Measuring and evaluating directional textures and using them in visual discovery

Manil Maskey

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MEASURING AND EVALUATING DIRECTIONAL TEXTURES AND USING THEM IN VISUAL DISCOVERY

by

MANIL MASKEY

A DISSERTATION

Submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in The Department of Computer Science to The School of Graduate Studies of The University of Alabama in Huntsville

HUNTSVILLE, ALABAMA

2019
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Submitted by Manil Maskey in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Computer Science and accepted on behalf of the Faculty of the School of Graduate Studies by the dissertation committee.

We, the undersigned members of the Graduate Faculty of The University of Alabama in Huntsville, certify that we have advised and/or supervised the candidate of the work described in this dissertation. We further certify that we have reviewed the dissertation manuscript and approve it in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Computer Science.

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This dissertation focuses on three aspects of directional textures. The first aspect is the development of a new directional texture-based visualization technique to address challenges in visualizing multivariate data in a single display. The technique uses a multi level Markov Random Field-based texture synthesis to progressively generate a visualization that encodes data variables using various texture features, especially texture direction. Since texture directionality has not been used extensively in visualization, this technique provides a new visual cue to display additional data variable in a single display. Evaluations of the new texture-based visualization technique are also presented. The second aspect is the development of a new texture directionality measure to determine directional status of textures. The new texture directionality measure considers both local and global characteristics of textures. A comprehensive comparison study of the new measure with existing measures is also presented. The comparison is the first such study that considers all textures from
the Brodatz texture database. The third aspect is applications of the new texture
directionality measure to several classification problems.

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<td>Dimension of an attribute block</td>
</tr>
<tr>
<td>$u$</td>
<td>x-direction component of wind velocity</td>
</tr>
<tr>
<td>$v$</td>
<td>y-direction component of wind velocity</td>
</tr>
<tr>
<td>$b$</td>
<td>Pressure variable</td>
</tr>
<tr>
<td>$c$</td>
<td>Precipitation variable</td>
</tr>
<tr>
<td>$P$</td>
<td>Location of pixel</td>
</tr>
<tr>
<td>$f(P)$</td>
<td>Pixel intensity at $P$</td>
</tr>
<tr>
<td>$N_P$</td>
<td>Set of offsets from pixel $P$ that expresses the relative position of the neighbors of $P$</td>
</tr>
<tr>
<td>$Q_r$</td>
<td>A coefficient for linear functions</td>
</tr>
<tr>
<td>$v$</td>
<td>Variance</td>
</tr>
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<td>$e(P)$</td>
<td>A stationary Gaussian noise sequence with zero mean at pixel $P$</td>
</tr>
<tr>
<td>$R$</td>
<td>A point in pixel’s neighborhood</td>
</tr>
<tr>
<td>$s$</td>
<td>Neighbors of pixel</td>
</tr>
<tr>
<td>$M^2$</td>
<td>Count of pixels with neighborhoods completely inside image</td>
</tr>
<tr>
<td>$q(s)$</td>
<td>Column vector</td>
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\( S(J) \)  \( \) Sum of squares within groups

\( S(T) \)  \( \) Sum of squares between groups

\( X_{ij} \)  \( j^{th} \) Timed result from \( i^{th} \) texture-based visualization

\( \bar{X}_i \)  \( \) Mean of timed results for \( i^{th} \) texture

\( \bar{X} \)  \( \) Grand mean

\( N_t \)  \( \) Number of textures

\( F_R \)  \( \) F-Ratio

\( M(T) \)  \( \) Mean squared observation between groups

\( M(J) \)  \( \) Mean squared error

\( N_j \)  \( \) Total number of results

\( C \)  \( \) Critical value

\( \alpha \)  \( \) Confidence level

\( s_\alpha \)  \( \) Studentized range statistic

\( g \)  \( \) Auto-covariance function

\( I \)  \( \) Image

\( n_c \)  \( \) Number of columns in image

\( n_r \)  \( \) Number of rows in image

\( \delta \)  \( \) Amount of shift in image

\( t \)  \( \) Threshold
\( \Theta_d \)  Dominant orientation

\( N_{\Theta_d} \)  Number of dominant pixels

\( N_{\Theta_{nd}} \)  Number of non-oriented pixels

\( D_H \)  Directionality measure using Discrete Fourier Polar Coordinates Matrix

\( f(i) \)  Sum of \( i^{th} \) column in Discrete Fourier Polar Coordinates Matrix

\( M(i) \)  Maximum value in \( i^{th} \) column in Discrete Fourier Polar Coordinates Matrix

\( d_3 \)  Max and min pixel intensity differences

\( t_1 \)  Threshold 1

\( t_2 \)  Threshold 2

\( x \)  x Coordinate of a point

\( y \)  y Coordinate of a point

\( \rho \)  Distance of a point from origin in polar space

\( \pi \)  A constant that is approximately 3.14159
CHAPTER 1

INTRODUCTION

Vast amounts of multivariate data are being produced every day from a variety of sources. Here, data that have values recorded for two or more attributes are considered multivariate. For example, some weather datasets contain values for multiple atmospheric variables (attributes), such as the temperature, pressure, and moisture at a given time and location in the atmosphere, etc. The high number of attributes makes this type of data a challenge to visualize effectively. In visualizations of multivariate data, it is useful if the visualization techniques depict the data in ways that facilitate users developing an understanding of the whole data distribution. These techniques should result in a visualization that preserves characteristics of each attribute and allows discovery and observation of inter-attribute correlations. Few visualization techniques are able to simultaneously well-display a high number of attributes of data. The few techniques that are available provide simultaneous visualization of only a few attributes or small, side-by-side displays of individual attributes. An example visualization of weather data with a few variables is shown in Figure 1.1, where wind speed is mapped to color and wind direction is mapped to an arrow glyph. Techniques like these provide only limited assistance to humans
needing to do a data analysis using the visualization. Thus, there is a gap in the visualization capabilities; there are few techniques available to provide insights into multiple attributes of data simultaneously.

![Image 1.1: Traditional multivariate weather data visualization. (Image source: NASA Earth Observatory)](image)

**Figure 1.1:** Traditional multivariate weather data visualization. (Image source: NASA Earth Observatory)

Dealing with multivariate data has been challenging to researchers in many disciplines. Typically, analysis of such data requires determination of outliers, clusters, gaps, and relationships between multiple attributes. Analysts may be able to quickly make actionable decisions if such characteristics are presented visually rather than presented otherwise. This dissertation addresses the challenges of multivariate data visualization by using textures.

Image texture, while hard to well-define, involves some local order repeating over a larger area [33]. In addition to having inherent features such as the size and
degree of regularity in repetition, some textures also have orientation or other inherent features. Texture features have been used extensively in a variety of computer vision and pattern recognition applications [29, 62, 74]. Texture features have also been extensively used to retrieve matching images from large image databases [43, 72, 77]. Methods presented in [29, 43, 62, 72, 74, 77] perform spatial-frequency analysis to encode texture features; however, they have not been used for visualization purposes.

Texture-based solutions are used in many image synthesis arenas. However, textures have not been used as extensively in visualization, despite the research showing that certain characteristics of textures are readily perceived by the human visual system [86]. One readily perceived texture characteristic is directionality. In particular, psychophysical research [15, 39] has suggested that structure orientation in the visual field is found by certain structures in the visual cortex. In addition, psychological experiments by Nothdurft [65, 66] has suggested that the visual cortex uses differences in texture orientations to segment textures. In addition to these motivations for using texture properties in visualization, a user study by Ware and Knight [86] has indicated that humans perceive there to be three fundamental visual characteristics of textures, one of which is orientation. (Texture size and contrast are the other two.) However, while the other two characteristics have been used to some degree in visualization, directionality (i.e., orientedness) of a texture has not been studied (or used) extensively. It should be noted that a few works have described how certain texture characteristics can be synthesized for data visualization ([44, 88]).

While there is a need to use texture directionality in visualization, texture directionality may also be a useful feature for vision and pattern recognition appli-
cations; especially in differentiating between (i.e., classifying) textures. To support using the directionality for texture discrimination, a new measure that can determine the directionality status for a texture is also needed.

The rest of this chapter summarizes the contributions of this dissertation.

1.1 Contribution of the Dissertation

In this dissertation, the focus is on three major aspects of texture directionality: (1) utilizing directional textures for visualization, (2) measuring texture directionality, and (3) using the texture directionality measure in applications.

The first aspect of the research, utilizing directional textures for visualization, focuses on development of a new texture-based visualization technique to address the challenges of simultaneously displaying multiple attributes of data in a single display. This aspect of the research advances use of multiple texture features as visual cues (as suggested by Ware and Knight [86] and Healey and Enns [35]) to support effective multivariate data visualization.

The second aspect of the research, measuring texture directionality, focuses on development of a new measure of texture directionality to determine the directionality status of textures. This aspect of the research advances the state of the art in the study of texture features by providing a widely applicable measure to determine the directionality status of textures.

The third aspect of the research, using the texture directionality measure in applications, focuses on applications of the new texture directionality measure.
This aspect of the research represents contributions to computer vision and pattern recognition knowledge.

This dissertation provides a number of valuable contributions:

1. A new texture-based visualization technique for multivariate data.
2. Evaluations of the new texture-based visualization technique with user studies.
3. A new measure that can determine the directionality status of a texture.
4. A comprehensive comparison study of the new texture directionality measure versus the existing texture directionality measures.
5. A comparative study of all texture directionality measures using human sentiment as a baseline.
6. A number of applications using the new texture directionality measure.

1.2 Organization

The rest of the dissertation is organized as follows. Chapter 2 covers related work. Chapter 3 introduces the new texture-based visualization technique. Chapter 4 presents evaluations of the new texture-based visualization technique. The new texture directionality measure, comparison with existing measures and application examples of the texture directionality measure are presented in Chapter 5. This dissertation concludes and discusses possible future work in Chapter 6.
CHAPTER 2

BACKGROUND AND RELATED WORK

This Ph.D. research is concerned with directional textures, especially utilizing directional textures for visualization and measuring texture directionality. Toward that end, this chapter provides background information on texture-based visualization and texture directionality measure.

2.1 Texture-based visualization

Next, the background work and some preliminary work on utilizing directional textures for visualization are discussed.

For many years, visualization researchers have studied the problem of visualizing multivariate data. A number of researchers have proposed visualization techniques based on texture synthesis for visualizing multivariate data. Here, we provide an overview of techniques in the literature that are related to utilizing textures for visualization.

Some early visualization work questioned the suitability of using textures for visualizing quantitative data [54]. However, the same work showed that features such as slope and angle in an image provided highly useful cues for displaying such data.
Slope and angle features are present in directional textures—textures that consist of texels arranged primarily as periodic linear structures. Later works [44, 86, 88] have demonstrated that texture directionality is a salient feature (a feature that stands out) in visualization. Our focus in this dissertation is on utilizing directional textures for visualization. Next, existing multivariate data visualization techniques, including texture-based techniques, are described.

An approach from Song et al. [78] combines multiple atmospheric datasets into a 3D texture that is then rendered using volume ray casting (VRC). The VRC uses a transfer function to map texture values to a color and opacity. Areas considered interesting by the user are highlighted with overlaid glyphs. Glyph forms are selected by the user. In addition to requiring manual selection of areas of interest, the system is not applicable to data with more than three attributes.

Recently, Khlebnikov et al. [44] have used procedural textures to visualize multivariate data. Their technique can map three data attributes to texture density, color, and directionality for visualization at multiple zoom levels. They have demonstrated and evaluated their visualization using NOAA’s sea surface temperature and precipitation flow data where they mapped a precipitation flow attribute to texture directionality.

Healey and Enns [35] have combined perceptually uniform colors and various glyphs in multivariate data visualization. They collected data attributes for typhoons from National Climate Data Center and Global Hydrology Resource Center for the month of August in 1997. Then they used height, density, and color of glyphs to represent windspeed, pressure, and precipitation data attributes, respectively. The
features and colors in their glyphs were selected based on user studies. In contrast to
texture-based visualization, glyphs take up more space, pressuring screen real estate.

Yang et al. [91] have developed the Value and Relation (VaR) technique to
visualize data with a large number of attributes. Their technique uses a dimensionality
reduction scheme, multidimensional scaling [14], to reduce the dimensionality of the
data and preserve inter-attribute relationships. It also uses standard information
visualization schemes, such as scatterplots. They used the technique to create visual-
ization that is used for exploration large datasets with high dimensionality, including
Image-838 dataset with 838 dimensions and Image-89 dataset with 89 dimensions.
However, the technique has not been used for data with spatial information since use
of the dimensionality reduction scheme does not preserve spatial information.

Hibbard and Santek [37] have developed the VIS-5D system that generates
three dimensional visualizations from up to five dimensional data. The tool is designed
for a specific type of gridded data used by earth scientists. Another system, VisAD,
also by Hibbard, can provide users with interactive visualizations of a set of numerical
simulation data [36]. Both of these systems support a few popular visualization
techniques, including vector glyphs. Several analytic capabilities are available in these
systems; however, the visualizations usually limit display to one or two attributes at a
time per spatial location defined in the data.

Tang et al. [82] have described a technique that uses natural textures that
follow a Markov Random Field model to visualize multivariate weather data. In their
technique, these natural textures are synthesized based on underlying data. The
technique creates triangular patches for each data attribute that is textured. These
triangular patches are used as building blocks for a texture synthesis process that creates a texture image. The resulting synthesized texture image encodes multiple attributes of the data.

Kniss et al. [45] have described use of a direct volume rendering technique to visualize weather data. In the work, a multi-dimensional transfer function is defined for the direct volume rendering. The visualization uses temperature and humidity attributes to help users discover weather fronts. Their approach is limited to visualizing only two attributes at a time. One of the limitations is that, in general, transfer function selection for direct volume rendering is not trivial.

Wickham et al. [89] have presented a visualization technique called glyph-maps for weather/climate data. It represents multiple climate attributes at each geographic location by a generated glyph. That glyph is generated by mapping each attribute of climate data to a graphical feature, such as length of the glyph. The technique takes advantage of the high correlation in space and time of attributes of climate. The technique allows creating a smooth representation of data at nearby locations or time points. Although the technique displays climate data with attributes that can vary over both space and time in a compact form, the resulting glyphs are very small in size, which could complicate analyzing the space-time climate data presented by the visualization.
Miller [61] has introduced the attribute block visualization technique. This technique involves dividing the display area into a number of rectangular sets of pixels, called attribute blocks. Each attribute block is equally subdivided into a group of pixels called a cell. Each cell represents the variation of a single data attribute within the region represented by the attribute block. Attribute blocks allow a number of data attributes at a location to be represented as a unit in a visual presentation [61], which enables visualizing multivariate data. An example attribute block is shown in Figure 2.1. The figure shows an attribute block that has 4 cells, representing 4 different attributes. The attribute block here is $M_a \times M_a$ pixels. Thus, each cell within

Figure 2.1: Sample 2x2 attribute block
the attribute block consists of a region of size \((M_a/2)\times(M_a/2)\) pixels. Each cell is colored distinctly.

Laidlaw et al. [48] and Laramee et al. [49] have presented comparisons of flow visualization techniques. Texture-based flow visualization techniques such as line integral convolution [16] and texture advection [60] are included in their comparisons. Visualizations from these techniques were evaluated using user studies. The evaluation suggested that line integral convolution had average performance across various tasks when compared to other methods. However, line integral convolution performed above average for flow speed detection and critical point detection tasks.

Texture-based visualization techniques require synthesizing a texture given a sample texture. Using a Markov Random Fields-based technique is one way to synthesize the texture. Markov Random Fields are described in detail in Chapter 3 where we discuss the new texture-based visualization technique.

2.1.1 Preliminary Work in Multivariate Data Visualization

Next, our preliminary work in multivariate data visualization is discussed.

2.1.1.1 Application Datasets

Our early work for this dissertation involved implementing a few multivariate data visualization techniques, and we applied them to Weather Research Forecast (WRF) data [3] and Intergovernmental Panel of Climate Change (IPCC) data [2]. WRF is output by simulation models. These models' output consists of 28 different atmospheric attributes, including temperature, precipitation, pressure, wind com-
ponents, and soil moisture content. IPCC is observational data. The IPCC data consists of several meteorological attributes, including temperature, precipitation, wind speed, and radiation. Both types of data include temporal and spatial attributes. The IPCC was established to study climate change and its impact. The IPCC data archive includes several years worth of data from around the world. The full archive is enormous in size. Next, we describe some of the experiments we have done using these data.

2.1.1.2 Multivariate Data Visualizations

The first visualization technique we used is the attribute blocks. As described earlier, attribute blocks can be used to visualize multiple attributes simultaneously [61]. We have applied attribute blocks to visualize the pressure ($b$), wind velocity ($u, v$) and precipitation ($c$) fields of Weather Research Forecast (WRF) [3] datasets. Figure 2.2 shows one attribute block-based visualization of WRF data for Hurricane Isabel for an area off the coast of Florida. The visualization uses attribute blocks that each consist of 4 cells arranged in 2 rows and 2 columns. Each cell uses a 2x2 set of pixels. To the right of the visualization in Figure 2.2, a zoomed view of an attribute block is shown. Here each cell represents a single data attribute. The color assignment for each cell and cell location within an attribute block is consistent throughout all attribute blocks. The top left cell of each block is assigned a greenish-blue color with an intensity that varies with the pressure ($b$) attribute. The top right cell of each block is assigned a reddish color with an intensity that varies with the $u$ attribute (the x-direction component of wind velocity). The bottom left cell of each block is assigned
a greenish color with an intensity that varies with the $v$ attribute (the y-direction component of wind velocity). Finally, the bottom right cell of each block is assigned a bluish color with an intensity that varies with the precipitation $c$ attribute. In the visualization, there are two greenish-blue blobs around the middle of the image indicating low pressure systems in the data. Low pressure systems are associated with the eyes of hurricanes. However, in the visualization, $b$, and $u-v$ cannot be perceived easily. Furthermore, selection of block size is challenging for attribute blocks-based visualization.

Figure 2.2: Attribute block-based visualization of WRF data for hurricane Isabel off the coast of Florida, displaying fields: pressure, $u$ component of wind velocity, $v$ component of wind velocity, and precipitation
Another multivariate data visualization technique that we employed in our early work was to use a visual model in the visualization (i.e., of the weather data) that has or follows a well-known model or structure. An example of such a technique is shown in Figure 2.3. In this case, the visual model is a model of the solar system. Weather data attributes are each mapped to one physical attribute of the model, such as planet size, planet distance from the sun, and the brightness of planets. Specifically, in the visualization, the size of the planet, brightness of the planet and the distance from the sun to the planet, respectively, represent the attributes temperature, pressure, and precipitation of weather data. One problem with such a technique is that as the number of attributes increases, the visualization has a reduced resemblance to the actual phenomenon. Furthermore, spatial relationships are not preserved by this technique.
While implementing these multivariate visualization techniques and applying them to weather data, we encountered issues mainly related to screen real estate constraints. Scaling the techniques to more than three attributes was another issue we encountered. Thus, an alternate technique that closely exploits the human visual system in perceiving multiple attributes seems to be needed. Textures are a good candidate for use in an alternate technique since there is evidence that humans can perceive there to be three fundamental visual characteristics of textures: directionality, size, and contrast in addition to perceiving color characteristics [86]. Thus, multivariate data could be visualized by exploiting color and texture characteristics.

2.2 Texture directionality measure

Next, the background work on measuring texture directionality is discussed.

Most textures can be said to have inherent features, like size and degree of regularity in repetition, and some textures also have directionality or other inherent features. Texture features have been used in many computer vision and pattern recognition applications. For example, Shiranita et al. [74] have used texture features to determine the meat quality. Gorkani and Picard [29] have used texture directionality to detect images of urban areas. Texture features have also been used for detecting tissue masses in mammograms [62] and to retrieve matching images from large image databases [43, 72]. Textures also help in visually differentiating surfaces [13, 64].

Psychological experiments have found that certain characteristics of textures are readily perceived by human and animal vision (e.g., the visual cortex of monkeys includes numerous detectors sensitive to orientation of structures in the visual field.
In addition, orientations within textures offer texture segregation cues to the visual system [66]. Additionally, Ware and Knight [87] have observed that humans perceive that textures have several visual characteristics, such as regularity, size, and orientation.

Here, we focus on determining if a texture is directional and on the use of directional textures in applications. Directionality may be a useful feature for vision and pattern recognition since it could allow differentiating between (i.e., classifying) textures. It may also be useful in other domains (e.g., multimedia).

There are four existing texture directionality measures: Tamura et al. [81] measure, Picard and Gorkani [70] measure, Abbadeni et al. [12] measure, and Hagh-Shenas and Interrante [30] measure. These existing texture directionality measures and applications of texture directionality measures are described in detail in Chapter 5.
CHAPTER 3

TEXTURE-BASED VISUALIZATION

Many image synthesis applications utilize some type of texture synthesis approach [20,76]. For example, texture has been used to synthesize hair and fur [42]. However, textures have not been used as extensively in visualization, despite research showing that certain features of textures are readily perceived by the human visual system [86] and useful for certain computer vision-based tasks, such as visually differentiating surfaces [13,64]. One readily perceived texture feature is directionality of the texture. In particular, psychophysical research [15,39] suggests that the human visual cortex includes numerous detectors sensitive to directionality of structures in the visual field. Also, a user study by Ware and Knight [86] has indicated that humans perceive there to be three fundamental visual features of textures, one of which is directionality. Notthdurft [66] has also suggested that directionalities within texture offer cues used in texture segregation in the visual system.

Ware and Knight’s [86] study found that the other two fundamental visual features of textures are texture size and contrast. These two features have been used to some degree in visualization. For example, Healey and Enns [34] have visualized typhoon data using texture features. They selected one daily observation dataset
focused around the Northwest Pacific Ocean region for their visualization. They depicted a windspeed variable using texture size, a pressure variable using texture density, and a precipitation variable using texture regularity. Sanna et al. [73] have highlighted areas of interest using texture contrast in flow data visualization.

It should be noted that a few works, such as those by Ware and Knight [88] and Khlebnikov et al. [44], have described how certain texture features can be synthesized for data visualization. In their work, Ware and Knight [88] applied Gabor functions-based texture synthesis to a magnetic field dataset where the magnetic field’s orientation was depicted with texture directionality and the magnetic field’s strength was depicted using texture size. Khlebnikov et al. [44] applied Gabor functions-based texture synthesis to a weather dataset where optical flow of precipitation was depicted using texture directionality, precipitation was depicted using texture frequency, and sea surface temperature was depicted using color.

In our research, one focus is on texture directionality and the use of directional textures in visualization, in particular, in multivariate visualization. Ware and Knight [86] and Healey and Enns [35] have suggested that texture features are suitable to use for visual cues for multivariate data visualization. Our work essentially extends a theme in the work of Healey and Enns, who depicted data variables using texture height, density, and regularity [35]. Since texture directionality has been used extensively as a feature for differentiating between textures, our work also has potential value for application to some computer vision, pattern recognition, and graphics problems. A few of these applications are discussed in the application section of the dissertation.
Specifically, in this chapter, we motivate and then describe a new directional texture-based multivariate data visualization technique, present applications of our technique to weather data, and apply texture directionality and other texture features to visualizations of several multivariate datasets to demonstrate that encoding of additional data variable is possible using texture directionality.

3.1 New texture-based data visualization motivations

In this section, we motivate our texture directionality-based visualization technique. The technique ties a dataset variable to texture directionality in visualization. We apply our technique on weather data variables. Next, we describe the reasons for using weather datasets in our new texture-based data visualization.

Weather affects everyday lives and encompasses numerous factors that influence our atmosphere. Weather observers typically log numerical values of atmospheric variables such as air temperature, precipitation, wind speed, etc., several times per day for certain locations. Datasets that aggregate such observations over some region and time interval exist.

Visualization of the weather datasets can assist humans in gaining insights from the weather data easily and promptly [71]. For example, studying the day’s temperature color map in a newspaper provides quick understanding of local and regional forecasts. Similarly, people can easily forecast rain by looking at visual animations of radar maps over time.

Figure 3.1 shows an example (generated by us) that uses a conventional presentation for visualizing temperature data over a map. In the visualization, the
temperature data for the continental United States for one time point is depicted using a rainbow color scale. Figure 3.2 shows an example (generated by us) that uses a conventional presentation for visualizing precipitation data over a map. In the visualization, precipitation data for the continental United States for one time point is depicted using a (non-rainbow) color scale. Both the temperature and precipitation data visualized here are from the National Weather Service (NWS) National Centers for Environmental Prediction (NCEP). These examples show visualization of one weather data variable at a time with the use of color. For simple weather data visualization tasks, such as visualizing one variable in isolation, visualizations that use coloring scales are widely used.

![Temperature data visualization](image)

**Figure 3.1:** Temperature data visualization
However, weather data logs are typically multivariate (i.e., there is more than one weather data variable at a given location and time). When several weather variables need to be studied at the same time, a common current visualization approach is to display multiple single-variable visualization canvases side-by-side (i.e., one canvas per variable). Furthermore, increases in the number of observations, increases in the spatial and temporal resolutions, increases in the number of variables observed, heterogeneous data sources, and advancements in sensors have resulted in increased data size and complexity. Consequently, visualization of such data is not trivial.
The work described in this dissertation chapter aims to improve capabilities for multivariate weather data visualization by displaying multiple variables in a single visualization canvas.

3.2 Technique Description

Next, we describe our new directional texture-based visualization technique.

Our method involves texture synthesis at multiple levels of resolution using a Markov Random Field (MRF) model [24]. A Markov Random Field based image is a random field with a particular property: the probability of a given pixel of the image having a certain value may be determined solely from the values of a fixed neighborhood of surrounding pixels. We give some MRF background next. MRF models of texture are popular in texture recognition in computer vision (e.g., [56]). There, like in our work here, the MRF is used to mathematically describe pixel inter-relationships in a texture. Such a mathematical description can be based on linear or probability functions of pixel intensities. When a linear function is used, the coefficients for each pixel are according to a linear model of the pattern of intensities of the nearby pixels. These coefficients are used as the texture features for each pixel. Various techniques have been used to estimate the coefficients in MRF applications. For example, Chellappa and Chatterjee [20] have used the linear functions of pixel intensities shown in Eqn. 3.1:

\[
    f(P) = \sum_{r \in N_P} Q_r(f(P + r) + f(P - r)) + e(P),
\]  

(3.1)
where \( f(P) \) is the pixel intensity at pixel \( P \), \( N_P \) is a set of offsets from \( P \) (with \( 0 \notin N_P \)) that expresses the relative position of the neighbors of \( P \), \( Q_r \) is a coefficient for the linear functions, and \( e(P) \) is a stationary Gaussian noise sequence with zero mean and variance \( v \). They estimate \( Q_r \) and \( v \) values for each pixel using least squares, then they build a feature vector consisting of the estimated \( Q_r \)'s and \( v \). The noise sequence, \( e(P) \), has the following properties, where \( R \) is a point \( R = P + r, r \in N_P \):

\[
E(e(P)e(R)) = -Q_r v, \quad \text{if} \quad r = P - R, r \in N_p, \\
E(e(P)e(R)) = v, \quad \text{if} \quad P = R, \\
E(e(P)e(R)) = 0, \quad \text{otherwise},
\]

where \( E \) is the expected value.

The estimators \( Q^* \) for \( Q \) and \( v^* \) for \( v \) are:

\[
Q^* = \left[ \sum_s q(s)q^t(s) \right]^{-1} \left[ \sum_s q(s)f(s) \right], \\
v^* = \frac{1}{M^2} \left[ \sum_s (f(s) - Q^* q(s))^2 \right].
\]

Here, the summations are taken over pixels \( s \) (neighbors of pixel \( P \)) whose neighborhood lies completely inside the image. \( M^2 \) is the count of pixels with neighborhoods completely inside the image, and \( q(s) \) is the column vector:

\[
q(s) = [f(s + r_1) + f(s - r_1), f(s + r_2) + f(s - r_2), \ldots, f(s + r_n) + f(s - r_n)],
\]
where \( r_1, r_2, \ldots, r_n \in N_s \), the neighborhood of \( s \). There are many types of neighborhoods that could be utilized based on the connectivity of the neighboring pixels with the pixel \( P \). One example neighborhood is the 8-connected neighborhood of pixel \( P \). It includes all the pixels that are adjacent to \( P \) horizontally, vertically, and diagonally. We use the 8-connected neighborhood in our MRF model.

In our technique, the multi-resolution Markov Random Field (MRF) uses a probabilistic function to describe the inter-pixel relationships. In our modeling of textured images with MRFs, we define the image as a collection of pixel values, each pixel value of which has a certain probability. Thus, for the textured image, we compute the probability of each pixel having a certain value given the value of its neighborhood pixel values, creating a random field (i.e., a field of probability).

Next, we explain our new technique by first describing the steps in detail, then summarizing with a pseudo code, and then finally using an example dataset.

### 3.2.1 Texture Synthesis

Our technique views texture synthesis as a process of producing samples from a Markov Random Field. The synthesis process involves synthesizing an image at multiple (four) scales (sizes). The finest scale (level 1) image is synthesized first followed by the next finest scale (level 2) image and so on. The finest scale is eight times the width and eight times the height of the coarsest scale (level 4). The coarsest scale image is the actual final output image. At each coarser level, the image is half the size of the previous finer scale image in each dimension, and it is formed from the pixels at every other row and column of pixels in the previous finer scale image.
Figure 3.3 illustrates a labelled example of the texture synthesis process at these four scales. The bottom scale is the finest scale and the top scale is the coarsest scale—the actual output image. The finest scale (bottom scale) is synthesized first followed by a coarser level, as shown in the Figure 3.3.

![Figure 3.3: Multi-scale texture synthesis](image)

The following steps make up the texture synthesis process:

Step 1. Initialization: The finest scale’s image pixels are initialized by setting their intensity values to random texels of a predefined set of directional textures. The process that follows begins with the finest scale image.

Step 2. Selection of texture direction: First, the data range for the data variable that is to be depicted using texture direction is determined. That range is then divided into even-sized quantiles. A set of directional textures with even angular separation are also created. The number of quantiles should match the number of directional textures...
so that each quantile can be associated with a directional texture. The association is
made as follows: the quantile containing the lowest data range is associated with the
directional texture having the smallest orientation angle, the quantile containing the
second lowest data range is associated with the directional texture having the next
smallest orientation angle, and so on. At each pixel of the image to be synthesized
(output image), corresponding data value is determined using the location of the pixel.
A quantile containing that data value is used to associate one instance of a directional
texture from the set of directional textures. This associated directional texture is
hereafter referred to as the input texture.

Step 3. Selection of pixel value for the output image: The output image’s pixels are
updated based on the probability density function of pixels from the input texture
(i.e., the selected directional texture from Step 2). For each pixel in the output image,
a probability density function is computed. That one is found by constructing a
histogram of pixel values in a 5x5 neighborhood centered at the pixel in the output
image. That probability density function is compared with each pixel’s (texel’s)
probability density function (also found by constructing a histogram of pixel values
in a 5x5 neighborhood centered at the pixel) in the input texture. In both cases
(probability density functions of pixels in input and output images), the histograms
consisted of 5 bins. We note that a two-pixel wide zero padding is performed around
the edges of both output image and input image so that the 5x5 neighborhoods
centered at the edge pixels could be computed. Euclidean distance is used to find
the distance between the two probability density functions for comparison. The pixel
in the input texture whose probability density function is closest to the probability density function of the pixel in the output image is found based on the Euclidean distance. The value of that input texture pixel is used as the pixel value for the corresponding pixel in the output image. This process is started at the top left pixel of the output image. The output image’s pixels are updated progressively row by row. Note: the 5x5 neighborhoods in the output image may include newly updated pixels and old pixels. The Step 3 is stopped when all pixels in output image have been assigned a value from the input textures.

Step 4. Building next coarser scale: The next scale image is built using the pixel values from the prior finer scale. First, pixels at every other row and column from the prior finer scale are selected. The resulting image is half the size of prior finer output image in each dimension. Step 3 is then applied on the resulting image. This process is repeated until the coarsest level output image is constructed.

Although we start at the first level with a random initialization of pixels, each additional level generates a refined mapping, that gets closer to the data’s local patterns. Thus, this approach is able to achieve an effective refinement.

**Technique Summary**

The pseudocode form of this texture synthesis algorithm is shown in Algorithm 1. The pseudocode describes synthesizing output image at one scale.
Algorithm 1 Texture Synthesis for One Level

**INPUT:** Oriented Textures, Input Data, Image Scale  
**OUTPUT:** Synthesized Output Image

**INITIALIZATION:**

if first level (bottommost finest level) then
    Set all output image pixels to random texels of a predefined set of directional textures
else
    Downsample to form next coarser level
end if

Determine the input data range and divide into even-sized quantiles where the number of quantiles matches the number of oriented textures

for each output image pixel (out pixel) do
    Get corresponding input data value at out pixel location
    Select quantile based on input data value
    Select texture direction based on the quantile the input data value is assigned to
    Compute probability density function (as histogram with 5 bins) of out pixel using 5x5 neighboring pixels (use zero padding for neighbors outside of output image)

    for each texel of oriented (input) texture do
        Compute probability density function (as histogram with 5 bins) of texel using 5x5 neighborhood pixels (use zero padding for neighbors outside of texture)
        Compare probability density functions of out pixel and texel
    end for
    Out pixel ← best matching texel (i.e., Euclidean distance)
end for

**Technique Example**

In Figure 3.4, we present an example application of our technique for one scale (level 1 in Figure 3.3) of the output image generation using a weather dataset. At the top of the figure is the grid that represents the data (labelled as “Data”). The callout labelled “Data Values” shows sample data values at the green dot and its surrounding locations.

First the data range of the dataset’s one variable to be depicted is determined. That range is then divided into 8 even-sized quantiles. 8 directional textures with...
even angular separation are also created; orientations were 22.5 degrees apart (that is, rotations of 0 degree (no rotation), 22.5 degrees, 45 degrees, 67.5 degrees, 90 degrees, 112.5 degrees, 135 degrees, and 157.5 degrees were applied to the texture). Each quantile is associated with a texture direction, where the quantile with the lowest data range is associated with the 0 degrees oriented texture, the quantile with the second lowest data range is associated with the 22.5 degrees oriented textures, and so on. The second row of images from the top in the figure shows the set of the used directional textures labelled as “Input Texture Orientations”. The third row of the figure shows the output image synthesis in progress (labelled as “Output Image”). In this example, the output image is still not yet fully synthesized. The green dot in the data grid (top of the figure) indicates the corresponding location in the input data for which the output image pixel (the red pixel in the output image) is being synthesized for one scale. The texture orientation used here (for every pixel in the output image) is determined as follows. Based on the data value at the green dot in the data grid, the data quantile is determined. Then the directional texture associated with the data quantile is determined.

Next, the probability density function at the output pixel (red pixel) is computed. The probability density function is computed by constructing a histogram of pixel values in a 5x5 neighborhood centered at the red pixel. In the Figure 3.4, this neighborhood is the red dotted square in the output image that is centered at the red pixel. A scaled version of the 5x5 neighborhood is shown in the callout at the bottom of the Figure 3.4. For each texel in the input texture, a probability density function is computed by constructing a histogram of pixel values in the 5x5 neighborhood.
centered at the pixel. In the Figure 3.4, some example neighborhoods are shown as yellow dotted squares for one of the input textures (i.e., the third texture from the left in the row labelled “Input Texture Orientations”). The probability density function for each texel in the input texture is compared against the probability density function at the output pixel (red pixel). The comparison is performed using the Euclidean distance. The texel with the most similar probability density function to the output pixel’s (red pixel) probability density function is chosen as the new value for the red pixel in the output image.

If multiple variables need to be used in the visualization, multiple texture properties are used to determine the output value for each pixel, based on the other data variable values for the dataset location associated with that pixel. For example, texture size and density can be used to depict the values of the other data variables. (Since the focus here is solely on texture directionality, we discuss just the one data variable mapped to direction.)

3.3 Technique Application

In this section, we show some example applications of the technique to Weather Research Forecast (WRF) [3] and Intergovernmental Panel of Climate Change (IPCC) data [2]. WRF and IPCC were described in Chapter 2. Both data types have temporal as well as spatial variables. The IPCC data includes several meteorological parameters. IPCC data is retrievable from the IPCC Data Distribution Centre (http://ipcc-data.org/). The IPCC data is from around the world, with some data from as far back as 1960. The large IPCC data archive is often used in climate change studies.
Figure 3.4: New texture synthesis technique at one scale (i.e., level 1 in Figure 3.3) of output image
First, we exhibit visualization of one WRF weather dataset for Hurricane Isabel off the Eastern Florida coast at 11 PM on September 17, 2003. The wind direction of the WRF data is visualized using texture. Wind direction values are quantized into 8 intervals where each quantile is mapped to one of eight directions (textures with even angular separation of 22.5 degrees) of the Brodatz D49 texture (we use a 25x25 instance of D49). Wind direction of 0° is indicated by horizontal orientation of the texture.

The visualization is shown in Figure 3.5. The circular wind pattern around the eye of the hurricane is noticeable here. (The eye is approximately at the figure center.)

In Figure 3.6, we show application to another scenario—of a gapwind event a common weather phenomena in Central America when wind speed reaches a high level along a coastline. The dataset here was an observational data on January 12, 2009.

Sea surface temperature is indicated here using texture direction. To do that, the sea surface temperature data values were first quantized into 18 intervals. Each quantile was then mapped to one of 18 texture directions, where the quantile with the lowest temperature range was mapped to the 10 degrees texture direction, the quantile with the next lowest temperature range was mapped to the 20 degrees texture rotation, and so on.

Wind speed is indicated here using texture size. To do that, the wind speed data values were first quantized into 4 intervals. Each quantile was then mapped to one of 4 texture sizes, where the quantile with the highest wind speed range was
Figure 3.5: Hurricane Isabel WRF data visualization

mapped to the largest texture size, the quantile with the next highest wind speed range was mapped to the next largest texture size, and so on.

In the Figure 3.6, the increased texture sizes around the coastline near the Gulf of Tehuantepec (near the center of the image) can be seen, indicating increased wind speed. Also in the figure, circular textures near the Gulf of Papagayo (near the bottom center of the image) can be seen, indicating varying sea surface temperature.
3.4 Texture Features for Multivariate Data

In this section, we discuss use of texture directionality and other texture features together for multivariate data visualizations. We focus on encoding more than 3 variables using texture features combined with other visualization mechanisms, such as color and glyphs.

The types of textures we use in rest of the section are shown in Figure 3.7. A few of these textures (e.g., nylon fabric) have unequal horizontal versus vertical spacing, resulting in them having less rotational symmetry than might first be expected.

3.4.1 Texture Features for Map-based Multivariate Data Visualization

Map-based visualizations are common for visualizing geospatial information. In the next few multivariate data visualizations, we extend map-based visualization...
Figure 3.7: Texture patterns used in multivariate data visualizations

Figure 3.8: Multivariate weather data visualization

to depict additional data variables using texture features (in particular, a directional texture feature) combined with other visualization mechanisms.

The first visualization is shown in Figure 3.8. That visualization shows an application of our directional texture-based visualization technique to multivariate

For this application, wind direction is indicated using texture direction. To do that, the wind direction data values were first quantized into 18 intervals. Each quantile was then mapped to one of 18 texture directions, where the quantile with the lowest wind direction range was mapped to the 0 degree texture direction, the quantile with the next lowest wind direction range was mapped to the 10 degrees texture rotation, and so on.

Temperature here is indicated using texture fineness. To do that, the temperature data values were first quantized into 5 intervals. Each quantile was then mapped to one of 5 texture scales, where the quantile with the highest temperature range was mapped to the finest scale, the quantile with the next highest temperature range was mapped to the next finest scale, and so on.

Tornado index (a probability measure for tornadic activity) here is indicated using a cyclone-shaped glyph, where higher index values are indicated with more circulation spirals in the glyph.

Wind speed here is indicated using glyph color. To do that, the wind speed data values were first quantized into 5 intervals. Each quantile was then mapped to one of 5 color tuples on a red, green, blue (RGB) scale with a range of [0,255]: (255,255,204), (161,218,180), (65,182,196), (44,127,184), and (37,52,148), in this order. That is, the quantile with the lowest wind speed range was mapped to (255,255,204), the quantile with the next lowest wind speed range was mapped to (161,218,180), and
so on. These colors are two shades of blue, two shades of green, and yellow. (These two blues and two greens form an analogous color harmony [26].)

This visualization is able to present four variables of the data simultaneously. In addition, location information is also encoded using the map-based visualization. In the Figure 3.8, it seems apparent that Gulf states have higher tornado index, higher temperature, and higher wind speed.

The second visualization is shown in Figure 3.9. That visualization shows an application of our directional texture-based visualization technique to multivariate economic data from the United States Census Bureau [4] for the contiguous U.S. states for the year 2005. The visualization uses texture, color, and a coin glyph.

For this application, each state’s amount of debt is indicated using texture directionality. To do that, the debt values were first quantized into 10 intervals. Each quantile was then mapped to one of 10 texture directions, where the quantile with
the highest debt range was mapped to the 90 degrees oriented texture (vertical), the quantile with the next highest debt range was mapped to the 80 degrees oriented texture, and so on.

Each state’s unemployment rate here is indicated using texture fineness. To do that, the unemployment rate data values were first quantized into 5 intervals. Each quantile was then mapped to one of 5 texture scales, where the quantile with the highest unemployment rate range was mapped to the finest scale, the quantile with the next highest unemployment rate range was mapped to the next finest scale, and so on.

Each state’s total population here is indicated using texture color. To do that, the population data values were first quantized into 7 intervals. Each quantile was then mapped to one of 7 color tuples on a red, green, blue (RGB) scale with a range of \([0,255]\): \((136,65,157), (179,0,0), (239,101,72), (255,237,160), (0,68,27), (116,196,118),\) and \((116,169,207)\), in this order. That is, the quantile with the highest population range was mapped to \((136,65,157)\), the quantile with the next highest population range was mapped to \((179,0,0)\), and so on.

Each state’s gross domestic product (GDP) here is indicated using the number of coins in the coin glyph. To do that, the GDP data values were first quantized into 8 intervals. Each quantile was then mapped to one of a stack of coins of height 1 to 8 coins, where the quantile with the highest GDP range was mapped to an 8 coin stack, the quantile with the next highest GDP range was mapped to a 7 coin stack, and so on.
This visualization is able to present four variables of the data simultaneously. In addition, location information is also encoded using the map-based visualization. In the Figure 3.9, it seems apparent that California has the highest population, most debt, and highest GDP.

Figure 3.10: Multivariate geospatial data visualization (5 variables per country) using multiple texture features

The third visualization is shown in Figure 3.10. That visualization shows an application of the directional texture-based visualization technique to multivariate data visualization of certain properties of countries. The data visualized here is from the World Bank [10] for the year 2016.
For this application, total population of countries is indicated using texture type. To do that, the total population values were first quantized into 8 intervals. Each quantile was then mapped to one of 8 texture types from the ones shown in Figure 3.7: wave texture pattern, weave texture pattern, circle texture pattern, square texture pattern, cross texture pattern, nylon fabric texture pattern, hat texture pattern, and line texture pattern, in this order. That is, the quantile with the highest population range was mapped to the wave texture pattern, the quantile with the next highest population range was mapped to the weave texture pattern, and so on.

Gross domestic product (GDP) of countries here is indicated using texture stroke color. To do that, the GDP values were first quantized into 10 intervals. Each quantile was then mapped to one of 10 texture stroke color tuples on a red, green, blue (RGB) scale with a range of [0,255]: (102,37,6), (153,52,4), (180,60,5), (204,76,2), (236,112,20), (254,153,41), (254,196,79), (254,227,145), (255,247,188) and (255,255,229), in this order. That is, the quantile with the lowest GDP range range was mapped to (102,37,6), the quantile with the next lowest GDP range was mapped to (153,52,4), and so on.

Literacy rate of countries here is indicated using texture direction. To do that, the literacy rate data values were first quantized into 18 intervals. Each quantile was then mapped to one of 18 texture directions, where the quantile with the lowest literacy rate range was mapped to the 170 degrees oriented texture, the quantile with the next lowest literacy rate range was mapped to the 160 degrees oriented texture, and so on.
Crime rate of countries here is indicated using texture background color. To do that, the crime rate data values were first quantized into 10 intervals. Each quantile was then mapped to one of 10 texture background color tuples on a red, green, blue (RGB) scale with a range of [0,255]: (240,244,238), (247,252,245), (229,245,224), (199,233,192), (161,217,155), (116,196,118), (65,171,93), (35,139,69), (0,109,44), and (0,68,27), in this order. That is, the quantile with the lowest crime rate range was mapped to (240, 244, 238), the quantile with the next lowest crime rate range was mapped (247,252,245), and so on.

Life expectancy of countries here is indicated using texture density (compactness of texture elements such as circles and squares). To do that, the life expectancy data values were first quantized into 5 intervals. Each quantile was then mapped to one of 5 texture densities, where the quantile with the highest life expectancy range was mapped to the most dense texture, the quantile with the next highest life expectancy range was mapped to the next most dense texture, and so on.

This visualization is able to present five variables of the data simultaneously. In addition, location information is also encoded using the map-based visualization. In the Figure 3.10, it seems apparent that most European countries have lower populations, have high literacy rates, and have minimal crime. Specifically, the very high literacy rates of most of the European countries stand out distinctly, which are indicated by the horizontal textures.
The fourth visualization is shown in Figure 3.11. That visualization shows an application of the directional texture-based visualization technique to multivariate weather data visualization. The data visualized here is from the weather forecast data [6] in and around Japan. The data has a spatial resolution of 0.25 degrees latitude and longitude. Here, we only use one type of texture, the hat texture.

For this application, air pressure is indicated using texture direction. To do that, the air pressure data values were first quantized into 9 intervals. Each quantile was then mapped to one of 9 texture directions, where the quantile with the lowest air pressure data range was mapped to the 80 degrees oriented texture, the quantile with the next lowest air pressure data range was mapped to the 70 degrees oriented texture, and so on.
Air temperature here is indicated using texture stroke color. To do that, the air temperature data values were first quantized into 4 intervals. Each quantile was then mapped to one of 4 texture stroke color tuples on a red, green, blue (RGB) scale with a range of $[0,255]$: (12,24,196), (34,94,168), (227,26,28), and (215,48,31), in this order. That is, the quantile with the lowest air temperature range was mapped to (12,24,196), the quantile with the next lowest air temperature was mapped to (34,94,168), and so on.

Soil moisture here is indicated using texture background color. To do that, the soil moisture data values were first quantized into 10 intervals. Each quantile was then mapped to one of 10 texture background color tuples on a red, green, blue (RGB) scale with a range of $[0,255]$: (240,244,238), (247,252,245), (229,245,224), (199,233,192), (161,217,155), (116,196,118), (65,171,93), (35,139,69), (0,109,44), and (0,68,27), in this order. That is, the quantile with the lowest soil moisture range was mapped to (240, 244, 238), the quantile with the next lowest soil moisture range was mapped to (247,252,245), and so on.

Wind speed here is indicated using texture size (i.e., the size of the “hat” texture element). To do that, the wind speed data values were first quantized into 8 intervals. Each quantile was then mapped to one of 8 texture sizes, where the quantile with the highest wind speed range was mapped to the largest texture size, the quantile with the next highest wind speed range was mapped to the next largest texture size, and so on.

This visualization is able to present four variables of the data simultaneously. In addition, location information is also encoded using the map-based visualization.
In the Figure 3.11, it seems apparent that the temperature and wind speed over seas and ocean are generally higher than over the land. Furthermore, the pressure over seas and ocean is lower in general than over land.

**Figure 3.12:** Multivariate US disease data visualization using multiple texture features
The fifth visualization is shown in Figure 3.12. That visualization shows an application of the directional texture-based visualization technique to multivariate disease cases data visualization. The data visualized here is from the Center for Disease Control [5] for the U.S. states during the year 2018.

For this application, the number of non-neuroinvasive disease cases is indicated using texture type. To do that, the number of non-neuroinvasive disease cases was first quantized into 6 intervals. Each quantile was then mapped to one of 6 texture types from the ones shown in Figure 3.7: wave texture pattern, square texture pattern, circle texture pattern, line texture pattern, cross texture pattern, and nylon fabric texture pattern, in this order. That is, the quantile with the largest range for the number of non-neuroinvasive disease cases was mapped to the wave texture pattern, the quantile with the next largest range for the number of non-neuroinvasive disease cases was mapped to the square texture pattern, and so on.

The number of presumptive viremic blood donors cases here is indicated using texture direction. To do that, the number of presumptive viremic blood donors cases was first quantized into 18 intervals. Each quantile was then mapped to one of 18 texture orientations, where the quantile with the lowest range for the number of presumptive viremic blood donors cases was mapped to the 10 degrees oriented texture, the quantile with the next lowest range for the number of presumptive viremic blood donors cases was mapped to the 20 degrees oriented texture, and so on.

The number of zika cases here is indicated using texture density. To do that, the number of zika cases was first quantized into 5 intervals. Each quantile was then mapped to one of 5 texture densities, where the quantile with the largest range for the
number of zika cases was mapped to the most dense texture, the quantile with the next largest range for the number of zika cases was mapped to the next most dense texture, and so on.

The number of deaths here is indicated using texture stroke color. To do that, the number of deaths data was first quantized into 10 intervals. Each quantile was then mapped to one of 10 texture stroke color tuples on a red, green, blue (RGB) scale with a range of $[0,255]$: (240,244,238), (247,252,245), (229,245,224), (199,233,192), (161,217,155), (116,196,118), (65,171,93), (35,139,69), (0,109,44), and (0,68,27), in this order. That is, the quantile with the lowest range for the number of deaths was mapped to (240, 244, 238), the quantile with the next lowest range for the number of deaths was mapped to (247,252,245), and so on.

This visualization is able to present four variables of the data simultaneously. In addition, location information is also encoded using the map-based visualization. In the Figure 3.12, it seems apparent that California had the highest number of cases for all the diseases and the highest number of deaths.

3.4.2 Texture Features for Non Map-based Multivariate Data

In this section, we present new multivariate data visualizations that we have constructed. They utilize texture features combined with other visualization mechanisms to depict data variables in non map-based visualizations.
Figure 3.13: Multivariate industrialized nation temporal economic data visualization using multiple texture features
The first visualization is shown in Figure 3.13. That visualization shows an application of the directional texture-based visualization technique to multivariate data visualization of economic indices for seven industrialized nations [9] during the years 1990-2013. The country labels are abbreviated along the rows as follows: AUS for Australia, ARG for Argentina, GER for Germany, UK for United Kingdom, USA for United States of America, FRA for France, and CAN for Canada.

For this application, productivity of countries is indicated using texture density. To do that, the productivity data values were first quantized into 5 intervals. Each quantile was then mapped to one of 5 texture densities, where the quantile with the lowest productivity range was mapped to the most dense texture, the quantile with the next lowest productivity range was mapped to the next most dense texture, and so on.

Purchasing power of countries here is indicated using texture direction. To do that, the purchasing power data values were first quantized into 18 intervals. Each quantile was then mapped to one of 18 texture directions, where the quantile with the lowest purchasing power range was mapped to the 10 degrees orientation, the quantile with the next lowest purchasing power range was mapped to the 20 degrees orientation, and so on.

Total hours worked of countries here is indicated using texture stroke color. To do that, the total hours worked data values were first quantized into 10 intervals. Each quantile was then mapped to one of 10 texture stroke color tuples on a red, green, blue (RGB) scale with a range of \([0,255]\): \((240,244,238)\), \((247,252,245)\), \((229,245,224)\), \((199,233,192)\), \((161,217,155)\), \((116,196,118)\), \((65,171,93)\), \((35,139,69)\), \((0,109,44)\), and
(0,68,27), in this order. That is, the quantile with the lowest total hours worked range was mapped to (240,244,238), the quantile with the next lowest total hours worked range was mapped to (247,252,245), and so on.

Gross domestic product (GDP) of countries here is indicated using texture background color. To do that, the GDP values were first quantized into 8 intervals. Each quantile was then mapped to one of 8 texture background color tuples on a red, green, blue (RGB) scale with a range of \([0,255]\): (237,248,177), (199,233,180), (127,205,187), (65,182,196), (29,145,192), (34,94,168), (12,44,132), and (44,127,184), in this order. That is, the quantile with the lowest GDP range was mapped to (237,248,177), the quantile with the next lowest GDP range was mapped to (199,233,180), and so on.

This visualization is able to present four variables of the data simultaneously. In addition, time information is also displayed in columns, and country identity is displayed in rows. In the Figure 3.13, it seems apparent that the United States of America has the most purchasing power and the highest GDP; people in the United States of America also work long hours. Furthermore, it also seems apparent that the United States of America’s GDP has risen over the years. Unusually high purchasing power of the United States of America can be distinctly noticed in the Figure 3.13. This is due to the texture orientations that are much higher in the row that represents the United States of America than any other rows.
The second visualization is shown in Figure 3.14. That visualization shows an application of the directional texture-based visualization technique to multivariate data visualization of global ocean health index [8] for the year 2016 for 8 coastal countries. The global ocean health index is a framework to monitor ocean health and includes several measures: natural product index, carbon storage index, fisheries index, mariculture opportunity, and artisanal fishing opportunity. Natural product
index [8] measures the amount of ocean-derived natural resources that are extracted from living marine resources, carbon storage index measures [8] the preservation of coastal habitats that store carbon, fisheries index measures [8] the wild-caught fish harvests with respect to overall potential, mariculture opportunity [8] measures the commercial harvest of seafood, and artisanal fishing opportunity [8] measures the availability of fish to those who rely on those fish for their livelihood.

For this application, we adapted a standard color pie chart diagram to visualize the global ocean health index data. The pie chart sectors were filled with textures.

The 8 countries here are indicated using 8 texture types from the ones shown in Figure 3.7. The United States of America was mapped to the wave texture pattern, the United Kingdom was mapped to the square texture pattern, Spain was mapped to the circle texture pattern, Sweden was mapped to the line texture pattern, Thailand was mapped to the weave texture pattern, China was mapped to the hat texture pattern, Japan was mapped to the cross texture pattern, and Canada was mapped to the nylon fabric texture pattern.

Natural product index here is indicated using texture direction. To do that, the natural product index data values were first quantized into 18 intervals. Each quantile was then mapped to one of 18 texture directions, where the quantile with the lowest natural product index range was mapped to the 10 degrees oriented texture, the quantile with the next lowest natural product index range was mapped to the 20 degrees oriented texture, and so on.

Carbon storage index here is indicated using texture density. To do that, the carbon storage index data values were first quantized into 5 intervals. Each quantile
was then mapped to one of 5 texture densities, where the quantile with the lowest carbon storage index range was mapped to the most dense texture, the quantile with the next lowest carbon storage index range was mapped to the next most dense texture, and so on.

Fisheries index here is indicated using texture stroke color. To do that, the fisheries index data values were first quantized into 10 intervals. Each quantile was then mapped to one of 10 texture stroke color tuples on a red, green, blue (RGB) scale with a range of \([0,255]\): \((240,244,238)\), \((247,252,245)\), \((229,245,224)\), \((199,233,192)\), \((161,217,155)\), \((116,196,118)\), \((65,171,93)\), \((35,139,69)\), \((0,109,44)\), and \((0,68,27)\), in this order. That is, the quantile with the lowest fisheries index range was mapped to \((240,244,238)\), the quantile with the next lowest fisheries index range was mapped to \((247,252,245)\), and so on.

This visualization is able to present four variables of the data simultaneously. In addition, mariculture and artisanal fishing opportunities are encoded using the arc width and arc length, respectively. In the Figure 3.14, it seems apparent that the United States of America has a high natural product index, a high carbon storage index, and a high fisheries index.

3.4.3 Texture Features for Positional Multivariate Data Visualization

In this section, we present another series of new multivariate data visualizations that we have constructed. They utilize texture features combined with other visualization mechanisms to depict data variables in a dataset with positional information.
Here, the positional multivariate datasets are from first half statistics for two soccer matches played by Wayne Rooney, a professional player, when he was playing for the Manchester United Football Club (Man-U, hereforward). The dataset includes positional information of Wayne Rooney on a soccer field and his activities at those positions.

The first visualization is shown in Figure 3.15. That visualization shows Wayne Rooney’s activities during a match between Man-U and Crystal Palace Football Club on November 8, 2014. The second visualization is shown in Figure 3.16. That visualization shows Wayne Rooney’s activities during a match between Man-U and Arsenal Football Club on November 22, 2014.

In both visualizations, time of the activity within the game here is indicated using texture direction. To do that, the time values were first quantized into 9 intervals. Each quantile was then mapped to one of 9 texture directions, where the quantile with the lowest time range was mapped to the 20 degrees texture orientation, the quantile with the next lowest time range was mapped to the 40 degrees texture orientation, and so on.

Type of pass here is indicated using texture size. To do that, aerial pass was mapped to large texture size and ground pass was mapped to small texture size.

Distance of the pass or shot here is indicated using texture stroke width. To do that, the pass or shot distance values were first quantized into 5 intervals. Each quantile was then mapped to one of 5 texture stroke widths, where the quantile with the longest pass or shot distance range was mapped to the largest texture stroke.
Figure 3.15: Visualization of Wayne Rooney's activities during Man-U vs. Crystal Palace Football Club.
Figure 3.16: Visualization of Wayne Rooney’s activities during Man-U vs. Arsenal Football Club
The quantile with the next longest pass or shot distance range was mapped to the next largest texture stroke width, and so on.

Type of action here is indicated using texture type (from the ones shown in Figure 3.7). To do that, driving pass was mapped to the wave texture pattern, volley was mapped to the square texture pattern, through pass was mapped to the hat texture pattern, and header was mapped to the cross texture pattern.

Pass recipient (for a completed pass), shot outcome, or incomplete pass here are indicated using texture stroke color. To do that, completed pass to a forward was mapped to a beige texture stroke color, completed pass to a midfielder was mapped to a blue texture stroke color, completed pass to a defender was mapped to a red texture stroke color, shot off target was mapped to a dark violet texture stroke color, shot on target was mapped to a magenta texture stroke color, and incomplete pass was mapped to a yellow texture stroke color.

These visualizations are able present five variables of the data simultaneously. In addition, the positional information is also displayed using circles, which indicate the positions of Wayne Rooney relative to the soccer field. In the Figures 3.15 and 3.16, it seems apparent that Wayne Rooney was more active around the center of the field in the game against Crystal Palace Football Club than the game against Arsenal Football Club. Additionally, he took more shots against Arsenal Football Club than against Crystal Palace Football Club.
3.4.4 Conclusion

In this chapter, we motivated and described a new texture-based visualization technique that utilizes a Markov Random Field-based probabilistic model for texture synthesis. The technique progressively achieves texture patterns that come to mimic local data patterns as the technique proceeds. We demonstrated our technique by applying it to weather data. We also used texture features (including directionality) combined with other visualization mechanisms to visualize different types of multivariate datasets. In all of our applications, texture directionality was used to depict one of the data variables, which allowed encoding of one more variable in a single display (than if only other, standard visual cues were used). We note that our technique, which is described in [57], has been extended by Kumpf et al. [46] to visualize ensemble weather forecasts.

Our visualization technique considers a uniform stepsize for texture directions, however, the visual system response to orientation has been shown to be non-uniform for images with certain levels of noise and spatial frequency of pattern [15]. Furthermore, it appears that there are stronger responses to some orientations of patterns than others [68]. Additional work in visualization evaluation is needed to determine the optimal number of texture directions and optimal stepsizing for the directions for visualization.

In the visualizations discussed in this chapter, we do not claim that we have selected the most optimal mapping of a set of data attributes to a set of visual attributes. The focus in these visualizations is the simultaneous display of multiple
attributes of data, and an important contribution of this work is the demonstration of such capability using directional textures.
EVALUATIONS OF TEXTURE-BASED VISUALIZATION

In this chapter, we describe evaluations of our texture-based visualization technique. The evaluations are based on user studies.

These evaluations consider the usefulness of texture directionality-based visualizations using two user studies, which are reported next. The first one is an image classification user study that involves classifying textures to construct a set of directional and non-directional baseline textures. The second one is an event discovery user study that involves a timed task to identify and locate an event within an image generated using the baseline textures. The baseline textures constructed from the image classification user study are ones that were used in our texture-based visualization described in Chapter 3. Statistical tests to determine statistical significance of the second user study results are also reported in this chapter.

The protocols for both user studies were approved by the institution’s human subjects committee. Different groups of participants were recruited for the two user studies. Next, the user studies are described.
4.1 Image Classification User Study (Study 1)

The image classification user study involved study participants classifying images. The goal of this user study was to construct a baseline set of directional and non-directional textures. Before participants attempted the main task of the user study, they were given a definition of texture: “a texture is an image sub-region that
consists of a semi-uniform pattern (e.g., stripes, textile weaves, etc.).” They were also all shown a sample texture image (Figure 4.1).

In the study, the main task for each participant was to classify 15 (256x256) Brodatz textures into one of three classes: highly directional, highly non-directional, and somewhat directional. These 15 textures, shown in Figure 4.2, were randomly selected from the Brodatz texture database. We used this subset rather than the complete set of Brodatz textures to avoid user fatigue. During the user study, the images were shown on a computer screen one at a time. The study was conducted in a room with well-distributed diffuse light. Three check boxes were displayed by each image labelled: “Highly Directional”, “Highly Non-Directional”, and “Somewhat Directional”. Participants were asked to check the box indicating their selections. Figure 4.3 shows a sample image used in the user study with the check boxes beside it. Each user selection was recorded in a text file.

4.1.1 Study 1 Subjects

Twenty two individuals participated in the image classification user study. All participants were recruited from a computer science classroom. Each participant completed the study isolated from the other participants. Each participant completed the study in the same room with the same lighting condition and on the same computer.
Figure 4.2: The Brodatz textures used in Study 1
4.1.2 Study 1 Results

The overall results from the image classification user study are shown in Table 4.1, where non-directional, highly directional, and somewhat directional textures are denoted by 0, 2, and 1, respectively.

Our goal of the image classification user study was to construct a baseline set of directional and non-directional textures. Toward that end, we examined the results for textures where all participants had agreement. All participants were in agreement in classifying two textures (D49 and D65) as highly directional textures and four textures (D9, D31, D60, and D86) as highly non-directional textures. Although participants did not agree unanimously on classifying any texture as a somewhat directional texture, the majority of the participants were in agreement in classifying one texture (D78) as somewhat directional. Since we only had two textures (D49 and
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

0: Highly non-directional texture classification  
1: Somewhat directional texture classification  
2: Highly directional texture classification

**Table 4.1:** Image classification user study results
D65) that all participants agreed were highly directional, to have the same number of highly non-directional textures in the baseline set of textures, we randomly selected two highly non-directional textures (D9 and D86) that all participants agreed upon for the baseline set. We only selected one somewhat directional texture (i.e., D78) for the baseline set, though, since there was less consensus on the somewhat directional textures. Thus, our baseline set of textures consisted of textures: D49, D65, D9, D86 and D78. The baseline set was used in the second user study, the event discovery user study, as input textures for our new texture-based visualizations. (We used those visualization for evaluations of texture directionality in visualization, as described next.)

4.2 Event Discovery User Study (Study 2)

The second user study, the event discovery user study, involved study participants evaluating images of visualizations. This study follows a guideline from Tory [83]—according to Tory, a user study designed to address a research question of whether a visualization is perceptually meaningful should include two major components. The first component is the use of a perceptual attribute for visualization. The second component is the use of the visualization to illustrate an event (that is, a phenomenon that may be present in the visualized data). Furthermore, Tory has suggested that the user study should be analyzed using a metric such as the time for user study participants to notice such events. In addition, Tory has suggested that using time as a metric provides finer granularity in measurement than using binary measures such as yes/no or true/false measures. Several researchers [47, 69]
have applied Tory’s suggestions successfully in their user studies for determining if a new visualization or a visual analytics system is useful. We have followed Tory’s user study design and measurement suggestions for evaluating the meaningfulness of our visualization: our event discovery user study includes a timed event detection task, hereafter called *event detection time*.

### 4.2.1 Visualizations Used in User Study (Study 2)

The visualizations used in this user study depicted WRF weather datasets’ pressure attribute. We built the visualizations based on identified cases of low pressure events. (The times and geographic regions for these events were known to us.) The events we used were in Western United States, Central United States, Eastern United States, Northeast Atlantic, Northcentral Atlantic, Northwest Atlantic, Southeast Atlantic, Southcentral Atlantic, and Southwest Atlantic regions. For each region, data at nine time points per event were used. For each of the 5 baseline textures, we generated 81 visualizations of the pressure attribute (i.e., one visualization per combination of time points and regions). For all the regions, times during the months of September and October were selected.

Next, the use of the texture directionality to generate the new texture-based visualizations for the abovementioned data is described. First, for each baseline texture, rotations of 0 degree (no rotation), 22.5 degrees, 45 degrees, 67.5 degrees, 90 degrees, 112.5 degrees, 135 degrees, and 157.5 degrees were applied to create 8 directional textures with even angular separation. Then, the WRF pressure attribute’s range was determined for all datasets. That range was quantized into 8 even-sized intervals.
Each quantile was associated with a texture direction, where the quantile of the lowest pressure values was associated with the 0 degree oriented texture, the quantile of the next lowest pressure values was associated with the 22.5 degree oriented texture, and so on. Our new texture-based visualization technique, described in Chapter 3, was performed using the same directional textures and the WRF pressure attribute data to create visualizations.

The visualizations shown to the users were of size 800x500 pixels.

### 4.2.2 Study 2 Task Detail

For each participant, the event discovery task involved the participant clicking on the location in the visualization (displayed on a computer screen) where he or she identified a weather event. Per Tory’s [83] suggestion of measuring time for the participants to notice an event illustrated in a visualization, if participants could correctly identify the existence and location of a weather event in one type of visualization faster than another, then the visualization enabling fastest task completion may be the most meaningful.

We determined the event detection time (in milliseconds) using a computer program we developed. Our program also recorded the location where the user clicked in the displayed visualization. The measured time was the time difference between when the participant was shown the image and when the participant clicked on the image.

Each participant was shown 5 visualizations: one visualization per baseline texture, with the one shown for the texture selected randomly from the 81 possible
visualizations that exist. The reason for selecting a random visualization for each baseline texture was to prevent visualizations of the same time points and the same regions being shown to the same participant; by showing 5 visualizations (of 5 different time points and geographic regions) to a participant, the participant was not biased by retained memory from previous visualizations of the same event. Participants were shown the visualizations in a random order (randomized on baseline textures). Thus, each participant was presented with the visualizations in a unique order. After examining each visualization, each participant was asked to identify the existence and location of a weather event. Each visualization was displayed in a computer screen one at a time in a room with well-distributed diffuse light.

We note that no participant was shown visualizations of all the events; the set of events presented to any one participant could have been different from a set of events presented to other participants. This practice does not bias the study result for the following reasons: (i) the selection of the events shown to each participant was random, (ii) all participants were experts who had studied weather events before, thus they were all familiar with the weather event here (a low pressure system), (iii) we only depicted one data attribute (pressure) using texture directionality in our visualizations, thus there are not interference effects caused by other visual attributes in the visualizations, and (iv) the low pressure systems that were used had similar spatial extents.

Figures 4.4, 4.5, 4.6, 4.7, and 4.8 show representative samples of the visualizations seen by the participants. In Figure 4.5, we highlight with the yellow rectangle the low pressure event. The visualizations shown in these figures depict the pressure
attribute of the WRF datasets using texture for central U.S. Great Plains on September 16, 2007 at 12 AM Greenwich Mean Time (GMT).

To provide a zoomed view of one of the events visualized, we show cropped views of the visualizations in Figure 4.9 (the top right quarter of the visualizations are shown) of weather visualizations using each of the five textures. We note that the cropped views are just for the dissertation reader’s convenience and were not shown to the participants.

Figure 4.4: Sample visualization #1, D9 texture used for WRF pressure visualization used in event discovery user study
Figure 4.5: Sample visualization #2, D49 texture used for WRF pressure visualization used in event discovery user study
**Figure 4.6:** Sample visualization #3, D65 texture used for WRF pressure visualization used in event discovery user study.
Figure 4.7: Sample visualization #4, D78 texture used for WRF pressure visualization used in event discovery user study.
Figure 4.8: Sample visualization #5, D86 texture used for WRF pressure visualization used in event discovery user study
Figure 4.9: (Cropped views of) Texture-based weather data visualizations used in event discovery user study
4.2.3 Study 2 Subjects

We recruited twenty two participants for the event discovery user study. Twelve of them were environmental scientists who were attending a workshop. Ten were graduate students from an atmospheric science class. Each participant completed the study isolated from the other participants. Each participant completed the study in the same room with the same lighting condition and on the same computer.

4.2.4 Study 2 Results

In Table 4.2, a summary of the times taken by the participants to complete the task (event detection task) in the event discovery user study is shown. The fastest event detection times were for the highly directional textures (D49 and D65). This observation may suggest that visualizations generated using directional textures aid users in identifying events faster. To determine if the resulting event detection times using each type of texture were significantly different, we performed statistical tests. The statistical test details are described next.

<table>
<thead>
<tr>
<th></th>
<th>Highly Directional</th>
<th>Highly Non-Directional</th>
<th>Somewhat Directional</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>D65</td>
<td>D49</td>
<td>D86</td>
</tr>
<tr>
<td>Min</td>
<td>0.44</td>
<td>0.47</td>
<td>1.96</td>
</tr>
<tr>
<td>Max</td>
<td>2.61</td>
<td>2.08</td>
<td>8.34</td>
</tr>
<tr>
<td>Average</td>
<td>1.11</td>
<td>0.99</td>
<td>4.71</td>
</tr>
</tbody>
</table>

Table 4.2: Timed task summary (in seconds), Study 2
4.3 Statistical Test and Analysis

Here, we report on the statistical tests we performed to determine if there was any significant difference in the event detection times (i.e., the times to identify existence and location of weather events) for our visualizations. The statistical test was the most frequently used test for significance, analysis of variance (ANOVA).

4.3.1 ANOVA Testing

Next, we describe our use of ANOVA, following the classical approach of testing a null hypothesis that population means are equal by comparing variances. Here, the comparison was of the event detection times (i.e., time to identify the location of the weather event). The analysis considered time within a particular texture-based visualization across all texture-based visualizations. Finding variances for ANOVA requires the sum of squares (S), as shown in Eqn. 4.1 [38]:

\[
S(J) = \sum_{i=1}^{t} \sum_{j=1}^{n_i} (X_{ij} - \bar{X}_i)^2 \quad \text{and} \quad S(T) = \sum_{i=1}^{t} n_i (\bar{X}_i - \bar{X})^2,
\]

where \(X_{ij}\) is the \(j^{th}\) timed result from the \(i^{th}\) texture-based visualization, \(\bar{X}_i\) is the mean of the timed results for the \(i^{th}\) texture, \(\bar{X}\) is the grand mean, \(n_i\) is the number of timed results for the \(i^{th}\) texture, \(t\) is the number of textures, \(S(J)\) is sum of squares within groups (a group is a collection of timed results per texture), and \(S(T)\) is sum of squares between groups.

Our ANOVA test statistic, the F-Ratio \((F_R)\) is:
\[ F_R = \frac{M(T)}{M(J)}, \quad (4.2) \]

where \( M(T) \) is mean squared observation between groups and \( M(J) \) is mean squared error, and those are computed as follows:

\[ M(T) = \frac{S(T)}{N_t-1} \text{ and } M(J) = \frac{S(J)}{N_j-N_t}, \quad (4.3) \]

where \( N_j \) is the total number of results, \( N_t - 1 \) is the degrees of freedom for the textures and \( N_j - N_t \) is the degrees of freedom for the mean squared error.

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>S</th>
<th>d.f.</th>
<th>M</th>
<th>F_R</th>
<th>P-value</th>
<th>F crit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between groups</td>
<td>394.06</td>
<td>4</td>
<td>98.52</td>
<td>75.08</td>
<td>6.36E-30</td>
<td>2.46</td>
</tr>
<tr>
<td>Within groups</td>
<td>137.77</td>
<td>105</td>
<td>1.31</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>531.83</td>
<td>109</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 4.3**: ANOVA test results, weather event detection times (event discovery task)

Our ANOVA results are shown in Table 4.3. In the table, \( d.f. \) refers to degrees of freedom. As suggested above, this table is based on the event detection times. The observed \( F_R \) is quite large, allowing the null hypothesis to be rejected with very high confidence; we conclude that for event discovery tasks in weather visualization, that the differences in times have statistical significance.
Since the ANOVA results indicated that there is a significant overall difference in the times taken to identify and locate events using various texture-based visualizations, we used the post hoc testing [63] with Tukey’s HSD test to compare which differences were significant. The Tukey’s HSD test applies simultaneously to the set of all pairwise comparisons. In our case, the times taken to identify and locate events in visualizations generated using every possible pair of textures were simultaneously compared.

### 4.3.2 Honest Significant Difference (HSD) Test

Tukey’s HSD test verifies if the difference in the means from the results of two techniques exceeds a critical value, $C$, computed as follows in our usage:

$$ C = s_\alpha \sqrt{\frac{M(J)}{N_j}}, $$  \hspace{1cm} (4.4)

where $M(J)$ is the mean squared error computed in ANOVA, $N_j$ is the number of texture-based visualization results, and $s_\alpha$ is the studentized range statistic for the confidence level $\alpha$. (We used $\alpha=0.95$.)
<table>
<thead>
<tr>
<th>Contrast</th>
<th>Mean Difference</th>
<th>Critical Value</th>
<th>Pr&gt;Mean Difference</th>
<th>Significant</th>
</tr>
</thead>
<tbody>
<tr>
<td>D9 vs D49</td>
<td>4.21</td>
<td>2.78</td>
<td>&lt;0.0001</td>
<td>Yes</td>
</tr>
<tr>
<td>D9 vs D65</td>
<td>4.10</td>
<td>2.78</td>
<td>&lt;0.0001</td>
<td>Yes</td>
</tr>
<tr>
<td>D9 vs D78</td>
<td>3.97</td>
<td>2.78</td>
<td>&lt;0.0001</td>
<td>Yes</td>
</tr>
<tr>
<td>D9 vs D86</td>
<td>0.48</td>
<td>2.78</td>
<td>0.63</td>
<td>No</td>
</tr>
<tr>
<td>D86 vs D49</td>
<td>3.73</td>
<td>2.78</td>
<td>&lt;0.0001</td>
<td>Yes</td>
</tr>
<tr>
<td>D86 vs D65</td>
<td>3.61</td>
<td>2.78</td>
<td>&lt;0.0001</td>
<td>Yes</td>
</tr>
<tr>
<td>D86 vs D78</td>
<td>3.49</td>
<td>2.78</td>
<td>&lt;0.0001</td>
<td>Yes</td>
</tr>
<tr>
<td>D78 vs D49</td>
<td>0.24</td>
<td>2.78</td>
<td>0.958</td>
<td>No</td>
</tr>
<tr>
<td>D78 vs D65</td>
<td>0.12</td>
<td>2.78</td>
<td>0.997</td>
<td>No</td>
</tr>
<tr>
<td>D65 vs D49</td>
<td>0.12</td>
<td>2.78</td>
<td>0.997</td>
<td>No</td>
</tr>
</tbody>
</table>

**Table 4.4**: Pairwise testing of texture use in event discovery task, Tukey’s test

The results of Tukey’s HSD test are presented in Table 4.4. The column *Mean Difference* lists the mean of differences in event detection time (during the event discovery task) between listed textures. The probability that there is not a difference in times taken by users to identify and locate weather event (for a pair of textures used for weather data visualizations) is listed in the column *Pr>Mean Difference*. These results suggest that the lower times taken when using the directional textures (D49, D78, and D65) for weather data visualization is statistically significant (versus time to identify and locate the weather event when using the non-directional textures (D9
Furthermore, the results shown in Table 4.4 suggest that the differences in times taken when using only the directional textures (D49, D78, and D65) for weather data visualization are not statistically significant (i.e., there was no statistically significant difference for the pairwise comparisons of times taken when using D49 versus D78, when using D49 versus D65, or when using D78 versus D65). Moreover, the differences in times taken when using only the non-directional textures (D9 and D86) for weather data visualization are not statistically significant (i.e., there was no statistically significant difference for the pairwise comparison of times taken when using D9 versus D86).

This study indicates that users are likely to quickly and correctly identify the location of weather events when highly or somewhat directional textures are used in visualization.

4.4 Conclusion

In this chapter, we reported evaluations of the new texture-based visualization technique that we presented in Chapter 3. The evaluations were based on user studies. The first user study was conducted to create a baseline set of directional and non-directional textures. The second user study involved event discovery tasks on visualizations of weather data using the textures baselined in the first user study. Event detection time was used as a measure to determine if certain classes of textures, when used in visualizations, resulted in faster identification of events. In doing so, we also assessed the suitability of using directional texture as visual cues for visualization. From the statistical tests done on the study results, we conclude that for event
discovery tasks, directional textures provide valuable visual cues. In particular, the study results and statistical analysis suggest that selected Brodatz directional textures are useful in multivariate weather data visualization. In addition, we believe that directional textures are more broadly useful for other visualization application areas. Another good emphasis for future work would be to perform a comparison of the new texture-based weather visualization against the traditional weather visualization, such as the one shown in Figure 1.1.
In this chapter, four major elements of our work on measuring texture directionality are discussed. The first of these is a measure we have developed that examines both local and global aspects of directionality to signal if a texture is directional or not. The local aspect is provided mostly from local pixel intensity differences, while a frequency domain analysis provides most of the global aspect. The second element is a comparison study (based on the full set of Brodatz textures) of the measure versus the known existing texture directionality determination measures. The third element considers all the measures relative to human evaluation. The fourth element considers computer vision applications of the measure.

5.1 Texture features

There are several definitions of textures. The simplest definition, stated by Hawkins et al. [33], is a local order that repeats over a larger area. Most textures can be said to have inherent features, like size and degree of regularity in repetition, and some textures also have orientation or other inherent features. Because of these inherent features, researchers have exploited them for many computer vision and
pattern recognition applications. For example, Shiranita et al. [74] and Lee et al. [51] have used texture features to determine meat quality. Kacem and Saïdani [41] have used texture features to distinguish between machine printed and handwritten words. Suvanchala and Kumar [80] have used texture synthesis to improve iris recognition. Gorkani and Picard [29] have used texture orientation to detect images of urban areas. Texture features have also been used for detecting tissue masses in mammograms [62] and to retrieve matching images from large image databases [43,72].

Past work has found that certain characteristics of textures are readily perceived by human and animal vision (e.g., the visual cortex of monkeys includes numerous detectors sensitive to orientation of structures in the visual field [15,39]). Textures also help in visually differentiating surfaces [13,64]. In addition, orientations within textures offer texture segregation cues to the visual system [66]. Moreover, Ware and Knight [87] have observed that humans perceive that textures have several visual characteristics, such as regularity, size, and orientation.

5.2 Texture directionality measure

Directionality may be a useful feature for vision and pattern recognition since it could allow differentiating between (i.e., classifying) textures. It may also be useful in other domains (e.g., multimedia). To support using the directionality for texture discrimination, a new measure that can determine the directionality status for a texture is described and validated in this chapter. We also present an extended discussion of our comparison study of texture directionality measures—that study includes comparison of the new measure against the existing measures, using human
sentiment as a baseline, and is the first comprehensive comparison study that includes the complete set of Brodatz textures. Our work was initially published in [58]. In this chapter, we also provide detailed information on computation of the new texture directionality measure and new application studies using computation of the measure and new application studies using the measure.

5.2.1 Background

In the literature (e.g., [32]), some frameworks that compute certain texture measures and applications that use those measures can be found. For instance, Chetverikov and Hanbury [22] have used a gray-level difference histogram feature that measures texture regularity [21] for structural defect detection. Another example can be found in work of Cao et al. [17], which describes a texture sharpness measure for quantifying sharpness of digital images. Hanzaei et al. [31] have presented a technique for defect detection and classification of ceramic tile using Rotation Invariant Measure of Local Variance (RIMLV) and structural methods, especially using the close morphological operator. They have successfully demonstrated the usefulness of their technique by integrating it into a tile production system.

Since our emphasis is directional textures, we next discuss previous work on texture directionality measures.

5.2.2 Existing texture directionality measures

Tamura et al. [81] have presented one of the first studies on texture directionality. Their work included study of the role of textures in human perception and introduced
measures based on spatial intensity variation, one of which aimed at estimating overall
directionality in an image. That measure was based on sharpness of peaks in a
histogram of high magnitude gradient pixels. The gradients were estimated using
mask-based horizontal and vertical directional difference estimates at each pixel. If
a pixel’s gradient magnitude was above a threshold, it was considered to be high
magnitude. They also reported user studies that considered the relation between
human perception and their texture measures. The studies used 16 (of the 112)
Brodatz image archive textures of various types. All possible combinations of pairs of
the images were shown to the study participants, who then identified one texture from
each pair that best exhibited the directionality characteristic. Their study suggested
high correlation between their directionality measure and human responses.

Another texture directionality measure that can be found in the literature was
defined by Picard and Gorkani [70]. The measure was based on a four level pyramid
defined with steerable filters like the ones described by Freeman and Adelson [27].
The pyramid’s lowest level was the actual texture. At each level, the steerable filters
were used to compute each pixel’s dominant orientation and orientation “strength.”
Then, orientation histograms were constructed for each level based on the orientation
strengths. After smoothing, the histogram peaks were found. Next, the orientation
histograms for each level were combined. Finally, the measure of texture directionality
was computed from this combination. Picard and Gorkani applied their measure to
all 112 Brodatz textures and subsequently validated the measure via a user study on
the same textures.
A measure of texture directionality based on a variance statistic, the auto-covariance function $g$, has been described by Abbadeni [11] and colleagues [12]. $g$ expresses the covariance between the original image and a shifted version of that image, as shown in Eqn. 5.1:

$$g(\delta_i, \delta_j) = \frac{1}{c_{ij}} \sum_{i=0}^{n_c-\delta_i-1} \sum_{j=0}^{n_r-\delta_j-1} I(i, j) I(i + \delta_i, j + \delta_j),$$  \hspace{1cm} (5.1)

where $n_c$ and $n_r$ are the number of columns and rows in the image $I$, respectively, the $\delta$ terms represent shifts, $0 \leq \delta_i \leq n_c - 1$ and $0 \leq \delta_j \leq n_r - 1$, and $c_{ij} = (n_c - \delta_i)(n_r - \delta_j)$.

The approach found the gradient of the auto-covariance at each pixel. The pixels whose gradient exceeded a threshold $t$ were considered to be oriented. In addition, if a sufficient number of pixels were considered to be oriented, then the image was considered to be a texture with a dominant orientation, denoted by $\Theta_d$, and a directionality value $N_{\Theta_d}$, defined as shown in Eqn. 5.2:

$$N_{\Theta_d} = \frac{\sum_{i=0}^{n_c-1} \sum_{j=0}^{n_r-1} \Theta_d(i, j)}{(n_c \times n_r) - N_{\Theta_{nd}}},$$  \hspace{1cm} (5.2)

where $N_{\Theta_{nd}}$ is the number of non-oriented pixels. Abbadeni also performed a user study to validate the measure.

Lastly, a texture directionality measure based on the Discrete Fourier Transform (DFT) was described by Hagh-Shenas and Interrante [30]. It applied a Hanning window to textures to reduce DFT aliasing artifacts and then applied DFT on the Hanning-modified texture. Next, the DFT output was Gaussian-smoothed and converted into
polar coordinates. The 180°-range of frequency values in the polar coordinates were divided into 18 equal intervals (through the DC point). Each interval was also radially divided by 64 circles, generating, in all, 18x64 locations. The values at these locations in the radially divided circles were stored in an 18x64 matrix called the Discrete Fourier Polar Coordinates Matrix (DFPM). Using the DFPM, a directionality measure, $D_H$, was computed, as shown in Eqn. 5.3:

$$D_H = \frac{\sum_{i=1}^{n}(M(i) - f(i))}{n \times M(i)},$$

(5.3)

where $f(i)$ is the sum of the $i^{th}$ column in the DFPM, $M(i)$ is the maximum value in that column, and $n=64$ columns.

There have also been studies that have used directional features but not for classifying textures as directional or non-directional. For example, Manjunath et al. [55] have also described texture descriptors that incorporate directional features for sub-regions of a texture. They have used sets of such features in image indexing and retrieval. Directionality of the texture itself was not explicitly computed however; hence, the texture is not classified as directional or non-directional by their descriptors. Sikora [75] and Wu et al. [90] have used Gabor filter banks with scale and orientation sensitive filters to design texture features, which were used to measure a concept related to directionality (structuredness) of an image.

Directional textures have been used in many computer vision applications. For example, Wang et al. [85] have used Gabor orientation features for iris recognition, Chaki et al. [18] have used Gabor orientation features and gray level co-occurrence
matrices for plant leaf recognition, and Li et al. [52] have used texture features, including directionality, to predict breast cancer risk from mammograms. Recently, Zheng et al. [92] have determined sea surface wind direction (SSWD) in synthetic aperture radar images using a dominant texture orientation estimate derived from a gray-level co-occurrence matrix. Lastly, we note that Healey and Enns [35] have outlined advances in texture understanding and application in computer vision, graphics, and visualization.

An evaluation of two of the texture directionality measures, the Abbadeni et al. [11,12] and Tamura et al. [81] ones, was described previously by Chamorro-Martinez et al. [19]. That evaluation found the Tamura directionality to be more suitable than the Abbadeni et al. one.

5.2.3 The new texture directionality measure

Next, the first major element of this chapter is described. That element is our new measure to find if a texture sample is directional. Here, we describe our texture directional determination scheme that considers both local and global aspects of directionality, which is one difference from most prior work, to determine if a texture is directional or non-directional.

Our measure examines directional intensity variations in texture as an initial step then does a frequency domain analysis of the texture. This examination of intensity variation along predefined directions is aimed at identifying the more certain highly directional and highly non-directional textures first. Frequency domain analysis of the remaining textures provides more information on the texture directionality.
Computing the measure consists of applying the following steps to the texture sample.

Step 1. Apply 3x3 masks on each pixel of the texture sample to find intensity differences in the pixel’s neighborhood in directions 0, 45, 90, and 135 degrees from the horizontal.

Step 2. Using the pixel differences found in Step 1, in the texture sample, find the mean of pixel intensity differences in each of the four directions.

Step 3. For each of the four directions, compute the maximum and minimum of the pixel intensity differences.

Step 4. Classify the texture as highly directional, highly non-directional, or possibly directional using the following rules. If the difference, $d_3$, between the max and min pixel intensity differences is greater than a threshold, $t_1$, classify the texture as highly directional. If $d_3$ is less than another threshold, $t_2$, then classify the texture as highly non-directional (we use $t_1 > t_2$). Classify all textures with $t_2 \leq d_3 \leq t_1$ as possibly directional. They need to be investigated further. (N.B. The local intensity variation approach taken here is similar to the local binary pattern (LBP) concept [67]. However, instead of using the variation as a texture discrimination measure like LBP does, here a global orientation measure is used for the texture.)

Step 5. Stop if the texture was classified as highly directional or highly non-directional. Otherwise, proceed to:

Step 5a. Apply a Fourier transform, which allows assessing geometric characteristics within a texture. (We used matlab image processing toolkit’s fft2 (two-dimensional discrete Fourier transformation) function.)
Step 5b. Apply a Hough line transform to Step 5a’s output to identify existence of lines (i.e., to find structures in the Fourier transformed texture), since linear-like structures in the Fourier transformed texture may indicate that the texture is oriented. This Hough transform uses the line formulation of Eqn. 5.4:

$$xcos\theta + ysin\theta = \rho.$$  \hspace{1cm} (5.4)

Eqn. 5.4 specifies a line passing through \((x, y)\) that is perpendicular to the line from the origin to \((\rho, \theta)\) in polar space. For each point \((x, y)\) on that line, \(\rho\) and \(\theta\) are constant. The set of possible lines passing through \((x, y)\) is obtained by solving for \(\rho\) and \(\theta\). An accumulator counts the number of times each \((\rho, \theta)\) combination describes a credible line passing through a pixel. Points that are collinear yield higher counts for the \((\rho, \theta)\) parameters describing their common line. Any time the accumulator count is high (we used 90 for our textures, which are size 128x128), hypothesize such a line is present. (We used \(\pi/90\) for spacing of the Hough transform bins along the \(\theta\)-axis and 1 for spacing of the Hough transform bins along the \(\rho\)-axis. The ranges for \(\rho\) and \(\theta\) were \([-64, 64]\) and \([-\pi/2, \pi/2]\), respectively.)

Step 5c. If one or many lines exist in the output of Step 5b, then classify the texture as a highly directional texture.

Using Hough processing after the Fourier step allows some textures with disconnected directional components to be identified as directional (e.g., Brodatz image archive texture D102); use of local pixel differences alone does not deal well with disconnected directional components. Moreover, our approach allows textures with
multiple dominant directions to be detected as directional. Figure 5.1 shows such a
texture, Brodatz image archive texture D102, with multiple dominant directions, and
its Fourier transformation. The presence of straight lines in Figure 5.1(b) indicates
that this Brodatz D102 texture is directional.

5.2.3.1 Mask size sensitivity

To determine whether neighborhood size alters the classification outcomes, we have experimented with using larger (i.e., 5x5 and 7x7) neighborhood masks in Step 1
for the same set of directions. The experiment was done on normalized versions of
the 112 images in the Brodatz image archive. (The images were normalized to [0,1].)
We computed the differences between the max and min pixel intensities, denoted as
d_5 and d_7 for 5x5 and 7x7 cases, respectively. In both cases, the overall classification
resulted in similar classification outcomes as the 3x3 neighborhood mask. We found
the differences, $|d_3 - d_5|$ and $|d_3 - d_7|$, over the 112 Brodatz image archive images to be 0.0200 and 0.0259, respectively. The results of the experiments of using larger neighborhood masks suggest that mask size has minimal impact on overall classification result.

5.2.3.2 Directional sensitivity

To determine whether using additional directional angles in the masks alters classification outcomes, we also experimented with the following cases: (i) 8 directional angles with the 5x5 neighborhood mask, (ii) 8 directional angles with the 7x7 neighborhood mask, and (iii) 16 directional angles with the 7x7 neighborhood mask. The experiments were done on the 112 (normalized) images in the Brodatz image archive (i.e., which are normalized to $[0,1]$).

In case (i), the results from the first step of our algorithm were similar to the results using 4 directions with the 3x3 mask. Moreover, the classification results from the Hough processing step for this case was identical to the classification result using 4 directions. In case (ii), 3 of the textures were classified differently than they were when 4 directions and the 3x3 mask were used. Finally, in the case (iii), 4 of the textures were classified differently than they were when 4 directions and the 3x3 mask were used. Since the classification results of using additional directions with various neighborhood masks were almost identical to the classification results of using 4 directions with the 3x3 neighborhood mask, the succeeding results in this paper are for trials based on using 4 directions with the 3x3 neighborhood mask.
5.2.3.3 Measure characteristics and limitations

Since most prior texture directionality measures have been based on a local texture model, they may ignore some global aspects of texture orientation that could be utilized in human visual perception. Our measure, however, considers both local and global texture directionality (via its use of local pixel difference and Fourier and Hough steps). One limitation is that our measure only reports if the texture is oriented or not; it does not report orientation angle. We hope to address this limitation in future work.

5.3 Texture directionality measure comparison

Next, the second major element of this chapter is described. That element is our comparison study of texture directionality measures. The comparison study evaluates the four abovementioned measures versus our measure. The study involves the complete set of the Brodatz textures. The complete set of Brodatz textures is shown in the figure set of Figures 5.2, 5.3, 5.4, and 5.5. Prior to our efforts, only Picard and Gorkani [70] had reported a complete test on the entire Brodatz textures and that was for their measure alone. Thus, our efforts constitute the first comprehensive comparison of the existing and new texture directionality measures.

For the Abbadeni et al. measure, we had to make two assumptions due to incomplete information in their paper: (1) the threshold for whether a pixel is oriented, and (2) the criterion to determine a dominant orientation. We have used the average orientation of all the pixels in the texture as the threshold to determine which pixels
Figure 5.2: Brodatz textures - I
Figure 5.3: Brodatz textures - II
Figure 5.4: Brodatz textures - III
are oriented. If more than half the texture’s pixels are oriented then we consider that texture to have a dominant orientation. We label textures with a dominant orientation as directional textures.
Figure 5.6: Overall consistency of Brodatz texture classification using all measures, D=Consistently classified directional textures, N=Consistently classified non-directional textures, I=Inconsistently classified textures.

Table 5.1: List of consistently-classified textures

<table>
<thead>
<tr>
<th>Directional</th>
<th>Non-directional</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1,D6,D11,D15,D18,D20, D24,D25,D26,D34,D36,D37, D47,D49,D50,D51,D52,D53, D55,D56,D65,D68,D70,D72, D76,D77,D78,D79,D83,D94, D95,D96,D105,D106</td>
<td>D2,D23,D28,D30, D32,D33,D40,D41, D54,D60,D62,D63, D66,D67,D75,D88, D89,D91,D100, D109,D111</td>
</tr>
</tbody>
</table>

Figure 5.6 shows a chart of overall inter-measure consistency of all the measures against all Brodatz textures. By inter-measure consistency, we mean agreement between the measures in classifying a texture into the same directionality class (i.e., directional or non-directional). In the Figure 5.6, column “D” represents the count
of textures that all the measures classified as directional, column “N” represents the count of textures that all the measures classified as non-directional, and column “I” represents the count of textures for which the measures had disagreement in classification. These measures are not in agreement on directionality of the majority of the Brodatz textures. Table 5.1 further details which of these textures were classified consistently by the directionality measures (i.e., it identifies the cases of agreement).

![Figure 5.7: Example textures that are consistently-classified (D1 and D6 directional; D2 and D23 non-directional)](image)
Figure 5.7 shows some examples of textures that are consistently-classified by all measures. Textures D1 and D6 in Figure 5.7 clearly contain highly directional features. Textures D2 and D23 in Figure 5.7 do not have an obvious directional feature.

**Figure 5.8**: Pearson Correlation Coefficient plot for inconsistent classification, T= Tamura et al., H=Hagh-Shenas and Interrante, P=Picard and Gorkani, A=Abbadeni et al., and M=Our measure

Next, we investigate the inconsistently classified textures further to determine whether there is a significant correlation between the measures that resulted in the inconsistently classified textures. To measure the correlation among all measures, we
have computed the Pearson correlation coefficient [40] for the inconsistently classified textures. Figure 5.8 shows a plot of the correlation coefficient using a 95% level of confidence. Here, our measure and the Hagh-Shenas and Interrante measure had the highest correlations. Our measure and Picard and Gorkani’s measure had the next highest correlation.

5.4 Comparison against user study result

Next, the third major element of this chapter is described. That element considers the new and existing texture directionality measures relative to human evaluation.

In Chapter 4 we described a user study where a subset of the Brodatz textures (15 textures) was categorized into highly directional, somewhat directional, and highly non-directional classes by 22 user study participants. For the comparison study in this chapter, the highly directional and somewhat directional classes from that user task are grouped together. They make up the human evaluation that the measures are considered against. Thus, a new set of baseline textures of two classes (directional and non-directional) are used here for the comparison studies. (We note that Tamura et al. [81] also used a small subset of Brodatz for their user study).
Table 5.2: Comparison of measures

<table>
<thead>
<tr>
<th>Measure</th>
<th>Correct</th>
<th>Incorrect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our Measure (M)</td>
<td>14</td>
<td>1</td>
</tr>
<tr>
<td>Abbadeni et al. (A)</td>
<td>11</td>
<td>4</td>
</tr>
<tr>
<td>Picard and Gorkani (P)</td>
<td>13</td>
<td>2</td>
</tr>
<tr>
<td>Hagh-Shenas and Interrante (H)</td>
<td>13</td>
<td>2</td>
</tr>
<tr>
<td>Tamura et al. (T)</td>
<td>12</td>
<td>3</td>
</tr>
</tbody>
</table>

Figure 5.9: Brodatz texture D21
The successes and failures for the existing directionality measures and our new measure (for this subset of Brodatz textures) are summarized in Table 5.2. Our measure concurs with the baseline texture categorizations 93% of the time. Our measure’s improved accuracy when compared to other measures can be attributed to our consideration of global aspects of the directionality. For example, Brodatz texture D21, which humans categorized as directional in the baseline texture study, was classified as non-directional by the Tamura et al. and Abbadeni et al. measures while being classified as directional by our measure. As shown in Figure 5.9, the D21 texture includes disjoint directional patterns, and these patterns are undetected by the Tamura et al. and Abbadeni et al. measures, which consider only local pixel differences. In Figure 5.10, we show the Fourier transformation (FT) of Brodatz texture D21. The FT clearly shows lines indicating the presence of directionality. The
FT-based frequency domain analysis that is used by our measure is what allows our method to use global features to classify textures like D21 as directional.

![Precision versus recall comparison of texture orientation measures](image.png)

**Figure 5.11**: Precision versus recall comparison of texture orientation measures

Figure 5.11 presents a comparison of the directionality measures performance using a comparison of classifiers mode, where each measure is used as a classifier on a set of textures baselined by the user study described in Chapter 4. Each measure is being evaluated against the ground truth labels (directional and non-directional) determined from those texture baselines. The performance reported in the figure uses precision versus recall. Precision is the ratio of the number of correct classifications to the total number of classifications. Recall is the ratio of the number of correct
classifications using the measure to the actual total number of correct classifications. The comparison shows that for directionality detection, our measure performs better than existing measures based on a human-defined ground truth.

5.5 Applications

Next, the fourth major element of this chapter that considers applications of our new texture directionality measure is described.

Here, the texture directionality measure is applied in two task types: image classification and initialization of convolution filters in a convolutional neural network.

5.5.1 Texture directionality measure for image classification

Texture classification, a process of assigning a known label to a texture, has many applications. One texture characterization technique, FLTP [79], that estimates the distribution of local texture pattern in an image, has been applied to Brodatz image classification with high accuracy. Texture classification based on histogram of gradients and local binary patterns has been described by Dong et al. [25].

Next, we use texture directionality measures in (1) classifying images of striped fabric, (2) classifying shirts as striped, and (3) classifying parts of mobile phone circuit boards.

5.5.1.1 Striped fabric classification

Automated classification of fabric can be useful in the textile industry. We have considered classification of striped fabric from the Describable Textures Dataset
(DTD) dataset [23] as directional fabric or non-directional fabric using our texture directionality measure and the four extant measures. The DTD dataset is a collection of textured images human-categorized and annotated. There are 5640 total images in the DTD texture database with 47 different categories: 120 images per category. We used two of its texture categories: banded fabric, called Dataset I, and paisley fabric, called Dataset II. The banded fabric category includes images containing striped fabrics that have stripes in various orientations. DTD banded fabric images are shown in the figure set of Figures 5.12, 5.13, and 5.14. The paisley fabric category includes images containing fabrics with some teardrop patterns. DTD paisley fabric images are shown in the figure set of Figures 5.15, 5.16, and 5.17. We consider all textures in the banded fabric category as directional and all textures in the paisley fabric category as non-directional.

Each texture of the banded and paisley fabric categories were classified as directional or not directional by each of the five texture directionality measures. We considered a measure to have produced a correct classification if a banded fabric image was classified as directional or if a paisley fabric image was classified as non-directional. Otherwise, the classification was considered incorrect. These classifications are shown in Table 5.3. Our measure was best: 117 out of 120 banded fabrics were correctly classified as directional and 119 out of 120 paisley fabrics were correctly classified as non-directional. The Hagh-Shenas and Interrante measure was a close second for both datasets. We attribute our measure achieving the best classification accuracy due to its use of both local and global directionality features.
Figure 5.13: DTD Banded Textures (Dataset I) - II
Figure 5.14: DTD Banded Textures (Dataset I) - III
Figure 5.15: DTD Paisley Textures (Dataset II) - I
Figure 5.16: DTD Paisley Textures (Dataset II) - II
Figure 5.17: DTD Paisley Textures (Dataset II) - III
Table 5.3: Classification accuracy using various texture measures on datasets: (I) DTD Banded Fabric, (II) DTD Paisley Fabric, and (III) Striped shirts. T= Tamura et al., H=Hagh-Shenas and Interrante, P=Picard and Gorkani, A=Abbadeni et al., and M=Our measure

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Total</th>
<th>T</th>
<th>H</th>
<th>P</th>
<th>A</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>120</td>
<td>110</td>
<td>117</td>
<td>115</td>
<td>106</td>
<td>117</td>
</tr>
<tr>
<td>II</td>
<td>120</td>
<td>109</td>
<td>118</td>
<td>120</td>
<td>105</td>
<td>119</td>
</tr>
<tr>
<td>III</td>
<td>160</td>
<td>142</td>
<td>155</td>
<td>154</td>
<td>132</td>
<td>158</td>
</tr>
</tbody>
</table>

5.5.1.2 Striped shirt classification

Determining if a person is wearing a striped shirt can be useful to determine fashion trends for textile industries as well as for forensic applications.

Next, we describe an experiment using our new texture directionality measure to determine if a person is wearing a striped shirt or not. The application considered 160 images of people wearing striped shirts that were collected online from a search for images of people wearing striped shirts. The search results were visually inspected for correctness. The image collection, called Dataset III, included indoor and outdoor settings. Figure 5.18 shows images similar to the ones used in the study. (The images used in our study were downloaded using online search and were later found to have copyright restrictions on their redisplay. Thus, we are displaying similar
non-copyrighted images in Figure 5.18 to demonstrate the types of images used in the study.)

We performed the following pre-processing steps before applying the texture directionality measure. First, we detected faces from the images using the Viola-Jones algorithm [84]. Viola-Jones uses a set of basis functions to extract features from an image. The features were selected for classification using the AdaBoost learning algorithm [28]. After the face was detected, we used heuristics to determine sub-images that included the torso (which is covered by the shirt). The heuristics were based on face size and location and were derived from the body proportion property that torso length and width are about thrice face height and about thrice face width, respectively. Figure 5.19 shows examples of segmented torsos.

We computed the directionality measures on the segmented images. If a measure indicated the texture was directional then we classified the person as wearing a striped shirt. Otherwise, we classified the person as not wearing a striped shirt. Results of such classifications are shown for our measure and the four extant measures in Table 5.3. Our measure was best; it correctly classified 158 out of 160 images of people wearing striped shirts. Again, the Hagh-Shenas and Interrante measure was the second best.
Figure 5.18: Similar images of people wearing striped shirt used in our study (images displayed here are non-copyrighted)
5.5.1.3 Mobile phone circuit board image classifications

Next, we discuss the third application area, a localization application (based on finding directional sections of a mobile phone circuit board) using our measure. Such localization can be useful for robot vision in assembly and inspection.

The application considered computer tomography images of a mobile phone circuit board from the University of Manchester’s Collaborative Computational Project in Tomographic Imaging [1]. It involved classifying sections of the images as directional or not. A sample image of the mobile phone circuit board is shown in Figure 5.20.

Next, we describe our approach in the creation of baseline image sections for our application.
First, we normalized the mobile phone circuit board images to [0,1] for our study. Then, we selected 100 sections of the mobile phone circuit board images: 50 of these had directional patterns present, according to our judgement, and 50 others had non-directional patterns present, according to our judgement. We performed a user study that included 22 participants. The user study consisted of the participants labeling the image sections as either directional or non-directional. 21 of the participants labeled all image sections in an identical manner to our judgement: 50 directional and 50 non-directional. One participant labeled one image section as directional, which was a section that was labeled as non-directional by the other 21 participants. Therefore, we did not include that image section in the subsequent experiment. These 99 labeled image sections (50 directional and 49 non-directional) serve as the baseline for our application.

Next, in addition to applying our texture directionality measure, we also applied the four extant measures on the 99 baseline image sections. The figure set in Figures 5.21, 5.22, and 5.23 shows 50 image sections that all 22 participants agreed were directional. The figure set in Figures 5.24, 5.25, and 5.26 shows 49 image sections that 21 participants agreed were non-directional. If a measure indicated that a baselined directional image section was directional or a baselined non-directional image section was non-directional then the classification was considered accurate. Otherwise, the classification was considered inaccurate.

The accuracy of the mobile circuit board is reported in Table 5.4. Overall, our measure was able to correctly classify directionality in 95 out of the 99 image sections. The Hagh-Shenas and Interrante measure produced the next best result, correctly
Figure 5.20: Computer tomography image of Mobile phone circuit board
classifying 91 out of the 99 image sections. All measures seem to do somewhat better classifying the directional sections of the board (than the non-directional sections).
Figure 5.21: Mobile phone directional sections - I
Figure 5.22: Mobile phone directional sections - II
Figure 5.23: Mobile phone directional sections - III
Figure 5.24: Mobile phone non-directional sections - I
Figure 5.25: Mobile phone non-directional sections - II
Table 5.4: Classification accuracy (%) using various texture measures on both directional and non-directional mobile phone circuit board image sections

<table>
<thead>
<tr>
<th>Measures</th>
<th>Directional</th>
<th>Non-Directional</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tamura et al. (T)</td>
<td>86</td>
<td>85.7</td>
</tr>
<tr>
<td>Hagh-Shenas and Interrante (H)</td>
<td>96</td>
<td>87.8</td>
</tr>
<tr>
<td>Picard and Gorkani (P)</td>
<td>94</td>
<td>87.8</td>
</tr>
<tr>
<td>Abbadeni et al. (A)</td>
<td>92</td>
<td>81.6</td>
</tr>
<tr>
<td>Our Measure (M)</td>
<td>98</td>
<td>93.9</td>
</tr>
</tbody>
</table>

5.5.2 Responsive filters for Convolutional neural network

Next, we describe using our texture directionality measure in initialization of convolution filters for convolutional neural networks.

Convolutional neural networks (CNNs) are deep learning algorithms that have been used to classify images [50,59]. The keys to CNN’s success are filters that are
learned in an iterative manner. In CNN, an initial set of filters are assigned randomly. The filters are then updated based on an error function computed using the actual class labels versus predicted class labels. We conducted experiments involving initializing CNNs with directional filters to test whether such initialization results in minimizing the error rate for classification of image datasets that include directional features.

We used CNN on MNIST [53], a benchmark dataset for image classification consisting of handwritten digits. The handwritten digits in the MNIST have directional features. We applied (1) the basic CNN and (2) CNN initialized using directional filters on the MNIST dataset. We computed the error rates after 200 epochs. The average error rate after repeating the experiment 5 times was 0.76% for basic CNN. For CNN initialized using directional filters, the error rate was 0.65%. The result suggests that for image classification tasks that include directional features, use of our directional filters enables higher accuracy in discriminating the classes.

5.5.3 Other applications

Other applications of the texture directionality measure could be considered for future work. Specially, computer vision applications with detection of directional features are the most suitable ones using the measure. Some example applications include: transverse cirrus band detection in satellite images, cloud contrail detection in satellite images, and extraction of directional sections from fingerprint images.
5.6 Conclusions

In this chapter, we have presented a new texture directionality measure that considers both local and global features of textures. We compared the new texture directionality measure with existing texture directionality measures using a classification task on the full set of Brodatz textures. This comparison was the first such comprehensive study. Our measure was found to be superior to the existing measures, using a human-specified baseline. We also applied the measure in a number of applications, including image classification and initialization of filters for a convolutional neural network. The image classification applications were performed using all the texture directionality measures. The results of the classification applications also suggest that our measure is superior to existing measures. The superiority of our measure versus the existing measures, as established by the comparison studies and applications, can be attributed to our measure’s consideration of local and global features. Furthermore, the result of using our directional filters for CNN initialization produced less error than using random filters, suggesting that directionality is a key component of learning features in a CNN. In the future, we hope to study other aspects of texture directionality, such as allowing for determination of which direction is a dominant one in a directed texture.
CHAPTER 6

CONCLUSIONS

This chapter draws conclusions from this Ph.D. research. The contributions are summarized. Possible future work is also discussed.

6.1 Contributions

The focus of the research was investigating three aspects of directional textures: (1) utilizing directional textures for visualization, (2) measuring texture directionality, and (3) using the texture directionality measure in some applications. The findings and contributions from these aspects are summarized next.

6.1.1 Utilizing directional textures for visualization

The first aspect of our research, utilizing directional textures for texture-based visualization, involved the development of a new visualization technique to address the challenges of simultaneously displaying multiple attributes of data in a single display. Our technique uses a multi-scale Markov Random Field (MRF) based approach for synthesizing the texture used in the visualization.
The input textures for this texture synthesis are directional textures determined by a user study that we conducted. This user study determined three baseline textures that were directional and two others that were non-directional from the Brodatz texture database.

These baseline textures were also used by a second user study that we conducted. The second user study was used to evaluate using directional texture in visualization. It involved expert assessment of the visualizations of a weather research forecast (WRF) dataset’s pressure attribute generated using our technique. A main finding of the second study was that using the directional textures in visualization can provide valuable visual cues that promote information discovery. In particular, the study found that experts were able to identify a weather phenomena (i.e., a low pressure system) significantly faster when a directional texture was used to visualize the pressure attribute of the WRF dataset as compared to when a non-directional texture was used to visualize the same attribute.

Our research also demonstrated that texture directionality could be used as a visual cue in dense weather data visualizations, multivariate geospatial data visualizations, information visualizations, multivariate temporal data visualizations, and multivariate positional data visualizations.

Typically, displaying multivariate data in a single visualization canvas is done using color and glyphs. However, visualization mechanisms that use color and glyphs can become limited by the screen pixel counts when there is a need to display a higher number of data variables (that is, more than three variables). Texture features provide a way to depict a high number of data variables in a compact way on a single
display. The new texture-based visualization technique advances the state of the art in multivariate data visualization by allowing a new visual cue, the directional property of texture, to be used in visualization. (Since directionality of texture has not been extensively used in the past for visualization, it adds another visual cue to the standard visual cues. Thus, more data variables can be depicted in a compact way on a single display.) The new technique could benefit those needing to extract information from multi-attribute data in order to discover knowledge from them.

6.1.2 Measure of texture directionality

The second aspect of our research involved developing a new measure of texture directionality to determine the directionality status of textures. Our measure examines both local and global aspects of directionality to signal if a texture is directional or not. The local aspect is provided mostly from local pixel intensity differences in the texture, while a frequency domain analysis of the texture provides most of the global aspect. The new measure was compared against the known texture directionality measures in the literature. The comparison involved testing the new and existing measures on the full set of Brodatz textures. It is the first comprehensive comparative study of texture directionality measures. The testing was primarily used on discriminating whether Brodatz textures were directional or not.

A main finding of the comprehensive comparison study was that the new texture directionality measure is more accurate in discriminating whether a texture is directional or not than the existing texture directionality measures. The next best measures were (1) the Hagh-Shenas and Interrante measure and (2) the Picard and
Gorkani measure. The superiority of our texture directionality measure is attributed to its consideration of both local and global features of the textures. Considering both aspects is also a novel property of our measure.

In summary, the new texture directionality measure advances the state of the art in the study of texture features by providing a widely applicable measure to determine the directionality status of textures.

6.1.3 Using the texture directionality measure in applications

The third aspect of our research involved applying the new texture directionality measure in four image-related tasks: classifying images of striped fabric, classifying shirts as striped, classifying parts of mobile phone circuit boards, and initializing filters for convolutional neural networks.

For comparison, the existing directionality measures were also applied in the three classification applications. Baselines for the comparisons were constructed using human sentiment. In these three classification applications, the new measure performed slightly better than existing measures. The Hagh-Shenas and Interrante measure was the second best in all three applications.

In the other task, the directional textures were used to initialize convolution filters for convolutional neural network-based image classification (where the task includes detection of directional features). The error rate was monitored and compared against using default random filters to initialize the convolution filters for the same classification task. The error rate dropped lower faster when the directional textures
were used as compared to when default random filters were used, indicating better performance when directional textures were used.

The application studies of the new texture directionality measure represent contributions to computer vision and pattern recognition knowledge, especially for situations needing to differentiate between directional and not directional sections of images (or of whole images).

6.2 Future work

In the future, other properties of textures, such as density (a texture property indicating the compactness of certain texture elements) and regularity (a texture property indicating degree of repetition of certain texture elements), can be examined in detail for multivariate visualization. In addition, most optimal mapping of a set of data attributes to a set of visual attributes for multivariate data visualization could be investigated.

One of the limitations of our texture directionality measure is that it only indicates whether a texture is directional or not. Future work could involve attempting to expand the measure to also determine the degree of directionality. Other aspects of texture directionality, such as determining which direction is a dominant one, could be investigated as well.

Although the texture directionality measure was only applied to limited classification and pattern recognition applications, in future work, using the measure for other detection and classification applications that include directional feature detection could be explored.
6.3 Summary

In summary, this dissertation has contributed a new texture-based visualization technique for multivariate data visualization in a single display and validated that new texture-based visualization. Also, a new texture directionality measure that can determine the directionality status for a broad set of textures has been contributed. It has also been evaluated. Thus, this dissertation advances visualization and pattern recognition.
REFERENCES


