Abstract

We present an information-theoretic framework to compute the shape similarity between 3D polygonal models. From an information channel between a sphere of viewpoints and the polygonal mesh of a model, an information sphere is obtained and used as a shape descriptor of the model. Given two models, the minimum distance between their information spheres, the distance between their information histograms, and the difference of their mutual information are introduced as methods to calculate the similarity matrix between 3D models. The performance of these techniques is tested using the Princeton Shape Benchmark database.

CR Categories: H.1.1 [Information Systems]: Models and Principles—Systems and Information Theory H.3.3 [Information Systems]: Information Storage and Retrieval—Information Search and Retrieval I.2.10 [Computing Methodologies]: Artificial Intelligence—Vision and Scene Understanding I.5.3 [Computing Methodologies]: Pattern Recognition—Clustering;

Keywords: shape similarity, information theory, mutual information

1 Introduction

Quantifying the shape similarity between 3D polygonal models is a key problem in different fields, such as computer graphics, computer vision and pattern recognition. Recently, as the number of large digital repositories of 3D models grows dramatically, such as the Princeton Shape Benchmark [Shilane et al. 2004] and the National Design Repository [Fang et al. 2008], 3D data are becoming ubiquitous. As a result, there is an increasing demand for search engines that are able to retrieve similar models using shape similarity measures. In the last few years, a number of algorithms have been proposed for the retrieval of both rigid [see (Tangelder and Veltkamp 2008) for a survey on content-based 3D shape retrieval] and non-rigid 3D shapes [Lian et al. 2013].

Best view selection is also a fundamental task in object recognition. Many works have demonstrated that the recognition process is view-dependent [Palmer et al. 1981; Tarr et al. 1997; Blanz et al. 1999]. Among them, Tarr et al. found that “visual recognition may be explained by a view-based theory in which viewpoint-specific representations encode both quantitative and qualitative features” [Tarr et al. 1997]. In computer graphics, several viewpoint quality measures, such as viewpoint entropy and viewpoint mutual information, have been applied in areas such as best view selection for polygonal models [Vázquez et al. 2001; Feixas et al. 2009] and scene exploration [Sokolov et al. 2006]. Several 3D shape-based retrieval methods are based on view similarity, where two 3D models are considered similar if they look similar from all viewing angles. See, for instance, the sketch-based shape retrieval method proposed by [Eitz et al. 2012]. We advance in this line by tackling the shape similarity problem from an information-theoretic framework introduced by [Feixas et al. 2009].

From our framework, different methods based on several information-theoretic measures are presented to compute the similarity matrix of a set of models. Given a 3D model, these information measures are obtained from a visibility channel created between the set of viewpoints and the polygonal mesh. We define three different information measures: the mutual information of a 3D model, and the specific information measures $I_1$ and $I_2$ associated with each viewpoint. The last-mentioned measures correspond to two different forms of decomposing the mutual information and enable us to create two different information spheres for each model.

From the above information-theoretic measures, we present three methods to obtain the similarity matrix for all the models of a database. In the first method, a registration process between the information spheres of two models is carried out to obtain the pose that achieves the minimum $L_2$ distance. This distance provides the degree of dissimilarity between the two shapes. In the second method, the earth mover’s distance between the information histograms of two models is also used to calculate the degree of dissimilarity between the corresponding shapes. In the third method, the mutual information of a 3D model is considered as a shape signature and the difference in absolute value of the mutual information of each model can be also seen as a shape discrimination measure.

This paper is organized as follows. In Section 2, we summarize some related work in 3D shape retrieval and we present some basic information-theoretic measures. In Section 3, we present the visibility channel and two information-theoretic measures that are applied to compute the information associated with a viewpoint. In Section 4, we propose several methods to compute the similarity between 3D models. In Section 5, experimental results show the behavior of the proposed measures for 3D shape retrieval. Finally, in Section 6, we present the conclusions and the future work.

2 Related Work and Information Theory Background

In this section, we review some related work in 3D shape matching and information-theoretic tools.
2.1 Related Work

Recent developments in techniques for modeling, digitizing and visualizing 3D shapes have provoked an explosion in the number of available 3D models on the Internet and in specific databases. This has led to the development of 3D shape retrieval systems (see [Tangelder and Veltkamp 2008] for a survey) that, given a query object, retrieve similar 3D objects.

At conceptual level, a typical shape retrieval framework consists of a database with an index structure created off-line and an on-line query engine. Each 3D model has to be identified with a shape descriptor, providing an overall description of its shape. The indexing data structure and the searching algorithm are used to search efficiently. The on-line query engine computes the query descriptor and the models similar to the query model are retrieved by matching descriptors to the query descriptor from the index structure of the database. The similarity between two descriptors is quantified by a dissimilarity measure.

According to [Tangelder and Veltkamp 2008], 3D shape retrieval systems are usually evaluated with respect to several requirements of content based 3D retrieval, such as: shape representations requirements, properties of dissimilarity measures, efficiency, discrimination abilities, ability to perform partial matching, robustness, and necessity of pose normalization. Shape matching methods can be divided in three broad categories: feature-based methods, graph-based methods, and view-based methods.

2.1.1 Feature-Based Methods

Feature-based methods are the most commonly used as features can directly denote the geometric and topological properties of 3D shapes. According to the type of shape features used, feature based methods can be further categorized into: global features, global feature distributions, spatial maps and local features, in all of which two models are compared according to their feature distance in the fixed d-dimensional space. The first three categories use a single d-dimensional vector to represent features, while local feature-based methods compute feature vectors for a number of surface points, which are often the salient points of a 3D model. Corresponding feature based methods of each category for the 3D shape retrieval include self-similarity (symmetry) [Kazhdan et al. 2004] and the global descriptors based on volume and area [Zhang and Chen 2001], distance distributions [Osada et al. 2002] and spectral shape analysis [Reuter et al. 2006; Lian et al. 2013], statistical moments [Kazhdan et al. 2003; Novotni and Klein 2003], and the local features combined with the bag-of-words model [Bronstein et al. 2011] or the heat kernel diffusion [Sun et al. 2009].

2.1.2 Graph-Based Methods

Graph-based methods use a graph to extract a geometric meaning from a 3D shape and utilize the topological properties of 3D objects to measure the similarity between them, rather than only considering the pure geometry of the shape as the feature-based methods, and they can be applicable to articulated models. According to the type of the used graphs, there are three categories in this technique including model graphs [El-mehalawi and Miller 2003a; El-mehalawi and Miller 2003b], Reeb graphs [Hilaga et al. 2001; Tung and Schmitt 2005], and skeletons [Sundar et al. 2003]. Compared with the feature based methods, the graph based methods are less robust, but the graph based structure is suitable for partial matching.

2.1.3 View-Based Methods

Based on the fact that 3D models are similar when they look similar from all viewing angles, view-based similarity methods are proposed. The earlier references to view based retrieval is given by Löffler et al. [Löffler 2000] who used a 2D query interface to retrieve 3D models. Funkhouser et al. describe an image based approach allowing users to query the engine by drawing one or more sketches [Funkhouser et al. 2003]. Chen et al. provide a system based on a set of lightfield descriptors [Chen et al. 2003], and one hundred orthogonal projections of an object are encoded both by Zernike moments and Fourier descriptors as features for retrieval. Gonzalez et al. use the sphere of viewpoints with viewpoint mutual information as a descriptor of the model [González et al. 2007]. The sketch-based 3D model retrieval system proposed by Yoon et al. [Yoon et al. 2010] is robust against variations of shape, pose or partial occlusion of the sketches, but the drawing process is still a little bothering. Although the discriminative and robust sketch-based 3D shape retrieval system by Shao et al. [Shao et al. 2011] requires dense sampling and registration and incurs a high computational cost, critical acceleration methods based on pre-computation and multi-core platforms or GPUs are designed to achieve interactive performance. Eitz et al. collect a significant number of sketches for the evaluation of shape retrieval performance and achieve significantly better result than the previous methods [Eitz et al. 2012], but realistic inputs are still a very hard problem, which is related to their bag-of-features and the new descriptor for line-art renderings. Liu et al. design a statistical measure based on sketch similarity for CAD model retrieval, which accounts for users’ drawing habits [Liu et al. 2013]. The limitation of the method is that a single freeform sketch mainly captures some geometric information other than semantic meanings.

3 Viewpoint Information Measures

In this section, we review the main elements of a communication channel between the set of viewpoints around a 3D model and the viewpoint information measures introduced by Boaventura et al. [Boaventura et al. 2011].

3.1 Visibility Channel

In [Feixas et al. 2009], a viewpoint selection framework was proposed from an information channel $V \rightarrow Z$ between the random variables $V$ (input) and $Z$ (output), which represent, respectively, a set of viewpoints $V$ and the set of polygons $Z$ of an object. This channel is defined by a conditional probability matrix obtained from the projected areas of polygons at each viewpoint and can be interpreted as a visibility channel where the conditional probabilities represent the probability of seeing a determined polygon from a given viewpoint (Figure 1). Viewpoints are indexed by $v$ and polygons by $z$. The three basic elements of the visibility channel are:

- Conditional probability matrix $p(Z|V)$, where each element $p(z|v) = \frac{a_z(v)}{a_t(v)}$ is defined by the normalized projected area of polygon $z$ over the sphere of directions centered at viewpoint $v$. $a_z(v)$ is the projected area of polygon $z$ at viewpoint $v$, and $a_t$ is the total projected area of all polygons over the sphere of directions. Conditional probabilities fulfill $\sum_{z \in Z} p(z|v) = 1$. The background is not taken into account.

- Input distribution $p(V)$, which represents the probability of selecting each viewpoint, is obtained from the normalization of the projected area of the object at each viewpoint. The input distribution can be interpreted as the importance assigned to each viewpoint $v$. 

3. View-Based Similarity Framework

In this section, we present three different methods to evaluate the 
shape similarity between two models and to obtain the distance 
matrix for all the models of a data set. These methods are respectively 
based on (1) the $L_2$ distance between information spheres, (2) the 
earth mover’s distance between information histograms, and (3) the 
absolute difference between the mutual information of each model.

4.1 $L_2$ Distance between Information Spheres

In this method, given a 3D model, two information spheres are 
respectively obtained by computing the information measures $I_1$ and $I_2$ for each viewpoint. Then, a registration process is done to find 
a minimum distance that characterizes the degree of dissimilarity 
between two models.

Figure 2 shows both the $I_1$-spheres and the $I_2$-spheres for four 
different models of the same class. Observe how similar information 
spheres are obtained for all the models, although the most 
similar patterns are provided by the measure $I_2$. The information 
spheres are considered as shape descriptors (or signatures) for 
a given model.

To compute the dissimilarity (or distance) between two $I_1$-spheres 
(or $I_2$-spheres), a registration process is carried out to obtain the 
pose that achieves the minimum distance between the viewpoint information values. In the registration process, we aim to find the
transformation that brings one sphere (floating) into the best possible spatial correspondence with the other one (fixed) by minimizing the distance between the information measures of the corresponding viewpoints. The distance used is the $D_2$ distance which is based on the absolute difference between each pair of matching viewpoint information values.

To achieve the best matching between both the fixed and the floating sphere, we consider the following points: First, the discrete nature of our information spheres (e.g., 642 viewpoints) requires an interpolator component. In our implementation, the nearest neighbor interpolator has been used. Second, the $D_2$ distance between the information spheres $S_1$ and $S_2$ (corresponding to the models $Z_1$ and $Z_2$) for a specific matching is given by

$$D(S_1, S_2) = \sqrt{\sum_{v \in V}(I(v; Z_1) - I(v; Z_2))^2}, \quad (4)$$

where $I(v; Z)$ stands for $I_1(v; Z)$ or $I_2(v; Z)$. Third, we use two transformation parameters (degrees of freedom): $R(\theta)$ and $R(\phi)$, defined respectively as the rotation around $Z$ and $Y$ axis. These two parameters take values in the range $[0^\circ, 360^\circ]$ and $[0^\circ, 180^\circ]$, respectively. Through this process we get the method to be robust to rotations of the models.

In this method, we assume that the correct matching is given by the minimum value of $D(S_1, S_2)$. Since this matching process is time-consuming if all the possible positions are checked, we use Powell’s method to speed up the registration [Powell 1964]. Powell’s method is a numerical optimizer that finds the minimum of a function without using derivatives.

To sum up, the fundamental idea of this view-based similarity approach is that the viewpoint measures used to build the information spheres supply an information measure for each viewpoint. Thus, the sphere of viewpoints can be seen as a shape representation of the object. In our case, two 3D models are similar when their corresponding information spheres are also similar, that is, capture a similar information distribution. Note that we only store one scalar value for each viewpoint, differently to other methods, that store the silhouette or the depth map [Eitz et al. 2012; Ohbuchi et al. 2008].

### 4.2 Earth Mover’s Distance between Information Histograms

As in Section 4.1, the first step is the creation of the $I_1$ and $I_2$ spheres corresponding to a given model. Then, we obtain the information histograms that are used as shape descriptors of the model.

To create both the $I_1$-histogram and the $I_2$-histogram from the corresponding information spheres, we need to fix three parameters: the minimum and the maximum values of the information measure (i.e., $I_1$ or $I_2$), and the number of bins of the histogram. Taking into account that $I_1$ is always greater or equal to 0, its minimum value has been fixed to 0. On the other hand, the maximum value of $I_1$ has been taken from the highest $I_1$ value among all the models in the database. In a similar way, the minimum and maximum values of $I_2$ have been obtained from the lowest and highest $I_2$ values among all the models in the database, respectively. The maximum and minimum values could be also fixed using a training set and doing some kind of clipping to avoid outliers. As we will see in the next section, our tests have been performed using different number of bins.

The dissimilarity between two models is computed by the Earth Mover’s Distance (EMD) between their histograms [Rubner et al. 1998]. EMD is a measure of the distance between two distributions. If the two distributions are interpreted like two ways of piling up an amount of earth, then EMD is the least amount of work needed to turn one pile into the other. A unit of work corresponds to transporting a unit of earth by a unit of distance. In our case, this distance is given by the distance between bins and the amount of earth is given by the probability of belonging to a bin. If both distributions have the same amount of earth, EMD is a true distance. This condition is also fulfilled in our case.

The earth mover’s distance between two information histograms $H_1$ and $H_2$ is defined as

$$EMD(H_1, H_2) = \frac{\sum_{i \in H_1} \sum_{j \in H_2} c_{ij} f_{ij}}{\sum_{i \in H_1} \sum_{j \in H_2} f_{ij}}, \quad (5)$$

where $c_{ij}$ represents the distance between bin $i$ of histogram $H_1$ and bin $j$ of histogram $H_2$, and $f_{ij}$ represents the amount of occurrences that is transferred between bin $i$ and bin $j$.

### 4.3 Mutual Information Difference

We can also use the mutual information $I(V; Z)$ between the set of viewpoints and the model as a signature of the model. Let us remember that the mutual information expresses the degree of correlation or dependence between the set of viewpoints and the model. The distance between two models is now computed as the difference between their mutual information in absolute value. This is a very coarse approach but the advantage is that the signature is represented by a single scalar value and the comparison between signatures is really fast. This would allow, at almost no cost, to build a short list of candidate matching models. In Figure 4, we see one example that shows how the objects of a same class have similar values of $I(V; Z)$.

### 5 Results and discussion

To calculate the information-theoretic measures presented in Section 3, we need to obtain the projected area of every polygon for every viewpoint, and these areas will enable us to obtain the probabilities of the visibility channel ($p(V)$, $p(Z|V)$, and $p(Z)$). In our experiments, all the models are centered inside a sphere of 642 viewpoints built from the recursive discretization of an icosahedron and the camera is looking at the center of this sphere. To obtain the viewpoint sphere, the smallest bounding sphere of the model is obtained and, then, the viewpoint sphere adopts the same center as the bounding sphere and a radius three times the radius of the bounding sphere. Centering the object to the center of the sphere we get a method invariant to translations and, as the viewpoints are uniformly distributed over the sphere, we have also invariance to rotations. The shape descriptors of each model are computed in advance and stored into a database. Table 1 shows the storage size for each descriptor in number of float values, the cost of computing

![Figure 2: (first row) $I_1$-spheres and (second row) $I_2$-spheres corresponding to four different 3D models of the same class.](Image 1)
In this paper, we have presented a framework for 3D shape retrieval based on the information channel between the set of viewpoints around a 3D model and the 3D model polygons. From this channel we derive different similarity measures, based on the decomposition of mutual information. The set of quality measures associated with the sphere of viewpoints can be seen as a shape representation of the object.

Future research will be addressed towards the optimization of the registration process, using other registration measures than $L_2$ distance, investigating other viewpoint measures derived from our framework as saliency and instability, and looking for an optimal combination of measures.

<table>
<thead>
<tr>
<th>Methods</th>
<th>NN</th>
<th>FT</th>
<th>ST</th>
<th>E-M</th>
<th>DCG</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_2$ ($I_1$-sphere)</td>
<td>39.4%</td>
<td>20.8%</td>
<td>27.9%</td>
<td>14.4%</td>
<td>43.3%</td>
</tr>
<tr>
<td>$L_2$ ($I_2$-sphere)</td>
<td>27.6%</td>
<td>12.5%</td>
<td>17.6%</td>
<td>9.3%</td>
<td>36.3%</td>
</tr>
<tr>
<td>EMD ($I_1$-hist)</td>
<td>18.2%</td>
<td>8.9%</td>
<td>14.0%</td>
<td>8.5%</td>
<td>32.9%</td>
</tr>
<tr>
<td>EMD ($I_2$-hist)</td>
<td>14.0%</td>
<td>6.9%</td>
<td>11.4%</td>
<td>6.8%</td>
<td>30.2%</td>
</tr>
<tr>
<td>diff ($I(V;Z)$)</td>
<td>4.0%</td>
<td>2.6%</td>
<td>5.0%</td>
<td>3.6%</td>
<td>25.0%</td>
</tr>
</tbody>
</table>

Table 2: Results of our methods using the Princeton Shape Benchmark test set (907 models).

The results for our 3D shape retrieval framework based on viewpoint information channel are preliminary and, compared with the results presented in [Shilane et al. 2004] (see Table 3), we can see that even with our best method, based on $I_1$-spheres, they are still far from being competitive. They depend heavily on the good construction of the models and, hence, we plan to check with databases of well-formed models. But we should also investigate a strategy to overcome this problem, maybe by projecting the triangles as a double face. We are also limited in principle to rigid models, but as far as they can identify the different poses of a same model as coming from the same family the retrieval would be correct.

6 Conclusions and Future Work

Figure 4: In the first row, three 3D models of the same class with a similar value of $I(V;Z)$. In the second row, three 3D models of the same class where $I(V;Z)$ is quite different between them.

Figure 5: The satellite dish class of the test set.

Each descriptor, and the comparison time between descriptors. The latter time depends on the computation method used.

To test the performance of our methods we use the Princeton Shape Benchmark (PSB) database and its utilities [Shilane et al. 2004]. The statistics used are (nearest neighbor (NN), first tier (FT), second tier (ST), E-Measure, and discounted cumulative gain (DCG)). The fifth statistic (discounted cumulative gain) (DCG) gives a sense of how well the overall retrieval would be viewed by a human. More information about these statistics can be seen at [Shilane et al. 2004]. In Table 2, the methods have been ordered using the NN statistic. Observe that the best results are obtained with the $L_2$ distance between $I_1$-spheres, which are clearly better than the ones obtained between $I_2$-spheres. Thus, these results confirm the visual hint (see Figure 3) that $I_1$-spheres are better descriptors than $I_2$-spheres. Concerning the information histograms, the EMD also achieves better results with $I_1$ than with $I_2$. The best results with the information histograms have been obtained using 96 bins. Finally, we can also see the results obtained with the mutual information difference, which being a scalar measure has a very low discrimination power.

The measure with clearly worst results is $I(V;Z)$ but if we go deeper we can observe why it fails and when this measure could be useful. As we can see in Figure 4, the objects of the same class tend to have a similar value of $I(V;Z)$. However, objects of different classes can also have a similar value of $I(V;Z)$. When in this case we check the information histograms, we can see that their patterns are considerably different (see Figure 3). That is, even though the distribution of the $I_1$ values on the sphere can be different, their average can be similar. Taking into account this behavior, the $I(V;Z)$ method could be used as a filter to select a subset of models with similar $I$ value and, then, other methods such the ones based on information histograms or information spheres could be applied. In some occasions we can see a class with the values of $I(V;Z)$ not so similar as expected (see Figure 4).

Figure 3: Two objects with similar $I(V;Z)$ values (1.58079 and 1.58275) and different patterns for the $I_1$-spheres.

Table 1: For each descriptor, size of the descriptor, time to generate it, and time to compare two models.

<table>
<thead>
<tr>
<th>Descriptors</th>
<th>Size (elements)</th>
<th>Generation time (s)</th>
<th>Comparison time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_1, I_2$-sphere</td>
<td>642</td>
<td>1.44</td>
<td>0.064236</td>
</tr>
<tr>
<td>$I_1, I_2$-histogram</td>
<td>96</td>
<td>1.44</td>
<td>0.001407</td>
</tr>
<tr>
<td>$I(V;Z)$</td>
<td>1</td>
<td>1.36</td>
<td>0.000000</td>
</tr>
</tbody>
</table>

Table 3: Comparison of the methods used to order the models in the test set.
### Table 3: Results from [Shilane et al. 2004], where we have merged the results of our 1-sphere method (see Table 2).

<table>
<thead>
<tr>
<th>Shape Descriptor</th>
<th>Storage Size (bytes)</th>
<th>Timing</th>
<th>Compare Time (s)</th>
<th>Nearest Neighbors</th>
<th>First Tier</th>
<th>Second Tier</th>
<th>E-Measure</th>
<th>DCG</th>
</tr>
</thead>
<tbody>
<tr>
<td>LFD</td>
<td>4,700</td>
<td>3.25</td>
<td>0.001300</td>
<td>65.7%</td>
<td>38.0%</td>
<td>48.7%</td>
<td>28.0%</td>
<td>64.3%</td>
</tr>
<tr>
<td>REXT</td>
<td>17,416</td>
<td>2.22</td>
<td>0.000229</td>
<td>60.2%</td>
<td>32.7%</td>
<td>43.2%</td>
<td>25.4%</td>
<td>60.1%</td>
</tr>
<tr>
<td>SHD</td>
<td>2,184</td>
<td>1.69</td>
<td>0.000027</td>
<td>55.6%</td>
<td>30.9%</td>
<td>41.1%</td>
<td>24.1%</td>
<td>58.4%</td>
</tr>
<tr>
<td>GEDT</td>
<td>32,776</td>
<td>1.69</td>
<td>0.000450</td>
<td>60.3%</td>
<td>31.3%</td>
<td>40.7%</td>
<td>23.7%</td>
<td>58.4%</td>
</tr>
<tr>
<td>EXT</td>
<td>552</td>
<td>1.17</td>
<td>0.000008</td>
<td>54.9%</td>
<td>28.6%</td>
<td>37.9%</td>
<td>21.9%</td>
<td>56.2%</td>
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<tr>
<td>SECSHEL</td>
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<td>1.38</td>
<td>0.000451</td>
<td>54.6%</td>
<td>26.7%</td>
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<tr>
<td>VOXEL</td>
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<td>54.0%</td>
<td>26.7%</td>
<td>35.3%</td>
<td>20.7%</td>
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<td>SECTORS</td>
<td>552</td>
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<td>CEGI</td>
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<td>42.0%</td>
<td>21.1%</td>
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<td>17.0%</td>
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<tr>
<td>L2(J-sphere)</td>
<td>2,568</td>
<td>1.44</td>
<td>0.064236</td>
<td>39.4%</td>
<td>20.8%</td>
<td>27.9%</td>
<td>14.4%</td>
<td>45.3%</td>
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<td>EGI</td>
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<td>37.7%</td>
<td>19.7%</td>
<td>27.7%</td>
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<td>DZ</td>
<td>156</td>
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<td>31.1%</td>
<td>15.8%</td>
<td>23.5%</td>
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<tr>
<td>SHELLS</td>
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<td>11.1%</td>
<td>17.3%</td>
<td>10.2%</td>
<td>38.6%</td>
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</table>

### Acknowledgements

This work has been founded in part by grant number TIN2010-21089-C03-01 and BES-2011-045252 of Spanish Government, grant number 2009-SGR-643 of Generalitat de Catalunya (Catalan Government), and National Natural Science Foundation of China (Nos. 61331018, 61372190).

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