proteome. Finally, our approach is applied to Plasmodium proteins. In this organism, it detects 558 additional domains with an estimated FDR <20%. Among these new domains, 159 domain types have never before been detected in Plasmodium proteins. Moreover, these domains provide new GO annotations. Analogous and congruent results are obtained when applying this method to related Plasmodium species (P. vivax and P. yoelii).

2 METHOD

In the following, the domain composition of a protein is the set of domains it contains. This property suggests functional cooperation. Indeed, two-thirds of yeast proteins. Finally, our approach is applied to artificial proteins obtained by simulating evolution events in the shuffling procedure that allows estimation of its false discovery rate.

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2.1 Set of potential domains

The set of potential domains \( P_i \) are inferred from the results of Pfam HMM searches using HMMER software (Eddy, 1998). Given a set of proteins and an HMM, this tool computes a score that measures the similarity between each protein sequence and the domain modeled by the HMM. Additionally, this score can be used to compute an \( E \)-value estimate that represents the expected number of random sequences that would obtain a score above that achieved by the protein. Here, the set of potential domains of each protein is built by considering all HMM hits that differ from the already known Pfam domains and which have an \( E \)-value below a given permissive threshold (e.g. 10). This \( E \)-value threshold is chosen to be much less conservative than the thresholds recommended by Pfam for each HMM. The results are then processed for each protein to obtain a list of non-overlapping potential domains. The policy applied for this selection is to favor domains with the most significant (lowest) \( E \)-values. Overlaps with already known Pfam domains are forbidden. The same domain may appear several times in this non-overlapping domain list, but redundancies are removed to obtain the final set of potential domains \( P_i \).

2.2 Set of validating domains

Different sets of validating domains \( V_i \) are considered here. The first solution is to use known Pfam domains of the protein. A complementary solution is to use InterPro non-Pfam domains already known in the protein. This allows us to increase the number of validating domains of each protein and thus the expected number of certifications. However, due to the heterogeneity of the InterPro database, the certifications achieved this way may be of lower quality than that achieved with Pfam domains. With these two first solutions, domains can be certified solely in proteins where at least one domain is already known. To overcome this limitation, a third solution is to consider the potential domains themselves as validating domains. In this solution, all pairs of potential domains of the protein are enumerated and, if the pair belongs to the CDP list, the two domains are certified. Of course this procedure is more prone to false positives than the two others, but we will see below how this can be controlled. Thus, the three types of validating domains are mutually exclusive and of decreasing quality a priori. Note that certifying a potential domain, only the validating domains that do not overlap this domain are considered. In the experiments below, the three types of validating domains are used and tested independently.

2.3 Selecting the CDPs

The list of CDPs is computed from the whole set of domain pairs observed in Uniprot proteins of all organisms but the query organism. Only pairs of different domains are considered in the CDP list, in order to avoid certifying one domain by itself. These pairs must reveal a conditional dependence between a Pfam domain and an InterPro (Pfam or non-Pfam) domain, that is, the presence of the InterPro domain has to be a strong clue of the presence of the Pfam domain. Testing the conditional dependence of a domain pair involves measuring the association between two variables. This can be done with a correlation test like \( \chi^2 \). Here, we use a one-tailed Fisher’s exact test to cope with small sample sizes. To this end, we compute, for each domain pair \( (A, B) \), the number \( x \) of proteins where both \( A \) and \( B \) are present, the numbers \( w \) (respectively \( y \)) of proteins where \( A \) is present but \( B \) is absent (respectively \( A \) is absent but \( B \) is present), and the number \( z \) of proteins where
This creates a situation where the potential domains are independent of the null hypothesis that domains are dependent, is computed as a sum of hypergeometrical laws:

\[ P_{\text{value}}(A,B) = \sum_{w=0}^{\min(x,y)} p(A+w, y-w, z+w, r+w) \]

with \( p(a, \beta, y, b) \) being the probability of observing exactly \( a \) proteins with \( B \) among \( a + y \) proteins, knowing that there are a total of \( a + \beta + y + b \) proteins. Hence, a \( P_{\text{value}} \) is computed with expression (1) for each domain pair. If this \( P_{\text{value}} \) is below a given threshold—1% in our experiments—the null hypothesis is rejected, the domains are considered as conditionally dependent, and the pair is added to the CDP list.

### 2.4 Estimating the number of false certifications

From the potential domains, the validating domains and the CDP list, we can certify a certain number of new domains. One issue is then to estimate the proportion of false positives among these new domains. To this end, we estimate the probability of certifying a potential domain under the null hypothesis \( H_0 \) that it has been randomly predicted. This is done through computer simulations, by shuffling the potential domains of all proteins. This procedure randomly permutes the potential domains, while avoiding the association of the same domain to a given protein more than once. This creates a situation where the potential domains are independent of the validating domains, while preserving the domain distribution and the number of validating and potential domains in each protein. The certification procedure is applied to the shuffled domains, and the number of random domains certified is computed. The entire procedure is resumed several times (typically 1000 times) to get a reliable estimate of the expected number of domains that our procedure would certify under the hypothesis that all potential domains are random. This number is then used to compute an estimate of the FDR of the certification process with the formula

\[ \text{FDR} = \frac{\text{number of certifications on original data}}{\text{expected number of certifications under } H_0} \]

This approach is similar to that proposed in Soric (1989) and Benjamini and Hochberg (1995) to control the FDR associated with the multiple testing of several hypotheses. We shall see that by modulating the \( E_{\text{value}} \) threshold used to define the set of potential domains, we can control the FDR associated with our certifications through this procedure.

### 3 RESULTS

#### 3.1 Method assessment

We first assessed the potential of the method to improve the Pfam sensitivity in divergent proteins. In this experiment, *Saccharomyces cerevisiae* was chosen for the quality of its annotations. The principle is as follows. Pfam HMMs were used with their score thresholds to determine a set of reference domains in yeast. All proteins with at least one Pfam domains were considered for the following steps. We simulated the evolution of these proteins using *seqgen* (Rambaut and Grassly, 1997) in order to change their global amino acid composition and make it close to that of *P. falciparum*. *seqgen* was used with the WAG substitution rate matrix, but we replaced the default standard amino acid composition by that of *P. falciparum* (Protein 5.5) (Whelan and Goldman, 2001). Starting from any sequence and applying substitutions based on this modified matrix, we obtained a sequence with an amino acid composition converging towards the *P. falciparum* distribution. Four different substitution rates were applied—0.1, 0.25, 0.5 and 0.75—yielding four sets of artificial protein sequences of increasing divergence from the original yeast proteins. For each of these sets, each HMM was used with the Pfam score thresholds to determine the set of validating domains. Some reference domains were no longer detected because of the sequence drift. The certification procedure was then applied with these validating domains to retrieve the lost domains. Table 1 summarizes the results. For example, with a substitution rate of 0.5, 907 domains are lost; among these, 645 might be retrieved (i.e. belong to a protein where at least another domain is still detected using Pfam thresholds), and 491 (76%) are actually retrieved. Moreover, 60 new domains (absent from the original reference set) are also certified (with a small 5.4% FDR). The number of new domains is even higher for lower substitution rates, and may appear surprisingly high in a well-annotated organism like yeast. This questions the validity of these new domains. Addressing this issue is not easy. One solution is to refer to the GO annotations already known in the corresponding proteins. The last column of Table 1 reports the proportion of new domains with GO annotations that are in agreement with those of the corresponding proteins. For example, for the 0.1 substitution rate, 130 of the 274 new discovered domains are annotated, among which 97 (75%) have annotations already known in the associated proteins. This high proportion suggests that a large part of the new domains are not false positives, but rather true domains recovered by our approach.

### 3.2 Reannotation of *P. falciparum* proteins

The method was applied to *P. falciparum* using the three different types of validating domains discussed in Section 2: (i) known Pfam domains; (ii) known InterPro domains (excluding Pfam domains); and (iii) potential domains themselves. Known Pfam and InterPro domains were obtained using the InterProScan software (release 19.0) that was applied to the *P. falciparum* proteome (Protein 5.5). Potential Pfam domains, different \( E_{\text{value}} \) thresholds were used in order to obtain predictions with various FDRs.

Figure 1 reports the number of certified domains and FDR achieved with known Pfam domains when varying the \( E_{\text{value}} \) threshold used to select the potential domains. Both the number of certified domains and the FDR increase with the \( E_{\text{value}} \) threshold,
The Supplementary Figure 1 shows the number of certifications as a function of the E-value. Number of certifications (thick line), expected number of certifications under $H_0$ (thin line) and FDR (dashed line) achieved when modulating the E-value thresholds (x-axis). The number of certifications and errors (thin and thick lines) are read on the left y-axis, whereas the FDR (dashed line) is read on the right one.

which illustrates the potential of the method to control the FDR by simply modulating this threshold.

Table 2 summarizes the results achieved for FDRs $<10\%$ and $20\%$ with the three types of validating domains. For example, for FDR $\leq 20\%$, 585 new domains are certified. This is an increase of $\sim 16\%$ compared with the 3683 already known Pfam domains in \textit{P.falciparum} proteins (only one occurrence of each known/new domain per protein is considered here; Pfam release 23.0). Among these, 479 involve a new InterPro domain family in the protein. The known Pfam domains allow certification of 363 of the 585 new domains, the known InterPro domains 395 and the potential domains themselves 130 (several new domains are certified by 2 or 3 of the validating domain types). Moreover, 159 new domain types are discovered—i.e. which had never been previously detected in \textit{P.falciparum} proteins—an increase of 11\% of the total number of domain types known in \textit{P.falciparum} proteins (see Supplementary Table 1).

The Supplementary Figure 1 shows the number of certifications as a function of the FDR achieved by each type of validating domain. For a given FDR, the potential domains allow the certification of fewer domains than the two other types. This is not a surprise, as these validating domains are potentially false. Hence, very low E-value thresholds are required to achieve low FDRs, which induces the selection of small amounts of potential-validating domains.

We then addressed the difficult issue concerning conservation of the functionality of the new domains. We tried to answer this question by looking at two different indicators. First, as explained in Section 1, \textit{P.falciparum} proteins often involve low-complexity regions and these regions are suspected to primarily affect the non-functional parts of sequences. However, a comparison of the proportions of low-complexity regions in newly certified domains and in already known domains does not reveal significant differences (Supplementary Table 2). We next investigated the positions where the new domains are discovered. Indeed, Weiner \textit{et al.} (2006) showed that domain divergence events (especially domain loss due to loss of functionality) occur primarily at the ends of the proteins. Here again, when comparing the distances separating known and new domains from protein ends (Supplementary Fig. 2), no bias toward the ends can be observed in the new domains. Hence, no bias is found in these two indicators, which seems to indicate that the proportion of new domains that are non-functional is not higher than that of the already known domains.

When browsing this database, several points can be noted. First, annotations of already annotated genes can be enriched by extending this policy to domain combinations—as described in Forslund and Sonnhammer (2008)—several additional GO terms can be deduced from the combination of two or more domains. To this end, we enumerated all Pfam domain combinations in the proteins of Swiss-Prot, and identified for each combination the GO terms shared by all annotated proteins possessing this domain. Moreover, by extending this policy to domain combinations—we described in Table 3 summarizes the results achieved for FDRs $\leq 10\%$ and $\leq 20\%$ with the three types of validating domains. For example, for FDR $\leq 20\%$, the newly certified domains leads to 85 new GO annotations, i.e. 6\% of the 5791 already known GO annotations of this organism (in three ontologies).

All results with FDR $\leq 40\%$ are available in an online database at http://www.lirmm.fr/~terrapon/codd/. The newly predicted Pfam domains of \textit{P.falciparum} proteins are displayed along with their associated FDR and the Pfam/InterPro validating domains used for certification. Figure 2 presents an extract from the database for the \textit{PF11_0389} gene.

When browsing this database, several points can be noted. First, annotations of already annotated genes can be enriched in numerous cases. For example, \textit{MAL7P1.12}, annotated as an ‘erythrocyte membrane-associated antigen’, is ascribed a novel possible molecular activity related to RNA control, based on detection of \textit{PF00035} and \textit{PF04851}. Next, a function is predicted which illustrates the potential of the method to control the FDR by simply modulating this threshold.

Table 2. Results on \textit{P.falciparum}

<table>
<thead>
<tr>
<th>Valid. dom.</th>
<th>Pfam</th>
<th>Interp.</th>
<th>Pot. All</th>
<th>Pfam</th>
<th>Interp.</th>
<th>Pot. All</th>
</tr>
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<tbody>
<tr>
<td>Certif. dom.</td>
<td>259</td>
<td>185</td>
<td>47</td>
<td>340</td>
<td>363</td>
<td>395</td>
</tr>
<tr>
<td>New Interp.</td>
<td>200</td>
<td>138</td>
<td>39</td>
<td>259</td>
<td>298</td>
<td>318</td>
</tr>
<tr>
<td>New dom. types</td>
<td>70</td>
<td>51</td>
<td>13</td>
<td>90</td>
<td>106</td>
<td>105</td>
</tr>
</tbody>
</table>

Valid. dom. indicates the type of validating domains used for certifications; Pfam: known Pfam domains from InterProScan; Interp.: known InterPro (non-Pfam) domains from InterProScan; Pot., potential domains themselves; All: results achieved when combining the three types. Certif. dom.: number of new certified domains; New Interp.: number of certification allowing us to identify a new InterPro Entry for the protein; New dom. types: number of domain types that were not previously detected in any Pfam/InterPro proteins.
Detection of new protein domains using co-occurrence

**Fig. 2.** Known and newly predicted domains of gene PF11_0189. Four domains are already known: three InterPro domains (G3DSA:3.30.830.10, PTHR11851:SF68 and SSF63411) and one Pfam domain (PF06675). We see the localizations of these domains and the associated GO terms. Moreover, two new Pfam domains have been discovered: PF08367 and PF05193. For example, PF05193 has been discovered in two positions: the first one with an E-value of 0.042 and the second one with an E-value of 0.044. These E-values are too high to be safely considered according to the recommended Pfam threshold for this domain. However, they have been certified by several validating domains. For example, the domain in second position is certified by the known Pfam domain PF00675 with an FDR = 4.71%, the known InterPro domains G3DSA:3.30.830.10 and SSF63411 (FDR = 9.66%) and the potential (and also newly certified) Pfam domain PF05193 (FDR = 19.5%). Note that the domain in first position is not certified by the two InterPro domains because it overlaps these domains. PF05193 is associated with two GO annotations already known for the gene (proteolysis and metalloendopeptidase activity) and one new annotation (zinc ion binding). Moreover, since it is found together with domains PF08367 and PF00675, it is also associated with GO terms mitochondrion and cell part.

For several genes listed as hypothetical in PlasmoDB 5.5. For example, MAL13P1.78 is possibly a protein kinase (based on the detection of the PF06743 domain). PF10_0040 a nuclease involved in DNA repair (based on PF00867 and PF00752 domains), PF10_0152 a nucleotidyltransferase (PF01909 and PF03828 domains), PF11_0244 an ATP-dependent protease (PF02190 domain), etc. In this list of new putative annotations, novel potential targets for antimalarial therapeutics might be envisaged, including, for example, the PF14_0052 protein for which certification of the PF07683 domain (confirming PF02492) indicates that it might be involved in the synthesis of cobalamin (vitamin B12), a molecule necessary for the parasite’s development. Similarly, the putative tetrahydrofolate dehydrogenase/cyclohydrolase PF14_0479 (confirmation of PF02882 by PF00763), is a new enzyme of the folate metabolism, which should now be experimentally investigated. Detection of the PF05605 domain in PF14_0479 is also very interesting, since it is extremely specific to the plant kingdom, associated with the response of plants to drought, and likely acquired in *P. falciparum* following ancestral endosymbiosis with an alga at the origin of the plant-like features in Apicomplexa (Kohler et al., 1997).

Overall, we observe that families of proteins containing domains related to RNA binding, modification and/or processing (Helicase C, RRM, DEAD) are amongst the largest in the *P. falciparum* genome. It also appears that domains involved in protein–protein interactions, e.g. WD40, together with TPR 1 (initially identified in...
Thus, 83% of the new domains are also found in proteins with a known homolog in humans and rodents, respectively. The results can be browsed at http://www.lirmm.fr/terrapon/codd/. Statistics on the number of domains known dom. is the number of supplementary GO annotations (different from the two previous columns) that can be deduced from combinations involving a newly certified domain. ‘Total prot.’ is the total number of proteins involved, and ‘Unannot. prot.’ is the number of proteins without any annotation and for which an annotation has been proposed.

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<tr>
<td>≤ 10</td>
<td>128</td>
<td>122</td>
<td>74</td>
<td>194</td>
<td>20</td>
</tr>
<tr>
<td>≥ 20</td>
<td>273</td>
<td>122</td>
<td>114</td>
<td>267</td>
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16 sequences, now in 28 proteins) or TPR 2 (initially identified in 12 sequences, now in 27 proteins), are also detected in large protein families. Moreover, the newly certified domains reveal proteins involved in chromatin interaction (such as PPP1385w, PFL0975w and PPF0_0106) and numerous transcription factor-associated proteins, which are of particular interest for future investigation considering the apparent lack of such proteins in initial studies (Callebaut et al., 2005; Couston et al., 2004). The present work therefore allows an in-depth analysis of these families, with greater genomic coverage. An extended biological appraisal of these results, with several additional examples, is available in the Supplementary Material.

3.3 Application to other Plasmodium species

Finally, we applied the procedure to the proteomes of *P. vivax* and *P. yoelii*, two other sequenced *Plasmodium* species infecting humans and rodents, respectively. The results can be browsed at http://www.lirmm.fr/~terrapon/codd/. Statistics on the number of newly certified domains and GO annotations are in Supplementary Tables 3 and 4 in and Supplementary Figure 3. The number of newly certified domains is slightly higher in *P. vivax* than in the other species. Importantly, a large part of the newly certified domains in *Plasmodium* proteins are also certified in *P. vivax* and *P. yoelii*, while another part corresponds to already known domains in these organisms (see Supplementary Tables 5 and 6). For example, among the newly certified domains (FDR ≤ 10%) in the *P. falciparum* proteins with a known homolog in *P. vivax*, 14% are already known in the *P. vivax* homolog and 69% are also certified in this homolog. Thus, 83% of the new domains are also found in *P. vivax* homologs. These results strongly support our method and our findings in the *P. falciparum* proteome, and can be seen as a third indicator that our new domains are still functional.

4 DISCUSSION AND CONCLUSIONS

Enhancing domain detection is a complex task. Practically, domain models are designed to ensure the presence of a domain thanks to manually curated score thresholds. Beyond the thresholds, avoiding false positives is no longer guaranteed. In this article, we propose a method to filter out false positives from hits with scores in the twilight zone below the thresholds. To the best of our knowledge, two previous works address related issues. Beaussart et al. (2007) designed a tool that helps to identify possible annotation artifacts, notably missing domains. This is achieved by searching for clusters of proteins with similar domains, and aligning the proteins of each cluster on the basis of their domain arrangement. Then a missing domain can be detected in a protein by looking at the domain composition of all proteins in the same cluster which have high similarity with the query sequence. This can be an efficient strategy if a protein homologous to the query protein is already known and correctly annotated. Coin et al. (2003) propose an elegant approach to increase the sensitivity of HMM domain detection by incorporating context information. Rather than independently detecting each domain of a protein sequence, the authors propose a Markov model that allows global detection of the domain composition of the protein. With this model, the score achieved by a domain at a given position is a function of both the protein sequence and the other potential domains of the protein. A precise comparison of the results achieved with this approach is difficult, as the databases they used have been enriched. However, we can get a rough comparison by concentrating on *P. falciparum* proteins present in the Swiss-Prot40 data that the authors analyzed. Swiss-Prot40 involved 491 *P. falciparum* proteins. In these proteins, our method allows the certification of 36 new domains with an FDR ≤ 20%, whereas Coin et al. (2003) propose nine new domains. Among these five domains, one is also certified by our method. Among the four remaining domains, a close inspection of the protein compositions reveals that two proteins contain repeats of a single domain. In other words, for two cases, the domain has been used to improve its own detection, which is a certification mechanism we did not consider here.

Compared with previous works, our approach has several appealing features. First, it is a simple and intuitive approach which has low-computing time and can potentially be used on any genome. Second, each prediction can be explained by exhibiting the validating domain(s) that enables the discovery of the new domain. Third, we can benefit from all types of domain information already known in the InterPro database, as well as in any other domain database. Finally, and most importantly, an estimate of the confidence of the certifications can be computed with our shuffling procedure.

The approach proved to be promising with *P. falciparum*. With FDR ≤ 20%, it allows us to increase the total number of known domains by 16%, the number of different known domain types by 16% and the number of known GO annotations by 6%. Analogous and congruent results are obtained on *P. vivax* and *P. yoelii*. Moreover, experiments on yeast showed that the method could also benefit better annotated organisms. Since domain co-occurrence is the strongest source of information, this work did not consider the adjacency and sequential order of the domains. However, as these features are also often conserved (Kummerfeld and Teichmann, 2009), it is likely that taking some ordering information into account would improve the approach.

AUTHORS’ CONTRIBUTIONS

N.T., O.G and L.B. conceived and designed the experiments. N.T. implemented the approach. E.M. biological results. N.T. and L.B. drafted the manuscript. revised the manuscript. O.G. initiated the project.
Detection of new protein domains using co-occurrence

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Conflict of Interest: none declared.

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