

Quantized Surface Complementarity Diversity (QSCD): A Model Based on Small Molecule–Target Complementarity

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A model of molecular diversity is presented. The model, termed “Quantized Surface Complementarity Diversity” (QSCD), defines molecular diversity by measuring molecular complementarity to a fully enumerated set of theoretical target surfaces. Molecular diversity space is defined as the molecular complement to this set of enumerated surfaces. Using a set of known test compounds, the model is shown to be biologically relevant, consistently scoring known actives as similar. At the resolution of the model, which examines molecules “quantized” into 4.24 Å cubic units and treats four points of specific energetic complementarity, the minimum number of compounds needed to fully cover molecular diversity space up to volume 1070 cubic Å is estimated to be on the order of 24 million molecules. Most importantly, QSCD allows for individual points in diversity space to be filled by direct modeling of molecular libraries into detailed 3D templates of shape and functionality.

Introduction

Combinatorial chemistry allows the creation of unprecedented numbers of organic compounds; what was once unthinkable – the rational synthesis of millions of small organic molecules – is now achievable in a matter of days.^{1–6} With this newly acquired ability comes a question which, prior to combinatorial chemistry, seemed foolish even to pose: How can one create a set of molecules of such diversity as to contain at least one potent binder to any given target of interest?

This question is central to drug discovery in the “post-genomic era”, a scientific midpoint characterized by a growing wealth of DNA sequence information and a relative dearth of corresponding target structures and their functions.^{7–9} Soon, there will be many more putative targets than can be studied by X-ray crystallography, multidimensional NMR, or other high-resolution biophysical techniques. Any attempt to generate biologically active ligands to these targets of unknown structure will require general screening libraries: libraries of molecules that cover a high percentage of so-called “diversity space”.^{10–13}

We define diversity as the measure, based on pre-defined criteria, of the difference or similarity between all members of a set. In a pharmaceutical setting, it follows that molecular diversity can be defined as the measure, based on biological criteria, of the difference or similarity between small molecules. Largely due to continuing advances in our understanding of the principles of molecular recognition,^{14–24} there exist today many methods of calculating biologically relevant diversity of small molecules.^{25,26} Each method defines slightly different criteria for molecular comparison, and each thereby presents a different configuration of diversity space as a whole. Examples include low-dimensional diversity space such as BCUT metrics,^{27–29} high-dimensional diversity space such as Chem-X/

ChemDiverse multiple-point pharmacophores,^{30–34} and empirical biological diversity space such as affinity fingerprinting.^{35–37}

For the most part, current methods are able to successfully identify compounds of the same pharmacological class as being similar and compounds of different pharmacological classes as being different.^{25,38} Given a starting pharmacophore from known ligands and/or the target site of a target crystal structure, such methods interface well with the design of complementary combinatorial libraries.

The design of combinatorial libraries to cover all of diversity space is a rather different problem, however. In this case, it is not enough to be able to compare existing molecules for differences or similarities. In addition to being able to place molecules relative to one another in diversity space, one must be able to point to an absolute area of diversity space *not yet covered* and from its coordinates design a novel set of compounds to fill that uncovered space.

At present, there are no methods which can directly facilitate the above process of filling empty diversity space, because the transformations by which existing models assign molecules to coordinates in diversity space are irreversible: molecules can be mapped to diversity coordinates, but diversity coordinates cannot be mapped directly to molecular structures.

For example, in the well-known BCUT method used to generate 4D to 6D diversity space, molecules are broken down into matrices according to connectivity and molecular interaction properties.^{25,27–29} Coordinates in diversity space are assigned through the resulting eigenvalues of these matrices, leading to highly useful multidimensional plots of molecular diversity. However, because the use of eigenvalues is an irreversible transformation (different 3D shapes can map to the same eigenvalues), it follows that an *empty* coordinate in BCUT diversity space cannot be translated into a 3D template of a “missing molecule”. Thus, while a model

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such as BCUT diversity is well-validated as a tool for finding combinatorial matches to a lead compound or pharmacophore, it cannot be directly used to populate the entire diversity space which it defines.

Similarly, in the popular Chem-X/ChemDiverse diversity package,³³ molecules are broken down into all accessible three- or four-point pharmacophores of triangular or tetrahedral functionality distances.^{30–32,34} If the model is used to display molecular diversity, coordinates in diversity space are assigned through the resulting string of accessible three- or four-point pharmacophores; this method has been shown to be highly effective in classifying molecules by pharmacological similarity. However, the mapping of complex 3D shapes to a set of triangular or tetrahedral functionality distances is an irreversible transformation; empty three- or four-point pharmacophores in Chem-X-derived diversity space cannot be translated into a 3D template of complex shape. Since a set of coordinates in Chem-X is insufficient to define the shape of “missing molecules”, Chem-X cannot be used to directly populate empty molecular diversity space.

A final example of current diversity methods is affinity fingerprinting, in which molecules are empirically assayed against a panel of 10–20 actual proteins selected to be promiscuous in their ability to bind small molecules.^{35,36} Position in molecular diversity space is assigned through the resulting string of IC₅₀ binding values, and these affinity fingerprints provide unprecedented ability to group similarly active compounds in diversity space. However, because the actual mode of binding in any assay is not incorporated in the resulting IC₅₀ value, the mapping of molecules to the selected protein panel is an irreversible transformation. Thus, an empty coordinate in affinity fingerprinting diversity space (an “unmatched” string of IC₅₀s to a given protein panel) cannot be back-translated into a 3D molecular template. A similar affinity fingerprinting diversity method has been put into practice using a panel of computational protein surfaces and a modified form of the DOCK program.³⁷ While this method shows similar promise in its ability to detect pharmacological similarity, it is, like its real-world counterpart, an irreversible mapping.

To rationally and systematically fill diversity space, an *informationally reversible* diversity model is needed. This model must be formulated such that: (1) members (in this case molecules) can be assigned to coordinates for similarity/dissimilarity comparison and (2) empty coordinates retain the information necessary to directly generate coordinate membership.

The path of least resistance to such a model is to use as coordinates the exact information that differentiates one member from another, without intervening, irreversible transformations. To apply this reasoning to molecular diversity, it must first be asked: What are the criteria by which diversity of compounds is to be measured (what information differentiates one molecule from another)? The most fundamental criterion in molecular drug discovery is the extent to which two molecules have similar or different binding affinities to a given target surface. With the assumption that similar binding affinity tracks with a molecule's complementarity to similar target surfaces,^{39,40} we have selected as

our criterion for diversity *complementarity to a fully enumerated set of theoretical target surfaces*.

Given the above definition of molecular diversity, it remains only to (a) provide a biologically relevant basis set of enumerated theoretical target surfaces and (b) quantify molecular complementarity to a given theoretical target surface at a level which is both in accordance with known principles of molecular recognition and computationally applicable to millions of compounds. With a numerical determination of complementarity and a biologically relevant basis set of surfaces, molecular diversity space is thus absolutely established as the molecular complement to a fully enumerated set of theoretical target surfaces.

Methods

Theoretical Target Surfaces. The model of this paper begins with a set of theoretical target surfaces that approximates all possible binding pockets with volume equal to or less than V . To generate a finite set of these surfaces, we consider each theoretical surface to be formed by successively carving cubic units out of an initially flat surface. These cubic units represent “negative space” that a potential ligand could occupy. Given cubic units with sides of length R (the resolution of the model), we use at most V/R^3 negative space cubes to describe each theoretical target surface. We note that others have previously employed cubic units to successfully approximate complementarity between small molecules and individual protein surfaces.⁴¹

The size of a negative space cube is directly related to the resolution and type of diversity data which the user desires as output. In the current formulation of the model, we wished to maximize negative space cube size such that the difference of a single cube in a surface is highly differentiating in terms of molecular recognition (i.e. every surface is orthogonal to every other surface). At the same time, we needed to retain information in each negative space cube sufficient to predict shape and functional complementarity at a ligand/surface interface. The former constraint minimizes overlap of diversity information while the latter constraint maximizes precision of diversity information. Together, the competing constraints result in a basis unit for the enumeration of theoretical target surfaces which minimizes the number of negative space cubes needed to accurately model diversity for a given volume V .

A resolution of 4.24 Å negative space cubes was found by computer optimization of test molecules to provide an upper limit of cube size while still maintaining an acceptable level of molecular shape information (see Experimental Section). Interestingly, 4.24 Å is the approximate VDW “cross-section” of a (CH₂)_{*n*} chain; a series of 4.24 Å units neatly encapsulates a (CH₂)_{*n*} chain in its ground-state conformation (Figure 1).

In the study described herein, we use as a basis set for diversity a set of theoretical target surfaces comprised of all possible shape combinations of 6–14 negative space cubes of resolution 4.24 Å (negative volume between 460 and 1070 cubic Å) subject to the following rules: (1) Surfaces are created by successively “carving out” negative space cubes from a flat block of infinite width and depth (the theoretical target). (2) All negative space cubes of a given surface must share at

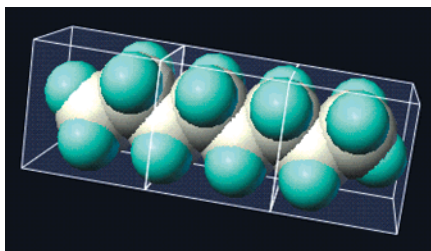


Figure 1. A $(\text{CH}_2)_n$ chain encapsulated by 4.24 Å cubic units.

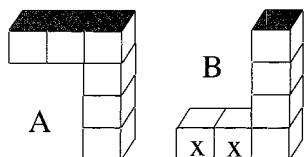


Figure 2. Example of surfaces allowed and disallowed by the nonocclusion parameter in the theoretical target surface generation algorithm of the text. Gray shading represents the opening of the theoretical surface: (A) allowed and (B) disallowed due to two occluded negative space cubes (marked X).

least one face with another negative space cube of the surface, and all must be part of a single, contiguous negative surface. (3) No negative space cubes may be occluded in the +Z axis of the infinite surface block; that is, there may be no solid surface between any negative space cube and the surface plane of the infinite block (see Figure 2). (4) Surfaces duplicating a previous surface with respect to rotation in the X–Y plane are discarded.

In this study, rule (3) above was added as a compromise between complete coverage of topological possibilities and desire to maintain computational speed. This compromise was made based on the topological assumption that occlusions of 4.24 Å or more are infrequent in small molecule/target interactions and that their omission would thus have only a small effect on predicting diversity of binding affinities of small molecules.

The above rules generate 49 268 918 unique negative surface shapes including chiral opposites. Covering a negative volume between 460 and 1070 cubic Å, these surface shapes are deemed sufficient to examine diversity of most small molecules. For instance, examining a previously published reference set of pharmaceutically relevant compounds (a filtered Comprehensive Medicinal Chemistry, or CMC, database),⁴² 5049 out of 5120 compounds (98.6%) have a volume of 1070 cubic Å or less.

Within each of the 49 268 918 unique negative surface shapes, each negative space cube is assigned a molecular property characteristic P_m that represents the dominant molecular environment which any atoms that are placed within that negative space will experience. Properties used are P_1 hydrophobic, P_2 polarizable (includes aromatics), P_3 H-bond acceptor, P_4 H-bond donor, P_5 H-bond donor/acceptor, P_6 potentially positively charged (basic), and P_7 potentially negatively charged (acidic). These seven types of molecular environments are assumed to represent a minimal basis set of factors that contributes to the electrostatic/VDW complementarity of a ligand and a target surface.^{14,15,18} In this study, four positions of particular molecular property P_{1-7} are assigned, leading to $7^{4*N}/((N-4)!*4!)$ surfaces for each surface shape of N negative space

Table 1. Numerical Breakdown of the Total Number of Theoretical Target Surfaces Created Using the Algorithm Given in the Text^a

vol (no. (N) of negative space cubes)	no. of unique surface shapes	approx. no. of functionally different surfaces per unique surface shape: $7^{4*N}/((N-4)!*4!)$	exact no. of unique surfaces
6	212	36 015	7 163 338
7	885	84 035	73 271 443
8	3 959	168 070	655 324 488
9	17 747	302 526	5 350 917 208
10	81 407	504 210	40 912 578 322
11	375 897	792 330	297 622 676 624
12	1 753 218	1 188 495	2 082 225 979 379
13	8 224 443	1 716 715	14 116 888 070 845
14	38 811 150	2 403 401	93 264 917 290 356
total 6–14	49 268 918		109 808 653 272 003

^a Surfaces consist of 6–14 negative space cubes and 4 sites of 7 possible molecular property characteristics. Number of functionally different surfaces per surface shape varies for infrequent cases in which a given shape has an axis of symmetry, so actual number of unique surfaces is slightly less than $(\text{no. surface shapes}) * 7^{4*N} / ((N-4)!*4!)$.

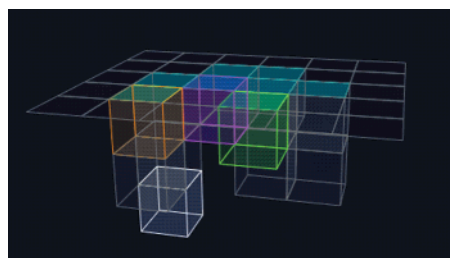


Figure 3. Theoretical target surface of 13 negative space cubes and 4 sites of specific molecular property interaction: hydrophobic (white), polarizable (purple), H-bond accepting (green), and H-bond donating (orange). Blue shading indicates the opening of the theoretical surface.

cubes. All other $(N-4)$ cubes not assigned a particular molecular property are given property P_8 , slightly hydrophobic. The latter assignment is based on an assumption that hydrophobic effects are, on average, the largest single component contributing to ligand/target interaction.¹⁷

In sum, the above process implies as a basis set for molecular diversity 1.1×10^{14} theoretical target surfaces of negative volume between 460 and 1070 cubic Å and having four sites of specific molecular property characteristics P_{1-7} . The numerical breakdown of these 110 trillion surfaces is listed in Table 1. One such surface is shown in Figure 3.

Molecular Quantization. To measure complementarity of small molecules to the above basis set of theoretical target surfaces, the small molecules to be compared must be formatted in a similar frame of reference. Thus, all molecules used in this study are “quantized” into positive space cubes (“quanta”) of resolution 4.24 Å according to the following algorithm (see also Figure 4):

(1) To represent each molecule, a set of up to 100 minimized conformations within user-defined parameters is created. In this study, Tripos Multisearch modeling was used and all conformations within 10 kcal of the lowest energy conformation found were accepted (see Experimental Section).

(2) For each conformation, a 4.24 Å 3D grid of cubes (quanta) is aligned on top of the 3D structure using the

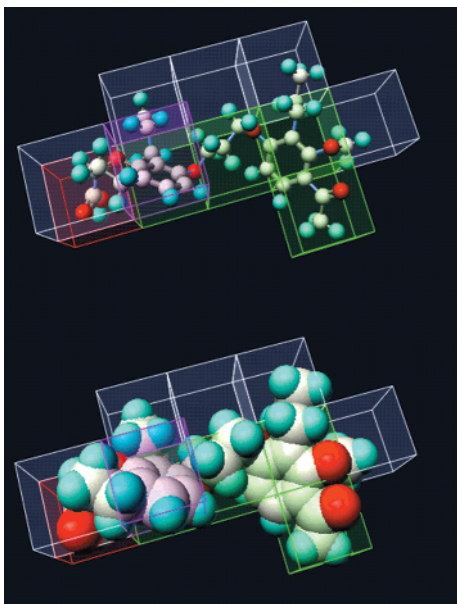


Figure 4. “Quantized” representation (Q-file) of one conformation of molecule **6a** superimposed on its atomic structure (ball-and-stick and space-filling model). Molecular property characteristics of the Q-file are hydrophobic (white quanta), polarizable (purple quanta), H-bond accepting (green quanta), and negatively charged (red quanta).

molecule’s principal axes of rotation (calculated with all atoms having mass 1).

(3) To all 4.24 Å quanta which contain at least a user-defined percentage of the VDW radius of any atom, a dominant molecular property characteristic is assigned based on connectivity rules (e.g. R-[C=O]-O-H yields P_7 , R-O-H yields P_5 ; see definitions of P_1 - P_7 above). Order of dominance is from P_7 to P_1 , in order of maximum complementarity score obtainable by a given characteristic (see Table 2). Minimum percentage of VDW radius parameter allows for a user-defined protrusion beyond the surface of a quantum cube, adding a measure of topological “flexibility” to the quantization process. 32% was found optimal for this study (see Experimental Section).

(4) The total number of 4.24 Å quanta that have been assigned a property characteristic is counted.

(5) The grid alignment is shifted per user-defined parameters and the process is repeated from step (2) until all shift combinations have been searched.

(6) For each conformation in step (1), the “Q-file” (3D configuration of property-assigned quanta) is saved that: (a) has the lowest number of quanta in step (4) and (b) is closest to the principal alignment in step (2).

Thus, an average molecule in this study is represented by 100 Q-files, each file consisting of N positive space cubes or quanta of 4.24 Å resolution having an assigned molecular property characteristic P_m ($m = 1-7$). A typical Q-file (molecule **6a**) is shown in Figure 4, superimposed upon its corresponding conformation. The process of optimization of quantization parameters is described in the Experimental Section.

Mapping. Given molecules which have been rendered into sets of Q-files, each quantized conformation can now be mapped into the diversity space defined by the set of 1.1×10^{14} theoretical target surfaces above. This is accomplished through the following algorithm:

(1) For each quantized conformation of each molecule, each of its 24 possible $X/Y/Z$ rotations (6 faces * 4 rotations per face) is fit to each of the 49 268 918 available surface shapes.

(2) For a given conformation-to-surface shape fit, if at least a user-defined minimum number of negative and positive space cubes overlap (in this case either 9 quanta or $N - 2$ quanta of a conformation of N quanta; see Experimental Section), and if no quanta of the conformation extend beyond the bounds of the surface shape except at the mouth of the surface shape, then the complementarity of the quantized conformation to all theoretical target surfaces of that shape is examined in detail in step (3). If the above conditions are not met, the next conformation is examined.

(3) A score is generated for the complementarity of the given conformation to each theoretical target surface of a given shape from step (2) by employing user-defined parameters. (The process of optimization of the complementarity parameters is described in the Experimental Section.) Complementarity parameters used in the model are as follows: (a) a negative parameter for each rotatable bond of the conformation; (b) if conformational energies are calculated, a negative parameter for the energy of the conformation above the lowest energy conformation from that molecule; (c) a positive parameter for the hydrophobic energy gained by removing “water” from any hydrophobic (P_1) or polarizable (P_2) surface face of either the conformation or the theoretical surface; (d) a positive parameter for the hydrophobic energy gained by removing “water” from any mildly hydrophobic (P_8) surface face of the theoretical surface; (e) a positive or negative molecular property interaction parameter for overlapping negative and positive space cubes as depicted in Table 2.

(4) If and only if the score in step (3) meets a user-defined minimum, then the conformation (and thus the molecule it represents) is said to be complementary to the given theoretical target surface.

The computational advantage inherent in the process of molecule and surface quantization is realized in the speed of complementarity checking. Whereas a traditional docking program must search a high-dimensional configuration space, QSCD resolves the problem to a framework bounded by 24 possible fitting orientations and a finite number of translations. This approximation allows 3D diversity computation on a scale that is applicable to very large sets of molecules.

Results and Discussion

The above process results in a complementarity map for any molecule that consists of a list of all theoretical target surfaces to which at least one conformation of the molecule is complementary. Comparison of these maps provides a novel method for measuring diversity of small molecules. We term the model on which this process is based “Quantized Surface Complementarity Diversity” (QSCD) because it calculates diversity by measuring complementarity to a quantized representation of theoretical target surfaces.

To maintain a computationally efficient complementarity scoring system, QSCD makes many approximations of molecular recognition. These include cubic units of 4.24 Å resolution, gross approximations of surface

Table 2. Relative Magnitudes of Parameters Used in Calculating Molecular Property Interactions between Negative Space Cubes (theoretical target surfaces) and Positive Space Cubes (quantized molecules)^a

theoretical target surface properties	quantized molecule properties						
	P_7 neg	P_6 pos	P_5 H-bond don/acc	P_4 H-bond don	P_3 H-bond acc	P_2 polarizable	P_1 hydrophobic
P_7 neg charged	---	+++	0	+	-	--	--
P_6 pos charged	+++	---	0	-	+	0	--
P_5 H-bond don/acc	0	0	++	+	+	-	--
P_4 H-bond don	+	-	+	--	++	-	--
P_3 H-bond acc	-	+	+	++	--	-	--
P_2 polarizable	--	0	-	-	-	++	0
P_1 hydrophobic	--	--	--	--	--	0	+
P_8 (surface only)	-	-	0	-	-	0	0

^a Magnitudes (listed from highest to lowest): +++, ++, +, 0, -, --, ---.

contact area, exactly four points of seven finite types of molecular property characteristics, static theoretical surfaces, and a limited set (up to 100) of low-energy conformers. Thus, the final complementarity scores are in no way presumed to give useful *binding energies* for any *individual* match of conformation to target surface. However, taken over all conformations of a molecule and across an enumerated set of theoretical target surfaces, the scoring system is proven to be statistically relevant. This is demonstrated below.

Model Validation. To test the validity of the QSCD model, we needed to prove that the method, at a minimum, satisfies the central criterion that it was designed to analyze: the extent to which two molecules have similar or different binding affinities.

Thus, eight sets of test molecules were analyzed (Figure 5), seven of which were known from the literature to have binding affinities to seven distinct targets (in addition to a known overlap between sets **3** and **4**). An eighth set with no known binding affinities was chosen with minor atomic and spatial changes to examine the sensitivity of the model at 4.24 Å resolution. Known activities of the molecules in Figure 5 are listed in Table 3 with references. The bulk of these molecules have previously been used as part of an in-depth study validating molecular descriptor approaches for the prediction of molecular diversity *within* compound classes.¹² This is a more stringent discrimination than the base criterion sought for our model, which seeks at a minimum to show accurate diversity prediction *between* compound classes.

As described above, conformations of all 20 test molecules were "quantized" and then mapped onto the basis set of 1.1×10^{14} theoretical surfaces. Complementary surfaces are tabulated for each molecule in Table 4. There are many ways to analyze the resulting set of complementarity mappings; since in this case individual molecule comparisons were desired, each of the 20 mappings was compared pairwise for a total of 190 data points. Mappings were scored in similarity from 0 to 1000 based on a function of the number of theoretical surfaces in common:

$$\text{Score} = \text{SS} * \text{FS} = \text{ShapeScore} * \text{FunctionalityScore}$$

$$\text{SS} = 100 * \frac{\text{\# theoretical target surface shapes common to A \& B}}{\text{total \# surface shapes complementary either to A or to B}}$$

$$\text{FS} = 10 * \left(\frac{\text{\# theoretical target surface shapes common to A \& B with at least 1 set of 4 common functionalities}}{\text{total \# theoretical target surface shapes common to A \& B}} \right)^\Phi$$

The first term in this equation gives a percentage measure (0–100) of shape similarity between molecules A and B, while the second term gives a measure from 0

to 10 of functional similarity per given shape overlap. The complete scores are detailed in Table 5. Using this scoring system, the maximum score obtainable by very rigid, structurally similar molecules is 1000. However, many molecules can only be *sampled* by an examination of up to 100 low-energy conformations (an average molecule w/5+ rotatable bonds will have at least $3^5 = 243$ conformations). Thus, for most molecules with more than 100 accessible conformations, similarity scores between 0 and 100 are observed. The scoring constant Φ in the equation above adjusts the influence of functionality on scoring. A value of 0.33 was found to be optimal (see Experimental Section), meaning that shape is the dominant criterion in our measure of diversity.

Figure 6 shows a plot of all 190 pairings ranked by similarity score. Orange circles show "heterogeneous" pairs of expected dissimilarity (e.g. **2a**, **6b**), while blue squares show "homogeneous" pairs of expected similarity (e.g. **2a**, **2b**). Clearly, the model ranks homogeneous pairs almost exclusively higher than heterogeneous pairs; all 15 pharmacologically similar pairs (blue) fell within the top 20 scores out of 190. All homogeneous scores were ranked above 25, while the median score in this experiment was 2.8, showing good "signal-to-noise". QSCD is thus a valid predictor of target binding similarity among these molecules.

A closer look at the pairings reveals further validation. As might be expected from their relative rigidity (low number of accessible conformations) and structural similarity, the highest scoring pairs are **2a/2b**, **8a/8b**, and **8d/8e**. Furthermore, examination of the pairings of **8c** with **8a, b, d, e** (yellow triangles in Figure 6, yellow in Table 5) yields scores that are within the top 20% of the pairing experiment but which are generally lower than the "homogeneous" pairs. This makes sense from a target-binding point of view, considering that one face of **8c** contains a large molecular difference (an extra phenyl substituent). To the extent that this face is not involved in complementarity to a target surface, the molecules are similar; to the extent that this face must be complementary for binding to occur, the molecules are quite different. Figure 7 shows one such case of a surface common to both **8a** and **8c**; the protruding phenyl substituent plays no role in complementarity.

As a rule, we have found close similarity of shape and functionality for molecules which score 25 or higher. In addition to the pairings that one would expect, several other pairs scored between 25 and 35. When these other molecules were examined by molecular modeling, significant overlaps were found, suggesting that these high scores are not just "noise" in the QSCD model. Figure 8

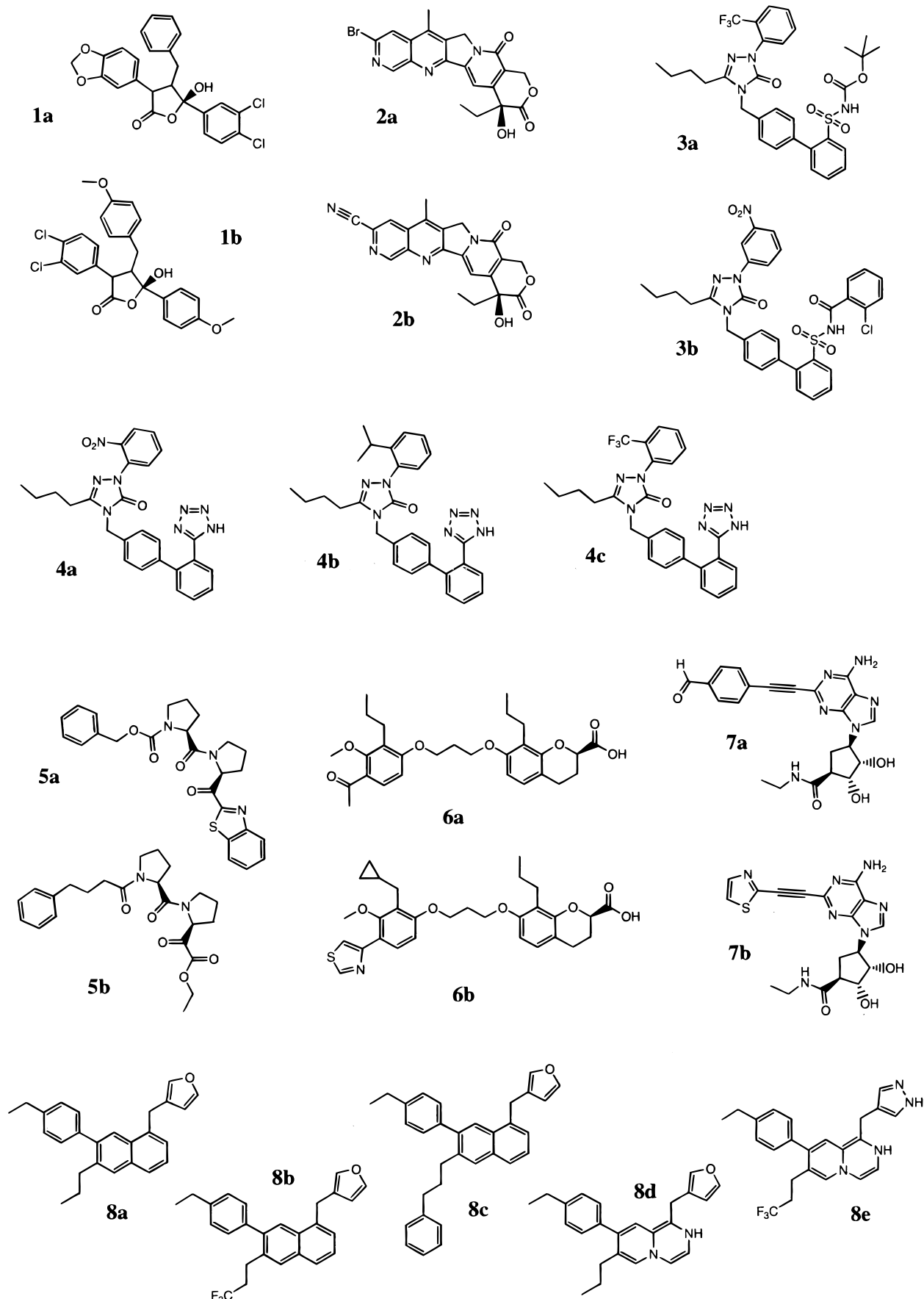


Figure 5. Test molecules used in this study.

depicts one such case between **1a** and **5a**; conformations of **1a** and **5a** are displayed that were found in QSCD to

be complementary to the same surface (Figure 8A,B). 3D overlays (Figure 8C) confirm correlation of general

Table 3. Pharmacological Activities of the Molecules Used in This Study (see Figure 5)

compd	assay	IC ₅₀ or K _i (nM)	ref
1a	binding to endothelin A receptor	400	<i>a</i>
1b	binding to endothelin A receptor	170	<i>a</i>
2a	inhibition of DNA fragmentation by topoisomerase I	28	<i>b</i>
2b	inhibition of DNA fragmentation by topoisomerase I	143	<i>b</i>
3a	binding to AT2 subtype of angiotensin II receptor	17 (0.45) ^{<i>b</i>}	<i>c</i>
3b	binding to AT2 subtype of angiotensin II receptor	173 (31) ^{<i>b</i>}	<i>c</i>
4a	binding to AT1 subtype of angiotensin II receptor	0.85	<i>d</i>
4b	binding to AT1 subtype of angiotensin II receptor	1.4	<i>d</i>
4c	binding to AT1 subtype of angiotensin II receptor	1.2 (23 000) ^{<i>i</i>}	<i>d</i>
5a	inhibition of prolylendopeptidase protease activity	5	<i>e</i>
5b	inhibition of prolylendopeptidase protease activity	10.3	<i>e</i>
6a	binding to leukotriene B4 receptor	320	<i>f</i>
6b	binding to leukotriene B4 receptor	3.2	<i>f</i>
7a	binding to A2A type adenosine receptor	6.3	<i>g</i>
7b	binding to A2A type adenosine receptor	41.3	<i>g</i>
8a	none		
8b	none		
8c	none		
8d	none		
8e	none		

^{*a*} Doherty et al. *J. Med. Chem.* **1995**, *38*, 1259–1263. ^{*b*} Uehling et al. *J. Med. Chem.* **1995**, *38*, 1106–1118. ^{*c*} Chang et al. *J. Med. Chem.* **1994**, *37*, 4464–4478. ^{*d*} Chang et al. *J. Med. Chem.* **1993**, *36*, 2558–2568. ^{*e*} Tsutsumi et al. *J. Med. Chem.* **1994**, *37*, 3492–3502. ^{*f*} Penning et al. *J. Med. Chem.* **1995**, *38*, 858–868. ^{*g*} Cristalli et al. *J. Med. Chem.* **1995**, *38*, 1462–1472. ^{*h*} Numbers in parentheses indicate IC₅₀ in AT1 subtype assay of series **4**. ^{*i*} Numbers in parentheses indicate IC₅₀ in AT2 subtype assay of series **3**.

Table 4. Tabulation of Surface Shapes and Total Number of Theoretical Target Surfaces Complementary to Each Molecule in Figure 5

compd	complementary surface shapes	complementary surfaces (shape plus functionality)
1a	376	16 127 687
1b	379	9 086 768
2a	27	545 584
2b	27	416 210
3a	414	4 970 816
3b	315	813 024
4a	487	4 542 463
4b	479	12 388 826
4c	482	7 595 982
5a	337	2 080 523
5b	374	1 966 837
6a	220	192 067
6b	186	153 436
7a	362	298 927
7b	269	22 367
8a	45	5 561 654
8b	41	3 959 678
8c	333	17 324 247
8d	64	2 059 546
8e	87	1 343 811
average	265	4 572 523

shape and four points of functionality, although they also make clear the limits of resolution of complementarity information using 4.24 Å units. As can be seen from Figure 8, the surface in question can detect general

shape and functional similarity, but by no means provides a basis to predict atom-for-atom overlap between molecules.

A final result of note comes from examination of the QSCD rankings of sets **3** and **4**. While set **4** is known to bind exclusively to the AT1 subtype of the angiotensin II receptor, set **3** is known to bind to both the AT1 subtype and the AT2 subtype. While QSCD found high similarity within sets **3** (score = 27) and **4** (av score = 54), it found an average similarity of 6.9 between **3a** and set **4** and an average similarity of 3.3 between **3b** and set **4** (green diamonds in Figure 6, green Table 5). On the basis of the model, one would therefore conclude that while sets **3** and **4** share a limited number of complementary theoretical surfaces, they are dissimilar with respect to the majority of theoretical target surfaces. This is in fact the case with the AT2 subtype of the angiotensin II receptor, to which **4c** binds 50 000 times more poorly than **3a** (see Table 3).

Fundamental Advantages. Having validated the basis set used for QSCD in the classification of molecular diversity, it must be noted that many other models may do as well or better in detecting target binding similarity/dissimilarity between molecules.^{12,29,37,39,43} For instance, Figure 9 and Table 6 show the same set of 20 molecules ranked by Tanimoto similarity³⁹ of standard 2D UNITY fingerprints (see Experimental Section). The data demonstrate that the 2D model is equally capable of predicting pharmacologically similar pairs; UNITY ranks similarity between AT1 and AT2 subtype binders much higher than QSCD, although it finds unusually high similarity between **8a** and **8c**. In general, such 2D fingerprint descriptors have been found highly effective in clustering pharmacologically similar compounds and are widely used in determining molecular diversity of existing structures.²⁵

The great advantage of QSCD, however, lies in the value of its *negative* information: QSCD determines not only diversity of existing structures, but also structure of nonexistent diversity. *Given theoretical surface shapes for which no complements exist in a general screening library, QSCD allows the design of molecules to fill the given diversity void.*

As stipulated in its formulation, the QSCD basis set is created through a reversible process; information *resolution* may be lost in fixing the parameters of a cube's size and functional scope, but information *content* is retained in either direction. Just as a single molecular conformation and orientation corresponds to a defined pattern in QSCD space, likewise, a single point in QSCD space (within the limits of volume *V*, resolution *R*, and *N* sites of functionality *P_m*) corresponds to a unique 3D shape with a defined 3D array of functionality. Given any starting set of molecules, unoccupied points in QSCD space directly define the molecular shapes and functionalities which those molecules do not cover. Thus, a set of detailed 3D molecular templates (at the resolution of the QSCD model used) is immediately available for the creation of novel molecules.

As an example, Figure 10 shows a plot of all of the theoretical surface shapes covered by all of the conformations of all of the molecules used in this study (see Figure 5). The total volume of the cube in Figure 10 encompasses all 49 268 918 theoretical surface shapes

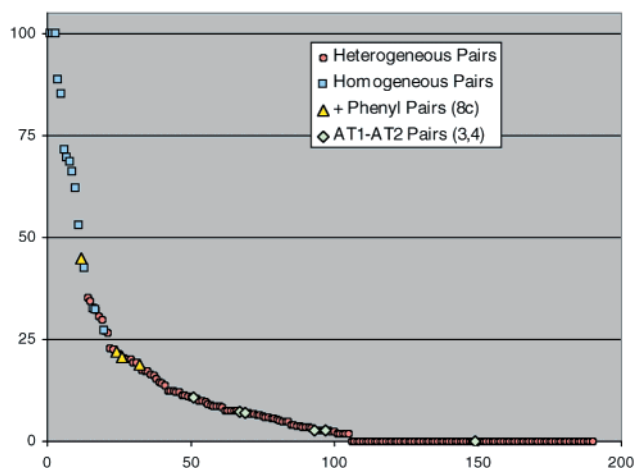


Figure 6. Ranking of molecules in Figure 5 by QSCD similarity scores.

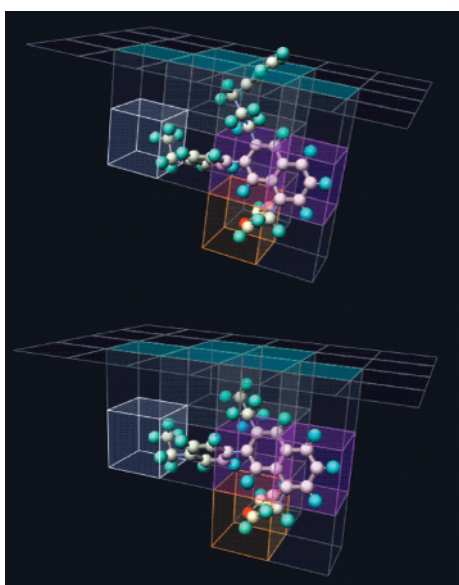


Figure 7. Examination of a theoretical target surface common to molecules **8c** (top) and **8a** (bottom). Blue shading indicates opening of the theoretical surface. Specific points of complementarity on the theoretical target surface are hydrophobic (white), polarizable (purple), and H-bond donating (orange). Superimposition of the original molecular conformations onto the theoretical target surface demonstrates that the extra phenyl substituent of **8c** protrudes from the opening of the theoretical surface and is not involved in complementarity to the surface.

as listed in Table 1. As can be seen from the plot and two expanded points, there are many theoretical surface shapes which are “unfilled” by the set of compounds shown in Figure 5. Thus, in searching for molecules or libraries to enhance the diversity of the given set of compounds, the chemist is presented with a set of actual 3D templates into which new compound libraries may be designed. In comparison, mapping the same set of compounds in a “nonreversible” diversity space would also display a set of coordinates to which the molecules map, but there would be no way to visualize the 3D shape of any point that was not filled by one of the compounds in the set. Using BCUT values^{27–29} for example (Figure 11), the coordinates specified for an unfilled point leave the chemist with a set of normalized eigenvalues. While these may give an idea of relative

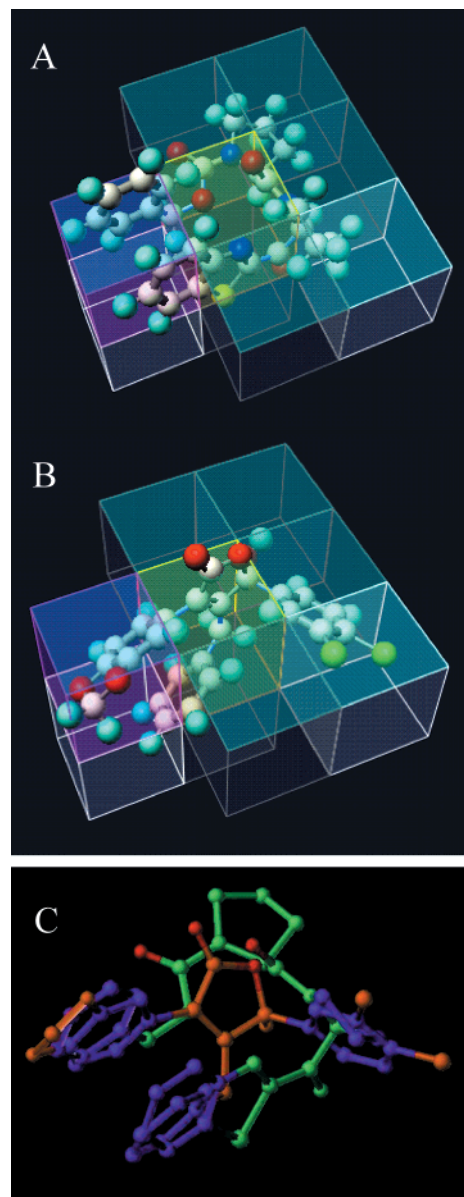


Figure 8. Examination of a theoretical target surface common to molecules **1a** (A) and **5a** (B). Blue shading indicates opening of the theoretical surface. Specific points of surface complementarity found by QSCD are hydrophobic (white), polarizable (purple), and H-bond donating/accepting (yellow). Overlay plot (C) of the non-hydrogen backbones of **1a** (orange) and **5a** (green) indicates similar features. Aromatic/hydrophobic overlaps are shown in purple; H-bond donating oxygens are in red. Overlay generated with Sybyl version 6.5 (Tripos Inc., 1699 S. Hanley Rd., St. Louis, MO 63144).

abundance of a given functionality (e.g. H-bond donor) at this point in diversity space, the coordinates give no hint of what shape or class of molecules might fill that diversity void.

The above example shows how QSCD is a reversible diversity model with respect to molecular shape. Within a given surface shape in QSCD, there are many combinations of functionality, leading to many different theoretical surfaces. If a given library fills only a portion of theoretical surfaces of a given surface shape, by following the same process outlined above and in Figure 10, unfilled surfaces of specific shape and functionality may be identified and filled with complementary libraries. By using data-mining algorithms to analyze and

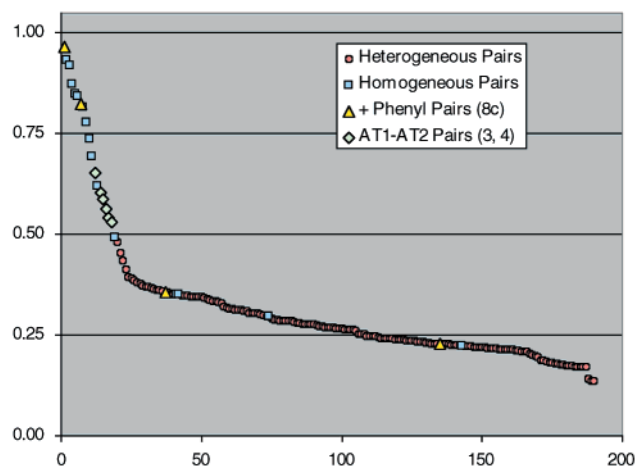


Figure 9. Ranking of molecules in Figure 5 by Tanimoto similarity score of 2D UNITY fingerprints.

intersect the shape and functionality of unfilled surfaces, a minimal set of “missing” 3D combinatorial templates can be deduced from the QSCD mapping of a given set of general screening compounds. These templates represent the smallest number of combinatorial syntheses which need to be executed in order to fill out the diversity of the set of screening compounds. One such template is depicted in Figure 12. In conjunction with the efficiency of core-based combinatorial chemistry,^{1–4,44,45} QSCD makes possible the contemplation of a “complete” library of screening molecules at a given resolution. The model thus offers a theoretical and practical answer to the problem of generating lead structures for genomic targets of unknown structure and function. Specific uses of the model in combinatorial library design will be the subject of further correspondence.

Extensions of the Model. As has been noted previously,^{25,46} an obvious extension of any diversity model based on an absolute frame of reference is that the same basis set may be used to classify actual proteins. By mapping onto the QSCD basis set all surfaces of volume V of a known protein, actual proteins can be compared and classified by their 3D binding sites. In addition to providing a rough diversity map of known protein binding sites, the theoretical surfaces of QSCD may thus be used to correlate protein classes to complementary molecular core structures. Comparison of known co-crystal structures to QSCD ligand-derived complementary surfaces will give solid benchmarks of the precision and predictive scope provided by a given set of QSCD parameters. An extension of the QSCD model to scan the known protein database is currently underway.

As described under the section on theoretical protein surfaces above, a 4.24 Å cube was found to be the largest predictive unit size of diversity measure for our criteria of designing general screening libraries. For example, both 4.48 and 4.00 Å units gave poorer prediction of homogeneous/heterogeneous pairs than the pairings of Figure 6 (4.24 Å units). This is likely due to the fact that most organic small molecules are themselves quantized by a limited basis set: the VDW radii of H, C, N, O, and a few other atoms (see, for example, Figure 1). If there is no constraint on size of cubic units, however (i.e. if there is no attempt to maximize orthogonality of theoretical target surfaces), other unit measures of diversity can be found. Most obviously, a unit

of 2.12 Å should also provide effective diversity information but at a much higher resolution. Such a “high-resolution” adaptation of QSCD brings with it numerical (and thus computational) challenges. 112 negative space cubes (14×8) are now required at the upper limit of theoretical target surface size, translating to exponentially greater numbers of theoretical target surfaces and, depending on the stringency of fitting parameters, correspondingly greater numbers of surface fits per molecule as in Table 4. At this resolution, the assumption of no occlusions in theoretical target surfaces becomes far less valid, and removal of this assumption increases computational complexity further. A full analysis of whether the use of “high-resolution” QSCD is practical as a diversity tool compared to other high-resolution methods (e.g. ref 43) is a subject of current research.

A final corollary of any absolute diversity model is a prediction of the total “size” of diversity space in terms of unique molecular points. In other words, what is the minimum set of molecules needed to fully cover a given diversity space. This calculation is dependent on two factors: the resolution stipulated in the model (e.g. what amount of molecular change is recognized as different) and the maximum values of each dimension of the model’s basis axes. In the model of QSCD used herein, resolution is fixed by cubic units of 4.24 Å, and maximum values are fixed at 14 units (molecular volume of 1070 cubic Å) and four points of seven types of molecular property characteristics. As describe above, the result is a set of 1.1×10^{14} unique molecular points. Since, using the parameters of this study, an average molecule covers 4.6 million of the unique molecular points bounded by QSCD space (Table 4), the model predicts a minimum of $(1.1 \times 10^{14}) / (4.6 \times 10^6) = 24$ million molecules would be necessary to completely cover diversity space.

We estimate that an *average* complementary molecule in the context of the QSCD model used herein has a ΔG of complementarity on the order of -11 kcal (Table 7).¹⁴ In other words, the resolution used to calculate diversity in this study translates roughly to nanomolar binding conditions for an average molecule/target surface pair. Given that some 24 million molecules are needed to completely cover diversity space under these conditions, a general screening library *guaranteed to contain at least one nanomolar binder to any given target of interest* would thus number at least 24 million molecules. This is a large number and will be attenuated by the fact that some molecules have significantly more than 100 conformations available to them. However, the QSCD model suggests that if, in the near future, combinatorial chemistry and high-throughput screening are to generate initial hits primarily in the nanomolar rather than micromolar range, then we must continue to focus our efforts on the development of numerically competent synthesis and screening technologies.^{1–4,47,48}

Conclusions

Like many other diversity models, QSCD is based on accepted tenets of molecular recognition, and its ability to group compounds that bind similar targets is one more piece of evidence that we are slowly progressing in our understanding of small molecule/target interac-

Table 6. Ranking of Molecules in Figure 5 by Tanimoto Similarity Score of 2D UNITY Fingerprints^a

AND	OR	Molecule A	Molecule B	Tanimoto Score	Rank	AND	OR	Molecule A	Molecule B	Tanimoto Score	Rank
112	116	8c	8a	0.97	1	115	434	5b	3b	0.26	101
370	397	2b	2a	0.93	2	119	450	8d	3b	0.26	102
195	212	1a	1b	0.92	3	84	318	5b	8d	0.26	103
276	316	4c	4b	0.87	4	114	433	6a	2b	0.26	104
112	132	8b	8a	0.85	5	122	466	6b	3b	0.26	105
275	326	7b	7a	0.84	6	104	410	8d	4a	0.25	106
112	136	8c	8b	0.82	7	104	410	8d	4c	0.25	107
266	326	4a	4b	0.82	8	112	442	6a	2a	0.25	108
265	341	4a	4c	0.78	9	83	335	5b	8e	0.25	109
186	252	8e	8d	0.74	10	98	396	5b	4c	0.25	110
292	421	3a	3b	0.69	11	104	421	8e	7a	0.25	111
260	398	3a	4c	0.65	12	56	227	8c	6a	0.25	112
152	245	6b	6a	0.62	13	111	455	8d	3a	0.24	113
249	412	3b	4a	0.60	14	97	399	5a	8d	0.24	114
238	406	3a	4b	0.59	15	61	251	8c	1b	0.24	115
233	414	3b	4b	0.56	16	85	350	8b	4c	0.24	116
232	429	3b	4c	0.54	17	100	412	5a	8e	0.24	117
228	430	3a	4a	0.53	18	79	326	8c	4b	0.24	118
157	319	5b	5a	0.49	19	54	225	8a	6a	0.24	119
118	245	6a	1b	0.48	20	110	459	1a	3b	0.24	120
118	260	6a	1a	0.45	21	99	415	1a	7b	0.24	121
129	297	6b	1b	0.43	22	109	457	1a	3a	0.24	122
129	312	6b	1a	0.41	23	63	265	8b	1b	0.24	123
192	486	2b	7a	0.40	24	77	324	8a	4b	0.24	124
101	257	5b	6a	0.39	25	59	249	8a	1b	0.24	125
191	494	2a	7a	0.39	26	97	412	8d	7a	0.24	126
188	495	2b	7b	0.38	27	95	404	1b	7b	0.24	127
184	488	5a	2a	0.38	28	95	405	1a	4b	0.23	128
181	484	5a	2b	0.37	29	89	381	6a	4a	0.23	129
159	429	5a	7b	0.37	30	86	370	6a	4b	0.23	130
186	504	2a	7b	0.37	31	104	450	1b	3b	0.23	131
108	294	5b	1a	0.37	32	79	344	8e	1b	0.23	132
156	427	5a	7a	0.37	33	76	331	8d	1b	0.23	133
103	284	5b	1b	0.36	34	98	427	6a	3b	0.23	134
157	434	8d	2b	0.36	35	64	279	8c	8e	0.23	135
177	492	2b	4b	0.36	36	61	266	8c	1a	0.23	136
86	241	8c	8d	0.36	37	78	343	8b	4b	0.23	137
157	441	8d	2a	0.36	38	102	449	1b	3a	0.23	138
158	449	8e	2b	0.35	39	64	282	8c	6b	0.23	139
134	381	5a	6b	0.35	40	55	244	8b	6a	0.23	140
84	239	8d	8a	0.35	41	81	360	8d	6b	0.23	141
89	254	8b	8d	0.35	42	63	280	8b	1a	0.23	142
159	455	8e	2a	0.35	43	62	277	8e	8a	0.22	143
176	507	2b	4a	0.35	44	94	420	1a	4a	0.22	144
126	363	5b	7a	0.35	45	59	264	8a	1a	0.22	145
191	551	2a	3a	0.35	46	95	427	6a	3a	0.22	146
174	502	2a	4b	0.35	47	88	397	1b	4b	0.22	147
189	546	2b	3a	0.35	48	76	343	8c	4a	0.22	148
168	488	3b	7a	0.34	49	62	280	8a	6b	0.22	149
189	549	2b	3b	0.34	50	79	359	8e	1a	0.22	150
153	448	4a	7a	0.34	51	76	346	8d	1a	0.22	151
189	556	2a	3b	0.34	52	82	375	8e	6b	0.22	152
106	315	5b	6b	0.34	53	55	252	5b	8c	0.22	153
173	517	2a	4a	0.33	54	84	386	6a	7b	0.22	154
147	440	4b	7a	0.33	55	74	341	8a	4a	0.22	155
170	513	2b	4c	0.33	56	94	436	8e	7b	0.22	156
132	401	6b	7b	0.33	57	67	311	8d	6a	0.22	157
168	522	2a	4c	0.32	58	64	298	8b	6b	0.21	158
146	460	4a	7b	0.32	59	74	345	8c	4c	0.21	159
139	439	5b	2a	0.32	60	83	387	6a	4c	0.21	160
146	464	6b	2b	0.31	61	88	411	1b	4a	0.21	161
153	487	5a	3a	0.31	62	90	424	1a	4c	0.21	162
158	503	3b	7b	0.31	63	53	250	5b	8a	0.21	163
143	458	4c	7a	0.31	64	72	343	8a	4c	0.21	164
140	452	4b	7b	0.31	65	84	403	8b	3a	0.21	165
135	436	5b	2b	0.31	66	75	360	8b	4a	0.21	166
153	500	3a	7a	0.31	67	87	427	8d	7b	0.20	167
144	473	6b	2a	0.30	68	66	328	8e	6a	0.20	168
137	451	5a	4a	0.30	69	83	416	1b	4c	0.20	169
115	379	5b	7b	0.30	70	53	270	5b	8b	0.20	170
123	407	8e	4c	0.30	71	75	399	8c	3b	0.19	171
122	406	6b	7a	0.30	72	77	413	8b	3b	0.19	172
147	496	5a	3b	0.30	73	77	419	8c	2b	0.18	173
82	277	8b	8e	0.30	74	79	433	8b	2b	0.18	174
112	384	5a	1a	0.29	75	72	398	8a	3b	0.18	175
136	470	4c	7b	0.29	76	75	417	8a	2b	0.18	176
128	446	5a	4b	0.29	77	63	351	8c	7a	0.18	177
115	401	8e	4b	0.29	78	78	441	8b	2a	0.18	178
128	448	1b	2b	0.29	79	60	341	5a	8c	0.18	179
146	512	3a	7b	0.29	80	75	428	8c	2a	0.18	180
131	460	1a	2b	0.28	81	61	349	8a	7a	0.17	181
115	404	6b	4b	0.28	82	59	338	5a	8a	0.17	182
106	375	5a	1b	0.28	83	63	367	8b	7a	0.17	183
108	386	5b	4a	0.28	84	69	402	8c	3a	0.17	184
111	398	1a	7a	0.28	85	73	426	8a	2a	0.17	185
127	456	1b	2a	0.28	86	61	356	5a	8b	0.17	186
116	417	6b	4a	0.28	87	68	399	8a	3a	0.17	187
130	468	1a	2a	0.28	88	52	367	8c	7b	0.14	188
127	458	6b	3a	0.28	89	50	365	8a	7b	0.14	189
107	387	1b	7a	0.28	90	52	383	8b	7b	0.14	190
125	457	8e	3a	0.27	91						
126	462	5a	4c	0.27	92						
107	393	8d	4b	0.27	93						
102	378	5b	4b	0.27	94						
116	430	5b	3a	0.27	95						
124	461	8e	3b	0.27	96						
112	418	8e	4a	0.27	97						
98	367	6a	7a	0.27	98						
95	357	5a	6a	0.27	99						
112	421	6b	4c	0.27	100						

^a Color code: blue = homogeneous pairs, yellow = +phenyl pairs (8c), green = AT1 and AT2 pairs (3, 4).

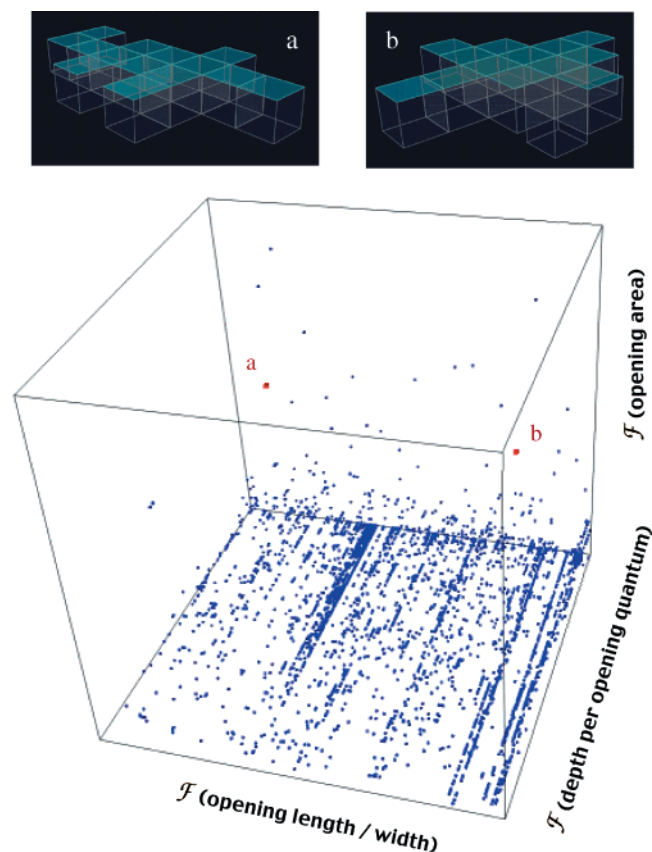


Figure 10. QSCD plot of all of the theoretical surface shapes covered by all of the conformations of all of the molecules shown in Figure 5 (blue dots). The total volume of the cube encompasses all 49 268 918 theoretical surface shapes as listed in Table 1. Red dots show two exemplary theoretical surface shapes (a, b) not covered by any of the molecules in Figure 5. Axes used are functions of opening area, opening length/width, and depth per opening quantum.

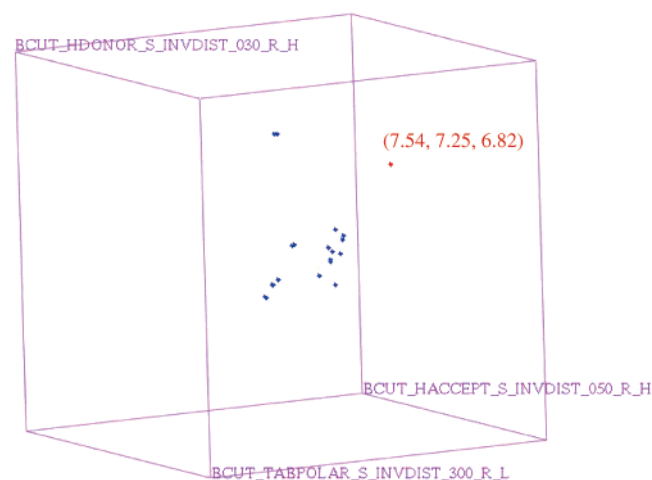


Figure 11. Map of the 20 compounds in Figure 5 (blue dots) in a representative BCUT three-axis diversity space.^{27–29} BCUT axes used are, respectively: (1) BCUT HACCEPT S INVDIST 050 R H, (2) BCUT HDONOR S INVDIST 030 R H, and (3) BCUT TABPOLAR S INVDIST 300 R L. Red dot shows an unfilled coordinate of diversity space, at (7.54, 7.25, 6.82). The information contained in this BCUT coordinate does not reveal information about the shape of a molecule which might be able to fill this position in diversity space.

tions. QSCD's singular advantage is that it is constructed on a basis set that allows for the reversible flow

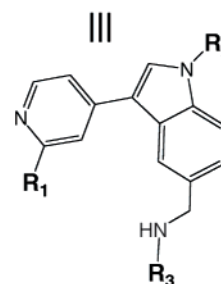
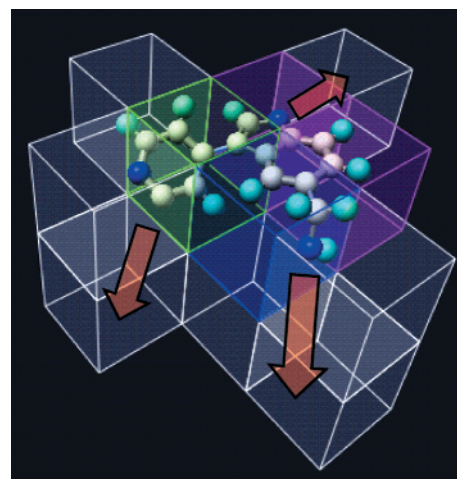


Figure 12. Use of QSCD to design complementary combinatorial libraries to unmatched theoretical target surfaces. Note that many conceivable libraries of a given shape and functionality may be designed to fill a given unmet diversity need.

Table 7. Summation of Binding Energies for an Interaction of an Average Complementary Molecule/Theoretical Target Surface Pair in the Context of the QSCD Model Used Herein^a

energetic contribution	av ΔG (kcal/mol)
translational/vibrational entropic loss (constant)	+9
constant +0.7 kcal/mol ($RT \ln 3$) per rotatable bond; assume rigid theoretical target surface	+7
$\Delta\Delta G$ conformation from ground state	+2
constant -0.03 kcal/mol/ \AA^2 nonpolar buried surface = -0.54 kcal/mol/ 4.24 \AA^2 nonpolar buried face; total 21 molecular faces + 21 theoretical surface faces	-23
total interaction from Table 2 (four complementary points)	-6.0
sum of binding energies	-11
binding affinity to nearest integer ($\div 1.363$)	$10^{-8} = 10$ nM

^a An average molecule is assumed to have a buried volume of 12 cubic quanta (≈ 915 cubic \AA at 4.24 \AA resolution), 36 exposed faces (4.24 \AA^2), 21 nonpolar exposed faces (60%), 10 rotatable bonds, 4 points of complementary electrostatic/VDW potential, and a conformational energy within 2 kcal/mol of ground state. An average complementary theoretical target surface is also assumed to have 60% nonpolar exposed faces. Constants used in the table are taken from Ajay and Murcko.¹⁴

of diversity information: by defining molecular diversity through a fixed reference frame of spatially and functionally enumerated 3D surfaces, the model determines not only diversity of existing structures but also structures of nonexisting diversity. In addition to numerically defining the absolute percentage of diversity space covered by any given set of screening molecules, QSCD allows for the rational and systematic population of the remaining, *unfilled* diversity space.

The model suggests that in order to ensure nanomolar ligands to any given target, a library of at least 24

million molecules will be required. While there is much computational and synthetic effort that stands between current combinatorial libraries and a general screening library of 20+ million molecules, the ever increasing speed of computer processors and the present ability to synthesize million-member libraries leave little doubt that such a feat can be achieved. Combined with the rapid miniaturization and efficiency of screening techniques, diversity models such as QSCD should help to bridge the gap between the myriad achievements of genomics and the next generation of small molecule therapeutics.

Experimental Section

Molecular conformations were generated with Multisearch in Sybyl (version 6.5; Tripos Inc., 1699 S. Hanley Rd., St. Louis, MO 63144) on an R10000 Silicon Graphics workstation. Conformations were subsequently sorted by energy and conformations within 10 kcal of the lowest energy were accepted. Overlay plots of molecules (Figure 8B) were also generated using Sybyl. UNITY 2D fingerprints (Unity 4.0; Tripos Inc., 1699 S. Hanley Rd., St. Louis, MO 63144) were generated on an R10000 Silicon Graphics workstation. Pairwise Tanimoto coefficients were computed as described by Dixon and KoeHLer.³⁹ QSCD software for molecule quantization, mapping of Q-files, and surface complementarity display was developed using the Java programming language (JDK 1.2) and the Java3D graphics API (version 1.1) on Intel-based workstations. Theoretical target surfaces were stored and indexed using an Oracle 7.3.3 database. Parameters for theoretical target surface generation/molecular quantization and parameters for complementarity mapping/scoring were alternately optimized in three successive rounds as below.

The parameters used for theoretical target surface generation and the closely related parameters for quantization of small molecules into quantized files (Q-files) were optimized in the context of the algorithms stated in the text. Parameters were iteratively optimized by varying a given parameter and then quantizing training molecules other than those in Figure 5. Training molecules used were taken from in house structures and two published SAR sets.^{49,50} Concomitant with molecular quantization, an enumerated set of theoretical target surfaces was created with corresponding parameters. Using the current optimized complementarity/scoring parameters, molecules were then mapped to theoretical target surfaces and all diversity pairing scores generated as described in the text. Parameters were chosen which accurately predicted known homogeneous/heterogeneous pairs and which maximized "signal-to-noise" of homogeneous scores over heterogeneous scores.

The parameters used for mapping/scoring molecular conformations to theoretical target surfaces were optimized in the context of the algorithm stated in the text. Parameters were iteratively optimized by varying a given parameter and then mapping a constant set of training molecules (see above) to a constant set of theoretical target surfaces, using the most current surface generation and quantization parameters. Diversity pairing scores were generated for all training molecules, and parameters were chosen which accurately predicted known homogeneous/heterogeneous pairs and which maximized "signal-to-noise" of homogeneous scores over heterogeneous scores.

As mentioned in the text, for a given conformation-to-surface shape fit to be accepted, the minimum overlap requirement was set to either 9 quanta or $N - 2$ quanta of a conformation of N quanta. This range allows large conformations to fit partially into a theoretical surface (protruding volume must be at the mouth of the surface) while also allowing smaller conformations to be considered for complementarity. It excludes large conformations which do not overlap at least 9 quanta.

Approximate computational speeds of typical QSCD operations are as follows on a single Pentium III 500 MHz worksta-

tion: generation of the basis set of theoretical target surface used in the study required 17 min; these data were stored for access by subsequent QSCD functions. Quantization of 100 conformations of a given molecule into 100 Q-files required 250 s. Complementarity mapping of 100 Q-files onto the basis set of theoretical target surfaces used in the study required 40 s.

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