Visual Fingerprints for Detecting Data Characteristics

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Abstract

Compact visualizations are often used to detect expected and unexpected data characteristics at a glance. The literature uses the terms fingerprints, thumbnails, or sketches for these bite-sized visualizations. To date, these visualizations have not been described in context and their discussion is fragmented across publications. In this paper, we propose the term *Visual Fingerprints* for these visualizations, highlight the task of visual detection for which they are designed, outline their visual properties, and discuss their commonalities and differences with related concepts. In doing so, we aim to bundle the existing research on these visualizations into a common concept and term that serves as a foundation and stepping stone for future developments in this direction.

1 Introduction

One of the main tenets of data visualization is that it speeds up feature identification and insight generation from large volumes of data. This principle has inspired definitions of the field like Stuart Card's famous quote that "information visualizations should do for the mind what automobiles do for the feet" [7, p.544], and it also lies at the foundation of evaluating visualizations using task completion times. After all, a good visualization is expected to not just be expressive of the underlying data but also to be effective and efficient in helping users to understand that data.

In this paper, we investigate visualizations that take this notion of accelerating the observation of data features as far as supporting their detection at a mere glance. The task of visual detection is rarely considered in the canon of visualization task taxonomies, as it is more of a "low-level visual task [that is] often executed pre-attentively" [35, p.111] being "so effortless as to seem to be an intrinsic part of other perceptual processes." [39, p.14]. Visualizations supporting visual detection are not meant to dwell on them, to visually scan them, or to even read off values from them. Instead, they are designed to be taken in with a single glimpse to detect "anything that sticks out." We call these visualizations *Visual Fingerprints* (VFPs) and define them as a family of data visualizations that enable the detection of data characteristics within a time span of $200-250$ *msec* [15], possibly extending up to 2 *sec* [5].

VFPs share the goal of extracting the essence from entire datasets with other types of visualizations – such as overview visualizations [16]. Yet, they go much beyond these notions by facilitating what seems like almost instantaneous insights, if there are any to be had. To that end, VFPs are quite unlike 'full-fledged visualizations' that offer a wealth of features and various possible interactions. Their merits rather lie in their ability to show a bite-sized big picture of whole datasets without requiring in-depth analysis or incurring interaction costs. In the literature, different instances of VFPs are introduced under a variety of terms, like *fingerprints* [22, 32], *thumbnails* [44], or *sketches* [1]. In some cases, visualizations are not explicitly mentioned or designed as VFPs, even though they can clearly be characterized and function as such. For example, the visualization for multi-granular trend detection [13] is not positioned as a fingerprint or thumbnail, but the intended task of "detection" gives a strong indication that it is indeed a VFP. Yet, discussion of this form of visualization has been scarce and scattered.

We consolidate these terms and propose VFPs as a particular form of visualization with unique overarching properties and special design considerations. To this end, we contribute: (1) a systematic break-down of the VFP landscape by the target patterns and scopes of visualization tasks they support; (2) a discussion of VFPs' visual properties to illustrate how they facilitate rapid insights; (3) a delineation of VFPs from related concepts.

2 Visual Detection in Visualization

Cognitive sciences commonly consider *visual detection* to lie at the foundation of a stack of perceptual processes ranging from the *detection* to the *discrimination* and the *recognition* of visual stimuli, whereby higher levels of this stack involve more attentive mechanisms than lower ones [39, p.xiii]. Detection is often a binary operation that determines if a signal appears among the noise (e.g., outlier or anomaly detection) or if a change occurs (e.g., detection of fluctuations or tipping points). Performing detection visually has the benefit of not having to pre-specify all possible detection targets, but to leave it to the visual system of the human to spot anything that is out of place in an "I-know-it-when-I-see-it" manner.

Visual detection can be used to observe known as well as unknown data patterns. For example, Correll et al. [9] used the concept of *visual detectability* to elicit suspected as well as unanticipated data quality issues for brief visual plausibility checks. At the same time, they also highlight how much visual detectability depends on carefully chosen visual encodings. This means that in order to support visual detection, VFPs must be designed to bring out any data pattern of interest – if present in the data – at the desired scope and within the desired timeframe.

Building upon the task framework by Munzner [26, pp.54-55], Figure 1 illustrates the landscape of VFPs with suitable examples from the literature. We enumerate the combinations of target patterns to be detected (*trends*; *outliers*; *features*) and their scope (*identify*, one dataset; *compare*, two datasets; *summarize*, more than two datasets). While these are pre-existing tasks, enabling them for rapid detection – i.e., carrying them out in less than 2*sec* – adds an important additional constraint to them.

For example, the Splatterplot technique [25] allows users to **identify outliers** by merging dense areas in a scatterplot, so that any outliers stand out as individual points, easily detectable at a glance without having to search for them. For **comparing features**, the Treebar Map [10] displays large networks as a series of nested subgraphs of increasing connectivity. By putting two of these VFPs side-by-side, one can immediately perceive commonalities and differences in how strongly connected subgraphs are embedded in lesser connected subgraphs just by briefly eyeballing the associated column charts. For **summarizing trends** across a whole ensemble of temporal datasets, multi-granular visualization [13] allows for detecting major trends and bifurcation points in a single, easy to take in visualization that is tailored towards this task.

Literature in cognitive psychology lists a number of perceptual guidelines for making targets (signals) accurately detectable among non-targets (noise) [30]. These include:

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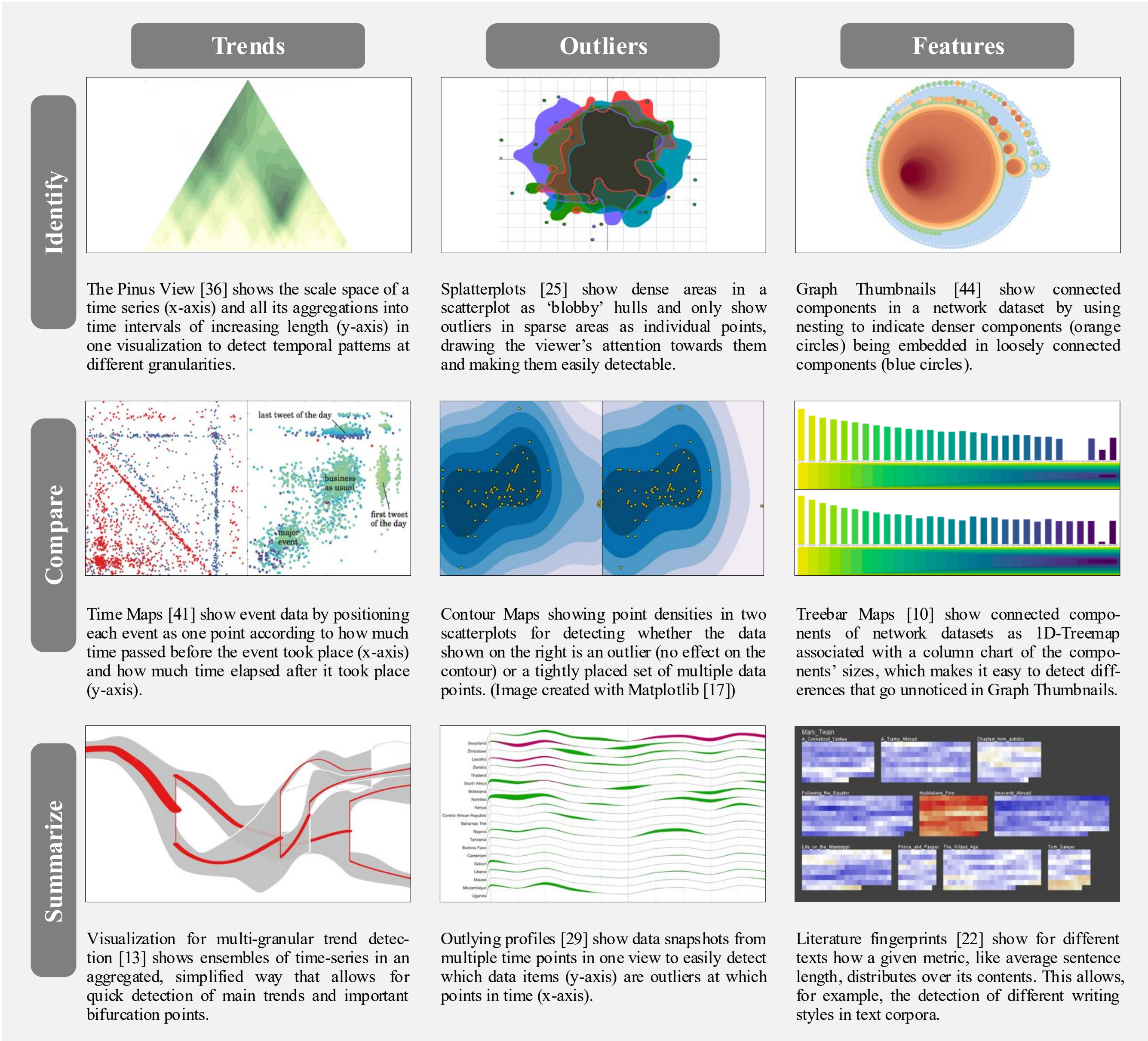


Figure 1: VFP examples illustrating the different scenarios of VFP use as combinations of detection targets (columns) and scopes (rows).

- the targets should not be too similar to the non-targets;
- the non-targets should not be too heterogeneous;
- targets should be spatially separated from non-targets.

We can find these fundamental guidelines reflected in some of the examples included in Figure 1. For example, the Splatterplot

- encodes outliers and inliers visually as points vs. areas, respectively, so that their visual appearance is quite different;
- encodes all inliers in the same way as colored 'blobs' without any distinction of their internal density, giving them a rather homogeneous look;
- by its nature, has outliers positioned not exclusively but in their majority towards the periphery of the plot, separating them well.

In the following section, we look at additional, more high-level visual properties that are shared among many VFPs in the literature.

3 Visual Properties

VFPs often exhibit similar visual properties that ease visual detection. These properties collectively characterize VFPs. As a rule of thumb, it is safe to say that the more of these properties a visualization meets, the better it supports visual detection and, thus, the clearer it fits into the visualization family of VFPs.

3.1 Compact Representation

VPFs are often small, condensed visualizations. Their compact size ensures they can be understood without lengthy visual scanning or even requiring head movement to be fully taken in. To achieve this, several encoding strategies can be used in combination, such as small visual marks, space-filling placement, reuse of drawing space through nesting, and visual simplification or aggregation.

Small Visual Marks such as points, pixels, or small shapes are a simple way to reduce the visual footprint of a visualization.

This strategy for achieving a high information density in limited screen space is not exclusive to VFPs, with pixel-based visualizations [21] being a prime example of its general applicability. Small visual marks are, for example, used in the Continuous Triangular Model [31], in Literature Fingerprinting [22], as well as in Point-based Tree Layouts [34].

Space-filling Layouts ensure that visualizations make the best use of the available drawing space, leaving minimal or no white space. Again, this property is by no means unique for VFPs, but well-known from popular visualization techniques like Treemaps [3, 42]. Space-filling visualizations are not just a means of maximizing space utilization but also of increasing the visual footprint of smaller data characteristics that might otherwise go unnoticed in a $200-250$ msec preattentive glance. For example, the Contour Maps in Figure 1 turn the rather sparse scatterplot into a space-filling visualization. This makes the points on the right side of the plots much more visually prominent, allowing the viewer to immediately detect that there are more points (higher density) in the first plot than in the second plot.

Nesting of visual marks allows for reusing drawing space to plot more than one data item in one place, maintaining an overall fixed screen space. While often being associated with Treemaps, the idea of nesting predates them and is already used by Bertin as a fundamental building block of graphic construction [4, p.128]. In the examples in Figure 1, Graph Thumbnails [44] and Treebar Maps [10] use nesting to indicate connected components embedded in large graphs, without actually showing the graphs themselves.

Visual simplification of large and complex datasets like documents, graphs, or multivariate time-series is crucial in cases where there are more data points to show than pixels available. Hierarchical aggregation [11] is often used to this end. An example is the multi-granular trend extraction [13] from Figure 1, which simplifies an otherwise unwieldy spaghetti plot by determining its main trends and only displaying them. Other possible simplifications include the removal of legends, axes, and labels as VFPs are not meant for close reading or detailed inspection that would require these additional visual elements.

3.2 Static Representation

VFPs often use static representations as static views introduce no interaction costs [24], not even the minimum required for *passive interaction* of, e.g., merely observing a moving display [37, p.167]. This property is not a limitation, but an enabler of preattentive processing that ensures that key data characteristics are communicated within a single timeframe, without requiring interaction sequences or animations to reveal insights. After all, VFPs afford neither the time to interact with a VFP by adjusting zoom levels or the like, nor the time to dwell on a VFP to watch it unfold in an animation. That being said, VFPs can subsequently support navigation in visualization systems by serving as a compact entry point to more detailed exploration of any detected data feature of interest. Yet, this is a secondary benefit rather than their primary design goal.

3.3 Change-Proportional Representation

In particular for detecting changes between two datasets (comparison) and more than two datasets (summarization), it is important that VFPs map the underlying data in a continuous way that reflects the relation of data characteristics in their respective visual elements. This essentially means that two similar data characteristics should produce visually similar VFPs, while dissimilar characteristics should generate visually distinct representations.

This property is noteworthy as it deviates from the definition of fingerprints in other fields. For example, two identical twins (i.e., exhibiting the highest possible similarity) will still have very different biometric fingerprints. Likewise, in cryptography, changing just one letter in a document should ideally yield a completely different message digest. Hence, biometric fingerprints and message digests cannot be used to draw any conclusions about the original person or document, respectively, other than establishing their identity. However, the term "fingerprint" is in all cases synonymous with mapping a larger entity to a small entity – i.e., a compact representation – that is easier to process, transmit, store, and check against. In this light, our choice of the term "Visual Fingerprint" is very much in line with its general use.

3.4 Interpretable Representation

Even when VFPs are simplified to enable quick visual detection of data characteristics, they must remain meaningful and communicate essential dataset characteristics. This property delineates VFP from visual representations that act like QR codes for datasets with no direct message or meaning hidden behind each pixel. This distinction is important, as so-called *identicons* or *hash visualizations* [28] exist that could otherwise be mistaken for a VFP. Time-series bitmaps [23], for example, generate colorful pixilated images for time-series datasets that serve as visual identifiers that can be remembered and refound more easily and quickly than a dataset's file name – yet, it does not give any insight in the dataset itself.

4 Related Visualization Concepts

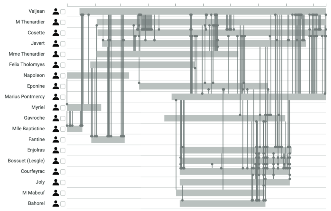
The idea of taking in data in one quick sweep has been looked at from other perspectives. Notions like *glanceable visualizations* [5], *summary visualizations* [33], and *overview visualizations* [16] have been proposed to capture similar classes of visualizations to VFPs. In this section, we briefly discuss their meaning, as well as if and how they might overlap with VFPs.

Glanceable visualizations are defined as "concise graphical representations of data primarily designed and used for enabling quick insight discovery at a glance without extensive exploration or analysis" [43]. While sharing this overall aim VFPs, their use in real-world contexts differs quite a bit. Glanceable visualizations are mostly used for small personal displays like smartwatches or situated visualizations [6] and often just show a single data value (e.g., the user's heart rate or step count). An example is shown in Figure 2a. Due to the simplicity of the data to be shown, the employed chart types are likewise simple, often using donut charts or bar graphs to depict the single data point to be communicated.

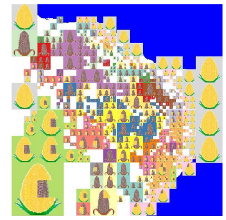
Summary visualizations "use visual and statistical techniques to purposefully reduce (i.e., summarize) the amount of data shown to viewers such that systems can manage the scale and complexity of large datasets" [33]. If the visual summary is done for large textual data, it may also be called a *Distant Reading Technique* [20, ch.4.2]. Likewise, VFPs might use visual simplification and data aggregation to condense large datasets into a compact VFP (cf. Sec. 3.1). Unsurprisingly, the VFPs in the 'Summarize' row of Figure 1 all "purposefully reduce" the amount of data to be shown and could thus rightfully also be called summary visualizations. Yet, on the one hand, there are VFPs that are not summary visualizations – e.g., the Pinus view [36] which does not reduce, but instead increases the amount of data by showing the whole scale space from individual data points at the bottom (the original time-series) to averages over time intervals of increasing lengths towards the top. On the other hand, there are summary visualizations that may reduce the data, but not to the degree that would allow detection of patterns within the timespan of detection – i.e., 200 *msec* – 2 *sec* – without the need of reading or parsing the figure. An example of this is shown in Figure 2b summarizing the contents of Les Misérables as a character interaction network, which is clearly a reduction of the original textual contents of the book, but not to the point that data characteristics become immediately detectable.

Overview visualizations provide "a display that shrinks an information space and shows information about it at a coarse level of granularity" [16]. This positions overview visualizations very

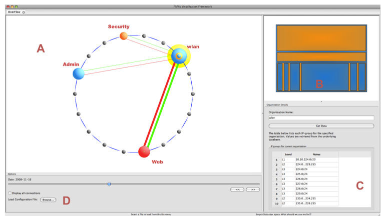
(a) Glanceable visualization using icons and simple gauges to display activity and weather data [18].



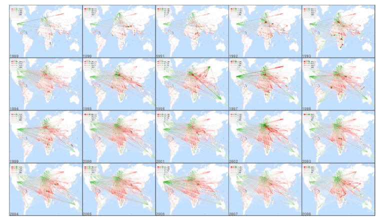
(b) Summary visualization showing the interaction of characters in Les Misérables [14].



(c) Corncob-shaped glyphs indicate six different corn-growing conditions in different regions of Brazil [27].



(d) Overview visualization of a computer network showing different network hierarchies and how they are connected [12].



(e) Small multiples showing worldwide migration flows between 1989-2008 [2, p.359]. ©Aigner et al. 2023. Reprinted under 🅭 license.

Figure 2: Overview of visualization concepts related to VFPs.

similarly to summary visualizations in the sense that there is some form of reduction or coarsening performed on the information to be displayed. This is exemplified in Figure 2d, which shows a high-level overview of different computer networks and their interaction. While such coarsening may be used for VFPs – e.g., Splatterplots reducing the visual fidelity of the dense areas – it does not have to be that way. For example, Time Maps [41] show an event sequence without any reduction by plotting each event as one pixel in the scatterplot (except for the first and last event in the sequence). That being said, Spence emphasizes that an "overview implies a qualitative awareness of one aspect of some data, preferably acquired rapidly and, even better, preattentively: that is, without cognitive effort" [37, p.19]. By emphasizing the speed of acquisition, Spence's notion of overview visualization shares this fundamental trait with VFPs (and glanceable visualizations for that matter).

Small multiples "resemble the frames of a movie: a series of graphics, showing the same combination of variables, indexed by changes in another variable." [38, p.170]. Often, these frames are different time points of a dataset, showing the evolution in a storyboard-like fashion, as illustrated in Figure 2e for easy comparison task in a storyboard-like fashion. Small multiples share their small form factor with VFPs. However, it is hard to compare or equate small multiples with VFPs, as small multiples function as a juxtaposition mechanism that combines smaller visualizations into larger views [19] rather than as visualization techniques in their own right. Like any visualization, VFPs sometimes utilize the organization principle of juxtaposition/small multiples—for example, Literature Fingerprints [22] visualizes multiple texts from a corpus (e.g., all books of the Bible) side by side.

Glyphs "are a popular method for conveying information visually. Individual dimensions/variables for a given data point are mapped to attributes of a particular shape or symbol, and variations, clusterings, and anomalies among these graphical entities may be readily perceived" [40, p.195]. As Chung et al. note, "glyph-based visualization approaches span a spectrum from dense arrangements of relatively simple shapes to individual instances of complex glyphs that reveal a lot of information" [8, p.130]. In particular, the individual, complex glyph is close to our notion of a VFP, sharing the property of condensing multi-dimensional data into compact visual forms to ease their perception. Yet, glyphs are very focused on the perception of the resulting form or shape, with similar shapes indicating similar multivariate data tuples. Figure 2c shows the use of a glyph that maps six different attributes onto the shape of a corncob, indicating growing conditions for corn in different regions. VFPs are not only broader in this regard, relying also on the perception of distributions, densities, and colors, but may also not show any deviations of form, as is the case for space-filling VFPs whose form is determined by the available drawing space.

It is evident that VFPs share some properties with existing visualizations. This comes as no surprise, as all visualizations aim to speed-up the perceptual acquisition of the chart by employing preattentive cues, filtering and focusing the data on relevant subsets and scales, and aiming not to waste drawing space. Yet, VFPs are the chart techniques at the far end of the spectrum that prioritize visual acquisition speed over all other design considerations.

5 Conclusion and Future Research Directions

This paper consolidates previously fragmented research in this area, providing the visualization community with a foundation for future empirical studies and theoretical refinement. To that end, the concept of VFPs surfaces the importance of turning visualization tasks into rapid detection tasks that allow for finding or comparing in up to 2 *secs*, which in turn will require different and potentially new ways to evaluate for. In addition, the collection of perceptual guidelines for making data patterns detectable and of representational aspects for making visual mappings condensed and space-efficient serves as a unique starting point for designing new, tailor-made VFPs. We anticipate that this will stimulate continued research and discussion around VFPs.

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