# Hydrocarbon Binding by Proteins: Structures of Protein Binding Sites for  $\geq$ C<sub>10</sub> Linear Alkanes or Long-Chain Alkyl and Alkenyl Groups

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ABSTRACT: In order to identify potential de novo enzyme templates for the cleavage of C−C single bonds in long-chain hydrocarbons, we analyzed protein structures that bind substrates containing alkyl and alkenyl functional groups. A survey of ligandcontaining protein structures deposited in the Protein Data Bank resulted in 874 entries, consisting of 194 unique ligands that have ≥10 carbons in a linear chain. Fatty acids and phospholipids are the most abundant types of ligands. Hydrophobic amino acids forming  $\alpha$ helical structures frequently line the binding pockets. Occupation of these binding sites was evaluated by calculating both the buried surface area and volume employed by the ligands; these quantities are similar to those computed for drug−protein complexes. Surface complementarity is relatively low due to the nonspecific nature of the interaction between the long-chain hydrocarbons and the hydro-



phobic amino acids. The selected PDB structures were annotated on the basis of their SCOP and EC identification numbers, which will facilitate design template searches based on structural and functional homologies. Relatively low surface complementarity and ∼55% volume occupancy, also observed in synthetic-host, alkane-guest systems, suggest general principles for the recognition of long-chain linear hydrocarbons.

## 1. INTRODUCTION

Long-chain alkyl or alkenyl groups are commonly found in nature; vital components of living organisms such as fatty acids, lipids, and biological surfactant molecules all contain long hydrocarbon moieties. Thus, the recognition of specific alkyl substrates by proteins is of utmost biological importance. For example, P450 enzymes containing a heme cofactor can catalyze the hydroxylation of long-chain alkanes under aerobic  $conditions<sub>i</sub><sup>1</sup>$  drawing interest from both science and engineering disciplines due to their potential utility in biofuel productio[n.](#page-8-0)<sup>2</sup> Intriguing examples of long-chain alkane recognition can also be found in microorganisms residing in deserted geographic[al](#page-8-0) regions such as swamps, marine sediment, and deep oil wells, where they have evolved to thrive under these harsh conditions by utilizing long-chain hydrocarbons as their carbon source.<sup>3</sup> More recently, microbial genomic studies suggest the presence of enzymes capable of decomposing longchain alkanes [un](#page-8-0)der anaerobic conditions; $4,5$  however, detailed structural information about the conformation of the bound substrate has yet to be determined.

The recognition of linear alkane motifs is of interest to biochemists as well as synthetic chemists. Because C−C bond activation has become an important research topic of synthetic chemistry, there is a growing interest in catalysts that are capable of promoting C−C bond activation with proper regioand stereoselectivity.<sup>6</sup> We envision de novo-designed enzymes capable of catalyzing the functionalization and cleavage of C−C bonds in long-chain alkanes.<sup>7</sup> As a first step in the design process, scaffolds are sought upon which the catalytic groups required to effect the chem[ic](#page-8-0)al reaction of interest can be installed. Further understanding of substrate−host interactions is necessary to optimize the substrate recognition capacity of these de novo enzymes, facilitating development of a regio- and stereoselective catalyst. These requirements motivated us to collect and curate the structural information on proteins bound to long-chain alkanes. Specifically, we aimed to answer the following questions: How do proteins recognize and bind longchain alkyl and alkenyl motifs? What characteristics are shared by the binding pockets of these proteins? Can structural and functional characterization of these proteins lead to valuable insights useful for the development of C−C bond-cleaving enzymes?

In order to answer these questions, we selectively retrieved atomic-resolution protein structures with bound ligands containing long-chain alkyl functional groups (10 carbons or greater) from the Protein Data Bank (PDB).<sup>8</sup> The selection criteria resulted in 874 hits in total, encompassing 194 unique ligands and 737 distinct proteins. We analyzed [b](#page-8-0)oth the bound substrates and the protein binding sites, generating statistics

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based on the following data: the type and size distribution of ligands, the binding pocket amino acids and their secondary structures, the solvent-accessible surface area  $(SASA)^9$  buried upon ligand binding, surface complementarity of the ligand− protein interface, and the fraction of the binding pocke[t](#page-8-0) volume occupied by the ligand. Finally, we classified select PDB entries according to both the structural classification of proteins  $(SCOP)^{10}$  and functional categories based on UniProt.<sup>11</sup> We also discuss similarities to synthetic hosts capable of recognizing linear al[kan](#page-8-0)es as guest molecules.

#### 2. RESULTS AND DISCUSSION

2.1. Searching for High-Resolution Protein Structures Containing Long-Chain Alkanes. We searched for known protein structures deposited in the PDB and retrieved entries containing linear alkane motifs (Figure 1). Out of over 87 000



Figure 1. Selection of ligands having linear alkane motifs. Non-amino acid ligands such as fatty acids, phospholipids, surfactants, and hydrocarbons were selectively retrieved from the PDB database. Linear alkane motifs are highlighted in cyan.

ligand-containing PDB structures, we filtered out any ligands having fewer than 10 carbon atoms in a linear chain or possessing a cyclic moiety. As summarized in Table 1, 874 PDB entries isolated with 194 unique ligands bound to proteins were identified (set 1). In the following sections, we present a

## Table 1. Description of the Different Protein−Ligand Complex Datasets



statistical analysis on the nature of interactions between proteins and long-chain alkyl ligands.

We also considered two subsets of proteins that are especially significant to the understanding of long-chain alkane recognition in aqueous solutions. Out of the 874 PDB entries with ligands containing linear alkyl groups ≥10 carbons, 428 entries were soluble proteins (set 2). Furthermore, 28 of those soluble proteins were bound to pure hydrocarbons (set 3), which are listed in Table 2. As our motivation was to identify scaffolds for

## Table 2. PDB Entries of Soluble Proteins and Their Corresponding Ligands Containing Alkyl and Alkenyl Groups Larger than  $C_{10}$



de novo-designed enzymes in aqueous media, we extended our statistical analysis to include the subsets of water-soluble proteins with ligands containing long-chain alkyl groups (set 2) and water-soluble proteins with hydrocarbon ligands (set 3).

2.2. Statistics of Bound Ligands Containing Alkyl Groups  $\geq C_{10}$ . Figure 2 contains histograms portraying the abundance of the different types of ligands with alkyl groups



Figure 2. Functional classification and the size distribution of the ligands containing linear alkane motifs. (a) Ligands were classified according to the functional group attached to the linear alkane motif. (b) The distribution of the number of carbon atoms in each ligand. Ligands from all proteins are color-coded in red, whereas those from water-soluble proteins are in green.

longer than  $C_{10}$  as well as the number of carbon atoms present in those ligands. As shown in Figure 2a, fatty acids are the most abundant type of ligand in set 1, followed by phospholipids, amine oxides, hydrocarbons, glycerides, and amides. Fatty acids remained the most common ligand once we limited our interest to only soluble proteins (set 2), whereas the abundance of other ligands significantly decreased; typical surfactants<sup>13</sup> like phospholipids and amine oxides are associated with membranebound proteins, significantly reducing their presence in [w](#page-8-0)atersoluble proteins.

We then considered the size of the bound ligands in Figure 2b. The number of carbon atoms was used as an index of ligand size. The histogram of set 1 has its maximum at 14 carbon atoms, composed of lauryl dimethylamine-N-oxide, myristic acid, (10E,12Z)-tetradeca-10,12-dien-1-ol, S-[2-(acetylamino) ethyl](3R)-3-hydroxydecanethioate, tetradecane, and (R)-3 hydroxytetradecanal (Figure 3). The largest entry found was cardiolipin  $(81 \text{ carbon atoms})$ ,<sup>14</sup> a diphosphatidylglycerol molecule having four linear alkyl functional groups. The histogram of long-chain alkanes i[nte](#page-8-0)racting with water-soluble proteins (set 2) was qualitatively similar to that of set 1; ligands with 16 carbons were now the most common, whose members include 16-hydroxyhexadecanoic acid, (11Z,13Z)-hexadeca-11,13-dien-1-ol, (4E,6E)-hexadeca-1,4,6-triene, (2,2 diphosphonoethyl)(dodecyl)dimethylphosphonium, (10E,12Z)-hexadeca-10,12-dienal, (10E)-hexadec-10-en-12-yn-1-ol, hexadeca-10,12-dien-1-ol, N-dodecyl-N,N-dimethylglycinate, decamethonium ion, 1-decyl-3-trifluoro ethyl-sn-glycero-2-phosphomethanol, 1-hexadecanesulfonic acid, 1-iodohexadecane, 10-oxohexadecanoic acid, hexadecan-1-ol, palmitic acid, and hexadecane. Once again, the largest ligand bound was cardiolipin.

2.3. Statistics on Amino Acids and Folds of Ligand-Binding Pockets. Figure 4a portrays the frequency of amino acids defining the ligand-binding pocket. As detailed in the Methods, Rosetta Interface [A](#page-3-0)nalyzer<sup>15</sup> was used to identify the binding pocket amino acids surrounding the bound ligand. The







Figure 3. Structures of the 14-carbon ligands, 16-carbon ligands, and cardiolipin.

analysis of all long-chain alkane-binding proteins (set 1) resulted in the hydrophobic residues leucine (14%) and phenylalanine (9%) as two of the most abundant amino acids. These became more abundant in water-soluble proteins (set 2) and hydrocarbon-bound soluble proteins (set 3). The binding pocket residues surrounding long-chain linear alkyl groups were then compared to those of drug−target proteins deposited in CSAR. <sup>12</sup> As drug-like molecules tend to include ring moieties and polar functional groups, this assessment could

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Figure 4. Statistics of the ligand-binding pockets: (a) population of amino acids, (b) backbone secondary structure distribution, (c) surface area burial per ligand-carbon atom, (d) occupied volume fraction of binding pocket by the ligand, and (e) surface complementarity between protein and ligand. Secondary structure abbreviations: B, β-bridge; E, β-sheet; G, turn; I, π-helix; H, α-helix; S, bend; T, hydrogen-bonded turn; and X, unstructured.

be beneficial for isolating unique features of ligand-binding pockets that specifically recognize alkyl groups that are linear, nonpolar, and hydrophobic. The comparison suggests that the populations of hydrophobic residues, including leucine, valine, and phenylalanine, are enriched in hydrocarbon-binding pockets relative to the binding pockets of drug molecules.

The secondary structures of the amino acids forming the protein backbone of the binding pocket were analyzed in Figure 4b using the DSSP software.<sup>16</sup> The  $\alpha$ -helices (H, 45%) and  $\beta$ sheets (E, 20%) are the two most prevalent secondary structures found from the [bin](#page-8-0)ding pocket residues of set 1. The higher frequency of  $\alpha$ -helices lining the binding pocket is consistent in sets 2 and 3. An examination of the CSAR data set (Figure 4b, orange) shows a dramatic decrease in  $\alpha$ -helices relative to the other secondary structures. The population of unstructured secondary structures is doubled in reference to set 3. These findings strongly indicate that the binding of longchain linear alkanes occurs at protein surfaces made of  $\alpha$ -helices more often than any other secondary structure elements.

In Figure 4c, we plot the results of the computed surface area burial (SAB) per ligand-carbon atom upon formation of the protein−ligand complex. SAB provides a quantitative measure of how tightly a protein captures its ligand. On average, each carbon atom of the ligands in set 1 buried  $47 \pm 14$  Å<sup>2</sup> of the solvent-accessible surface area (SASA) of the binding pocket. Water-soluble proteins bound to ligands containing long-chain alkanes (set 2) and to pure hydrocarbons (set 3) resulted in 50  $\pm$  12 and 52  $\pm$  12 Å<sup>2</sup> of the SAB, respectively. Although the average SAB is largest for set 3, the difference from set 1 is within statistical uncertainty. The SAB of drug-binding pockets  $(49 \pm 22 \text{ Å}^2)$  is also comparable to that of the long-chain

alkane-binding proteins. In short, the SAB per ligand-carbon atom of long-chain alkane-binding proteins is  $47-52$  Å<sup>2</sup> on average and is similar to that of drug−target proteins.

In addition to surface area burial, we also analyzed the binding pocket volume occupied by the ligand (occupied volume fraction, OVF) in Figure 4d. Mecozzi and Rebek pointed out that 55% is an optimal value for OVF, considering both the favorable enthalpic interactions between ligand and host as well as the entropic penalty associated with the limited conformational degrees of freedom imposed on the bound ligand.<sup>17</sup> We computed the OVF of ligand binding pockets using POVME software.<sup>18</sup> For both set 1 and set 2, the OVF is cl[o](#page-8-0)se to the conjectured optimal value:  $57 \pm 18$  and  $61 \pm 17$ %, respectively. The same [c](#page-8-0)omputation on the CSAR data set resulted in a similar observation: the OVF was  $59 \pm 13$ %. The average OVF values of naturally occurring proteins bound to long-chain alkanes and of designed drug-like molecules are similar and are close to the optimal OVF value of 55%.

Finally, we computed the surface complementarity<sup>19</sup> (SC) between the binding pocket residues and the bound ligands. SC quantifies the congruency between two interacting [mol](#page-8-0)ecular surfaces, where the SC of two perfectly complementary surfaces is 1 and that of two adjacent random shapes approaches 0. This quantity has been understood to be one of the fundamental descriptors of the compliance of two interacting molecules.<sup>20</sup> For the long-chain alkane-binding proteins, computed SC values are similar regardless of their solubility profile:  $0.66 \pm$ 0.08, 0.66  $\pm$  0.09, and 0.63  $\pm$  0.09 for set 1, set 2, and set 3, respectively. On the other hand, the interfaces of drug-like molecules showed enhanced SC over that of the alkane-binding proteins: SC of the CSAR data set is  $0.78 \pm 0.06$ . SC is known

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Figure 5. Left: A resorcinarene-based cavitand that can dimerize, creating a molecular capsule. Right: Top and side views of encapsulation of n- $\rm C_{10}H_{22}$  in a straight-chain conformation (yellow) and n-C<sub>14</sub>H<sub>30</sub> (red) in a helical arrangement. Reprinted from ref 23. Copyright 2004 American Chemical Society.





to be correlated with the specificity of the interaction between a ligand and its binding pocket. $^{21}$  The SC of interacting protein surfaces ranges from  $0.70$  to  $0.76<sup>19</sup>$  resembling that of the CSAR data set. Furthermore, drug molecules are optimized to

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Figure 6. Frequently observed SCOP folds binding ligands with linear alkane motifs: (a) bacterial photosystem II reaction center protein (PDB ID: 1AIJ) bound to lauryl dimethylamine-N-oxide, (b) family A G protein-coupled receptor-like protein (PDB ID: 1BRR) bound to 3,7,11,15 tetramethyl-1-hexadecanol, (c) nucleoplasmin-like/VP protein (PDB ID: 1AL2) bound to sphingosine, (d) lipocalin (PDB ID: 1B56) bound to palmitic acid, (e) cytochrome c oxidase, subunit III (PDB ID: 1M56) bound to distearoyl-3-*sn-*phosphatidylethanolamine, and (f) serum albumin-<br>like protein (PDB ID: 1H9Z) bound to myristic acid. PyMOL was used for molecul arrangements of the protein, and bound ligands and binding pocket residues are shown using stick representations.

achieve enhanced selectivity toward their targets, exploiting specific interactions such as hydrogen bonding and electrostatic interactions. These tendencies are expected to result in higher SC values. In contrast, naturally occurring alkane-binding proteins stabilize their substrates through relatively weaker nonpolar interactions, resulting in smaller SC values than the protein−protein or protein−drug interfaces.

2.4. Alkane Binding by Synthetic Hosts. Aside from the naturally occurring biomolecules we surveyed, synthetic supramolecular hosts have also been shown to bind diverse substrates. Cram pioneered the uses of carcerands, cavitands, and other molecular capsules as molecular containers and to catalyze reactions or stabilize reactive intermediates, garnering much interest in t[he](#page-8-0) scientific community.<sup>22</sup> Of particular relevance, Rebek investigated the kinetics and thermodynamics of binding medium-chain alkanes with re[sor](#page-8-0)cinarene-based cavitands.<sup>23,24</sup> The host molecules dimerize, as shown in Figure 5, forming pill-shaped compartments capable of enclosing nalkanes, [from](#page-8-0)  $C_9$  to  $C_{14}$ ; shorter alkanes are bound in an [ex](#page-4-0)tended straight-chain conformation, whereas longer chains adopt a folded and helical arrangement. Although the coiling of the longer alkanes results in unfavorable gauche conformations, the favorable C−H···π interactions with the aromatic walls of the cavitand compensates for the increased torsional strain. The usual cutoff distance for C−H···π interactions is considered to be approximately 3 Å, calculated from the respective van der

## <span id="page-6-0"></span>Table 4. Subset of the Selected PDB Entries Having Enzymatic Activity



Waals radii. Both computational<sup>25</sup> and crystallographic data<sup>26</sup> of encapsulated alkyl guests exhibit these interactions.

For guest molecules with nar[ro](#page-8-0)w, extended conformatio[ns,](#page-8-0) the cavitand host deforms not only to increase C−H···π interactions but also to attain more suitable packing coefficients. Rebek's dimeric host has a calculated volume of 425 Å<sup>3</sup> and can bind guests that occupy about 55  $\pm$  9% of the available volume, similar to the packing efficiency of most organic liquids.<sup>17</sup> Guests that do not sufficiently fill the empty

space suffer from the large entropic penalty of complexation; the empty hosts prefer to be filled with solvent when the alkane is too small. In contrast, larger guests cause the binding site to be too crowded, thus experiencing steric repulsion. Other groups have shown that this general 55% parameter also applies to enzyme binding pockets.<sup>27</sup> The lack of observed complexes of the Rebek host cavitands with alkanes smaller than 9 carbons or longer than 14 carbons [is](#page-8-0) a testament to the importance of

<span id="page-7-0"></span>size and shape complementarity when encapsulating substrates without any functional handles.

Through minor modifications of the cavitand molecules, formation of the dimer was suppressed, and hydrophilic feet were incorporated to create water-soluble supramolecules that were capable of binding medium-chain alcohols.<sup>28</sup> The polar hydroxyl group remains exposed to the aqueous environment, and the hydrophobic alkyl chain coils toward the i[nn](#page-8-0)er cavity of the host, similar to the alkane conformations mentioned earlier. The alkane size and shape complementarity exhibited by these complexes bears some resemblance to the naturally occurring hydrocarbon-binding sites in proteins.

2.5. Structural and Functional Classification of Long-Chain Alkane-Binding Proteins. We classified each hit from the selected PDB entries based on the structural classification of proteins (SCOP). In general, protein structure determination in the presence of a ligand is more difficult than that in its absence. This implies that high-resolution structures with bound ligands may represent only a subset of proteins having the potential to recognize linear alkanes. Fortunately, structurally similar proteins (homologues) share many functional similarities. Thus, one may establish the structures of proteins interacting with linear hydrocarbon motifs through homologue relationships. As of 2013, only 38 222 PDB entries had SCOP classification IDs, from which we were able to classify 407 out of the 874 hits (Table 3). SCOP classifies proteins into several hierarchical levels, utilizing either their evolutionary relationships or structural s[im](#page-4-0)ilarities: the fold hierarchy of a protein reflects structural relationships with other proteins, whereas both family and superfamily hierarchies are based on evolutionary origin and functional similarity. We focused on the fold classification of proteins in the PDB search hits because we use this classification with the alkane-binding proteins to facilitate identification of protein design scaffolds sharing similar structural features. There are 72 distinct SCOP folds identified out of 407 proteins having SCOP IDs. For multidomain proteins, each domain in contact with the linear hydrocarbon ligand was analyzed separately. The most prevalent fold is the bacterial photosystem II reaction center, L and M subunits. Representative structures of the top six most frequently found SCOP folds are depicted in Figure 6a−f.

Next, we considered functional attributes of the selected protein templates. Our specific interest was to identi[fy](#page-5-0) alkanebinding proteins that have enzymatic activity. These proteins possess catalytic functional groups and/or bound cofactors that have more easily modifiable characteristics than nonenzymatic proteins. UniProt $11$  is the central information repository of genomic sequence and functional information on proteins. Each entry in the [PD](#page-8-0)B has one or more UniProt identification numbers, enabling us to annotate the functional role of each PDB structure containing ligands with a long-chain alkane motif. A subset of the selected PDB templates has enzymatic activity, which is identified by the enzyme commission (EC) number. On the basis of these functional descriptions of each entry from the UniProt database, we classified the 874 selected protein templates into functional categories. First, we identified enzymes having catalytic functionality with specific ligands (Table 4): there are 202 enzymes identified, catalyzing 89 distinct chemical reactions. The most frequently identified enzyme [w](#page-6-0)as cytochrome c oxidase (UniProt ID: P00396, 17 entries), and the second was viral protease/RNA transferases (UniProt ID: P03300, 10 entries). There are also enzymes associated with biological reactions involving linear alkyl and alkenyl functional groups, such as 3-oxoacyl-[acyl-carrierprotein] synthase III (UniProt ID: P0A574), phospholipase A2 (UniProt ID: P00592), and cytochrome-P450 monooxygenase (UniProt ID: P14779).

Finally, we questioned whether the binding sites of enzymes are significantly different from those of the nonenzymatic hydrocarbon-binding proteins, as enzyme catalysis usually requires the precise placement of substrates, leading to an enhanced binding specificity. However, statistics such as SC and OVF of the enzymes  $(0.68 \pm 0.08$  and  $57 \pm 13\%$ , respectively) are almost identical to those of long-chain alkanebinding proteins (set 1). The findings suggest that enzymatic proteins recognize their substrates based on the same chemical principles governing the binding of long-chain alkanes in nonenzymatic proteins.

#### 3. CONCLUSIONS

We have surveyed proteins capable of recognizing long-chain hydrocarbons and long-chain alkyl groups and have considered various factors that influence this binding. Hydrophobic amino acids forming  $\alpha$ -helical secondary structures are frequently a major component of the binding sites. The surface complementarity of the ligand−protein interfaces in alkanebinding proteins is lower than that of drug-binding proteins, which typically have more polar substrates. However, the occupied volume fraction and the surface area burial by the ligand−protein interfaces are both comparable to those of drugbinding sites. The volume fraction occupied by the substrates is close to the ideal value of 55%, suggesting substrate recognition mechanisms similar to those of synthetic host molecules. Moreover, structural and functional classifications of the longchain alkane-binding proteins will aid future efforts in searching for potential protein scaffolds. The protein structures and the analyzed binding-site characteristics should guide the design of new enzymes that can selectively recognize large alkyl substrates and catalyze their functionalization.

#### 4. METHODS

4.1. PDB Database Search. PDB entries containing one or more ligands with 10 or more carbons were selected using the PDB websearch interface. A Python programming library (OEChem<sup>29</sup>) was used to postprocess the initial hits, ruling out any entry possessing rings. OEChem was also used to identify functional motif[s i](#page-8-0)n the identified ligands, leading to the classification of each ligand.

4.2. Analysis of Ligand Binding Pockets. The amino acids located in the binding pockets were identified using the Interface Analyzer module in the Rosetta software package.<sup>15</sup> The surface area burial upon binding of the ligand was computed using the same package. The DSSP program was used to define the backbone sec[o](#page-8-0)ndary structure of the binding pocket amino acids.<sup>16</sup> We used POVME software to calculate the binding pocket volume and the occupied volume fraction.<sup>18</sup> For each statistic provided h[ere](#page-8-0), standard deviations were used as a measure of statistical uncertainty.

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#### Notes

The authors declare no competing financial interest.

## <span id="page-8-0"></span>■ ACKNOWLEDGMENTS

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