

2. Prior Works:

This study involves three major components i. Generate time series forecasted data from COVID-19 data using four machine learning predictive models ii. Calculate corresponding uncertainties for different countries and visualize uncertainties in terms of Chromatic Aberration (CA) in a graphical presentation surface ~~for better user perception~~ iii. Conduct user studies to evaluate user perceptions and applicability ~~and then apply CA mechanism in real life applications such as bubble charts, stream charts, usage chart etc.~~ In this section, we are going to include some related studies of each component separately conforming to the aspects of the research.

(We don't assume that prior to the study)

with commonly used visualization

2.1 Works related to prediction in Machine Learning Models

On the machine learning forecasting side, Song et. al. [1] compiled monthly data of influenza incidences from all provinces in mainland China from January 2004 to December 2011, comprehensively evaluated and classified these data, and then randomly selected 4 provinces with higher, median and lower incidences, using time series analysis to construct an ARIMA model. The same model but different analysis and forecasting approaches was conducted on the coronavirus disease by other researchers [2]. Recent studies of [3, 4] use Facebook's Prophet Forecasting Model and ARIMA Forecasting Model to compare their performance and accuracy on the dataset containing the confirmed cases, deaths, and recovered numbers, obtained from the Kaggle website. The forecast models are then compared to the last 2 weeks of the actual data to measure their performance against each other. The result shows that Prophet generally outperforms ARIMA. Several neural network predictive models are used to evaluate their performance against more common machine learning models in a Dengue forecasting project [7]. Srivenkatesh applied Naïve Bayes, logistic regression, support vector machines, Random Forest, K Nearest Neighbour for the examination of liver malady. The classifications are assessed with 5 distinctive execution measurements, i.e., precision, kappa, Mean absolute error (MAE), Root mean square error (RMSE), and F measures. The objective of this query work is to foresee liver infections with different machine learning approaches and pick most efficient algorithm [9]. Results of the examination demonstrated that Logistic Regression classifier demonstrated the best outcomes regarding precision with the least execution times.

(Page numbers seem to cut off in printing)

2.2 Uncertainty related prior works

Botchen et al. [29] focuses on uncertainty that occurs during data acquisition and demonstrates the usefulness of the methods for the example of real-world fluid flow data measured with the particle image velocimetry (PIV) technique. They present two novel texture-based techniques to visualize uncertainty in time-dependent 2D flow fields where in the first method, texture advection is employed to show flow direction by streaklines and convey uncertainty by blurring these streaklines and in a second method isotropic diffusion implemented by Gaussian filtering to continuous change of the density of flow representation.

Error in data is inherent so it cannot be ignored in visualization. Improper or eliminated presentations in visualizations can mislead decision making for data analysts. The goal of uncertainty visualization is to minimize the errors in judgment and represent the information as accurately as possible. This survey Aasim Kamal et al. [30] discusses state-of-the-art approaches such as Quantification approach to uncertainty visualization, along with the concept of uncertainty and its sources.

Bonneau et al. [16] explores uncertainty in the visualization domain by comparing different results, such as a weather forecast generated with different parameters and to detect similarities or differences in the results a comparative visualization technique is employed. To compare certain regions in more detail, e.g., borders, they suggested to consider larger comparison areas than individual pixels and it is crucial that data sets which should be compared are visualized next to each other to get a direct comparison for a certain area.

Objective uncertainty of a visual system is evaluated by Barthelme et al. [17] where they discuss the natural perceptual systems involvement with systematic uncertainty because sensory information is imperfect and insufficient to uniquely designate the environment. In their experiment, observers were presented with pairs of images of oriented objects embedded in high levels of noise and had to report the orientation of the image of their choice. In their experiment, they compare objective uncertainty (computed using the Bayesian framework) with subjective uncertainty (the confidence observers report about their visual perception). To this end, they used a visual task with well-defined statistical properties, discrimination under noise. They report a surprising degree of agreement between objective and subjective

uncertainty and discuss possible computational models that could explain this ability of the visual system. Even though the two images contained the same extent of noise, one particular noise structure made an image orientation more obvious than the other. Eventually, observers reliably chose the more obvious of the two images, thereby providing evidence of a capacity to accurately evaluate objective uncertainty.

A statement on the position of uncertainty visualization today is explained in Griethe et al. [18] that defines the basic concept of uncertainty and discusses sources and necessary measures. Visualization is an indispensable approach to the exploration and communication of large data sets of different domains where data sets may contain an unavoidable amount of uncertainty that needs to be included in the visualization process to enable the correct cognition of hidden facts and figures. In addition, it explains how existing approaches could be systematically presented to the acquisition and display of uncertainty can be transferred to new fields, e.g., the visualization of uncertainty in structures.

Uncertainty visualization is a research area that integrates visualization with the study of uncertainty. Among many uncertainties representation of participant-based empirical techniques, there is little evidence in Deitrick et al. [19] to suggest that uncertainty visualization influences in results or decisions. Through a human-subjects experiment, this research evaluates uncertainty visualization methods and indicates that it may affect decisions, but the degree of influence is affected by how the uncertainty is expressed.

State-of-the-art visualization techniques have been successfully engaged in diagnostic medical imaging and Direct Volume Rendering (DVR) sectors and attained maturity in regular clinical works. However, still a major problem is the lack of information on the uncertainty of the tissue classification, which is addressed in the paper Lundstrom et al. [20] by proposing animation methods to convey uncertainty in the rendering. The rendering is animated by sampling the probability domain over time that allows direct user interaction with the classification and it outperforms traditional rendering in terms of assessment accuracy.

Most of the visualization research has ignored the presentation of uncertainty from data because of the inherent difficulty in defining, characterizing and controlling the uncertainty in the visualization process. The paper Pang et al. [21] introduced a wide variety of new uncertainty visualization methods like adding glyphs, adding geometry, modifying attributes, modifying

geometry, animation and applied to many applications. The results of the research show that there are a wide variety of possible means to map uncertainty into a scene. The methods presented in the paper represent significant steps toward achieving the goals of uncertainty visualization.

(use same
line
spacing)

→ introduced.

A common goal in the communication of uncertainty is uncertainty-aware decision making where the audience should be aware of the risks and rewards of certain decisions, modulate their confidence in their conclusions, and perhaps restrain from deciding when there is high uncertainty perceived. Michael Correl et al. [35] came up with the idea of allocating smaller ranges of a visual channel to data when uncertainty is high and larger ranges when uncertainty is low. This allocation of visual variables promotes patterns of decision-making that make responsible use of uncertainty information, discouraging comparison of values in unreliable regions of the data, and promoting comparison in regions of high certainty. In traditional bivariate maps, outputs for each combination of value and uncertainty might be represented as a 2D square whereas they approached it as arcs mapping values to smaller and smaller sets of outputs for higher uncertainty. But the main limitation of that research is they have used single color to represent both value and uncertainty in a single cell encoding system and suppresses the values for decision making when uncertainties are high. *It also requires imperfect data value quantization.*

Being complex topic, most of the authors try to eliminate the existence of uncertainty from their visualization outcome, so the researcher of Jessica Hullman conducted a survey and interviewed over 103 visualization authors in [36]. They identified that perceptions, practices, challenges, and attitudes are associated with uncertainty visualization and majority of them agreed upon or at least sympathetic about importance of uncertainty communication.

Data analysts face unique challenges in interpreting the results on applying machine learning and statistical methods to timestamped event sequences to tackle various problems. Through a controlled study, the researcher Sunan Guo et. al [37] found that users get more confidence in making decisions when alternative predictions are displayed alongside uncertainty information, and they consider the alternatives more when deciding between two options with similar top predictions. There are several limitations of this research, for example: they have used darkness to address uncertainty but that is not suitable to determine exact uncertainty values and make accurate decisions. Also, it requires the participants to be domain experts and they did not formally compare with alternative design options.

It also requires data with alternatives. experience.
Since uncertainty is a multi-faceted concept, there are various kinds of uncertainties, and the visualization of such uncertainties are applied in many contexts with different objectives, so there cannot be a single optimal uncertainty visualization technique. The study of Michelle Korpela et al. [38] investigates how data uncertainty visualized in maps might influence the process and outcomes of spatial decision-making, especially when made under time pressure in risky situations. The limitation of the research is that they have not considered the effect of stress along with time constraints. In addition, they have used only one type of texture(dotted) in their visualization experiment. So, the result cannot be generalized with non-texture, non-color based or gradients.

Earthquake models can produce aftershock forecasts but research on uncertainty visualization is comparatively missing from earthquake science. So, Max Schneider et al [39] conducted

often.

research where three different uncertainty visualizations were produced: (1) forecast and uncertainty maps adjacent to one another; (2) the forecast map depicted in a color scheme, with the uncertainty shown by the transparency of the color; and (3) two maps that showed the lower and upper bounds of the forecast distribution at each location. Limitations of the paper includes ~~it~~ needed to fix either the forecasted aftershock rate or its uncertainty in the comparative judgment task, geographical features, such as roads and landmarks were omitted from the maps to avoid potential confounding effects on judgments which lowers the ecological validity of the study, the evaluation used a single judgment task with three uncertainty visualizations.

The authors Ken Brodlie et al. [40] have reviewed the state of the art in uncertainty visualization, looking at both the visualization of uncertainty (which considers how to depict uncertainty specified with the data) and the uncertainty of visualization (which considers how much inaccuracy occurs in data processing through the pipeline of Haber and McNabb uncertainty reference model). They have seen that the visualization research community has enthusiastically taken up the challenge of uncertainty and most of the popular visualization techniques have been extended in some way to handle uncertain data.

When making an inference or comparison with uncertainty, noise, or incomplete data, measurement error and confidence intervals can be as important for judgment as the actual mean values of different groups. The paper [41] investigates drawbacks with the standard encoding and considers a set of alternatives and conducted a series of crowd-sourced experiments that confirms the encoding of mean and error significantly changes and by which viewers make decisions about uncertainty. They use gradient plots with transparency to encode uncertainty and violin plots with width as better alternatives. One area not well-covered by their experimental tasks was decision making and did not collect a great deal of qualitative data such as viewer preferences for different chart types which could be an important consideration for how data are perceived and used, especially for issues of trust and uncertainty.

In daily life, people regularly make decisions based on uncertain data navigating through gadgets or looking at the weather forecast ~~in~~ online. The authors Miriam Greis et al. [42] published a web-based game on Facebook and compared four representations that communicate different amounts of uncertainty information to the user and compared. The results show that abundance of uncertainty information leads to taking unnecessary risks. Absence of uncertainty information reduces the risk taking and leads to more won turns, but with the lowest money gain. Representations with aggregated detailed uncertainty provide a good trade-off between being understandable by the players and encouraging medium risks with high gains. The paper doesn't visualize the uncertainties but uses kind of weight to the representations.

In statistics, people usually quantify uncertainty to help determine the accuracy of estimates, yet this crucial piece of information is rarely included on maps visualizing areal data estimates. The authors Lydia R Lucchesi et al. [43] develop and present three approaches to include uncertainty on maps: (1) the bivariate choropleth map repurposed to visualize uncertainty; (2) the pixelation of counties to include values within an estimate's margin of error; and (3) the rotation of a glyph, located at a county's centroid, to represent an estimate's uncertainty. They have not conducted user studies to determine whether these three methods effectively communicate uncertainty by drawing conclusions and answering questions in visualization. Although users can see which counties have high uncertainties, they cannot determine the exact quantities of the margins of error by looking at the pixelated map.

The many types of
Uncertainty is a fact of information; all information contains uncertainty, usually of heterogeneous categories. While there have been many calls for research about uncertainty visualization, understanding of when and why one uncertainty visualization strategy should be used over others remains incomplete. To address the gap Alan M MacEachren et al. [44] presents two linked conceptual perspectives focused on uncertainty visualization. First, a typology of uncertainty is used to delineate kinds of uncertainty matched with space, time, and attribute components of data. Second, concepts from visual semiotics are applied to representing different categories of uncertainty. They address representation intuitiveness and relative performance, considering visual variables and iconic representations of uncertainty. The study does not cover finding the best symbolization method by integrating both data and data uncertainty representation into the same sign-vehicles. Also, they have not tested symbol size impact.

Many information fusion applications process and present huge quantities of data to enable an operator to make effective decisions. Maria Reveiro came up with the paper [45] to provide a general overview on uncertainty representations techniques and explains why the recognition of uncertainty plays an important role in decision making. In addition, it suggests the techniques developed in information visualization can be applied in information fusion and outlines how information fusion research might proceed further. The major contributions of this paper are (1) to highlight the importance of uncertainty visualization in decision-making, (2) to briefly review relevant modern uncertainty visualization techniques, (3) to propose general theories and results of user experiments for their theoretical analysis, (4) to suggest that techniques developed in information visualization can be applied in information fusion and (5) to outline how information fusion research might proceed further. The weakness of the paper is they theoretically evaluate the weakness and strengths of the uncertainty visualizations representations. *only*

Visual representations of information are challenged to incorporate a thought of confidence or certainty because the factors that influence the uncertainty of information vary with the type of information. Visualization researchers have no abstract model or framework for describing and constructing visualizations of uncertainty as it relates to intelligence analysis. The paper [46] of Judi Thomson presents a typology describing the aspects of uncertainty related to intelligence analysis, drawing on existing frameworks for uncertainty representation. They do not do any uncertainty visualization work but organizes the uncertainties into a logical framework or typology and then explores frameworks for uncertainty that have been developed for representation within the geosciences and scientific visualization community. *conduct*

Instead of professional data scientists, the authors N. Boukhelifa et al. [47] engage domain experts with varying skill levels to find pertinent patterns, build a new uncertainty-aware sensemaking model. They describe their various coping strategies to understand, minimise, exploit, or even ignore the uncertainty influenced by accepted domain practices, but appears to depend on the types and sources of uncertainty. Participants of the study have different technical skill levels which may have had an impact on their behaviour and coping strategies. Moreover, the recruitment scheme was in potential bias due to snowball and social network effects. *the*

Evaluating the impact of an uncertainty visualization is complex due to challenge of defining correct behavior with uncertainty information and difficulties of interpreting uncertainty by

people. The authors Hullman et al. [48] present a taxonomy of methods for evaluating uncertainty visualizations and describe the results of a qualitative analysis applying their own framework to 86 publications which represent the state of uncertainty visualization evaluation. The taxonomy differentiates six levels of decisions that comprise an uncertainty visualization evaluation: the behavioral targets of the study, expected effects from an uncertainty visualization, evaluation goals, measures, elicitation techniques, and analysis approaches. They characterize overall trends in evaluation paths of uncertainty visualization which indicate distinctions between methods for measuring accuracy and decision, as well as different methods for eliciting and assessing subjective confidence. They recommend specific steps that researchers should take when designing uncertainty visualization evaluations to strive for valid and transparent findings.

Understanding how effectively to display uncertain information has become increasingly important because uncertain information can be shown in many formats ranging from simple text to graphical representations. The paper [49] describes two studies in which degraded or blended icons were used to convey uncertainty regarding the identity of a radar contact as hostile or friendly. A classification study first showed that participants could sort, order and rank icons from five sets intended to represent different levels of uncertainty. Contacts and probabilistic estimates of their identities were depicted on a simulated radar screen in one of three ways: with degraded icons and probabilities, with non-degraded icons and probabilities and with degraded icons only. Results showed that participants using displays with only degraded icons performed better, that means the presence of numeric probabilities did not provide a statistically significant advantage in this task. Future research can be conducted to determine the suitability of the display techniques across different and more realistic task situations such as defence applications. Also, there was some evidence to suggest that the use of such icons in combination with numeric probabilities causes decision-makers to be hesitating to expect for more information.

(I wasn't sure what you meant)

Since many visual depictions of probability distributions, such as error bars are difficult for users to accurately interpret, the authors Hullman et al. present a study [50] of alternative representation, Hypothetical Outcome Plots (HOPs). In contrast to the many static representations of distributions, HOPs require relatively little background knowledge to interpret. Results showed that with HOPs, people made much more accurate judgments than error bars and violin plots. Authors suspect that viewers of HOPs could make even more accurate probability hypothesis if provided with interactive graphical annotations. HOPs with more abstract, static depictions might be useful in such a way that the static display is more fully understood.

(users)

??

Authors Kay et al. [51] came up and present a novel mobile interface design and visualization of uncertainty for transit predictions on mobile phones based on discrete outcomes. To develop it, they identified domain specific design requirements for visualizing uncertainty in transit prediction through 1) a literature review, 2) a large survey of users of a popular real-time transit application, and 3) an iterative design process. In a controlled experiment they find that quantile dotplots reduce the variance of probabilistic estimates by ~1.15 times compared to density plots and facilitate more confident estimation by end-users in the context of real-time transit prediction scenarios. Fernandes et al. [52] noticed that when using uncertainty displays, decision quality may ameliorate over time. In real world, bus riders decide to leave for a bus using a real-time transit prediction application and everyone's utility function remains personal and changes according to each situation dynamically. But participants of their studies use same utility functions for all which may make people feel complicit in bad

found

the

the

leading to
decisions of missing bus. Respondents gave mixed opinions about the usefulness of the uncertainty information provided by the app and so future work is necessary to see how widespread such reactions may be in real-world deployments. They both suggested for the presented designs should be evaluated in longitudinal field studies to assess actual acceptability and use.

that

By developing ways to include uncertainty in traditional information visualizations, we can provide more accurate depictions of critical data sets so that people can make more informed and accurate decisions. Researcher M. Skeels [53] reviewed existing work from several domains on uncertainty and created a classification of uncertainty based on the literature. They empirically evaluated and improved upon their classification by conducting interviews with participants from several domains. Their classification better describes the broad range of uncertainty across domains and provides a structure for more readily understandable uncertainty visualization. One of the most promising aspects of their classification for uncertainty is the concept of 'layers' of uncertainty that add complexity to data and is not simple to conceptualize or convey with current techniques. This creates a wide-open opportunity for visualization.

often omitted.

Inherent uncertainties from environmental data (e.g., Meteorological stations and doppler radars, etc.) is usually ignored from visualization. The authors C. M. Whittenbrink et al. [54] showed scientific data collected from different sources, derived uncertainty information, and presented some ideas on designing uncertainty vector glyphs. They have developed a new vector glyph to visualize uncertainty in winds and ocean currents. Their approach is to include uncertainty in direction and magnitude, as well as the mean direction and length, in vector glyph plots. They defined visualization overloading and verity visualization, illustrating how their new glyphs represent the latter. They use both quantitative and qualitative methods to compare their glyphs and their glyphs are superior compared to traditional ones in terms of uses because of their ease of understanding and information presentation.

showing they are.

2.3. Chromatic Aberration related prior works

(did this section change too?)

Again, from a vision perspective, chromatic aberration leads to various forms of color imperfections in the image. When tampering with an image, these aberrations are often disturbed and fail to be consistent across the image. Koh et. al. [10] presented a user study to observe the effect on users' judgment with Lateral Chromatic Aberration (LCA) for Chart Reading in Information Visualization on Display Devices and suggested guidelines for information visualization designers to avoid such issues. LCA occurs when the lens does not focus all lights with different wavelengths to the same convergent point. Although the effect can be observed from natural scenes, they focus on LCA on modern display devices and they present a series of controlled user experiments to show how people can misjudge information due to LCA. Although humans can compensate for the error especially with monochromatic aberration, the ability to correct errors caused by polychromatic aberration is still limited. There is an open task to investigate different degrees of aberration. A quantitative prediction on the amount of aberration depending on the wavelength and the power of eyeglasses will let us estimate the threshold on which viewers start to misinterpret the chart.

Colour is widely used in information visualisation to deliver different types of information such as extreme values, patterns and attribute values. Colour coding is known to be a particularly effective way to represent extreme values for human viewers due to the nature of pre-attentive vision. Therefore, Hyun Seung Yoo et. al. [11] study undertaken in order to identify appropriate interventions and propose design guidelines for information visualisation, especially in applications where size judgement is critical. The colour size illusion was replicated on an LCD monitor, revealing that yellow images appeared the smallest among a series of red, yellow, green and blue images on a white background.

Lens flare is an effect caused by light passing through a photographic lens in any other way than the one intended by design. In the paper [14] Matthias Hullin et al. present a novel method to interactively compute physically plausible flare renderings for photographic lenses where underlying model covers many components that are important for realism, such as imperfections, chromatic and geometric lens aberrations, and anti-reflective lens coatings. A common problem arises when triangles become smaller than one pixel in rasterization aliasing it can lead to very high intensity, but potentially error-prone rasterization.

Real cameras have an aperture through which light falls on an image plane containing receptors to register an image. For a sharp image, a small aperture is preferable, but then less light would hit these sensors and diffraction becomes an issue. Sungkil Lee et al. [15] nicely present a novel rendering system for defocus blur and lens effects. The efficient solution achieved by approximating the image-capturing process by considering not only aperture but also aspects of the lens interaction itself. They approximate optical aberrations, which is a unique feature for real-time approaches, and sometimes considered as crucial for realism. More precisely, the major contributions of the paper are: i an efficient algorithm for DOF and lens blur effects ii. An interactive and intuitive focus control system iii. A generalized method for expressive DOF rendering. They think combining their approach with single-pass depth peeling can be an interesting avenue for future work and mentioned single-pass decomposition of their depth peeling is slower, but their cache-efficient ray tracing mechanism helps to achieve better quality with a strong speedup.

One of the interesting research projects conducted by Micah K. Johnson et al. [13] shows that inconsistencies in lateral chromatic aberration can be used to detect tampering in visually plausible forgeries. They describe a computational technique for automatically estimating lateral chromatic aberration and show the efficacy of the approach for detecting digital tampering in synthetic and real images. They considered only lateral chromatic aberration for their study where the lateral aberration can be modeled as an expansion/contraction of the color channels with respect to one another. When tampering with an image, these aberrations are often disturbed and fail to be consistent throughout the image.

2.4. Texture related prior works

Particle Tracing and Line Integral Convolution (LIC) in Netzel et al. [22] are parallelly and independently used on every pixel of the texture to reduce the computational cost. On top of that a Gaussian low-pass filter with sparse input noise is used for phase shifting along the streamlines. But there is no indication of how high pass filter and/or variable input noise impacts on the result and performance in terms computation and rendering. Streamline computations were replaced by texture advection that works well for both steady and unsteady flow and provides extremely quick results. But the disadvantage of this setup is coupling exponential filter that cannot handle trends properly.

Existing techniques are not capable of accurately aligning and tracking dynamic time-varying data because of the segmentation problem, key feature identification or absence of overlap in consecutive timestep. So, Caban et al. [23] introduces a texture-based feature tracking technique capable of tracking multiple features over time by analyzing local textural properties and finding correspondent properties from synthetic and real-world time varying volumetric data. The main limitation specified in the paper is the cumulative error issue that is caused from the “drifting problem” which exists when small errors are introduced to the texture-based multi-dimensional feature vector over time.

The authors Bachthaler et al. [24] have introduced a new technique of utilising the overlay of two different LIC (line integral convolution) textures to combine the visualization of the tangential and orthogonal vector fields. They have applied a weaving of high-frequency spatial textures of different colors and avoided avoid a direct color blending for compositing. Different filter kernels and filter methods are compared and discussed in terms of visualization quality and speed to obtain a consistent and temporally coherent animation. A perception study was carried out to measure the discrimination and perceived speed of moving patterns under realistic settings. Also, there is an open question to study the implication of global motion perception and the effectiveness of conveying flow structures since they have focused on low-level local motion perception only. The approach of the study is restricted to 2D manifolds and cannot be extended to higher dimensions.

To avoid color blurring and inconsistencies in popular Line Integral Convolution (LIC) scheme and mitigate the expensive computation or memory cost, eliminating surface parameterization, Huang et al. [25] have introduced a novel image-space surface flow visualization approach that

preserves the coherence during user interactions. They have employed a precomputed sequence of triangle textures on coordinates of each vertex to ensure noise textures under different viewpoints remain coherent. Although the approach works fine for most models, popping artifacts can be still visible for some complicated models. For example: when the viewpoint is very far away from or very close to the surface.

Kratz et al. [26] have presented a method for the generation of anisotropic sample distributions in the planar and the two-manifold domains. They also presented interactive rendering of anisotropic Voronoi cells. They have used a special sampling approach to generate sample distributions that cover the underlying domain densely while significant holes and cluttered areas are avoided. They use quadratic textures as GPU data structures, which results in some redundant storage that consumes higher memory than it should be required. The most time-consuming step during initial sampling and relaxation in the two-manifold domain is the back-projection. Influence of adding noise to the cell boundaries are not tested in their experiment but have plan to do in future.

To improve the use of color in combination with motion where the author Weiskopf [27] has distinguished between the detection of patterns in motion (seeing the existence) and the actual perception of motion (recognizing speed and direction). It discussed on how calibration is needed to represent data by the perceived speeds of colored patterns and demonstrated how the guidelines of design of animated graphics and the calibration approach can be used. Although they defined and explained the guidelines, they were not able to make a well-established computational model. Finally, they have mentioned several of possible future works, firstly - user studies could be conducted to test the proposed guidelines for various application scenarios, secondly - evaluate the calibration process in more detail by statistically significant user tests, thirdly - address specific combinations of chromatic motion and further perceptual features like texture.

Healey et al. [28] presents a new method for using texture to visualize multidimensional data elements arranged on an underlying three-dimensional height field. Perceptual texture elements are built by controlling three separate texture dimensions: height, density, and regularity. They conducted a set of controlled experiments to measure the effectiveness of these dimensions, and to identify any visual interference that may occur when all three are displayed simultaneously at the same spatial location. Ad-hoc mapping often introduces visual artifacts that actively interfere with a user's ability to perform their visual analysis tasks. Additionally,

it is found that taller, shorter, denser, and sparser pexels can be easily identified, but that certain background texture patterns must be avoided to ensure accurate performance.

References:

- [1] Song, Xin; Xiao, Jun PhD; Deng, Jiang PhD; Kang, et al. Time series analysis of influenza incidence in Chinese provinces from 2004 to 2011. Received March 1, 2016, Accepted May 20, 2016, Medicine: June 2016 - Volume 95 - Issue 26 - p e3929
- [2] Muhammad Ali, Dost Muhammad Khan, et al. Forecasting COVID-19 in Pakistan, received: August 17, 2020; Accepted: November 10, 2020; Published: November 30, 2020.
- [3] COVID-19: A Comparison of Time Series Methods to Forecast Percentage of Active Cases per Population. Appl. Sci. 2020, 10(11), 3880; Received: 5 May 2020 / Revised: 23 May 2020 / Accepted: 29 May 2020 / Published: 3 June 2020
- [4] Christophorus Beneditto, Aditya Satrio et al. Time series analysis and forecasting of coronavirus disease in Indonesia using ARIMA model and PROPHET, <https://doi.org/10.1016/j.procs.2021.01.036>
- [5] Leo J, Luhanga E, Michael K. Machine Learning Model for Imbalanced Cholera Dataset in Tanzania. The Scientific World Journal. 2019 Jul; 2019: p. 1–12.
- [6] Emrah Gecili, Assem Ziady, Rhonda D. Szczesniak. Forecasting COVID-19 confirmed cases, deaths and recoveries: Revisiting established time series modeling through novel applications for the USA and Italy. Received: June 30, 2020; Accepted: December 5, 2020; Published: January 7, 2021.
- [7] Sathler C, Luciano J. Predictive modeling of dengue fever epidemics: A Neural Network Approach. 2017. Data Science for Drug Discovery, Health and Translational Medicine. December 10, 2017. I590.
- [8] Miranda GHB, Baetens JM, Bossuyt N, Bruno OM, Baets BD. Real-time prediction of influenza outbreaks in Belgium. Epidemics. 2019 Sep; 28: p. 100341.
- [9] Muktevi Srivenkatesh, Performance Evolution of Different Machine Learning Algorithms for Prediction of Liver Disease. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-2, December 2019.
- [10] K. Koh, B. Kim & J. Seo. 2014. Effect of lateral chromatic aberration for chart reading in information visualization on display devices. Advanced Visual Interfaces. Como, Italy, 289-292.
- [11] H. S. Yoo. 2007. Color illusions on liquid crystal displays and design guidelines for information visualization. Master of Science, Virginia Tech.
- [12] T. Boult & W. Wolberg. 1992. Correcting chromatic aberrations using image warping. CVPR, Champaign, IL, 684–87.
- [13] M. K. Johnson & H. Farid. 2006. Exposing digital forgeries through chromatic aberration. Multimedia and security, Geneva, Switzerland, 48-55.

- [14] M. Hullin, E. Eisemann H.P. Seidel & S. Lee. 2011. Physically-based real-time lens flare rendering. ACM SIGGRAPH, Vancouver, 108:1–108:9.
- [15] S. Lee, E. Eisemann & H.P. Seidel. 2010. Real-time lens blur effects and focus control. ACM SIGGRAPH, Los Angeles, 1-7.
- [16] Bonneau et al. Overview and State-of-the-Art of Uncertainty Visualization, The University of Grenoble, France e-mail: Georges-Pierre.Bonneau@ujf-grenoble. fr. ISBN: 978-1-4471-6496-8
- [17] Simon Barthelme, Pascal Mamassian. Evaluation of Objective Uncertainty in the Visual System. Received June 8, 2009; Accepted August 12, 2009; Published September 11, 2009.
- [18] Henning Griethe et al. The Visualization of Uncertain Data: Methods and Problems. Computer Graphics, 18051 Rostock, Germany. January 2006, 2,988 reads, 36 publications, 262 citations.
- [19] Deitrick, S., Edsall, R.: The influence of uncertainty visualization on decision making: An empirical evaluation. In: Progress in Spatial Data Handling, pp. 719–738. Springer Berlin Heidelberg (2006).
- [20] Lundström, C., Ljung, P., Persson, A., Ynnerman, A.: Uncertainty visualization in medical volume rendering using probabilistic animation. IEEE Transactions on Visualization and Computer Graphics 13(6), 1648–1655 (2007).
- [21] Pang, A., Wittenbrink, C., Lodha., S.: Approaches to uncertainty visualization. The Visual Computer 13(8), 370–390 (1997).
- [22] Rudolf Netzel and Daniel Weiskopf, Texture Based Flow VisualizaTion. November 2013, Computing in Science and Engineering 15(6): 96-102,
- [23] Jesus J. Caban, Alark Joshi, and Penny Rheingans. Texture-based feature tracking for effective time-varying data visualization, IEEE Transactions on Visualization and Computer Graphics (Volume: 13, Issue: 6, Nov.-Dec. 2007). Page(s): 1472 – 1479.
- [24] Sven Bachthaler, Daniel Weiskopf. Animation of Orthogonal Texture Patterns for Vector Field Visualization. IEEE Transactions on Visualization and Computer Graphics (Volume: 14, Issue: 4, July-Aug. 2008), Page(s): 741 – 755.
- [25] Jin Huang, Zherong Pan, Guoning Chen, Wei Chen, Hujun Bao. Image-Space Texture-Based Output-Coherent Surface Flow Visualization. IEEE Transactions on Visualization and Computer Graphics (Volume: 19, Issue: 9, Sept. 2013). Page(s): 1476 – 1487.
- [26] Andrea Kratz, Daniel Baum, and Ingrid Hotz. Anisotropic Sampling of Planar and Two-Manifold Domains for Texture Generation and Glyph Distribution. IEEE Transactions on Visualization and Computer Graphics (Volume: 19, Issue: 11, Nov. 2013). Page(s): 1782 – 1794.

- [27] D. Weiskopf. On the role of color in the perception of motion in animated visualizations. Conference: 10-15 Oct. 2004, Austin, TX, USA. IEEE Visualization 2004. ISBN: 0-7803-8788-0.
- [28] C.G. Healey; J.T. Enns. Building perceptual textures to visualize multidimensional datasets. 18-23 Oct. Research Triangle Park, NC, USA. 1998. Proceedings Visualization '98 (Cat. No.98CB36276). ISBN: 0-8186-9176-X.
- [29] R.P. Botchen; D. Weiskopf; T. Ertl. Texture-based visualization of uncertainty in flow fields. VIS 05. IEEE Visualization, Minneapolis, MN, USA. 23-28 Oct. 2005. ISBN: 0-7803-9462-3.
- [30] Aasim Kamal · Parashar Dhakal, et al. Recent advances and challenges in uncertainty visualization: a survey. May 2021, Journal of Visualization 24(5):1-30.
- [31] Galit Shmueli, Kenneth C. Lichtendahl Jr. Practical Time Series Forecasting with R: A Hands-On Guide [2nd Edition] (Practical Analytics) Paperback – July 19, 2016. Page 18-19. ISBN-13 978-0997847918
- [32] Jason Brownlee. Deep Learning Models for Univariate Time Series Forecasting. <https://machinelearningmastery.com/how-to-develop-deep-learning-models-for-univariate-time-series-forecasting>.
- [33] Aayush Agrawal, Building Neural Network from scratch. <https://towardsdatascience.com/building-neural-network-from-scratch-9c88535bf8e9>
- [34] Akinori Hidaka, Takio Kurita. Consecutive Dimensionality Reduction by Canonical Correlation Analysis for Visualization of Convolutional Neural Networks. Conference: Proceedings of the ISCIE International Symposium on Stochastic Systems Theory and its Applications. December 2017. Pages 160 – 167.
- [35] Michael Correll, Dominik Moritz, Jeffrey Heer. Value-Suppressing Uncertainty Palettes. Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. April 2018. Paper No.: 642 Pages 1–11.
- [36] Jessica Hullman. Why Authors Don't Visualize Uncertainty. IEEE Transactions on Visualization and Computer Graphic. Jan. 2020, pp. 130-139, vol. 26.
- [37] Shunan Guo, Fan Du, Sana Malik, et al. Visualizing Uncertainty and Alternatives in Event Sequence Predictions. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. May 2019. Paper No.: 573. Pages 1–12.
- [38] Michelle Korpela, Ian T. Ruginski, and Sara Irina Fabrikant. Effects of Uncertainty Visualization on Map-Based Decision Making Under Time Pressure. Human-Media Interaction, a section of the journal Frontiers in Computer Science. Received: 22 May 2020. doi: 10.3389/fcomp.2020.00032.
- [39] Max Schneider, Michelle McDowell et al. Effective uncertainty visualization for aftershock forecast maps. Natural Hazards and Earth System Sciences. Discussion started: 3 September 2021. <https://doi.org/10.5194/nhess-2021-237>.

- [40] Ken Brodlie, Rodolfo Allendes Osorio, and Adriano Lopes. 2012. A review of uncertainty in data visualization. In Expanding the frontiers of visual analytics and visualization. Springer, 81–109. DOI: http://dx.doi.org/10.1007/978-1-4471-2804-5_6
- [41] Michael Correll and Michael Gleicher. 2014. Error bars considered harmful: Exploring alternate encodings for mean and error. *IEEE Transactions on Visualization and Computer Graphics* 20, 12 (2014), 2142–2151. DOI: <http://dx.doi.org/10.1109/TVCG.2014.2346298>
- [42] Miriam Greis, Passant El Agroudy, et al. 2016. Decision-Making under Uncertainty: How the Amount of Presented Uncertainty Influences User Behavior. In Proceedings of the 9th Nordic Conference on Human-Computer Interaction. ACM, 52. DOI: <http://dx.doi.org/10.1145/2971485.2971535>
- [43] Lydia R Lucchesi and Christopher K Wikle. 2017. Visualizing uncertainty in areal data with bivariate choropleth maps, map pixelation and glyph rotation. *Stat* (2017). DOI:<http://dx.doi.org/10.1002/sta4.150>
- [44] Alan M MacEachren, Robert E Roth, James O'Brien, Bonan Li, Derek Swingley, and Mark Gahegan. 2012. Visual semiotics & uncertainty visualization: An empirical study. *IEEE Transactions on Visualization and Computer Graphics* 18, 12 (2012), 2496–2505. DOI: <http://dx.doi.org/10.1109/TVCG.2012.279>
- [45] Maria Riveiro. 2007. Evaluation of uncertainty visualization techniques for information fusion. In 10th International Conference on Information Fusion. IEEE, 1–8. DOI: <http://dx.doi.org/10.1109/ICIF.2007.4408049>
- [46] Judi Thomson, Elizabeth Hetzler, Alan MacEachren, Mark Gahegan, and Misha Pavel. 2005. A typology for visualizing uncertainty. In Electronic Imaging 2005. International Society for Optics and Photonics, 146–157.
- [47] N. Boukhelifa, M.-E. Perrin, S. Huron, and J. Eagan. How data workers cope with uncertainty: A task characterisation study. In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, pages 3645–3656. ACM, 2017.
- [48] J. Hullman, X. Qiao, M. Correll, A. Kale, and M. Kay. In pursuit of error: A survey of uncertainty visualization evaluation. *IEEE transactions on visualization and computer graphics*, 25(1):903–913, 2019.

- [49] R. Finger and A. M. Bisantz. Utilizing graphical formats to convey uncertainty in a decision-making task. *Theoretical Issues in Ergonomics Science*, 3(1):1–25, 2002.
- [50] J. Hullman, P. Resnick, and E. Adar. Hypothetical outcome plots outperform error bars and violin plots for inferences about reliability of variable ordering. *PloS one*, 10(11):e0142444, 2015.
- [51] M. Kay, T. Kola, J. R. Hullman, and S. A. Munson. When (ish) is my bus?: User-centered visualizations of uncertainty in everyday, mobile predictive systems. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 5092–5103. ACM, 2016.
- [52] M. Fernandes, L. Walls, S. Munson, J. Hullman, and M. Kay. Uncertainty displays using quantile dotplots or cdfs improve transit decision-making. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, page 144. ACM, 2018.
- [53] M. Skeels, B. Lee, G. Smith, and G. G. Robertson. Revealing uncertainty for information visualization. *Information Visualization*, 9(1):70–81, 2010.
- [54] C. M. Wittenbrink, A. T. Pang, and S. K. Lodha. Glyphs for visualizing uncertainty in vector fields. *IEEE transactions on Visualization and Computer Graphics*, 2(3):266–279, 1996.
- [55] Z. Wang et al. Model identification of reduced order fluid dynamics systems using deep learning. *International Journal for Numerical Methods in Fluids*. Int. J. Numer. Meth. Fluids 2014; 00:1-18.

