Introducing a general purpose visual formalism based on procedurally generated geometry

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Abstract The visualization of complex knowledge spaces requires balancing of visual models, metaphors and formalisms. For abstract domains of knowledge most aspects of entities have to be represented by formalisms due to the absence of real-world models and the small number of dimensions conveyable through a metaphor. We investigate the use of solid objects based on three-dimensional extensions of the superformula as a visual formalism. The dimensions of the knowledge space can be mapped to parameters of the formula to generate objects expressing abstract aspects of knowledge entities. First, we give an introduction to the design of visual formalisms for knowledge visualization. Then, the superformula and its extension to three dimensions are presented. Further, possible mappings of dimensions to superformula parameters are discussed, and examples based on real-world data are given. Finally, an outlook on an evaluation is given which will be realized with the cognitive psychology group at our institution.

Keywords: Knowledge Visualization, Computer Graphics, Human Computer Interaction

1 Introduction

Over the years more and more data and information has become available [1]. Knowledge emerges from the process of analyzing information, e.g. a query is performed; the result is visualized and can then be interpreted by the user. Knowledge visualization enables better understanding of information and often works with metaphors or real-world models, e.g. geospatial visualization. However, very abstract or diverse information makes it hard to find metaphors especially in case of non-existing real-world models. Therefore we need a visual formalism which should be generic, easy to compute and versatile. For example, if news articles are queried the result may be 20000 articles and the clustering procedure yields 10 clusters. The challenge is the representation of the cluster and how the relation between a given document and each cluster denoting a topic is expressed. Though the cluster content varies over time, it remains a concrete dimension in a 10-dimensional space in which each article could be placed. Consequently, we need a visual formalism able to express this without evoking associations to concrete real-world topics. The use of the superformula is our solution to this; in figure 1 an example of the proposed visual formalism is given.

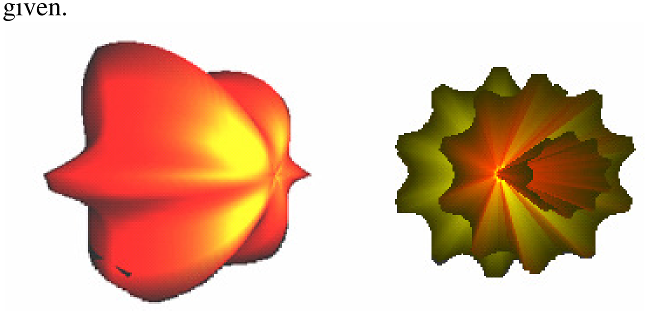

Fig. 1. Example of the superformula as formalism for data visualization

2 Domain

In this section a short introduction to designing visual formalisms for knowledge visualization is given. Further, the terms knowledge visualization and visual formalisms are briefly explained and some examples of methods using visual formalisms are given.

Knowledge visualization is defined as a technique to examine the use of visual representations to improve the transfer of knowledge between groups of people. In contrast to information visualization, where computer-aided and interactive tools are used to visually represent abstract data, knowledge visualization deals with creating and communicating knowledge among people [2].

Visual formalisms are generally used to display complex data and relationships in an abstract way. They are diagrammatic notations with well-defined semantics in order to express relations and have a great potential for defining a semantic user interface. Visual formalisms take advantage of human abilities, e.g. cognition of patterns and hierarchically structuring of data. Common examples for visual formalisms are simple notations, e.g. tables, maps and graphs. Visual formalisms can be adapted to many kinds of applications, for instance specializations of tables like spread sheets and calendars [3]. The semantics a visual formalism uses depend strongly on the information to be displayed and are distinctly determined by the designer [4].

When designing a visual formalism for knowledge visualization the semantic of the visual formalism itself and the presentation of the visual formalism have to be defined. The visual formalism then defines the semantic of the application [3].

In literature, a manifold of methods has been proposed to use visual formalisms for information and knowledge visualization. Many algorithms combine visual formalisms with other techniques, e.g. visual metaphors in order to reach an appealing result for visualizing data. To highlight the concept of knowledge visualization several proposed algorithms are explained briefly in this section. Besides, the limitations of the described systems are given to emphasize the need for a special visual formalism.

Tube Map Visualization [5] Knowledge is visualized using a tube map as a visual metaphor to represent a project in a company. The lines correspond to target groups and the stops to milestones where the target groups are involved. Furthermore, the stops provide descriptions, dates and instructions. Consequently the visualization gives an overview plus detailed information about a specific topic. The limitations of the Tube Map Visualization are that the approach fails if multiple dimensions are present and especially when one item is taken out because then no methodology exists to construct a symbol for it representing its state in the visualization.

InfoSky [6] InfoSky is a system to explore a large, hierarchically organized set of document collections. It uses a visual formalism inspired by a galaxy of stars in order to structure documents into thematic clusters. Documents with related content are visualized close to each other in form of stars. Collections of documents at a particular level in the hierarchy are displayed as bounding polygons. The main limitations of InfoSky are the lack of a symbolism and the dependency on the level of detail of the knowledge space [6].

Gyro 3D Visualisation Framework [7] The Gyro Visualization Framework is a three-dimensional visualization of knowledge networks. Basically topics are placed on a disc which is divided into thematic segments. Thus this visualization provides a lot of information at a glance. Generally, visual metaphors are used but additionally visual components e.g. color and shape, are introduced to make the concept more efficient and improve the visualization. The main limitations of this approach are that each article is labeled with a symbol denoting the type of the article, which means that dynamic types cannot be handled.

3 Description of the Superformula

3.1 Supershape in 2D

The Supershape formula, proposed in [8] [9], is an extension of the equation of the superellipse [10] and the equation of both the sphere and the ellipse. The superformula enables description and computation of different shapes using only one formula. In (1) the superformula in two-dimensional space is given.

$$\frac{1}{r} = \sqrt[n1]{\left|\frac{1}{a}\cos\left(\frac{m}{4}\phi\right)\right|^{n2} + \left|\frac{1}{b}\sin\left(\frac{m}{4}\phi\right)\right|^{n3}} \quad . \tag{1}$$

The superformula is a mathematical construct with six free parameters. The radius r denotes the distance from the origin; φ is the angle to the x axis. Both r and φ are expressed in polar coordinates. The parameters m, n1, n2, n3 are defined in ℝ. The parameters a, b also take real numbers but are restricted to non-zero values. The parameter m relates to the number of vertices of a shape, parameter n1 determines flatness and sharpness of corners and convexity of sides. Both parameters n2 and n3 denote whether the shape is inscribed or circumscribed in the unit circle [8]. Varying those parameters results in a set of diverse kinds of shapes, for instance, if m is set to zero, unit circles are obtained [11].

In figure 2 a range of different shapes is shown, obtained by varying parameter m of the superformula.

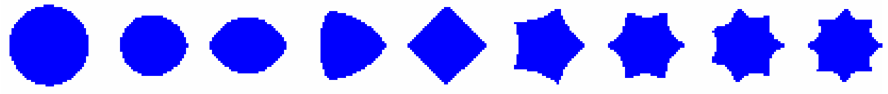

Fig. 2. Different shapes derived by varying parameter m

3.2 Supershape in 3D

The above described superformula can be extended to three-dimensional space. One method is via computation of the spherical product of two supershapes [12], but also other mappings are possible. In (2) the mathematical description of the spherical product is given.

$$\begin{aligned} x &= r1(\theta)\cos(\theta)r2(\varphi)\cos(\varphi) \\ y &= r1(\theta)\sin(\theta)r2(\varphi)\cos(\varphi) \\ z &= r2(\varphi)\sin(\varphi) \end{aligned} \quad . \tag{2}$$

The latitude φ is defined in $-\pi/2 \leq \varphi \leq \pi/2$ and the longitude θ is defined in $-\pi \leq \theta \leq \pi$ [11].

Using the superformula both classical shapes like cube, cone or sphere and also a lot more complicated shapes can be obtained. In particular the generated shapes have to be high-tessellated in order to be able to approximate special classic and simple objects.

In figure 3 the same range of shape as in figure 2 is shown but in that case the shapes are three-dimensional.

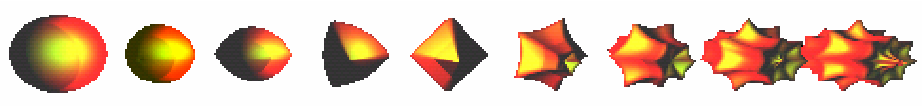

Fig. 3. Shapes of Fig.2 in 3D space

Supershapes can be used for a variety of applications, e.g. surface modeling [13] and surface recovery [12]. In our case we will investigate the use of supershapes a as a general purpose visual formalism.

4 Experiments and Results

In this chapter various ways of mapping abstract dimensions to superformula parameters will be discussed and examples based on real-world data will be given to illustrate the benefits and shortcomings of the approach.

The proposed method uses three-dimensional supershapes as a visual formalism to describe knowledge entities and therefore enhance the user's ability to understand and evaluate abstract data. Examples of possible supershapes are given at [11].

The knowledge entities result from a knowledge retrieval process and can be results of a search or distinct objects like e.g. articles. Each entity is assigned to a set of abstract information, e.g. the term occurrence. The challenge is how to represent the objects and at the same time provide as much abstract information as possible. A possible answer to this question is to use supershapes and map the abstract information to parameters of the shapes. The problem of the proposed approach is that the particular supershapes are hard to distinguish therefore suitable dimensions have to be found experimentally. In the next paragraph an example based on real-world data is described.

We intend to map output values of a service based knowledge retrieving framework [14] to a set of supershapes. The output values of the knowledge retrieving framework correspond to a number of places occurring within a set of documents. Therefore each occurrence should result in a characteristic supershape. Abstract dimensions are used to determine the parameters of a particular supershape in relation to the value of its according occurrence. Consequently distinctive dimensions have to be found to get discriminative supershapes. Several dimensions were obtained experimentally; figures 4-6 show three example dimensions. All figures contain four supershapes whereas each supershape corresponds to an occurrence of a place, the leftmost shape to the occurrence of place_4 and the rightmost to the occurrence of place_1.

Table 1. Places and their according occurrences in a set of documents

Place	Occurrence
place_1	61
place_2	28
place_3	25
place_4	22

Due to the fact that two supershapes are needed for creating a supershape in three-dimensional space, two dimensions have to be assigned for each particular supershape. An example computation of the supershape parameters is given for the leftmost supershape representing the occurrence of place_4; the remaining shapes are obtained accordingly.

In figure 4 a possible dimension is shown, in table 2 and table 3 the values and the computation of the parameters for the left supershape are given.

Table 2. Computation of the parameters for the first supershape of the left shape of figure 4

a	b	n1	n2	n3	m
1	1	occurrence/100= 0.22	occurrence=22	occurrence/100= 0.22	n1*n2*n3 = 1.0648

Table 3. Parameters for the second supershape of the left shape of figure 4

a	b	n1	n2	n3	m
1	1	1	occurrence/10=2.2	occurrence/100=0.22	n1*n2*n3 = 0.484

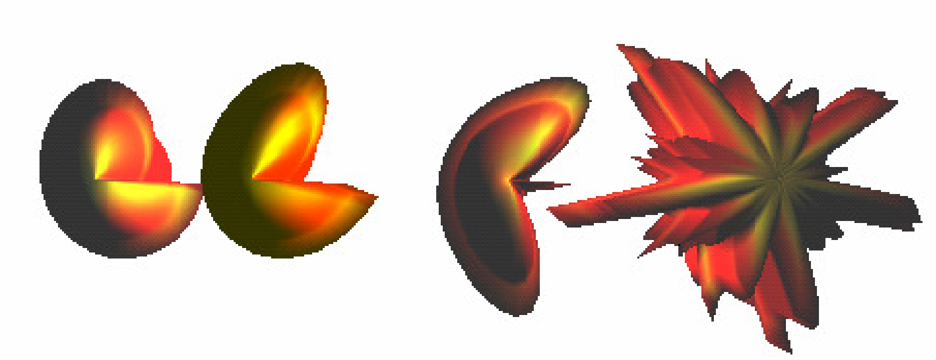

Fig. 4. Supershapes resulting from the values of table 2 and table 3

Figure 5 shows another possible dimension; in table 4 and table 5 the parameters for the leftmost supershape are given.

Table 4. Parameters for the first supershape of the left shape of figure 5

a	b	n1	n2	n3	m
1	1	occurrence = 22	occurrence=22	occurrence = 22	10

Table 5. Parameters for the second supershape of the left shape of figure 5

a	b	n1	n2	n3	m
1	1	occurrence/100= 0.22	occurrence/100 =0.22	occurrence/100=0.22	1

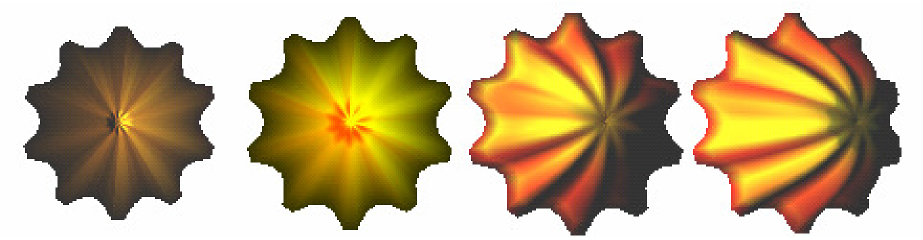

Fig. 5. Supershapes computed with the values of table 4 and table 5

In figure 6 another possible dimension for representing occurrences is shown, the parameters for the first shape are given in table 6 and table 7.

Table 6. Example computation of the parameters for the first of the leftmost supershape of figure 6

a	b	n1	n2	n3	M
1	1	1	occurrence/100=0.22	occurrence/100= 0.22	5

Table 7. Computation of the parameters for the second supershape of the leftmost supershape of figure 6

a	b	n1	n2	n3	m
1	1	1	occurrence/100 =0.22	occurrence/100=0.2 2	occurrence*(occurrence/100)/2=2.42

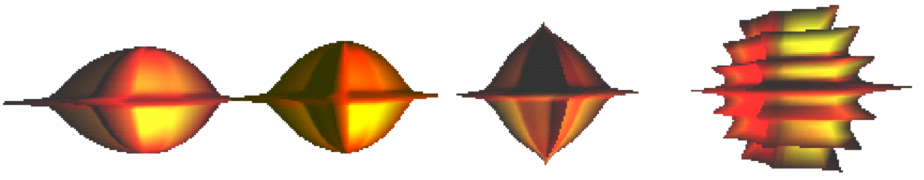

Fig. 6. Supershapes, an example computation for the occurrence of place_1 resulting in the leftmost shape is shown in table 6 and table 7

The proposed method leads to satisfactory results when displaying occurrences with discriminate values. In that case the obtained supershapes are distinct and therefore result in a significant visualization. On closer examination the supershapes representing the occurrences of place_1 and place_4 are clearly distinguishable regarding their appearance but the supershapes representing place_1 and place_2 are harder to assign correctly. In general, similar values result mostly in similar supershapes; consequently this is the most important drawback of the proposed approach.

5 Future Work

In this section we will provide an outlook on an evaluation of the concept which we intend to realize in close cooperation with the cognitive psychology group at our institution.

Basically, the obtained supershapes are very abstract; therefore we use principles of the field of cognitive psychology to determine whether the particular supershapes are really separable and recallable by the human mental apparatus. We will perform a special test showing a scale of 1-n versus the supershapes for a defined amount of time, the training phase. The user is then asked to rank the particular shape in the provided scale. This procedure will be repeated for many users in order to achieve an outcome that should identify visual dimensions - that means specific combinations of the parameters of the superformula - which are easy to identify. This evaluation will be enhanced to providing two dimensions at once in order to identify which visual dimensions combine well.
The evaluation procedure will be performed in cooperation with psychologist at our institution during 2007. Besides we will investigate how continuous transitions can be visualized by morphing of objects in order to display change over time. This will be done via morphing parameters over time between two discrete measured states at different timestamps. For example, it can be highlighted how a cluster changes from very smooth to controversial.

6 Conclusion

In this paper we presented an approach to use supershapes as a general visual formalism to display knowledge entities. The proposed method provides appealing results when the data to be displayed is sufficiently discriminative. In this particular case significant visual representations can be achieved which help to amplify the user's ability to understand and classify data. Nevertheless the approach has some limitations when dealing with very similar data, as this aggravates finding dimensions which produce distinguishable and therefore meaningful supershapes.

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