CorFish: Coordinating Emphasis across Multiple Views using Spatial Distortion

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Gaëlle Richer* Romain Bourqui† David Auber‡

LaBRI, UMR CNRS 5800, University of Bordeaux, Bordeaux, France

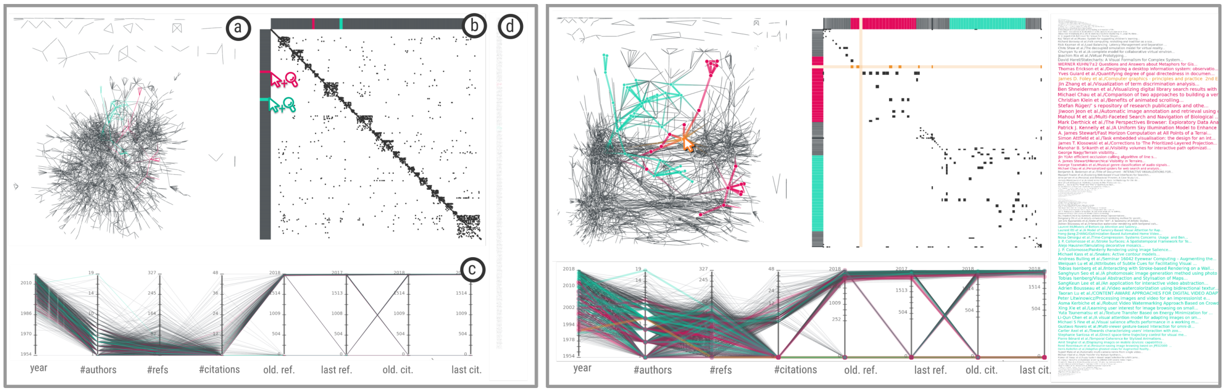


Figure 1: Before (left) and after (right) coordinated distortion emphasis of two subsets (denoted by pink and teal highlight) of the displayed entities on four views. On the right panel, a single entity is highlighted in yellow. The input data is a citation graph extracted from the Open Research Corpus [1] in which nodes are research papers and edges are citing relationships. The graph is displayed as a node-link diagram (a) and as an adjacency matrix (b). (c) and (d) display properties of the papers.

Abstract

In the context of multiple views, coordination is essential to navigate and grasp the relationships lying behind the different juxtaposed views. Linked highlighting is a typical example of coordination where a subset of the data points is emphasized simultaneously on all views. The strength of this approach is that the selected data can be studied within its context. Other approaches have been used to implement coordination such as using varying levels of transparency or visual links. We propose to use spatial distortion to contribute a similar effect in multiple views. It is particularly suited to the context of multiple views since it alleviates the lack of screen space by reallocating it based on a certain definition of user interest. The proposed method targets coordination between views that represent the same entities and readily adapts to various visualization forms. It is based on a user degree-of-interest function, defined on these entities, that acts as a common ground for the distortion of all views. Views are distorted such that empty areas and areas holding entities of lesser interest are compressed to the benefit of areas holding entities of higher interest. To demonstrate its feasibility and versatility, we describe how to technically apply our approach to several common visualization techniques.

Keywords: coordinated multiple views, focus+context visualization, interactive visualization

Index Terms: Human-centered computing—Visualization—Visualization techniques—;

*e-mail: gricher@labri.fr
†e-mail:bourqui@labri.fr
‡e-mail:auber@labri.fr

1 Introduction

When studying complex data such as relational data where entities have more than three or four attributes, single-view visualization can result in highly complex representations that impede user understanding. One solution to overcome this problem lies in *faceting* data across several juxtaposed views, each presenting a different aspect of the data or using a different form of representation that complements others. One common example of such configuration is dashboards. The relationship that exists between the supporting data of the resulting multiple views inherently links the views; hence it is natural to coordinate interactions between them. The idea of coordination is to automatically apply changes made by the user on one view to all the others based on how they are interlinked, thus reflecting the inner relationship between them. Coordination enables the expression of complex visual queries through simple interactions applied consecutively to different views, and may promote insights through serendipitous discoveries. *Brushing & linking* [2] also called *linked highlighting* [24], is the emblematic example of coordinated interactions. On one view, the user selects a group of visual entities which are simultaneously highlighted on all views, usually with a discriminating color hue. This interaction facilitates recognition of entities across views and the identification of outliers. The challenge of supporting coordinated interactions originates in the differences between the linked views: they can differ both in the form of their supporting data and in the form of their representation. For instance, one can conceive and implement scatterplot matrices as multiple scatterplot views presenting the same conceptual entities, although different aspects of them. Another example of the use of multiple views of the same form is the comparison of two different hierarchical structures laid out over the same conceptual entities and represented next to each other using the same visualization method [25]. On the contrary, *multiform* views [30] use alternate forms for presenting the same data such that different aspects of the data can be compared (e. g. an adjacency matrix alongside a node-link diagram for relational data). Overall, views of different forms may not support the same operations (different affordance, different visual mappings) while views based on different data may have complex relationships that make coordinated operations equally complex to render but also to understand.

For views that share data, linked highlighting consists in propagating a selection across views with a shared encoding such as a contrasting color. *Dynamic filtering* is another approach that filters out data simultaneously on all linked views, through the use of sliders for instance. On views of the same form, the *overview+detail* idiom links selection on a view to navigation in another, and *vice versa*. Navigational actions, such as scrolling, can also be synchronized between views that share the same notion of space. All these types of coordination are manners of bringing *focus* to an interesting part of the data, but highlighting is the sole that preserves and integrates the *context*, i. e. the lesser interesting parts. Other techniques either suppress the context (synchronized navigation, filtering) or separate it from the focus (overview+detail idiom). While such suppression can be beneficial in some cases, we focus on context-preserving techniques in this work. Preserving context, even in a reduced form, is motivated by the fact that global information can facilitate the understanding of local information and that retaining visual entities of lesser interest may help to orientate the user when its interest shifts towards other parts [10]. Moreover, preserving context may also be desirable when the definition of the user's interest is not as binary as a selection is [18]. Further, integrating the focus in context has the advantage of helping preserve the user's *mental map* throughout changes of focus, by conserving the representation and relative position of every entity [23].

When bringing focus to a selection of entities, the goal is to make them salient, i. e. make them appear more *visually prominent* [13] than the rest such that they can be noticed and even discriminated at a glance. Generally, the effectiveness of the *emphasis* technique used for this goal depends on the changes applied to the selected entities, and how they integrate into the original mappings of the visual representation. Usually highlighting uses a visual channel distinct from the original mapping, while fisheye views use distortion of existing spatial mappings (position and size). Spatial distortion can alleviate two related problems [15, 20]:

- **The spatial problem** (so-called *screen real-estate* problem): visualizations grow over-crowded as the data they represent gets more massive, which hiders their readability. Locally expanding focus regions tend to reduce the incurred clutter and thus results in representations of the current data in interest that are more understandable.
- **The information density problem**: as screen resolutions increase year after year, the amount of information that can be displayed at once may become overwhelming. In this context, interactive techniques for enhancing specific regions, such as local magnification, provide guidance and can assist the user in maintaining its attention on the focus area.

In our context of coordinated emphasis for multiple views, the advantages of spatial distortion are two-fold. First, the position encoding is prevalent in any visualization, often mapping for a direct or indirect data attribute; thus, it is available for distortion for most view types. Secondly, spatial distortion alleviates the screen real-estate problem resulting from the partitioning of the screen space into multiple view spaces, each of small size.

On the one hand, previous work has used various visual channels to create coordinated emphasis effects for multiple views [31]. On the other hand, multiple visualization forms have been augmented with interactive spatial distortion for emphasizing the parts of the data matching the user's interest. We propose a linked spatial distortion for multiple views that takes inspiration from both techniques. Prior work [12, 25] has also shown the interest of linking hierarchy representations using spatial distortion. Our contribution is a method for coordinating spatial distortion across multiple and multiform views as a way of interactively emphasize entities of interest. To the best of our knowledge, it is the first method to target coordination of spatial distortion for multiform views.

Our approach, CorFish, relies on a *degree-of-interest* function (DOI) that models the user's interest on entities under observation regardless of how entities are laid out on any views. We suppose a prior definition of this function and, without loss of generality, assume it associates non-discrete values of interest to entities. This approach accommodates multiple levels of interest, supports iterative refinement of the DOI, and fits multiple methods for defining the DOI. The proposed method is not concerned with how the DOI is defined and, in particular, on which view the user interacted to specify it. Rather, it takes interest in how to render the DOI through coordinated distortion. View position mappings are distorted around each entity position according to their respective DOI. The versatility of CorFish originates from two aspects. First, the DOI being defined on entities constitutes a common ground between views, although view-specific interactions may modify it. Secondly, position mappings are processed collectively irrespective of the view they correspond to.

The rest of this work is organized as follows. We first review existing work on spatial distortion and coordinated emphasis (Sect. 2). Then, we lay out the requirements for a coordinated emphasis method and compare existing methods in the light of them (Sect. 3). In Sect. 4, we detail the principles of the method, and in Sect. 5, we expand on how they are applied to parallel coordinates, scatterplot matrices, and other visualization techniques. Finally, in Sect. 6 and Sect. 7 we discuss the advantages and limitations of the method and propose directions for future work.

2 Related Work

In this work, we are interested in coordinating an emphasis effect across multiform views using spatial distortion. In this section, we review two related topics: techniques for spatial distortion and existing coordination methods for emphasizing selections of entities in multiple views. Both relate to interactive emphasis techniques [13, 27] which aim is to make a part of the data more prominent than the rest. Emphasis techniques can be separated in three groups: **filtering**, that suppresses or elides non-selected entities; **distortion** (or magnification) that alters geometrical aspects (size, position, and possibly shape) to make selected entities more visually prominent; and **cue-based** that modifies non-spatial visual properties (color, transparency) or add decorations (contour, halo) [13, 27]. Those last two groups also relate to *focus+context* visualization which idea is to seamlessly integrate the *focus*, enhanced or detailed parts of the data, into the *context*, the rest [5, 14].

2.1 Distortion-Based Emphasis Techniques

The original presentation of *fisheye views* and *degree-of-interest* for quantifying user interest by Furnas [10] was concerned with filtering but was later extended to graphical distortions that smoothly integrates the focus in the context [32]. Leung and Apperley [20] unified various spatial distortion techniques for one-dimensional space under the *magnification-transformation* model and distinguished continuous and non-continuous distortions. Keahey and Robertson [15] studied various forms of transformations and proposed using piecewise linear functions as approximations for computationally costly continuous functions. Carpendale et al. [3] further decomposed the characteristics a distortion method could exhibit. For instance, a spatial distortion may affect both position and size in an interlinked manner (magnification), or position only (displacement). Distortion may be global, affecting the whole representation, or constrained to certain extents around a specific target (e. g. magnifying lenses).

For two-dimensional spaces in general, two proposed frameworks [4, 16] are based on surface elevation to define and manipulate the distortion effect. On specific visualization forms, distortion has been used for different goals. On tables and node-link diagrams, browsing methods [19, 29] allow for one part of the visualization to be displayed in more detail. For clutter reduction, global displacement based on density distribution served reducing overlap of visual entities in scatter plots [17] and parallel coordinates [26]. Some techniques magnify multiple areas of interest at once such that their content can be compared in detail [9, 33, 36]. The rubber sheet approach [33] transforms node-link diagrams in geometric space by stretching the space such that areas of interest are mapped to user-chosen destination positions. Mélange [9] distorts the image space in multiple points by mimicking paper folding. PRISAD [34] uses accordion drawing: geometrical objects are partitioned on a grid which cells are stretched depending on user interest. These methods mostly tackle multiple but non-superimposing areas of focus. Keahey and Robertson [15] described three types of combinations for multiple foci using the non-linear transformation framework: sequential application of transformations, clipping to prevent overlap when applying transformations and averaging of transformations.

2.2 Coordinated Emphasis in Multiple Views

Coordinated interactions are distinguished by how two coordinated views are modified (selection or navigation) and if they hold the same data [28]. More generally, coordinated interactions are formed on top of a *coupling function* that maps visual entities or position in one view to those in another, a *propagation model* that specifies conditions of coordination, and finally, a rendering algorithm that dictates the visual changes propagated [37]. A challenge in designing coordination is the potential differences between the multiple views. On the one hand, coordinating views holding different data (subsets, aggregates) relates to complex coupling functions. On the other hand, views of different forms may use different visual channels for mapping data and present different affordance [37]. To facilitate comprehension of coordinated systems and limit ambiguity, Wang et al. [37] advocates for the consistency of their interface and state. Thus, views should present the same affordance whenever possible (consistent interaction), and changes should be propagated to all views holding the same data (consistent state).

Several techniques have been used to convey emphasis in a context of multiple views. **Cue-based** methods, also referred to as highlighting [24] or brushing & linking [2], deal with enhancement of elements of interest based on variations of visual channels other than position and size to create an emphasis effect, for instance, color hue [2, 7, 22, 31]. The multiplicity of view forms in a given system may limit the options for a consistent highlighting that does not interfere with any original mapping of the coordinated views [31]. On visualization for hierarchical data, TreeJuxtaposer [25] and Graham & Kennedy [12] have shown the advantage of linking views with **distortion-based** techniques for comparing hierarchies. This approach has enabled visualizing and comparing large data sets that otherwise produced representations where visual entities are displayed too small to be manipulated. **Overlay** is another category of methods that use additional visual elements to draw attention on a subset of entities across multiple views. A first example is visual links (also called leader lines) that consists of lines, or bundled lines, drawn on top of the views that connect marks corresponding to the same conceptual entities under focus [6, 35]. A second example are coordinated lenses like the extension of Bring&Go proposed by Dubois et al. for linking node-link diagrams [8]. Overlay approaches have the advantage of being more form-independent than the others. Their limitation emerges for large selection bodies: as the number of entities in focus increases, the addition of new visual elements tends to create occlusion.

While spatial distortion has been explored on multiple forms of single views, its application as a coordinated emphasis method for multiform views has not. Yet, similar to blur and transparency, spatial distortion possesses the property to implicitly implement smooth filtering of context information.

3 Requirements

We introduce a set of requirements for a distortion-based emphasis technique coordinating multiple views representing the same conceptual entities. An example of entities may be individuals with different personal attributes and connections to one another. Here, multiple views are helpful to separately represent the distinct aspects of the data (network topology, personal attributes) and coordinated emphasis interactions are useful for comparing those different aspects. We focus on multiforms views, i. e. multiple views using different visualization techniques, possible drawn small compared to the available screen space. Our choice of requirements for a coordinated distortion technique is based on this context and on the literature of both distortion techniques and coordinated emphasis techniques.

R1 Non-binary interest An emphasis technique visually renders the user interest by making entities in focus more prominent (e. g. with color in *brushing & linking*). The idea of focus can be generalized to multiple levels of interest [14]. Therefore, the technique should support interest values lying within a continuous interval and, accordingly, emphasize visual entities to *a certain degree*.

R2 Multiple-form coordination The technique should be able to coordinate an emphasis effect across multiform views, i. e. simultaneously emphasize entities of interest on all views, accommodating different visualization techniques. This relates to the linking part of *brushing & linking*. Supporting different forms allows the technique to be used in configurations where different view forms present different facets of the data [30].

R3 Scalability The context of multiple views present challenges for emphasis stemming from the reduced screen space left for each view [37]. The emphasis should remain effective as the number of views (R3.1) or entities (R3.2) increases. Additionally, the technique should handle large and small selection sizes (R3.3). This way, the user can adopt a drill-down approach by starting with a large study group and incrementally refining it.

R4 Comparison The goal of emphasis is to draw attention on a subset of entities but also to allow visual discrimination of these entities from the rest (R4.1) [14]. Further, it is useful to be able to compare different subsets of entities (R4.2) [12, 35].

These requirements are used to evaluate the previous work through the three categories introduced in Sect. 2.2 and to review CorFish, the proposed technique, in Sect. 5.3. Table 1 summarizes how existing methods meet these requirements.

In **distortion-based** emphasis methods, we selected previous work explicitly supporting multiple focal areas since entities of interest may not necessarily lie close to each other on all views. These methods support different levels of emphasis through the variation of the distortion intensity (R1) and work particularly well in contexts where visual entities may be displayed small. This arises, for instance, when the multiplicity of views combined with the limited available screen space significantly reduces the number of pixels available per view (R3.1). Spatial distortion creates emphasis by simultaneously enlarging areas of interest and shrinking the others. It can accommodate to large amounts of visual entities since squeezing the context allows for entities in focus to be enlarged, independently of the fact that visual entities are large enough to be visible on the initial overview (R3.2). In the context of non-superimposed marks like in matrices, the emphasis effect is diminished when large groups of entities are in focus as noted by Graham & Kennedy [12] (R3.3). To the best of our knowledge, existing works supporting coordination in this category are specific to hierarchy representations and link views of the same form [12, 25] (R2). Linked Treemaps [21] use two forms for visualizing the same hierarchy, which suggests that, although the method is not readily compatible with multiple forms, it could be investigated. Another major limitation for distortion-only methods is

	R1: Non-binary interest	R2: Multiform coordination	R3: Scalability			R4: Comparison	
			R3.1	R3.2	R3.3	R4.1	R4.2
Distortion-based emphasis							
[9, 33, 36]	✓	×	✓	✓	~	×	×
[12, 25]	✓	~	✓	✓	~	×	×
Cue-based emphasis [2, 7, 22, 31]	✓	~	×	×	✓	✓	✓
Overlays [6, 8, 35]	×	✓	×	✓	×	✓	✓

Table 1: Comparison of previous work in light of the chosen requirements. (R3.1: Scalability with the number of views, R3.2: Scalability with to the number of entities, R3.3: Scalability relative to selection size, R4.1: Comparison with context, R4.2: Comparison between selections).

that it does not generally allow the discrimination of magnified areas from the rest (R4.1) nor comparison of different selections (R4.2). However, several previous work combined distortion techniques with color cues to support these features [12, 25].

The strength of **cue-based** methods, related to brushing & linking [2] or linked highlighting [24], is that they usually support the comparison of different selections: for instance, using different hues or shapes (R4.2). These methods become less effective or impractical as marks become small i. e. when the number of views or entities increases. Then, changes in their visual properties such as their fill color become less noticeable and therefore less effective to create emphasis (R3.1 and R3.2). Generally, these methods function by *replacing* one visual property of the selected marks (e. g. fill hue) by the highlighting property (e. g. red). When the highlighting encoding is superimposed to each existing encoding rather than *blended*, there is a possibility that it creates ambiguity, for instance when using fill hue for highlighting with a view encoding a data attribute with a gradient of fill colors (R2).

Overlay methods, by making use of additional visual elements, readily support multiform views (R2) and create emphasis regardless of the size of visual elements (R3.2) while allowing to discriminate multiple selections (R4.1 and R4.2). However, they have the general drawback of using additional visual objects which may create occlusion and tend to create clutter as the number of focused entities increases. Hence, they are impractical when views are allocated little screen-space (R3.1) or when many elements are selected (R3.3). Moreover, they are adapted to binary selection and do not directly support multiple levels of interest since they produce an emphasis effect based on the presence or absence of the overlay. Consequently, they do not readily support non-binary interest (R1).

CorFish aims to complement other methods of emphasis in multiple views and specifically targets contexts where non-distortion methods perform poorly: multiple visualizations each drawn small compared to the screen space. The method is based on linked distortion and completed by additional methods, such as filling hue, to enhance the emphasis effect and bridge the weaknesses of distortion relative to the comparison requirements (see Sect. 5.3). As opposed to existing methods for coordinating spatial distortion, CorFish is intended to readily adapt to various visualization forms and coordinate multiple views by being built on a single and common definition of the focus, independent of the views.

4 From entity interest to spatial distortion

By *conceptual entities*, we refer to the set $E = \{e_1, e_2, ... e_n\}$ of data items under observation. Conceptual entities are associated to various attributes and relations that are the basis for their visual representation. By *visual entity*, we refer to a visual mark on a view that corresponds to a conceptual entity. Consider m views and the sets of visual entities $V_1, ..., V_m$ where each V_i is the set of visual entities displayed on the i-th view. For the sake of simplicity, we consider in this section that all views represent the whole set of conceptual entities. Then, we denote by $(v_i)_{1 \leq i \leq m}$ with $v_i : E \rightarrow V_i$, the functions that associate a conceptual entity to a visual entity for each view. These functions are not necessarily surjective nor injective as some marks may represent multiple entities and other none (see Sect. 5). Since they provide the mark positions, they link conceptual entities to points or areas of each view space.

The main idea is to use of a single and common definition of interest over conceptual entities that is subsequently used to transform all coordinated views, including their marks positions. We model the user interest by a non-binary *degree-of-interest* function $doi : E \rightarrow \mathbb{R}+$. The *focus* consists of all entities with non-null doi, the rest is the *context*. Entities with a higher doi value are considered of higher importance and are to be emphasized, i. e. presented more visually prominent than others, on all views. In the remainder of this section, we first present an overview of the method. Secondly, we introduce the key idea of the method. Then, we describe how we compute a transformation over a 1-dimensional (1D) space that magnifies areas in coherence with the doi, provided how entities are distributed over this space. Finally, we give insight into how each parameter of the method influences the distortion effect.

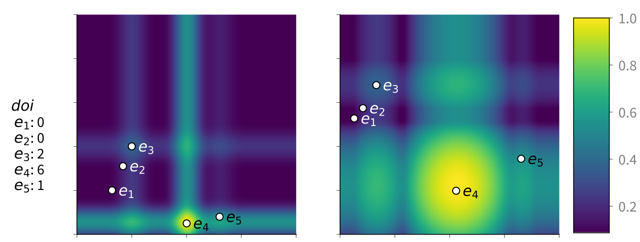


Figure 2: From a map of interest to distortion. The left plot shows the initial entity positions, and the interest field induced by the doi mapped to a color scale, with 1 being the highest interest. The interest field is computed by averaging the x and y magnification functions. The right plot shows the distorted entity positions and the distorted interest field. Notice the stretching of areas of higher interest (yellow) and the shrinking of those of lesser interest (violet).

4.1 Overview

The proposed method distorts the position of visual entities on each view depending on their corresponding doi values such that areas holding entities of higher interest are magnified. The distortion is based both on the initial entity positions and the current doi which values are to change upon user interaction. The goal of the method is to translate an interest defined over the *discrete* set of conceptual entities (doi) into maps of interest over the *continuous* visualization space of each view. Fig. 2 presents an example of such maps: each point in space is associated to an interest value mapped to a color scale. The distortion is computed such that local interest values translate to distortion factors. The expected outcome is that the resulting distorted space stretches areas of higher interest and shrinks those of lower or null interest. On Fig. 2, the area of highest interest

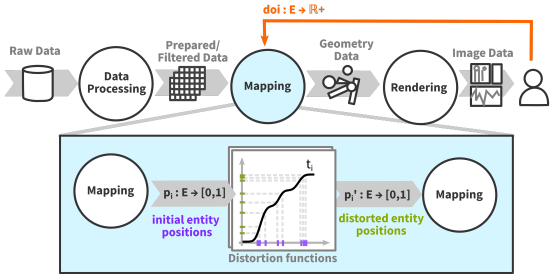


Figure 3: Overview of the method. The distortion process occurs at the mapping stage, once an initial pass has associated positions to every visual entity on each view. Distortion functions (t_i) are computed over 1-dimensional spaces, based on the *doi* and the initial entity positions (p_i). Distortion functions are subsequently applied to input entity positions and the resulting positions $p'_i = t_i \circ p_i$ are remapped to obtain the distorted views.

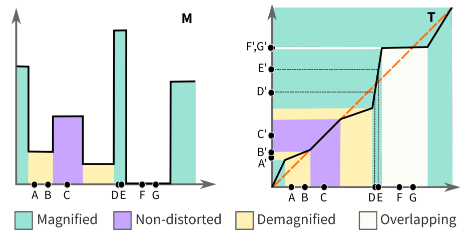


Figure 4: Schematic view of a constrained transformation function T of a 1D space (right) and its corresponding magnification function M (left). Areas of magnification (respectively demagnification) correspond to local slope ratio greater than 1 (respectively lower than 1) on T. Intervals are shrunk in demagnified areas (e.g. $[A,B]$ mapped to $[A',B']$) and enlarged in magnified areas (e.g. $[D,E]$ mapped to $[D',E']$). Around C, T is identical to the identity transformation (in dotted orange) therefore its image C' under T is identical to C relative to the domain. M is null from F to G therefore their images, F' and G', are the same.

(in yellow), around e_4, is significantly enlarged at the expense of the areas of lesser interest (in violet). Putting it another way, if interest is diluted by stretching and concentrated by shrinking, the resulting distorted space tends to present a uniform interest.

Distortion functions are computed at the mapping stage of the visualization pipeline since they depend on the initial positions of visual entities (see Fig. 3). Our approach breaks down each visualization space into separate 1D spaces corresponding to their associated coordinate domains. For instance, we may output two or three domains from a view based on Cartesian coordinates and one domain per axis from a view based on parallel coordinates. This approach has the advantages of being simple and flexible. It handles multidimensional visualization like parallel coordinates more adequately than distorting their 2D visualization space without structure consideration. For visualization based on Cartesian coordinates, it corresponds to what is called an *orthogonal* distortion [15].

Provided the mark mapping of a view and its associate coordinate system, we isolate a series of positional functions that link conceptual entities to positions in the normalized space of each domain of the view (for instance abscissa and ordinate). For a set of views, we call these positional functions $(p_i)_{1 \leq i \leq d}$ with $p_i : E \rightarrow [0,1]$ and index them regardless of the view they correspond to. In general, the number of positional functions d is larger than the number of views, with possibly one positional function per coordinate domain of each view. However, all coordinate domains of a view may not be selected for distortion, and some may be shared between several views (discussed in Sect. 5). To distort entity positions, a positional function p_i is composed with a continuous function $t_i : [0,1] \rightarrow [0,1]$, the distortion function. The resulting positions are the basis for the final mapping stage (see Fig. 3). Distortion functions are to reallocate space to reflect both the distribution of entities and their respective *doi* such that low-interest areas are shrunk to allow high-interest areas to appear larger. The following two sections detail the properties of distortion functions of 1D spaces (t_i) and how they are computed given the entity positions (p_i) and the *doi* function.

4.2 Preliminaries

A distortion over a 1D space is characterized by a function from $\mathbb{R}$ to $\mathbb{R}$. Under the formalism presented by Leung and Apperley [20], this function is called a *transformation* (T) and can also be defined by its derivative called *magnification* function (M). The magnification function represents the amount of magnification for any point of its domain. Fig. 4 depicts an example of magnification function and its corresponding transformation function. An area may be stretched (in teal), shrunk (in yellow) or unchanged (in violet) through a transformation. An area with zero magnification is mapped to a single point by the transformation (in white). In general, M and T are not necessarily piece-wise linear as on Fig. 4. We define *distortion functions*, named t_i in the previous section, as transformation functions that fulfill the following three properties, expressed for an arbitrary transformation T and its associated magnification function M:

P1: Fisheye effect T should enlarge the surrounding area of entities of higher interest meaning M should exhibit a local maximum near points of high interest.

P2: Ordering To preserve the ordering of visual entities, T should be increasing which translates to M being non-negative. Additional occlusion arises where M is null (see the white area on Fig. 4). Therefore, to avoid such occlusion in areas of interest, T should be strictly increasing, i. e. M strictly positive, around positions of interest.

P3: Boundaries To preserve view boundaries after distortion, the domain and range of T should correspond. If T is increasing, it means that the extrema of its domain should be mapped to themselves which translates to M being normalized so that it integrates to one. When applied on a constrained space, the magnification of some areas naturally incurs demagnification of some others.

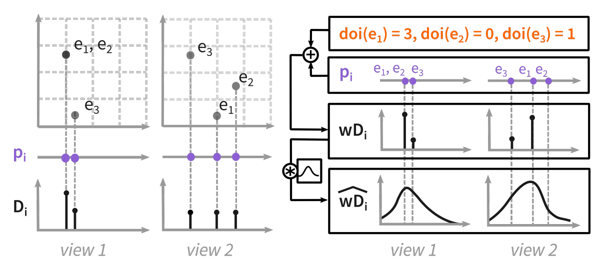


Figure 5: Schematic view of the computation of $\widehat{wD_i}$ for the x-domains of two scatterplots. D_i is the distribution of the value of p_i. wD_i is the distribution of values of p_i weighted by their *doi*. $\widehat{wD_i}$ is the smoothing of wD_i, it associates an interest value to every point.

4.3 From Weighted Distribution to Distortion Function

The distortion function is computed in term of a magnification function that associates an interest value based on the *doi* to any point of its domain. To reflect both the *doi* and the distribution of entities, the magnification function is computed as the smoothed weighted-distribution of the entity positions. This process is schematized for two 1D spaces on Fig. 5 and detailed in what follows. In the following, we assume that at least one of the entities has a non-null *doi* and thus $\sum_{e \in E} doi(e) > 0$. No distortion should be performed otherwise. For the i-th positional function p_i, the distribution function $D_i : [0,1] \to \mathbb{N}$ of entity positions associates to each point $x \in [0,1]$ the number of entities positioned on this point as follows:

$$D_i(x) = \sum_{e \in E} \delta(x - p_i(e)) \text{ where } \delta(t) = \begin{cases} 1, & t = 0 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

This distribution D_i is then combined with the *doi* by weighting each *impulse* function δ with the weighting function $w : E \to [0,1]$ corresponding to the normalized *doi* (see Fig. 5):

$$wD_i(x) = \sum_{e \in E} w(e) \cdot \delta(x - p_i(e)) \tag{2}$$

$$w(e) = \frac{doi(e)}{\sum_{f \in E} doi(f)} \tag{3}$$

The weights w are values of *doi* adjusted so that they sum up to one. Normalizing the *doi* relates to the fact that, in the context of spatial distortion, interest values are relative to each other and not to a common scale. Indeed, the magnification of one part of the data corresponds to an increase in the screen space it occupies and, inherently, to the decrease of the space occupied by other parts since the total amount of available screen space remains the same. The weighted distribution reflects how the user interest is distributed over the space. However, it does not spread entity interest around their position. Moreover, in this form, the integral of the distribution function is not a suitable transformation function. Therefore, we smooth wD_i to obtain $\widehat{wD_i}$ as illustrated on Fig. 5. The smoothing is done by convolving wD_i with a scaled kernel function k_h ($*$ denotes the convolution operation). For $x \in [0,1]$:

$$\widehat{wD_i}(x) = (wD_i * k_h)(x) = \int_{\mathbb{R}} wD_i(x-t) \cdot k_h(t) \mathrm{d}t \tag{4}$$

Kernel functions are chosen among integrable, positive and symmetric functions that reach their maximum in 0, integrate to one, and have bounded support. To obtain k_h, a kernel k is scaled by a bandwidth factor h which controls the extents of k_h and consequently the smoothness of $\widehat{wD_i}$. Sect. 4.4 elaborates on how k_h may be chosen.

$$k_h(x) = \frac{1}{h} \cdot k\left(\frac{x}{h}\right) \text{ with } h > 0 \tag{5}$$

Given the definition of wD_i and the symmetry of k, another expression for $\widehat{wD_i}$ is:

$$\begin{aligned} \widehat{wD_i}(x) &= \sum_{e \in E} w(e) \cdot k_h(x - p_i(e)) \\ &= \frac{1}{h} \sum_{e \in E} w(e) \cdot k\left(\frac{x - p_i(e)}{h}\right) \end{aligned} \tag{6}$$

Smoothing causes the spreading of entity interest around their position within a range of $\frac{h}{2}$, which we call the *area of influence* of the entity. More precisely, each non-null summed kernel is centered on an entity of interest which leads to $\widehat{wD_i}$ having a local maximum within the area of influence of each entity of interest. Conversely, the amount of magnification of a given point of the domain depends on its proximity entities of interest. Thus, $\widehat{wD_i}$ addresses the *fisheye effect* (P1) property defined in Sect. 4.2. Secondly, as a summation of positive kernels centered on entity positions, wD_i and therefore m_i are positive and strictly positive around entities in focus which addresses the *ordering* property (P2). Finally, to address the *boundaries* property (P3), the magnification has to integrate to one. In the general case, entities of interest close to the borders of the constrained space only contribute partly to $\widehat{wD_i}$ which leads to $\int_{[0,1]} \widehat{wD_i} < 1$. More precisely, this concerns kernels centered on entities within $\frac{h}{2}$ from the border of the domain. These kernels are integrated over an interval smaller than their support, for instance like the kernel centered on e_1 on Fig. 6. Therefore, the magnification function m_i is defined as $\widehat{wD_i}$ normalized by its integral over $[0,1]$:

$$m_i(x) = \frac{\widehat{wD_i}(x)}{\int_0^1 \widehat{wD_i}} \tag{7}$$

To strengthen or weaken the distortion effect, we redefine m_i as a linear interpolate with the identity magnification $x \mapsto 1$:

$$m_i(x) = \alpha \cdot \frac{\widehat{wD_i}(x)}{\int_0^1 \widehat{wD_i}} + (1 - \alpha), \text{ where } 0 \leq \alpha \leq 1 \tag{8}$$

The higher α is, the stronger the effect. Additionally, setting the α strictly inferior to 1 ensures that m_i is strictly positive if required. For instance, on Fig. 6, intervals showed in gray are non-null on the magnification plot only thanks to α being strictly positive. Finally, t_i is obtained by integration of m_i which captures both the distribution of entities and their interest values.

$$t_i(x) = \int_0^x m_i(t) \mathrm{d}t = \frac{\alpha}{\int_0^1 \widehat{wD_i}} \cdot \int_0^x \widehat{wD_i}(t) \mathrm{d}t + (1 - \alpha) \cdot x \tag{9}$$

Three examples of magnification (m) and transformation (t) are represented on Fig. 6 for the same entity. For each row, the left-most plot represents m as well the steps leading to its computation (wD and $\widehat{wD}$). The middle plot represents t, and the distorted entity positions can be read on its ordinate axis as well as on the right-most plot. The

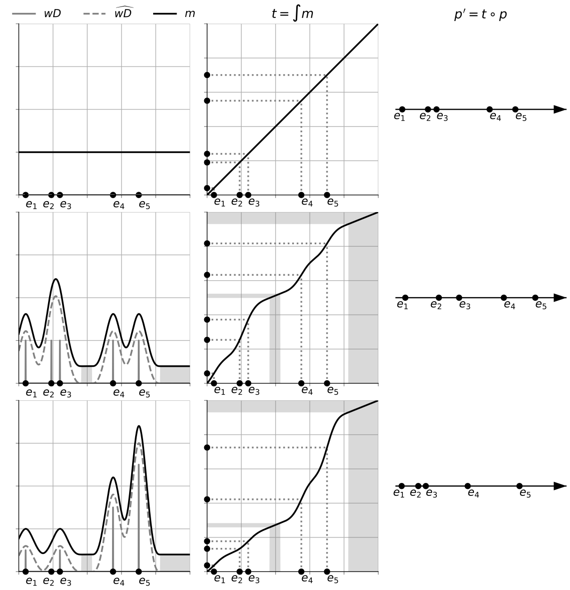


Figure 6: Examples of magnification (m) and transformation (t) for a set of entities $E = \{e_1, e_2, e_3, e_4, e_5\}$. The left column displays m, wD and $\widehat{wD}$ for different *doi*, with $\alpha = 0.6$. The middle column shows the corresponding t and the right column is the plot of the distorted positions. The top row displays undistorted positions. *doi* values are uniform on the middle row, and non-uniform on the bottom row, with e_4 and e_5 being the entities of highest interest. Shadowed intervals cover points that belong to no area of influence.

first row shows the non-distortion case for comparison purpose. On the second and third, *empty* regions are shadowed to show how they are shrunk to allow the expansion of other regions. On the second row, *doi* values are uniform which translates to distorted positions leaning towards being uniformly spread. On the third row, e_4 and e_5 have the highest interest and appear separated by the distortion.

4.4 Adjusting the Distortion

The different components and parameters used for computing the magnification directly affect the resulting distortion.

Degree-of-interest *doi* A non-uniform *doi* translates to a distortion function that reallocates space to enlarge areas around entities of high *relative* interest to the cost of other areas. Augmenting the relative interest of one entity makes it appear more separated from the rest since its area of influence is displayed with a higher scaling factor. Fig. 7 shows the effect of increasing the *doi* of an entity. On the top row, the first plot is the reference (undistorted) and the other two show that *doi* values are accounted for relatively to each other. Indeed, the result is the same with e_3 having two different *doi* but the same weight. On the bottom row, the first plot illustrates the effect of a uniform *doi*. Here, all areas of influence are enlarged by the same factor at the expense of empty regions. In consequence, the densest areas, where areas of influence overlap, appear the most enlarged. This leans towards positioning entities uniformly. The two other plots show how increasing the *doi* of e_3 enlarges its area of influence at the expense of empty regions and areas of influence of lesser interest entities. Here, this tends to push the other entities towards the border of the plot.

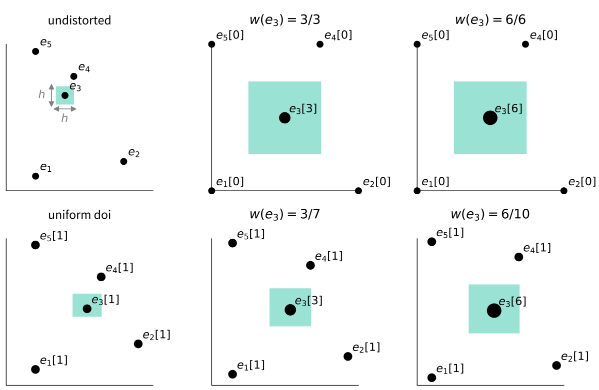


Figure 7: Effect of increasing the *doi* of the entity e_3, from left to right, relative to null (top) and uniform (bottom) *doi* values for other entities. The area of influence of e_3 is represented in teal. On distorted plots it may appear non-square. *doi* values are displayed in brackets and mapped to mark size ($\alpha = 1$, $h = 1/8$, boxcar kernel).

Kernel function k and bandwidth h The shape of the kernel function k impacts the spreading of the interest around an entity. For instance, the distortion induced by the uniform kernel (boxcar function) is weaker on its center than the one induced by a triangular-shaped kernel. The bandwidth of the kernel h affects the smoothness of the magnification function. Higher values of bandwidth result in over-smoothed magnification functions with weaker distortion effect. Consequently, the resulting distorted view overall resembles its original state. On the contrary, lower values of bandwidth result in more contrasted magnification functions with stronger distortion effect on their kernel centers. Fig. 8 shows this behavior: the bandwidth increases from left to right, with the reference plotted on the top and the distortion on the bottom. The left-most plot displays the strongest distortion: e_3 and e_4, close on the reference plot, are the farthest from each other for the lowest value of h. Conversely, the right-most plot displays the least distortion: all entities are close to their reference position for the highest value of h.

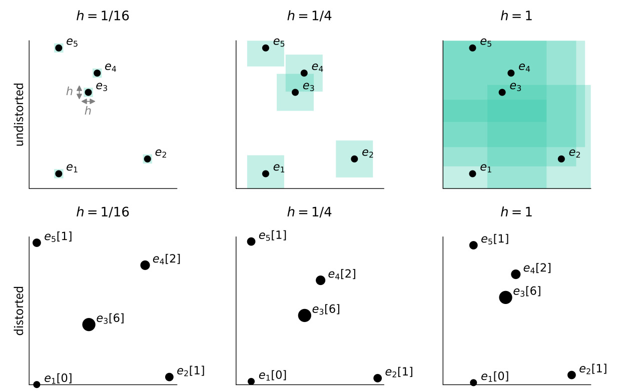


Figure 8: Effect of increasing the bandwidth h (from left to right). Top plots are undistorted and show the extents of kernels in teal. Bottom plots are distorted based on the same *doi*, displayed in brackets and mapped to mark size ($\alpha = 1$, boxcar kernel).

Interpolation parameter α This parameter controls how much the distortion weighs compared to the linear transformation in the final transformation. It accounts simultaneously for the strength of the distortion and the interest of intervals that vanish the magnification function, i. e. empty regions. An emphasis effect based on spatial distortion has two orthogonal goals: producing a strong magnification effect to emphasize areas holding entities of interest and minimizing the distortion of the global visualization such that most of its original properties are preserved. Since the optimal trade-off is not trivial and may not be unique, it is useful to provide an interactive control on α, for instance as a slider, to move back and forth between a distorted state and the original state. Fig. 9 presents two examples of distortions with different value for α.

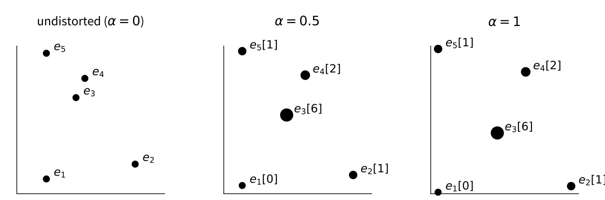


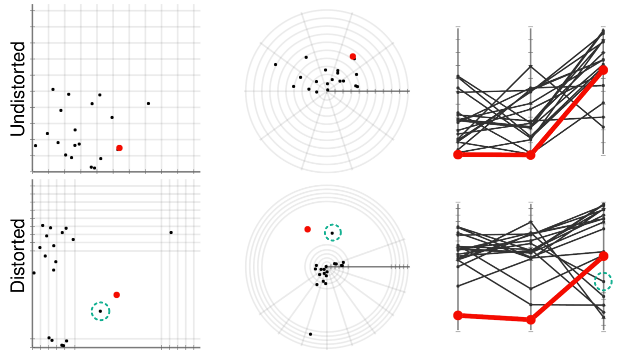
Figure 9: Effect of increasing the interpolation parameter α. The left-most plot is undistorted and acts as a reference for the others, distorted based on the same *doi* displayed in brackets and mapped to mark size ($h = 1/8$, boxcar kernel).

5 Examples of Application

In the previous section, we have presented a complete system for distorting entity positions laid out in 1D depending on three parameters: the *doi*, the bandwidth h, and the interpolation parameter α. In this section, we present applications of this system to several visualization forms.

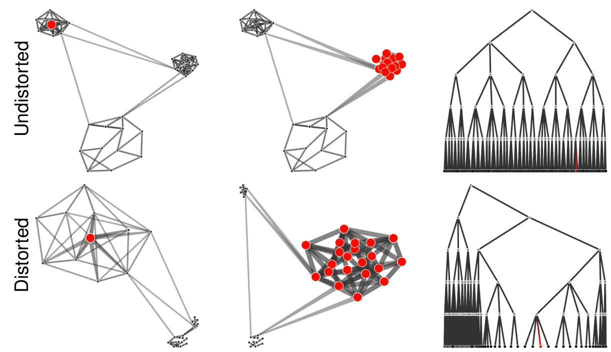
5.1 Linking Views with Point-Like Visual Entities

Applying the method is straightforward for visualization forms where mark positions are to be compared to a drawn or implicit frame of reference. A frame of reference defines different axes of comparison that determines mark coordinates. Thus, mark coordinates associated to each axis are chosen as 1D input entity positions



(a) Cartesian (scatter) plot. (b) Polar (scatter) plot. (c) Parallel coordinates.

Figure 10: Straightforward applications for point-like visualizations with axis coordinates as 1D input positions for distortion ($\mathit{doi}({\color{red}\bullet}) = 1$, $\mathit{doi}(\bullet) = 0$). Notice the marks circled in teal, completely or partly concealed on the top and clearly visible on the bottom.



(a) Graph (single). (b) Graph (multiple). (c) Tree (single).

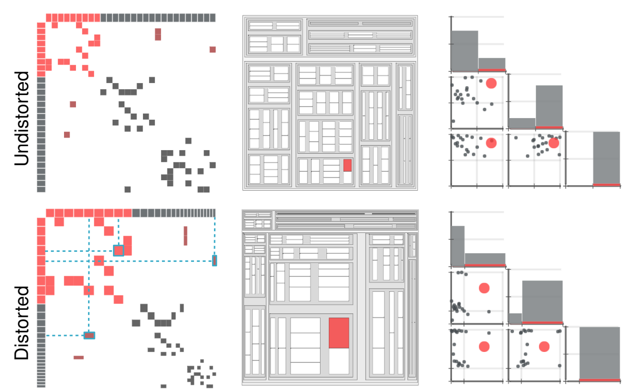
Figure 11: Application on node-link diagrams of graphs and rooted tree. Here, Cartesian coordinates are used as input positions for distortion (only abscissa for c). ($\mathit{doi}({\color{red}\bullet}) = 1$, $\mathit{doi}(\bullet) = 0$).

for distortion. Then, distorted marks are placed at their distorted coordinates. Effectively, this links the distortion effect on each coordinate, on any number of views. For instance, on scatterplots where entities are associated to dot marks plotted with Cartesian coordinates, dot abscissa and ordinates form two sets of input positions, distorted separately. In parallel coordinates where entities are associated to polylines crossing multiple axes, each dimension constitutes a set of 1D input positions. Fig. 10 shows three examples using different coordinate systems. The bottom-row plots represent the distorted version of their top counterpart, with the entities in focus being the ones which marks are red. Notice that on each example, an entity (circled in teal) is concealed by the entity in focus on the top, and revealed by the distortion on the bottom.

Node-link diagrams are another example of visualization technique presenting point-like marks. Although mark positions do not directly map for some entity attribute, they render a sense of similarity or relationship through geometric proximity. In this case, our approach is to consider the Cartesian coordinates of marks as 1D input entity positions for distortion. Fig. 11a and b show the distortion of a node-link diagram, where nodes are the entities receiving interest. Fig. 11a illustrates how the distortion enhances nodes neighbors to the entity in focus: the whole topological community which the entity in focus belongs to is enlarged which help identify its five direct neighbors. On Fig. 11b, a community is in focus which enables one to examine and count nodes of the community. Fig. 11c shows a rooted tree which leaves are the entities. Here, the entity marks are aligned, therefore only their abscissa is distorted. Besides being applied to entities mark, the resulting distortion function is applied to other marks as well. Since the x-coordinate order is preserved by the distortion, parent nodes remain on top of their children. Consequently, the coherence of the layout is maintained. After distortion, it is easier to count and target the siblings of the entity in focus as well as its parents.

5.2 From Distorting Points to Distorting Mark Shapes

Depending on the semantics of the position of visual entities and their shapes, distortion may be used to change mark positions (displacement as seen so far), mark size, or both (magnification). Changing the size of visual entities without displacement is prone to overlap which is not desirable. To create magnification, i. e. distort both size and position, we take multiple anchors per visual entity as input positions for distortion, typically positions of points on the boundaries of mark shapes. For instance, with the adjacency matrix of Fig. 12a, conceptual entities are linked to one row and one column each. Here, since rows and columns are sorted the same way, we only consider one set of 1D input positions for distortion of both rows and columns. These positions are made of two points per visual entity: one for each extremity of the covered interval. Then each resulting position is associated to half the *doi* of the entity it corresponds to. The resulting distortion function is applied to marks for each row and column, including the inner marks that represent the graph edges. Edges that join nodes in focus have their mark enlarged in both directions while edges that join an entity in focus to one in context are enlarged in one direction only (see Fig. 12a). Fig. 1 shows another example with a text list. Fig. 12b presents an example



(a) Adjacency matrix. (b) Tree map. (c) Histogram.

Figure 12: Examples of distortion applied to mark shapes rather than points ($\mathit{doi}({\color{red}\bullet}) = 1$, $\mathit{doi}(\bullet) = 0$).

of treemap representing a tree which leaves are the entities. The innermost rectangles are the marks for these entities. They translate to two sets of positions (their abscissa and ordinate extremities) processed the same way the adjacency matrix rows/columns are. Like for the node-link tree, marks of the parent nodes are distorted by the same distortion function. Again, since the distortion preserves order, marks preserve their containment property through distortion.

Another example of marks that conceptually correspond to multiples entities are the bars of the histograms on a scatterplot matrix (see Fig. 12c). In this case, the matrix arrangement of the plots requires that all axes on the same column or row, including the abscissa axis of histograms, be distorted in the same way since they correspond to the same data. Consequently, the bar coordinates of a histogram are transformed by the same distortion function that distort all the abscissa coordinates of plots from the same column.

5.3 Back to Requirements: Additional Cues

We now evaluate CorFish with the requirements presented in Sect. 3. As shown through several examples, CorFish can be applied to multiple visual forms (R2). As a spatial distortion method, it is adapted to views displaying small visual entities (R3.1 and R3.2). Since the distortion is locally weighted by non-binary *doi* values, it supports non-binary interest (R1). Distortion only does not support multiple selections nor distinguishing entities in focus from others (R4.2 and R4.1). Additionally, an idea of the distortion should be rendered on each view to avoid misleading users. These last two points are addressed with additional cues, simple to implement, described in the following.

Distinguishing focus from context is not possible in the general case due both to the fact that displacement and magnification are *distortion methods* and that interest is spread by the smoothing of the magnification function. This means that, although the changes in the views are based on the *doi*, *doi* values cannot be read directly from the distorted views. However, distortion conveniently creates space around points of interest that can be used to enlarge visual entities based on *doi* values. Then, visual entities can also be filled with a color encoding their *doi* value for non-binary selection (R4.1) or selection membership for multiple selections (R4.2) like illustrated on Fig. 1. If the viewer is familiar with the positions of visual items pre-distortion, for uniformly spaced-out marks for instance, the amount and location of distortion can be apprehended. Based on this idea, a way of providing an indication on how the displayed points are distorted is to apply the distortion function to a superimposed uniform grid and other landmark items such as labeled ticks (Fig. 10 and Fig. 1c). Another possibility is to visually represent the scalar field of the amount of distortion with a color gradient, mapping each point of the visualization space to its local magnification factor (e. g. Fig. 2). Animating transitions between changes of *doi* values and interactive changes of α and h also provide assistance to understand the distortion of views and preserving the user's mental model.

The method magnifies areas around entities of interest by shrinking empty or uninteresting areas. Reducing the bandwidth decreases the size of areas of interest and therefore tends to increase the size of empty regions. This allows balancing the weakening of the distortion effect arising from an increasing number of areas of interest. Consequently, it scales to larger selections of entities (R3.3). Overall, by combining distortion with other emphasis methods such as color hue, CorFish fills the requirements listed in Sect. 3.

6 Discussion

In the context of multiple views, screen space is scarce which makes spatial distortion a relevant addition to other interactive mechanisms for emphasis. CorFish effectively enlarges some areas based on the *doi* which allows for smaller details (e. g. labels) and discriminating encoding (e. g. filling hue) to appear more visible than without spatial distortion. On many types of visualization, ad hoc solution for emphasis may be preferable since they most likely make better use of the original data type and the specific algorithm from which the representation results. For instance, on node-link diagrams, topology-aware techniques produce more pleasant results by seamlessly coarsening the context, thus reducing its cluttered aspect [11]. Rather, the main strengths of CorFish are its simplicity and technical versatility, which are key to coordinating multiple forms of visualization. It provides a unique implementation for multiple representations and may be a good starting point to design better distortion on specific representation.

6.1 Distortion

Although distortion techniques serves an emphasis purpose, they transform the spatial properties of a visualization in a way that may render some tasks more cognitively expensive than with simple highlighting and may render some interpretations incorrect. Moreover, as mentioned in Sect. 5.3, it is essential that the distortion in effect is noticeable to avoid misleading interpretations. How perceivable the distortion is and how it impacts the understanding and usefulness of a visualization depends on the underlying visualization technique.

For distortion of point-like marks representing quantitative data, like scatterplots, the distortion is not perceivable in general since the position channel encodes both the data and the *doi* which are not separable in consequence. Additional cues presented in Sect. 5.3 can help mitigate the limitations of this conflicting use of the position channel. For instance, grids lines help perceive the current distortion and therefore protect from making incorrect observations. To some extents, they also allow estimating an entity's attribute values based on its position relative to grid cells and labels, although the process is cognitively costlier than on the undistorted view. Filling color enhances the emphasis effect which is beneficial in this case since the extrinsic emphasis effect (spatial distortion) conflicts with the intrinsic emphasis effect (original entity positions) [13].

For distortion of mark shapes, we distinguish the cases (1) where shape areas are uniform and (2) where shape areas encode data. In the first case, with adjacency matrices for example, the magnification effect does not directly conflict with the original areas, thus the distortion is directly perceivable without the addition of cues which is the expected effect. In the second case, however, using magnification for emphasis is not as relevant. Indeed the conflicting use of the size visual channel may impede the perception of both the distortion and the encoded data. To the best of our knowledge there is no technique, comparable to the distorted grid lines, for mitigating this issue.

6.2 1D Approach

A major limitation of CorFish is that distortions are computed independently on coordinate domains. This is what makes the method straightforward but that also limits its adaptation to certain forms of visualization. Indeed, even though many visual representations are laid out in the Cartesian coordinate system, some visualizations do not possess the necessary symmetries to be distorted without drastically damaging their readability (e. g. bubble treemap). Advanced techniques based on optimization could be used to extend CorFish to 2D distortion such as the work of Wu et al. [38] and Zhao et al. [39]. However, one advantage of the CorFish 1D approach is that attributes plotted on multiple plots may be distorted once, provided they use the same kernel, bandwidth and interpolation factor. For instance, on a scatterplot matrix displaying d attributes on $(d \cdot (d-1))/2$ plots, only d distortion mappings are computed. A second advantage is the preservation of coherence as mentioned for scatterplot matrices.

6.3 Distribution Smoothing and its Parameters

Graham & Kennedy [12] qualified the possible superposition of entity points in scatterplot as a difficulty for designing linked distortion compared to visual representation like tree layouts where entities usually don't overlap. We addressed this by combining the superimposing and weighted kernels with summation. Therefore, on each plot, the scaling factor of a point does not solely depend on the *doi* value of the entity positioned there (or not); it also depends on the accumulated interest of all the nearby entities. A limitation of this approach is that combining weighted kernel functions with summation may render dense areas of mid-*doi* entities more enlarged than another less dense areas holding higher-*doi* entities. This behavior may be unexpected and even unwelcomed although, from the serendipity point of view, it is arguably interesting to uncover such areas. To address this behavior, other manners of combining kernel functions could be investigated such as using the maximum or average of the different kernels superimposed on a point.

Another limitation of the smoothing approach is its parameters. Given some *doi* values, two values shape a distorted view: (i) the kernel bandwidth h which determines how much entity spread their interest, and (ii) the interpolation parameter α which drives the shrinking of empty and context regions. To simplify interaction, these parameters could be abstracted into a single meta-parameter that would strengthen or weaken the distortion effect. Another option could be to leave the choice of bandwidth h, given some data and views, to the visualization designer as for the kernel k. We believe that the α parameter however should remain in the hand of the user, as a possibility to interactively and progressively switch between distorted and undistorted views. We expect this control to help the user understand the distortion and maintain its mental model when switching it on and off for specific tasks.

7 Conclusion & Perspectives

In this work, we have presented CorFish, a method for coordinating spatial distortion across multiple views, as well as several applications on visual representations. Coordinating spatial distortion is motivated by the fact that many emphasis methods are limited in efficiency in contexts where marks are rendered using few pixels. We propose a method that coordinates multiple views based on a common definition of the user interest that associates numerical values to the conceptual entities represented on each view. Based on these values, each view space is distorted such that the amount of magnification of an area conveys the interest on the entity points it contains. View spaces are distorted by combining separate distortions of multiple coordinate domains. With additional cues, simple to implement, the proposed method fulfills the identified requirements.

In future work, we would like to extend the entity-centered distortion approach to 2D spaces. In particular, we want to investigate which geometric properties should be and could be preserved by such distortion. Secondly, it would be interesting to investigate the ways of coordinating marks that correspond to multiple entities rather than a single one. Finally, although we have shown the feasibility of CorFish for multiple visualization forms, future work should evaluate its usability and performances for different tasks and on different view forms.

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