A Survey of Display Device Properties and Visual Acuity for Visualization

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Abstract

The advent of computers with high processing power has led to the generation of huge datasets containing large numbers of elements, where each element is often characterized by multiple attributes. This has led to a critical need for ways to explore and analyze large, multidimensional information spaces. Visualization lends itself well to this challenge by enabling users to visually explore, analyze, and discover patterns within their data. Most visualization techniques are based on the assumption that the display device has sufficient resolution, and that our visual acuity is adequate to complete the analysis tasks. This may not be true however, particularly for specialized display devices (e.g., PDAs, or large-format projection walls). This paper discusses which properties of a display device need to be considered when visualizing large, multidimensional datasets. We also investigate the strengths and limitations of our visual system, in particular to understand how basic visual properties like color, texture, and motion are distinguished. These findings will form the basis for new research on how to best match a visualization design to a display's physical characteristics and a viewer's visual abilities.

1 Introduction

Visualization is an area of computer graphics that manages and presents information in a visual form to facilitate rapid, effective, and meaningful analysis and interpretation. Visualization is used in areas like geographic information systems, land and satellite weather information, scientific simulations, aerospace research, molecular biology, defense, and medicine. Visualization also supports more abstract domains, for example, program visualization, data mining, and network security. In situations where user collaboration is required or time is a critical factor, visualization enables people to analyze and interpret vast amounts of information and make important decisions. The desire to extract knowledge rapidly and efficiently from large, complex datasets motivates the need for effective visualization systems [36].

More formally, a dataset $D = \{e_1, .., e_n\}$ contains n sample points, or data elements, e_i. A multidimensional dataset represents two or more data attributes, $A = \{A_1, ..., A_m\}$, $m > 1$. The data elements encode values for each attribute: $e_i = \{a_{i,1}, ..., a_{i,m}\}$, $a_{i,j} \in A_j$. A data-feature mapping converts the raw data into images that can be presented to a viewer. Such a mapping is denoted by $M(V, \Phi)$, where $V = \{V_1, ..., V_m\}$ is a set of m visual features with V_j selected to represent each attribute A_j, and $\Phi_j : A_j \rightarrow V_j$ maps the domain of A_j to the range of displayable values in V_j. Visualization is thus the selection of M together with a viewer's ability to comprehend the images generated by M. An effective M produces images that support rapid, accurate, and effortless exploration and analysis [20].

Knowledge of perception can be used to generate visualizations that harness the strengths of the low-level human visual system. Applying perceptual guidelines to "take full advantage of the available bandwidth of the human visual system" has been cited as an important area of current and future research in visualization [25, 38]. "Visual bandwidth" depends on the following criteria:

1. Physical characteristics of the display device (e.g., resolution in terms of the total number of pixels, and the physical size of the display).

2. Acuity of the human visual system (e.g., the limits of distinguishability of the human eye for different image features like color, orientation and size, and the visual angle subtended by elements on the viewer's eye).

3. Visualization technique (e.g., the methods used to map a data element's values to a visual representation).

4. Properties of the data (e.g., its dimensionality and number of elements) and the analysis tasks to be performed by the viewer.

To date, significant research effort has been expended on the last two criteria, constructing new visualization techniques and studying how different types of data can be displayed effectively. Much less work has been conducted on the first two criteria: understanding how display resolution and visual acuity affect the expressiveness of a visualization. Knowledge from human psychophysics and computer vision could be used as a foundation for these types of studies.

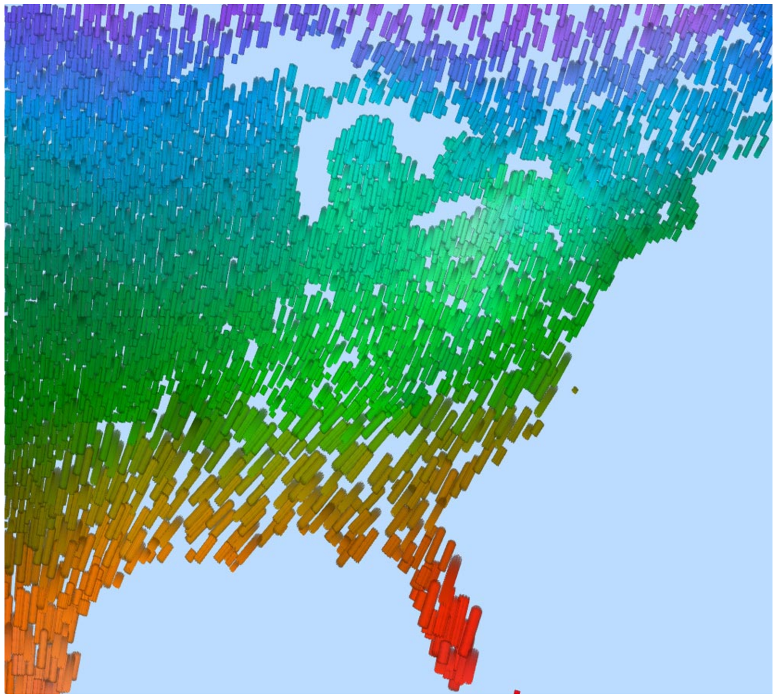

Figure 1: Visualization of a weather dataset using perceptual texture elements with *temperature* → hue, *wind speed* → density, *pressure* → size, *precipitation* → orientation, and *cloud coverage* → luminance

One important goal of our work is to identify and extend these basic findings of display resolution and visual acuity to our visualization domain.

As an example of a typical multidimensional visualization, consider Figure 1 which visualizes a weather dataset made up of monthly environmental and weather conditions provided by the Intergovernmental Panel on Climate Change. This multidimensional dataset contains mean monthly surface climate readings in $\frac{1}{2}^{\circ}$ latitude and longitude steps for the years 1961 to 1990 (e.g., readings for January averaged over the years 1961-1990 and so on). Individual weather readings (or data elements) are visualized using stroke glyphs (2D rectangular objects) that vary their color and texture properties. Hue represents *temperature*: blue strokes for cold temperatures to red strokes for hot temperatures. Density represents *wind speed*: more strokes displayed in a fixed area of screen space for stronger wind speed. Size represents *pressure*: larger strokes for higher pressure. Orientation represents *precipitation*: tilted strokes for heavier rainfall. Finally, luminance represents *cloud coverage*: brighter strokes for heavier cloud coverage.

Figure 2 visualizes a more abstract dataset of query results representing movie recommendations from the MovieLens[1] recommender system. MovieLens returns a movie's *title*, its *genre* and a predicted *user rating*. This data was augmented with information taken from the

[1]MovieLens (movielens.umn.edu) is a collaborative filtering research site run by the GroupLens Research Group at the University of Minnesota.

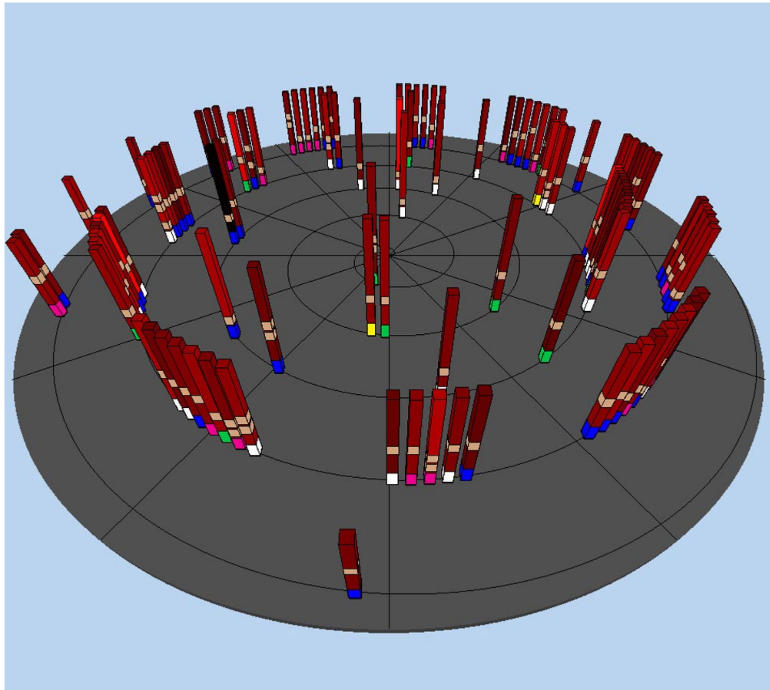

Figure 2: Visualization of a movie dataset using perceptual texture elements with *user rating* mapped to spatial position and height, *year* mapped to colored flag at the bottom of the glyph, *genre* mapped to light brown flags at different heights, and *length* mapped to luminance

Internet Movie Database (IMDB)[2] to include the *year* the movie was released, the *length* of the movie in minutes, and the IMDB *rating* of the movie. Tower-like glyphs are positioned along a spiral embedded in a plane based on how much MovieLens thinks the user will enjoy the movie (predicted *user rating*). The value of the *user rating* decreases as glyphs move away from the center of the spiral, that is, movies closest to the center of the spiral are the ones MovieLens ranked highest. Predicted *user rating* is also mapped to the height of each tower to reinforce this important value. *Year* is mapped to a colored flag at the bottom of the glyph: yellow for 1921 to 1940, green for 1941 to 1960, purple for 1961 to 1980, blue for 1981 to 2000, and white for after 2000. *Genre* is mapped to light brown flags wrapped around the glyph at different heights; the order of the flags from bottom to top represent Action, Comedy, Drama, and Romance, respectively. Since a movie can be classified into multiple genres, multiple genre flags may appear on a glyph. Finally, *length* is mapped to luminance (dark red for short to bright red for long) [36].

Most visualization algorithms to date (including the two examples shown above) assume that a sufficient display resolution will be available to generate visualizations that can be processed effectively by the viewer. The increased use of non-traditional display devices such as multi-projector powerwalls, responsive workbenches, high-resolution monitors (e.g., with 200 or more pixels-per-inch), PDAs, and mobile phones, each with different display characteristics,

[2] www.imdb.com

can have a significant effect on a particular visualization technique. The physical size, pixel resolution, and standard viewing distance varies across different display devices. This directly impacts which part of a dataset we can display effectively. Another issue that needs to be considered is the human visual system itself. For example, an on-screen element must subtend a minimum visual angle on the viewer's retina to be distinguishable. Increasing a display device's pixel resolution (i.e., increasing pixels-per-inch and therefore decreasing the size of the on-screen elements) beyond a certain limit will produce diminishing results.

Consider a simple example of visualizing a large, multidimensional dataset on a typical CRT monitor, and assume that the viewer has zoomed in on a small subset of the dataset. At this point, a full-detail visualization containing as many attributes as can be shown effectively will be most useful. Now, if the viewer zooms out to see an overview of the entire dataset, only a few pixels of screen space will be allocated to each data element, and thus many of the visual features used to represent different data attributes may not be easy to distinguish. This "background clutter" could be counterproductive, since it may interfere with our ability to identify important data values at this low resolution. One possible solution is to have a visualization system that smoothly reduces the number of attributes it represents as the viewer zooms out, and redisplays the attributes as the viewer zooms in. The idea is to maximize the utilization of the display's capabilities in an effective and efficient manner, maintaining a balance in the display environment: more elements with fewer attributes encoded, or fewer elements with more attributes encoded.

Figure 3 shows an example of this situation. The dataset being visualized is the same as used in Figure 1. In the top image *temperature*, *pressure*, *wind speed*, *cloud coverage*, and *precipitation* are mapped to hue, luminance, size, orientation, and regularity, respectively. In the bottom-left image the same data is visualized, but for the entire continent of North America. Because only a few pixels are available for each data element, many of the visual feature values are difficult to identify. Moreover, the presence of certain features (e.g., small sizes) interferes with our ability to see other features (e.g., color). In the bottom-right image the same elements are visualized, but the number of attributes are reduced to two: *temperature* and *pressure*. Since both hue and luminance are distinguishable even at small physical resolutions, the underlying data patterns are easy to identify.

An obvious question is: how can we define this kind of visualization hierarchy? The answer will depend on how many pixels (i.e., what display resolutions) are needed for a visual feature to represent information effectively, and how much physical size (i.e., what visual acuity) is needed for our visual system to accurately identify and interpret the visual feature. This survey summarizes what is currently known about these topics, and offers suggestions on how future research could fill in missing details, and then combine the results into a working visualization system. Understanding limits on display resolution and visual acuity will allow us to better validate a given visualization technique, and characterize to what extent the technique saturates "visual bandwidth".

When we design a visualization, properties of the dataset and the visual features used to represent its data elements must be carefully controlled to produce an effective result. Important characteristics that must be considered include [48]:

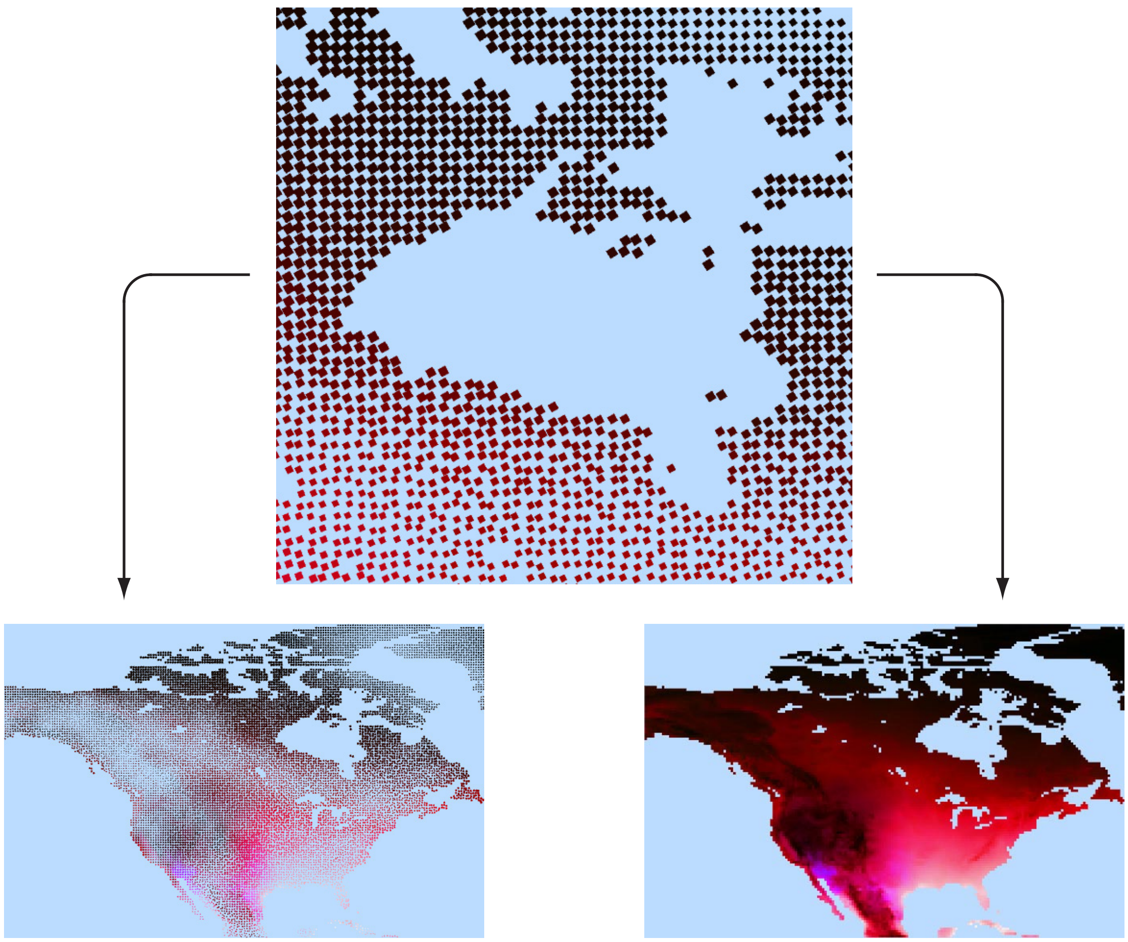

Figure 3: Examples of visualizing with different viewing parameters: (top) a close-up of Hudson Bay, each square represents weather conditions on a $\frac{1}{2}^\circ$ longitude by $\frac{1}{2}^\circ$ latitude grid, *temperature* mapped to hue (blue for cold to red for hot), *pressure* mapped to luminance (brighter for higher), *wind speed* mapped to size (larger for stronger), *cloud coverage* mapped to orientation (more tilted for denser), and *precipitation* mapped to regularity (more irregular for heavier); (left) North America with all five attributes visualized; (right) North America with only *temperature* and *pressure* visualized

1. *Dimensionality*: as the number of attributes m in the dataset grows, additional visual features must be identified to represent each attribute; for large m, this may be difficult or impossible, necessitating the display of only a subset of the dataset's attributes.

2. *Number of elements*: as the number of elements n increases all of the elements may not fit on-screen.

3. *Visual-feature salience*: each visual feature has strengths and limitations that make it suitable for certain types of data attributes and analysis tasks; an effective visualization needs to respect these properties.

4. *Visual interference*: different visual features can interact with one another, producing visual interference; this must be controlled or eliminated to guarantee effective exploration and analysis.

Display resolution and visual acuity will further impact how a dataset can be visualized, for example, how many data elements and data attributes we can represent at once, and which visual features are best suited for displaying different attribute values.

The remainder of the survey proceeds as follows. In Section 2, we review the important physical characteristics of display devices. Section 3 discusses physical vision and visual acuity. Section 4 focuses on the properties of different visual features such as color, texture, and motion. Finally, Section 5 discusses conclusions and future work.

2 Display Device Properties

Properties of a display device that can have a significant effect on its visualization capabilities include: display resolution, physical size, and viewing distance. This leads us to ask: (1) What fraction of a dataset can a display represent effectively? and (2) What fraction of a display can a viewer attend to at any given time? The physical size and the viewing distance affect the visual angle formed by the object.

Visual angle is the angle subtended by an object on the eye of an observer. Visual angles are generally defined in degrees, minutes, and seconds of arc (a minute is $\frac{1}{60}$ degree and a second is $\frac{1}{60}$ minute). For example, a 0.4-inch object viewed at 22-inches has a visual angle of approximately 1 degree. In Figure 4, visual angle can be calculated as [47]:

$$\frac{\theta}{2} = \arctan(\frac{ab}{d}) \quad (1)$$

The visual angle depends on two factors: (1) it is proportional to the actual size of the object; and (2) it is inversely proportional to the distance of the object from the eye. The larger the size of the object, the larger the visual angle; and the larger the distance of the object from the eye, the smaller the visual angle.

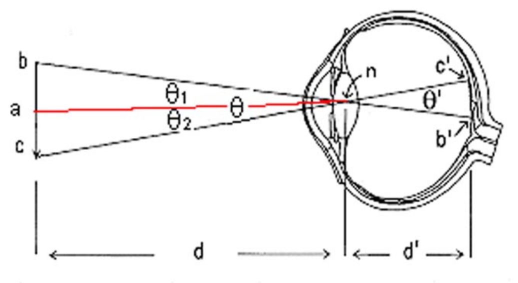

Figure 4: Visual angle subtended by an object on a human eye

2.1 Display Resolution

A display device's resolution defines the number of pixels it contains, expressed in the horizontal and vertical directions. The sharpness of the display depends on its resolution and on its physical size. The same resolution will be sharper on a smaller monitor compared to a larger monitor because the same number of pixels are being spread out over a larger physical region [34]. We use the term *display resolution* to refer to the resolution and the physical size of a particular display device. Real-world data are visualized on a range of display devices such as computer monitors (traditional CRTs and LCDs), PDAs, mobile phones, and powerwalls[3]. Table 1 shows common display resolutions for these types of display devices [26, 29, 30, 27, 28].

The low display resolution of devices like mobile phones and PDAs limits the amount of information they can display at any given time. A common display resolution for a PDA is 240×320 pixels at 3.5-inches diagonal. Consider the example of visualizing a large dataset on a PDA screen. This would allocate very few pixels to each data element. Even if the resolution is increased dramatically (i.e., a significant increase in pixels-per-inch), it would not fully resolve the issue. An element must subtend a minimum visual angle on the viewer's retina to be distinguishable. Increasing pixels-per-inch beyond a certain point will produce diminishing results in terms of the amount of additional information a viewer can see. At the opposite extreme, a large display device such as a powerwall typically results in a large field of view (FOV)[4]. But, there is a limitation on the amount of information human eyes can perceive based on the horizontal and vertical FOV. Also, as the FOV increases users have to utilize their peripheral vision [3], and it is a known fact that static visual features do not perform well under peripheral conditions [2].

2.2 Physical Size

Physical size is an important cue to sensory and judgment processes in humans. In a series of studies, Simmons [37] showed that users performed better on productivity tasks using large 21-inch monitors as compared to smaller ones. Chapanis and Scarpa [10] conducted experiments

[3] A multi-projector display that is typically both physically large as well as very high in resolution

[4] "The maximum number of degrees of visual angle that can be seen instantaneously on a display" [3]

Display Device	Manufacturer	Model	Resolution	Screen Size
Mobile Phone	Vodofone Sharp	GX30	858×1144	2.2-inch screen
	Sanyo	SCP-5300	132×176	2.1-inch screen
	Samsung	SPH-A600	128×160	2.0-inch screen
	Nokia	6200	128×128	27.3×27.3 mm
PDA	Toshiba	e805(BT)	800×600	4.0-inch screen
	Sony Clie	PEG-UX50	480×320	4.0-inch screen
	Hewlett Packard	iPAQ RZ1715	240×320	3.5-inch screen
	T-Mobile	Sidekick II	240×160	2.75-inch screen
Monitors	Auto Vision Inc	AVHRPC703	640×480	7.0-inch screen
	COMPAQ	MV520	800×600	15.0-inch screen
	ViewSonic	VX510	1024×768	15.0-inch screen
	Sony	CPD-E240	1280×1024	17.0-inch screen
	ViewSonic	G90fb	1600×1200	19.0-inch screen
	LG	L2320A	1920×1200	23.0-inch screen
PowerWall	SGI	Onyx2	6400×3072	8×2.85 m
		POWER Onyx	3200×2400	6×8 feet
		Exec CUG	2560×2048	14×10 feet

Table 1: Display Resolution of current display devices

comparing the readability of physical dials at different distances to examine the psychophysical effects of distance and size. They used dials of different sizes and markings that were proportional to the viewing distance so as to keep visual angles constant. They found that beyond 28-inches, dials were read more easily. The effects they found, however, were relatively small.

Studies conducted by Desney et al. [13] suggest that users performed better on spatial orientation tasks that require mental rotation on large displays compared to desktop monitors. The visual angle was held constant by adjusting the viewing distance to each of the displays. Large displays provide users with a greater sense of presence, allowing them to imagine rotating their bodies within the environment. Smaller display force users to imagine rotating the environment around themselves [9, 50]. Large displays normally cast a larger retinal image, offering a wider FOV. Czerwinski et al. [12] reports that a wider FOV increases the sense of presence and improves performance in 3D navigation tasks, many of which are important in visualization.

The physical size of a display device has a direct affect on the available FOV. Also, for a fixed pixels-per-inch, larger display devices have higher resolutions and therefore may be capable of visualizing more information.

2.3 Viewing Distance

The standard distance to the viewer from the computer screen is approximately 22-inches [47]. For large displays such as powerwalls, the optimal viewing distance is about twice the width of the display [41]. As the viewing distance increases, the FOV decreases. For example, a 16-inch display placed 22-inches from the user produces a FOV of approximately $40°$. Increasing the viewing distance to 30-inches reduces the FOV to $30°$.

Display resolution for current display devices range from as low as 128×128 to as high as 6400×3072. A good visualization technique should take into account the display resolution, physical size, and standard viewing distance in order to maximize both the quantity and the quality of the information it displays. The number of pixels allocated to each data element is directly proportional to the display resolution. For a particular display resolution, it is important to determine which visual features can be rapidly identified and which cannot, based on the number of the pixels that need to be allocated to each visual feature to make its values distinguishable. This knowledge is necessary to build data elements that generate effective and efficient visualization.

3 Physical Vision and Visual Acuity

3.1 Physical Vision

Figure 5 shows the internal structure of the human eye. The important features are: the retina, the lens, the fovea, the iris, the cornea, and the eye muscle. Light focused by the lens falls on the retina. The retina consists of two types of photosensitive cells: rods and cones. Cones are primarily responsible for color perception and rods are responsible for intensity, though they are typically ten times more sensitive to light than cones. There is a small region at the center of the visual axis known as the fovea that subtends 1 or 2 degrees of visual angle. The structure of the retina is roughly radially symmetric around the fovea. The fovea contains only cones, and linearly, there are about 147,000 cones per millimeter [14]. The fovea is the region of sharpest vision. As we move outward from the fovea, rods begin to appear among the cones, and at the edge of the fovea there are more rods than cones. The human eye contains separate systems to encode spatial properties such as size, location and orientation, and object properties such as color, shape and texture. These spatial and object properties are important features that have been successfully used by researchers in psychology for simple exploration and data analysis tasks such as target detection, boundary detection and counting, and by researchers in visualization to represent high-dimensional data collections [47].

The human eye contains a limited number of rods and cones (about 120 million rods and 6 million cones), and due to this it can only manage a certain amount of information over a given time frame. Thus, even though we can generate images with a high number of pixels-per-inch, it will not improve our analysis abilities once it crosses the threshold where pixels blur together with their neighbors. This poses an interesting question for the visualization field: “What is the minimum number of pixels required to represent different visual features such as color, texture,

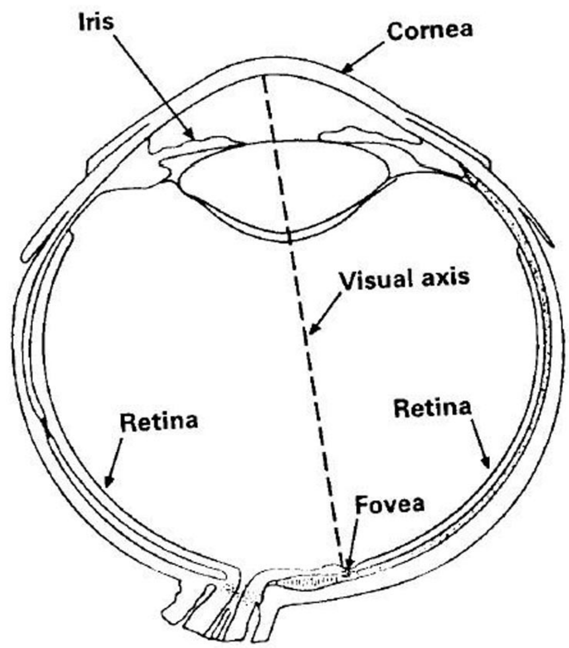

Figure 5: Internal structure of a human eye

and motion in order for it to be perceptually identifiable?" More discussion about this can be found in the next section.

3.2 Visual Acuity

Visual acuities are measurements of our ability to see detail. Acuities are important because they define absolute limits on the information densities that can be perceived. Some of the basic acuities are summarized in Table 2 [47]. Visual acuity for a person with 20/20 vision[5] is measured as the minimum angle of the viewing field that must be filled with an image to recognize one feature from the rest of the image (measured in "minutes"), $\frac{20}{20}$ = 1 minute [45].

Most of the acuity measurements in Table 2 suggest that we can resolve visual phenomena, such as the presence of two distinct lines, down to about 1 minute ($\frac{1}{60}^{\circ}$) of visual angle. This is in rough agreement with the spacing of receptors in the center of the fovea. For us to see that two lines are distinct, the blank space between them should lie on a receptor; therefore, we should only be able to perceive lines separated by roughly twice the receptor spacing. However, there are a number of superacuities, like stereo acuity and vernier acuity. A superacuity is the ability to perceive visual properties of the world to a greater precision than could be achieved based on a simple receptor model.

[5] A person with vision that is able to recognize at 20 feet what the average person with good eyesight can recognize at 20 feet

Type	Description
Point acuity (1 arc minute)	The ability to resolve two distinct point targets.
Grating acuity (1-2 arc minutes)	The ability to distinguish a pattern of bright and dark bars from a uniform grey patch.
Letter acuity (5 arc minutes)	The ability to resolve a letter. The Snellen eye chart is a standard way of measuring this ability. 20/20 vision means that a 5-minute letter target can be seen 90% of the time.
Stereo acuity (10 arc seconds)	The ability to resolve objects in depth. The acuity is measured as the difference between two angles for a just-detectable depth difference.
Vernier acuity (10 arc seconds)	The ability to see if two line segments are collinear.

Table 2: Some basic acuities

Postreceptor mechanisms are capable of integrating the input from many receptors to obtain better single-receptor resolution. A good example of this is vernier acuity, the ability to judge the collinearity of two fine line segments. This can be done with amazing accuracy to better than 10 arc second. The resolution of the eye is often measured in cycles per degree and ranges from $\frac{1}{2}$ arc minute (120 cycles/degree) to 1 arc minute (60 cycles/degree). Resolution of 1 arc minute allows one to distinguish detail of 0.01 seconds at 3 feet. Consider a display screen that is 20-inches wide and positioned 22-inches from the viewer. How many pixels across one scanline subtending $45°$ would it take to match human visual acuity? If we assume human visual acuity to be $\frac{1}{2}$ arc minute, then we would need $120 \cdot 45$ = 5400 pixels to match our visual ability [46].

Neural postprocessing can efficiently combine input from two eyes. The area of the overlap is approximately $120°$ with 30-$35°$ monocular vision on each side. Combined horizontal FOV is 180-$190°$ and vertical FOV is 120-$135°$ for both eyes [46]. This suggests that if the data elements in a visualization environment lie within this region of overlap they are identified more accurately than the data elements that lie in the monocular region. Campbell and Green [8] found that binocular viewing improves acuity by 7% as compared with monocular viewing. Interestingly, Campbell and Green's findings suggest that we should be able to use the ability of the eye to integrate information over space and time to allow perception of higher-resolution information than is actually available on our display device. One technique for achieving higher-than-device resolution is anti-aliasing. There is also an intriguing possibility that the temporal-integration capability of the human eye may allow us to distribute information in a high-resolution image over a sequence of frames on a lower-resolution display in a way that the brain integrates back into a single, coherent result.

In the next section we focus on different visual features such as color, texture, and motion with respect to display resolution, visual acuity, applicability to spatial frequency and data domain, and visual interference.

4 Visual Features

A variety of visual features have been used in visualization. Some of them are listed in Table 3 [19]. In this section we describe what we know about the visual features (hue, luminance, texture, and motion), and provide suggestions on how future research could fill in the missing details, and then combine this knowledge into a working visualization system that defines a visualization hierarchy. The next few sections discuss hue, luminance, texture, and motion properties based on domain, visual interference, and spatial frequency, then present examples of each feature within a visualization display.

Feature	**Author**
line (blob) orientation	Julész & Bergen (1983); Wolfe (1992)
length	Triesman & Gormican (1988)
width	Julész (1984)
size	Triesman & Gelade (1980)
curvature	Triesman & Gormican (1988)
number	Julész (1985); Trick and Pylyshyn (1994)
terminators	Julész & Bergen (1983)
intersection	Julész & Bergen (1983)
closure	Enns (1986); Triesman & Souther (1986)
color (hue)	Triesman & Gormican (1988); Nagy and Sanchez (1990); DZmura (1991)
intensity	Beck et al. (1983); Triesman & Gormican (1988)
flicker	Julész (1971)
direction of motion	Nakayama & Silverman (1986); Driver and McLeod (1992)
binocular lustre	Wolfe & Franzel (1988)
stereoscopic depth	Nakayama & Silverman (1986)
3D depth cues	Enns (1990)
lighting direction	Enns (1990)

Table 3: Different Visual Features used in Visualization

4.1 Hue

Color is a visual feature commonly used in visualization. An individual color can be described by providing its hue, saturation, and luminance. Hue is the wavelength we see when viewing light of the given color. Saturation describes how strong (or how far from grey) the color is. Luminance refers to the intensity or brightness of the color. In this report we refer to colors by their hue names. Examples of simple color scales include the rainbow spectrum, red-blue or red-green ramps, and the grey-red saturation scale. More sophisticated techniques divide color along dimensions like luminance, hue, and saturation to better control the difference viewers perceive between different colors. Researchers in visualization have combined perceptually

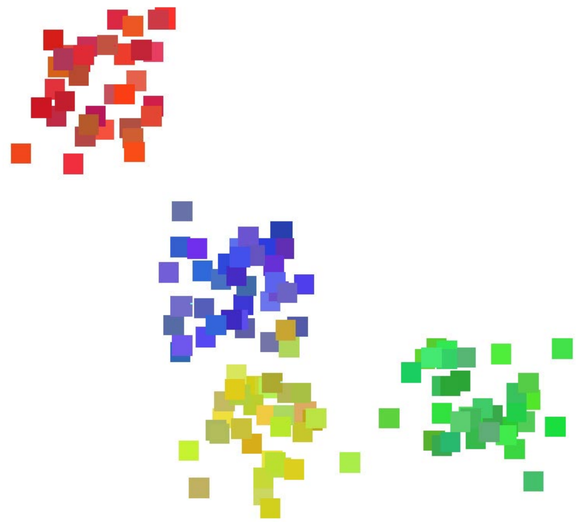

Figure 6: An example of Ware and Beatty's coherency visualization technique, the four clouds of similarly-colored squares represent four coherent groups of data elements

balanced color models with nonlinear mappings to emphasize changes across specific parts of an attribute's domain, and have also proposed automatic colormap selection algorithms based on an attribute's spatial frequency, continuous or discrete nature, and the analysis tasks to be performed. Experiments have shown that color distance, linear separation, and color category must all be controlled to select discrete collections of distinguishable colors [16, 18].

Results show that the preattentive nature of a color depends on the saturation and size of the color patch as well as the degree of difference from its surrounding colors. As a rule of thumb, $\frac{1}{2}^{\circ}$ of visual angle is probably a minimum size for color-coded objects in order to avoid small-field color blindness [47]. One of the limitations of using color as a visual feature is that in peripheral conditions humans are almost colorblind [51] and hence the ability to differentiate between colors drops off drastically at the periphery. Healey showed that at most seven isoluminant colors can be rapidly distinguished from one another in a display [16]. Hue is best suited to represent low spatial frequency nominal data.

One example use of color was proposed by Ware and Beatty to display correlation in a five-dimensional dataset [11]. Each of the five data attributes is mapped to one of the following visual features: position along the *x-axis*, position along the *y-axis*, *red* color, *green* color, and *blue* color. The result is a two-dimensional display of colored squares, each square representing an element in the dataset. Figure 6 shows that groups of elements with all five attributes in common will appear as a spatial cloud of similarly-colored squares.

4.2 Luminance

Luminance is a physical measure that is used to define an amount of light in the visible region of the electromagnetic spectrum [47]. High spatial frequency data (i.e., data with sharp spatial

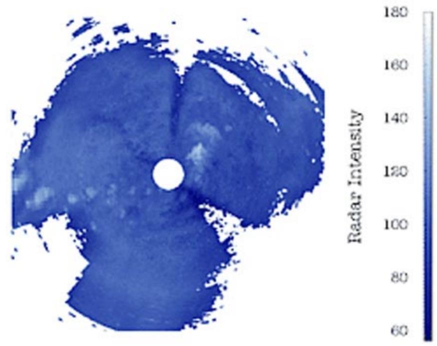

Figure 7: Isomorphic colormap for high spatial frequency data. The high frequency colormap reveals more information in the radar data.

variations in its values) is best represented using luminance. Luminance is also best suited to represent ordinal data. Levkowitz and Herman studied the problem of creating colormaps for data visualization [23]. They knew that a grey-scale (i.e., luminance-based) colormap can provide somewhere between 60 and 90 just-noticeable difference (JND) steps. They attempted to build a linearized optimal color scale (LOCS) that offers a larger perceptual dynamic range during visualization. Levkowitz and Herman showed that an LOCS with 32 values has a perceived color-pair difference six times larger than a linear grey-scale colormap with 32 values [17]. Some other possible color scales are non-linearized grey scale, heated object scale, rainbow scale, and linear optimized color scale.

Previous work reported in [5, 6, 7] showed that a random variation of luminance can interfere with the identification of a boundary between two groups of differently colored elements. Callaghan suggests that intensity is more important than hue to the low-level visual system during boundary identification [5]. In practical terms, this suggests that our low-level visual system "sees" luminance patterns first, and then hue patterns.

Figure 7 shows a radial sweep from a weather radar sensor, measuring the high spatial frequency variation of reflected intensity (e.g., from thick clouds). The luminance-based colormap being used offers a good representation of the minute details in the data [35].

4.3 Texture

Texture refers to the characteristic appearance of a surface having a tactile quality [40]. Texture can be decomposed into a collection of fundamental perceptual properties. Researchers in computer graphics have applied density, height, regularity, directionality, contrast, size, shape, coarseness, and orientation to display information [15, 32, 33, 39]. Individual values of a data attribute can be used to control one of the texture dimensions. The result is a texture pattern that changes its visual appearance based on the underlying data within a dataset.

Height is not considered an "intrinsic textural cue", but is one aspect of element size, that is an important property of a texture pattern. Results from cognitive vision have shown that differences in height are detected preattentively by the low-level visual system [1, 42]. Results from [22] suggest that height is best suited to represent quantitative data, and can support up to five discrete values. Experimental results have shown that hue and luminance cause visual interference with height [22]. In Figure 2, predicted *user rating* is mapped to the height of each tower such that the taller the glyph, the higher the *user rating* and vice-versa.

Density is an important visual feature for performing texture segmentation and classification [39]. Results from [22] suggest that density is best suited to represent low spatial frequency ordinal data. Hue, luminance, and height cause visual interference with density [22].

The visual system differentiates orientation using a collection of perceptual direction categories. Some researchers believe only three categories of orientation exist: flat, tilted, and upright. Wolfe suggests orientation might be divisible into four categories: steep, flat, left, and right [49]. More recent work found that 2D orientation can be used to encode information [48]; a difference of 15° is sufficient to rapidly distinguish elements from one another. Based on perceptual experiments, it was found that hue and luminance cause visual interference with orientation [22]. In Figure 1, *precipitation* is mapped to orientation such that vertical strokes represent little or no rainfall and horizontal strokes represent high rainfall.

Regularity refers to the uniformity of a texture element's spatial position, and is a visual feature that is commonly used to perform texture segmentation and classification in computer vision algorithms [39]. In the human visual system, however, differences in regularity are difficult to detect. Regularity can normally encode only binary information, and is best suited to represent low spatial frequency data. Hue, luminance, height, and density all cause visual interference with regularity [22].

4.4 Motion

Motion is a visual feature that possesses strong perceptual cues. Motion elicits "pop-out" effects in which moving objects can be searched in parallel by the visual system [43]. Motion aids in the process of grouping elements and is effective at providing a general overview of trends in data [4]. The human visual system can also perceive, track and predict movement. Results have shown that motion detection does not deteriorate at the periphery. Motion compares very favorably to color and shape if we are concerned with designing icons to attract a user's attention at the edge of a computer screen [2]. Motion comprises of different features such as motion shape, frequency, amplitude, direction, phase, flicker, and velocity.

Flicker refers to a repeating on-off pattern applied to an image or an object, and is normally measured as the frequency of repetition F in cycles per second (cps). The rate at which successive images need to be presented in order to perceive continuous motion is known as the critical flicker frequency (CFF). F = 60 cps is an often-cited rule of thumb for the CFF, but this number varies depending on the color, brightness, or size of the object being displayed, and on its eccentricity (i.e., the distance in visual angle from the viewer's current focal point to the object). Huber et al. found that for rapid and accurate target detection, flicker must be coherent and must have a cycle length greater than 120 milliseconds [21].

Direction of motion can be used in visualization to help discriminate between groups of elements with similar values. Differences in the direction of motion of glyphs provide cues to help identify individual elements that differ from the neighboring background glyphs. Humans can preattentively and simultaneously track up to five unrelated motion trajectories in the same visual field [31]. Huber et al. found a target patch of moving glyphs can be rapidly and accurately detected within a field of moving glyphs when the angular difference is greater than 20° [21].

The velocity that objects move with is a third property of motion that is rapidly detectable by our visual system. van Doorn and Koenderink showed that higher initial velocities produce a faster response to a change in the velocity [44]. This is due to the need for the target to traverse a "critical distance" before it can be detected. Follow-on work by Mateeff et al. [24] showed that for a baseline velocity V_1 and a target velocity V_2 = $2V_1$, approximately 100 milliseconds is needed to see the velocity change from V_1 to V_2 for slow V_1 (1° per second) and approximately 50 milliseconds for faster V_1 (2° per second or higher). Huber et al. found that velocity of motion must differ by at least 0.43° of subtended visual angle in order to distinguish between different velocities [21].

4.5 Display Resolution and Visual Acuity for Visual Features

Most visualization techniques assume that sufficient display resolution is available and our visual acuity is adequate to complete the required analysis tasks. But, as established in the previous sections, this may not be true. Thus, it is important to determine how many pixels are needed for a visual feature to represent the values of a data attribute effectively, and how much physical size is needed for our visual system to accurately identify and interpret the visual feature. There has been little research to date in this area, particularly in the visualization community. Thus, an important research opportunity is to find out how display resolution and visual acuity affect the mapping of a data attribute to a particular visual feature on a given display device.

5 Conclusions and Future Work

The desire to extract knowledge rapidly and efficiently from large, complex datasets motivates the need for effective visualization techniques. This report suggests that a visualization technique must consider display resolution, physical size, and standard viewing distance in order to maximize the utilization of a display's capabilities in an effective and efficient manner. This report also shows how display resolution and visual acuity can affect the expressiveness of a visualization technique, and begins to characterize to what extent a given technique saturates "visual bandwidth".

Not much is known about the limits of resolution and acuity for visual features common in visualization. Based on our current knowledge of visual features (hue, luminance, texture, and motion), we plan to investigate how display resolution and visual acuity affect our ability to recognize these features during visualization. We plan to design and run controlled experiments that will allow us to determine how many pixels are needed to distinguish different values for a particular visual feature, and what visual resolution is required to "see" the feature. We can then accumulate this knowledge and build a system that allows us to dynamically add or remove information based on a display's resolution properties, our visual abilities, and the type and amount of data we are trying to visualize.

Results from the research described in this report will be used to: (1) investigate how display resolution, visual resolution, and field-of-view angle limit our ability to see different color, texture, and motion properties; (2) construct perceptual display hierarchies that maximizes the amount of information we can see for a given display environment; (3) combine our knowledge of perception and display hierarchies to build a software system that assists users in creating visualizations that are best-suited to their data, analysis tasks and viewing environment; and (4) validate our theoretical findings using real-world application data. Our results will form guidelines on the use of color, texture, and motion across a broad range of display environments.

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