Task-based Colormap Design Supporting Visual Comprehension in Process Tomography

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Abstract

*Color coding is a fundamental technique for mapping data to visual representations, allowing people to carry out comprehension-based tasks. Process tomography is a rapidly developing non-invasive imaging technique used in various fields of science due to its effective flow monitoring and data acquisition [KŁS*19]. To study how well colormaps can support visual comprehension of tomographic data, we conduct a feasibility evaluation of 11 widely-used color schemes. We employ the same segmentation tasks characterized by Microwave Tomography (MWT) on each individual chosen colormap, and then conduct a quantitative assessment of those schemes. Based on the insight gained, we conclude that autumn, viridis, and parula colormaps yield the best segmentation results. According to our findings, we propose a colormap design guideline for practitioners and researchers in the field of process tomography.*

CCS Concepts

• ***Human-centered computing*** → ***Visualization design and evaluation methods;***

1. Introduction

Color coding plays a critical role in a wide range of visualization tasks which are pervasively used in miscellaneous application scenarios. Appropriate color scheme usage in graphs, images, and animations contributes to better expressiveness and persuasiveness among visual representations. Color is a retinal variable which is conventionally determined by hue, saturation and brightness (HSB) as dimensions in perception-based applications [SWTS05]. Research has proven that using different colormaps can cause differing interpretations, depending on how the visualization is perceived by the human eye [SGS*18]. That is, the selection of colormaps significantly influences a person's visual comprehension of data.

Tomography is a widely-used imaging technique in medical and industrial contexts. Microwave tomography (MWT) is a specific type of tomography with non-ionizing properties that is commonly used in industrial process applications [WW17]. MWT can significantly contribute to a more sustainable process industry by reducing the use of energy and material. A critical problem in leveraging these benefits is achieving a more accurate control of the heating process. MWT images–offering information that can be visualized using colormaps–are key in controlling the heating process. For example, Figure 1 presents the set of 8 MWT image samples used in our study. Each sample was acquired from a confined microwave foam drying, revealing post-process moisture levels. An operator's comprehension of an MWT image is key in recognizing those moisture levels on images. In this short paper, we implement a systematic study followed by a quantitative evaluation to develop a colormap design guideline for supporting visual comprehensibility for MWT images.

Colormap design and selection has received attention over recent decades. Bergman et al. explore a rule-based tool to help choose the best colormap for isomorphic, segmentation, and highlighting tasks [BRT95]. Schulze-Wollgast et al. exploit an enhanced automatic color coding framework by encapsulating metadata extraction, colormap adaptation, and color legend creation [SWTS05]. Tominski et al. have developed a color coding function to choose color scales according to particular tasks [TFS08]. Similarly, Mittelstädt et al. [MJSK15] propose a guided tool for selecting suitable colormaps for combined analysis tasks. By conducting several hands-on crowdsourcing experiments with appropriate participants, Reda et al. [RNAK18] have designed a guideline indicating that rainbow scheme or diverging colormaps afford superior accuracy for tasks requiring gradient perception. Likewise, Turton et al. [TWSR17] also leverage a crowdsourced tool called *Ware color key* to assess various colormaps.

In this paper, we concentrate on colormap design for visual comprehension of MWT images based on a segmentation task. To balance energy effectiveness, material flow, and safety aspects, it is

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DOI: 10.2312/evs.20201049

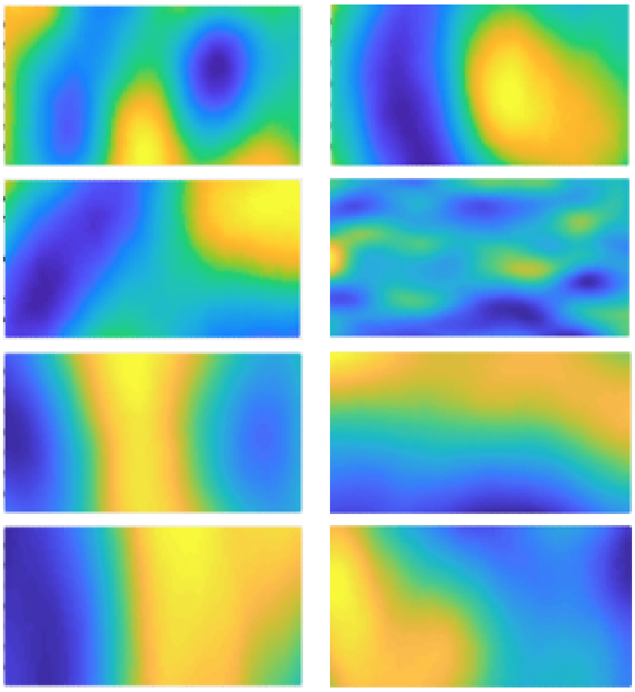

Figure 1: *The 8 MWT image samples in our study. Different colors represent different foam moisture levels; blue is the desired color, representing lower moisture levels.*

Colormap		Hues	Design Strategy
parula		multiple	**default** (colormap in MATLAB)
viridis		multiple	**sequential** (perceptually uniform)
magma		multiple	**sequential** (perceptually uniform)
Greys		single	**sequential** (lightness increase monotonically)
Blues		single	**sequential** (lightness increase monotonically)
cool		two	**sequential** (lightness function has plateau)
autumn		multiple	**sequential** (lightness function has plateau)
hot		multiple	**sequential** (lightness function has kink)
copper		two	**sequential** (lightness function has kink)
Spectral		multiple	**diverging**
coolwarm		two	**diverging**

Figure 2: *The illustration of 11 chosen colormaps.*

crucial that humans – or computers – accurately interpret such images. As an extension of recently presented work [ZMO*19], we implement a more extensive study focusing on a segmentation task. The main contributions of this paper are investigating how various colormaps affect task accuracy in the context of MWT and proposing a design guideline for selecting colormaps yielding accurate visual understanding.

2. Methodology

There is a total of 8 MWT images included in this study obtained from 8 different and independent industrial microwave foam drying processes, as shown in Figure 1. Different colors displayed on the images imply different foam moisture levels. To judge the success of the designated drying processes, it is crucial to measure the low moisture areas and levels by inspecting the MWT images. Typically, the preferred color to show low moisture level in an MWT image is blue.

The MWT image reconstructed from a microwave foam drying process possesses an intrinsic continuous colormap throughout being handled in MATLAB, which is denoted as parula. Thus, all the 8 images in our study are presented in this colormap. In addition, we choose another 10 commonly-used continuous colormaps (listed and elaborated in Figure 2) which are able to reveal the useful information in MWT according to different categories, with which we deploy the same segmentation task, in total 11.

2.1. Colormaps

In the following sections, we investigate whether the commonly adopted colormaps varying the degrees in luminance and hues differ the efficiency and effectiveness in the same segmentation task. The selection of colormaps is based on recently published colormap design papers, composing following 5 (4+1) design strategies.

– **Sequential:** Change in lightness and often incremental saturation of color, often using a single hue; should be used for representing information that has ordering.

  ∗ **Sequential 1:** Perceptually uniform, with each new color equally perceptually distinct from the previous and following colors.
  ∗ **Sequential 2:** Lightness values monotonically increase.
  ∗ **Sequential 3:** In the lightness function space, there will be a plateau, or the function may go both up and down.
  ∗ **Sequential 4:** In the lightness function space, there are some kinks in the function.

– **Diverging:** Change in lightness and possibly saturation of two different colors that meet in the middle at an unsaturated color; used in information being plotted has a critical middle value, such as topography or when the data deviates around zero.

  The design strategy for each colormap is elaborated as follows.

∗ **parula:** The default colormap in MATLAB.
∗ **viridis:** The default blue-green-yellow colormap in Matplotlib, a nice sequential colormap [Mor09, Bre94].
∗ **magma:** Another perceptually-uniform black-purple-pink colormap [Mor09, Bre94].
∗ **Greys:** Simple grayscale color bar [SGS*18].
∗ **Blues:** Simple blue color bar [SGS*18, RNAK18].
∗ **cool:** Cyan-magenta color map; based on colormap of the same name in Matlab [BRT95].
∗ **autumn:** Sequential increasing shades of red-orange-yellow [SGS*18].
∗ **hot:** Sequential black-red-yellow-white, to emulate blackbody radiation from an object at increasing temperatures [SGS*18].

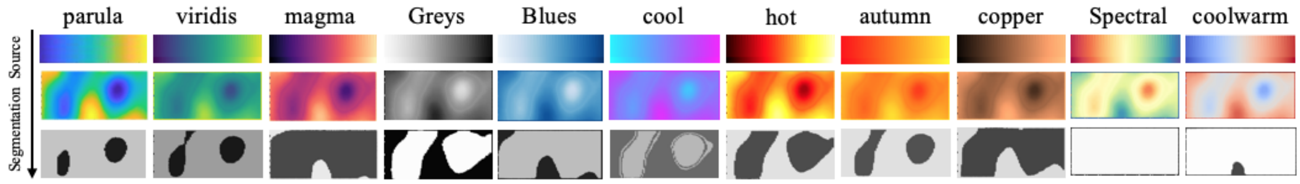

Figure 3: *Top-down image processing pipeline (arrow): each of the 11 colormaps (1st row) is applied to the same MWT image sample resulting in (2nd row), and yielding corresponding segmented images (3rd row). Due to limited space, here we randomly choose one sample from our whole 8 samples.*

* **copper:** Sequential increasing shades of black-copper [Bre94].
* **Spectral:** Diverging, multi-hue encompassing a subset of the rainbow with a yellow middle [RNAK18].
* **coolwarm:** Diverging blue-gray-red, meant to avoid issues with 3D shading, color blindness, and ordering of colors [Mor09, RNAK18].

2.2. Quantitative Evaluation

After selection, we convert our MWT images with the chosen colormaps by using OpenCV. Thus, we are able to observe each colormap in segmenting the the desired low moisture areas (blue parts on the images in parula colormap). Following such implementation, we have acquired the underlying ability of the selected 11 colormaps in context of the MWT segmentation task (Figure 3). The segmentation with each colormap is conducted by the same automatic method proposed in [ZMO*19]. From the preliminary results, we are able to infer that parula, viridis, cool, hot, and autumn schemes are capable to visualize the blue parts from the source image in segmentation. To validate the outcome acquired, we adopt three data-driven metrics to quantitatively assess the performance of the colormaps by following [ZMO*19] as well. We employ Jaccard index, Dice coefficient, and false positive as assessments (Equations 1–3). Source denotes the source MWT image to be segmented while segmentation represents the segmented image.

$$Jaccard\ index = \frac{|Source \cap Segmentation|}{|Source \cup Segmentation|} \tag{1}$$

$$Dice\ coefficient = 2 \times \frac{|Source| \cap |Segmentation|}{|Source| + |Segmentation|} \tag{2}$$

$$False\ positive = \frac{|Segmentation| - |Source \cap Segmentation|}{|Source|} \tag{3}$$

3. Result

As mentioned in the introduction, this study allows us to find the colormaps which best facilitate visual comprehension for MWT in segmentation tasks. We pick the whole 8 MWT image samples then implement the same segmentation for them with each of the 11 colormaps. By the three metrics on all sample and colormap combinations, we obtain the output shown in Tables 1-3 and Figures 4-6.

Table 1: *Jaccard index data: Comprehensive performance comparison between 11 colormaps for 8 samples.*

	1	2	3	4	5	6	7	8
parula	0.942	0.938	0.950	0.976	0.985	0.986	0.986	0.932
viridis	0.995	0.981	0.990	0.928	0.993	0.971	0.987	0.950
magma	0.325	0.374	0.332	0.378	0.368	0.657	0.282	0.527
Greys	0.687	0.703	0.683	0.664	0.694	0.534	0.624	0.733
Blues	0.497	0.393	0.390	0.388	0.699	0.692	0.391	0.393
cool	0.797	0.793	0.780	0.796	0.795	0.792	0.895	0.895
hot	0.897	0.793	0.785	0.796	0.795	0.798	0.839	0.884
autumn	0.997	0.993	0.990	0.908	1.0	0.995	1.0	0.995
copper	0.607	0.636	0.664	0.631	0.675	0.781	0.602	0.749
Spectral	0.396	0.193	0.287	0.198	0.192	0.321	0.174	0.268
coolwarm	0.297	0.288	0.281	0.299	0.199	0.285	0.195	0.256

For Jaccard index and Dice coefficient, the higher value represents the better performance while vice versa in false positive values.

From the output shown, we note that all colormaps perform uniformly across all examples. In both Jaccard index and Dice coefficient, autumn scheme reaches very a high value, even approaching 1.0 in some cases, which demonstrates excellent performance. Similarly, it yields considerably low false positive assessment over the whole samples. Colormaps viridis and parula obtain brilliant performance consistently among the three metrics assessment. By observing the tables and diagrams, it is noteworthy that colormaps Spectral, coolwarm, and magma have the low evaluation outcomes (low Jaccard index and Dice coefficient values but high false positive values) corresponding to initial results (In Figure 3, those 3 colormaps are not able to visualize the blue parts correctly). By combining the complete results, it is fair to conclude that autumn, viridis, and parula schemes appear to be the most desirable choices.

4. Discussions and Guideline

Firstly, inspired by the previous studies, we intend to investigate which colormaps are viewed as the most accurate in supporting a comprehension-based MWT segmentation task. Secondly, the 11 selected colormaps are chosen based on different design strategies to verify our hypothesis. Our integrated quantitative evaluation suggests that autumn, viridis, and parula are the most appropriate color schemes. Our study also suggests that some colormaps are not applicable in the context of MWT. This is because diverse colormaps perform differently in computer vision related tasks due to they

Table 2: *Dice coefficient data: Comprehensive performance comparison between 11 colormaps for 8 samples.*

	1	2	3	4	5	6	7	8
parula	0.976	0.994	0.975	0.988	0.991	0.997	0.977	0.956
viridis	0.992	0.990	0.977	0.929	0.941	0.985	0.993	0.973
magma	0.361	0.387	0.354	0.389	0.284	0.678	0.291	0.605
Greys	0.656	0.753	0.815	0.723	0.645	0.507	0.695	0.703
Blues	0.498	0.596	0.595	0.494	0.699	0.696	0.305	0.396
cool	0.798	0.696	0.695	0.798	0.797	0.782	0.827	0.857
hot	0.788	0.696	0.692	0.798	0.795	0.789	0.879	0.897
autumn	0.998	0.996	0.995	0.926	0.915	0.997	1.0	0.976
copper	0.593	0.5676	0.667	0.667	0.633	0.738	0.648	0.756
Spectral	0.198	0.296	0.233	0.199	0.179	0.386	0.174	0.189
coolwarm	0.198	0.194	0.250	0.199	0.187	0.397	0.157	0.206

Table 3: *False positive data: Comprehensive performance comparison between 11 colormaps for 8 samples.*

	1	2	3	4	5	6	7	8
parula	0.084	0.083	0.081	0.068	0.064	0.077	0.085	0.085
viridis	0.075	0.065	0.077	0.075	0.076	0.085	0.087	0.080
magma	0.468	0.570	0.471	0.474	0.472	0.172	0.569	0.437
Greys	0.158	0.160	0.161	0.174	0.257	0.262	0.352	0.264
Blues	0.302	0.306	0.357	0.355	0.304	0.184	0.504	0.506
cool	0.142	0.186	0.177	0.124	0.153	0.164	0.124	0.134
hot	0.162	0.186	0.137	0.121	0.165	0.161	0.130	0.135
autumn	0.039	0.065	0.075	0.095	0.094	0.045	0.049	0.046
copper	0.344	0.345	0.346	0.344	0.354	0.147	0.343	0.150
Spectral	0.503	0.436	0.507	0.501	0.610	0.450	0.632	0.482
coolwarm	0.502	0.406	0.427	0.499	0.566	0.570	0.572	0.505

possess own luminance and hues. Since human perception differs individually [HT62] of colors and images, the determination for specific colormaps is somewhat subjective. While the quantitative assessment validates the objectivity of our findings, it also supports the robustness of our work. Hence, we select these three colormaps autumn, viridis, and parula as benchmarks for a design guideline.

- **Guideline:** For comprehension-based segmentation scientific analysis for MWT, we recommend the colormaps *autumn*, *viridis*, and *parula* as the most suitable color schemes. For the same context of use, we do not suggest *Spectral*, *coolwarm* or *magma* schemes.

5. Conclusions

MWT can strongly contribute to a more sustainable process industry including reduced energy and material consumption. To leverage such gains, it is key to enable process operators to accurately perceive MWT images in order to control the process. This partly relies on the design and choice of colormaps. This paper presents the results of a study to assess alternative colormaps for their capacity to support visual comprehension in the context of an MWT segmentation microtask [BBA15], verified by a data-driven evaluation of those colormaps using three objective metrics. According to our findings, we present a design guideline that recommends hot and cool schemes for operators and researchers in process tomography

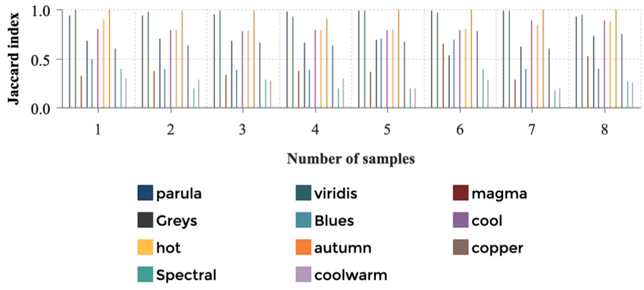

Figure 4: *Jaccard index evaluation of 11 colormaps over 8 samples.*

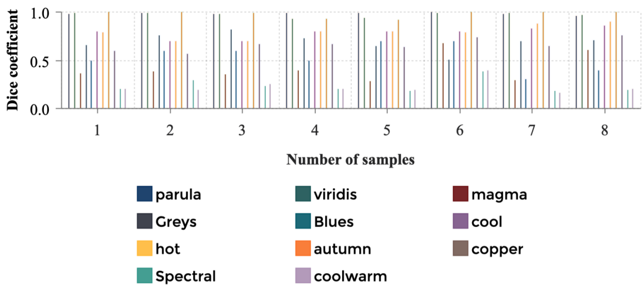

Figure 5: *Dice coefficient evaluation of 11 colormaps over 8 samples.*

applications and research. In future work, a higher number of samples and more specific tasks could be examined. Finally, when mapping process tomography data to visual representations [CWR*16], there is need for deeper understanding of combining human perception factors and quantitative approaches as well as the corresponding user studies. Our future work will be focusing on such an emerging area of research.

6. Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No. 764902. We thank Heidrun Schumann and Philippa Beckman for their helpful feedback.

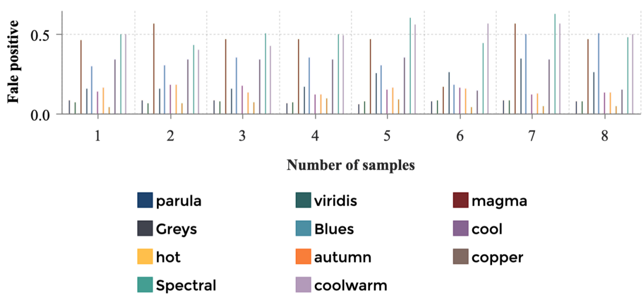

Figure 6: *False positive evaluation of 11 colormaps over 8 samples.*

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