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SpatialRugs: Enhancing Spatial Awareness of Movement in Dense Pixel Visualizations

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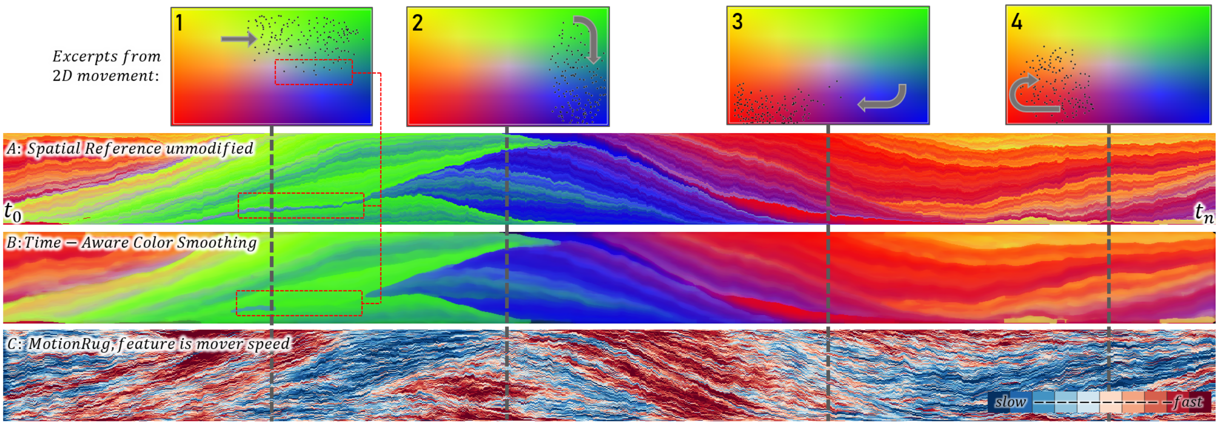


Figure 1: *SpatialRugs* (A+B) and *MotionRugs* (C), all with the same underlying dataset of 151 fish moving in a tank for about 90 seconds. Excerpts 1-4 show static snippets of the fish turning from the upper right over the lower right to the lower left. Part A shows unmodified *SpatialRugs*, where colors can be related to spatial positions (compare colors to Parts 1-4). Part B shows color-smoothed *SpatialRugs* that mitigate distorted patterns (outlined in red boxes). Part C shows mover speed encoded in the colors instead of the position. In conjunction, *SpatialRugs* and *MotionRugs* can be applied to relate space to features (e.g., in which areas of A movers are fast or slow as indicated in C.)

Abstract

Compact visual summaries of spatio-temporal movement data often strive to express accurate positions of movers. We present SpatialRugs, a technique to enhance the spatial awareness of movements in dense pixel visualizations. SpatialRugs apply 2D colormaps to visualize location mapped to a juxtaposed display. We explore the effect of various colormaps discussing perceptual limitations and introduce a custom color-smoothing method to mitigate distorted patterns of collective movement behavior.

CCS Concepts

• ***Human-centered computing*** → ***Visualization techniques;***

1. Introduction

The visualization of movement data faces challenges in scalability towards time and amount of displayed movers. Especially, uncovering spatio-temporal patterns in collective movements is challenging due to large numbers of entities moving similarly over long periods. To overcome these issues, *MotionRugs* has been proposed, displaying movers in a static, compact fashion [BJC*18]. In *MotionRugs* (Figure 1 C), each pixel represents one mover, while the X-axis denotes time and the Y-axis represents a 1D spatial aggregation of all movers derived by spatial linearization. Color can encode any numeric feature of interest, e.g., the speed of the entities. To illustrate, Figure 1 C shows mover speed; several trends of slowing down (red) and speeding up (blue) are visible at a glance, while the curvature reveals spatial dynamics of the collective behavior (e.g., changes in group orientation and position). Despite the space-efficiency of *MotionRugs*, users cannot relate movers to their original locations due to the spatial linearization, as is possible with other techniques like simple static plotting or animation [AA13]. This is a major drawback, as spatial context is often important when analyzing movements, for example, to explain mover's behavior using contextual information such as the locations of food sources for animals.

We combine the space-efficiency of *MotionRugs* with the space-awareness advantages of other advanced techniques for trajectory visualization [AAB*13, HTC09, TSAA12]. We propose *SpatialRugs* (Figure 1 A and B), a technique that applies 2D color maps to dense pixel visualizations, using colors to express the spatial positions of movers. We also refine *SpatialRugs* with a time-aware color correction to mitigate perceptual issues arising from color space transformations (see Figure 1 B). We compare the results to a naive gaussian-based approach and discuss suitable color spaces.

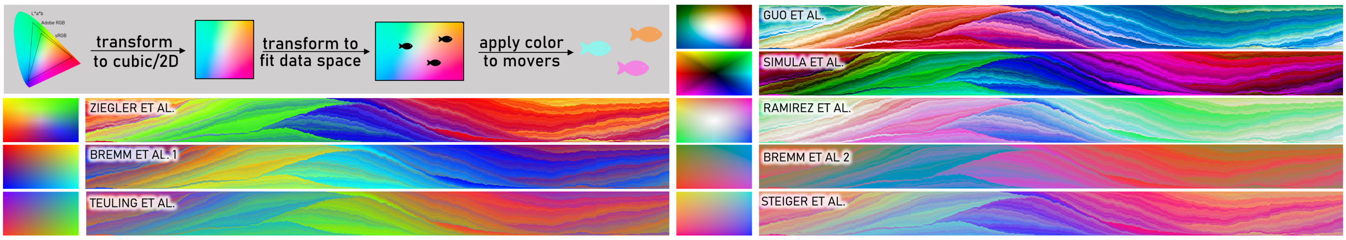


Figure 2: Upper left: In *SpatialRugs*, a color space is transformed into a 2D cubic, then adapted to the extent of the moving area. A position is then encoded using the corresponding color from the color space. Below: Application examples of different colormaps [BSM*15] to the demo dataset containing 151 movers showing collective behavior. Left of each visualization, we see the underlying transformed 2D color space.

2. MotionRugs & Collective Movement Visualization

Visual analysis of movement capitalizes on human perception to uncover patterns over time and space [AA13]. Andrienko et al. [AAB*13] provide an example of spatial abstraction for collective movement, transforming physical mover positions to relative ones regarding a group-centered reference point. *MotionRugs* [BJC*18] further reduce the space of the moving entities from a 2-D to a dense 1-D representation, while still reflecting physical distances between the movers as accurately as possible. To create the 1-D order from a set of 2-D positions, spatial linearization strategies such as space-filling curves or spatial index structures [LO93] are used to retain neighborhoods as good as possible.

In a MotionRug, every mover in one frame is represented by a single pixel which is colored according to a feature (e.g., speed in Fig. 1 C). The process is repeated for each time frame, ordering the slices on the x-axis by time. This process creates the wave-like patterns in *MotionRugs*, which allow the identification of spatial dynamics. The result is a static, dense pixel display [Kei01], showing the feature development of the movers over time. Alternative dense representations for spatiotemporal relations exist, for example by Bergner et al. [BSM*13] or Luboschik et al. [LRB*15] in the area of parameter exploration for spatiotemporal modeling.

In contrast, *MotionRugs* are primarily used to retain an overview of the spatial dynamics reflected in curved spatial dynamics patterns, which can as well be employed to detect trends in features and feature distributions. However, unlike most other techniques for trajectory visualization [AAB*13, HTC09, TSAA12], *MotionRugs* lacks spatial awareness, as it does not depict the accurate spatial locations of the movers. While *MotionRugs* capture changes in space and mover orientation over time, it is unable to show *where* entities are moving to specifically. This limitation is critical for many use cases where analysts need to be aware of the region the entities are moving in. To enhance spatial awareness, while preserving the spatial efficiency of *MotionRugs*, we propose an alternative approach. Below, we propose *SpatialRugs*, a technique that reintroduces spatial positions into *MotionRugs*, eliminating the necessity for tedious analyses (e.g., clutter-prone static trajectory plots or time-consuming animations).

3. Retaining spatial readability with *SpatialRugs*

SpatialRugs is a compact visualization technique for collective movement data that enhances spatial awareness by projecting a 2D-color space into the 1D-linearization of *MotionRugs*. *SpatialRugs* apply a color scale method to the original movement space. Fig. 2 (upper left corner) demonstrates our approach: (i) We transform the color space to a 2-D cubic representation in order to serve as a base for the second step. (ii) We transform the 2-D color space to cover the maximum extent of the spatial dimensions used by the mover dataset. (iii) We assign the 2-D position of a mover to the corresponding color of the transformed color map. Spatial positions are now represented by color, which can be used in conjunction with pixel-based visualizations of movement, such as *MotionRugs*, to encode mover locations. With the colormap reference, users are able to identify the spatial distribution of entities at a given time. Fig. 1 shows that the movers come from the upper right corner (green, first excerpt), take a right turn towards the lower right (blue, second excerpt), move through the lower middle of the represented space in purple to the lower (red, third excerpt) and finally middle left in orange color tones (fourth excerpt). The resulting patterns allow perceiving the movers' spatial distribution, while viewers can also estimate how the movers progress within the color zones. For example, between excerpts 1 and 2, just a few movers start to move towards the blue until everyone follows. This behavior is shown as a cone-shaped transition from green to blue. Consequently, the color mapping enables to compactly see patterns over long periods of time, also relating the spatial development to the feature development by comparing the excerpts (e.g., by relating Fig. 1 A and C).

4. Color Space Considerations

Color space mappings have been applied to represent spatio-temporal relations before. Northern Lights Maps [JMBK09] map spatio-temporal properties of movers to an RGB color scale. PhenoVis [LSA*16] presents color-coded normalized stacked bar charts to allow comparative analysis over longer time spans. MotionExplorer [BDV*17] employs 2D color-coding to highlight temporal patterns in human motions. Similarly, *SpatialRugs* applies a 2D color space mapping to map colors of data points in an abstract visualization to their real spatial positions. As reflected in the color map task assessment ER1-3 by Bernard et al. [BSM*15], a viewer should be able to distinguish different locations by comparing their color representations accurately **(I)**. Also, a viewer has to maintain a mental map to link colors with spatial positions precisely **(II)**. Finally, our approach should allow for two or more locations to be compared with each other **(III)**.

Yet, standard color spaces, e.g., CIELAB, HSV, or sRGB are mostly organized in three dimensions and usually not of a symmetrical shape. Thus, the transformation to a regular 2D form as required by *SpatialRugs* is challenging. Also, color perception is individually different in viewers [DPR*18], resulting in different abilities to identify fine-grained differences. Thus, a sensible color space choice is critical for the effectiveness of *SpatialRugs*. Many

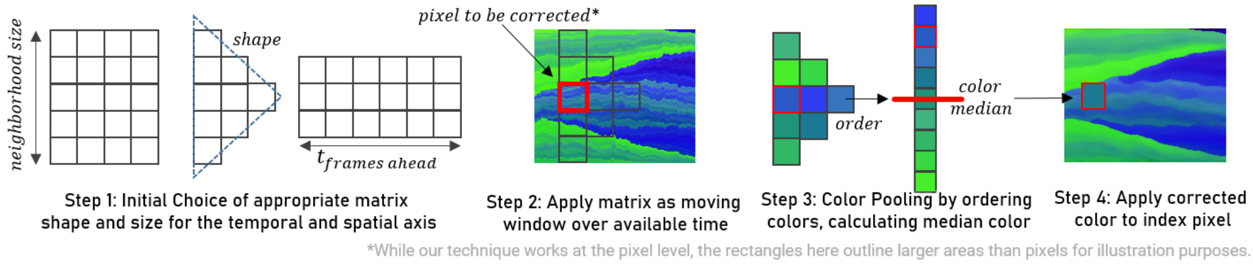


Figure 3: Pooling-based color correction. One matrix dimension determines the size of the regarded neighborhood, the other the time ahead to be considered for the correction. Selecting a use-case appropriate shape and size, the matrix is shifted over each pixel in every time step. Each step, the colors of the matrix cells are ordered by Euclidean distance in the RGB-space. The median color is then applied to the original pixel.

related approaches have employed 2D colormaps in different use cases. In an extensive survey, Bernard et al. [BSM*15] investigate the capabilities of 22 different 2-D color maps with respect to analytical tasks and perceptual properties.

Task assessment: Fig. 2 shows a comparison of the color maps taken from Bernard et al. [BSM*15] generated with the data described in Fig. 1. According to the task assessment table of Bernard et al., colormaps provided by Bremm et al. [BvLBS11], Ramirez et al. [RAGG12], Steiger et al. [SBM*14] and Teuling et al. [TSS11] would be best suitable given our defined tasks **I-III**. Yet, the task-based recommendations [BSM*15] do not regard the perceptibility of visual structures *within* the visualization space. As retaining these structures is important to our approach, we turn to the quality assessment measures [BSM*15].

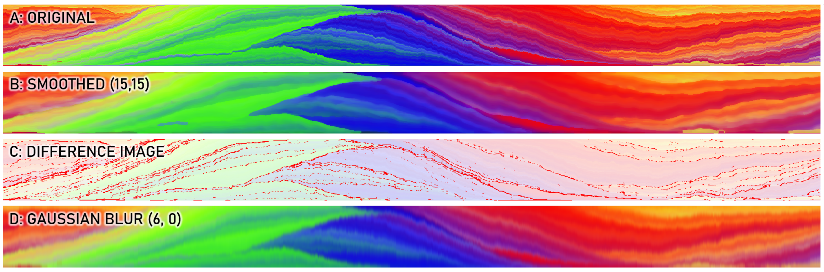
Quality assessment: The JND measure describes the "Just Noticeably Different Colors" [BSM*15], indicating how well a colormap exploits a color space. Here, the colormaps by Simula and Alhoniemi [SA99] and Guo et al [GGMZ05] perform well, but iterate over black or white. Such color maps with a low black- or white distance score work well only in conjunction with backgrounds of the opposite color [BSM*15]. As dense pixel technique, *SpatialRugs* does not feature intermediate spaces between the data points, using color maps with black or white color ranges could interfere with the perceived brightness and saturation of the surrounding colors, making the color map difficult for our case. The next best color maps according to the JND feature are Cube Diagonal Cut B-C-Y-R [BvLBS11] and the Four Corners R-B-G-Y color map [ZNK07].

Transformation assessment: The visual outcome of *SpatialRugs* is also determined by the amount of applied transformation to the color space. Changing the ratio of an original color space in one axis affects the color discriminability along the same axis. This holds even if the ratio is changed in both axes. In both directions (either shrinking or enlarging the color space), color discriminability suffers, since either there will be less space to represent all colors a color space can provide, or the same colors are stretched over a larger space. Yet, since color perception is not necessarily linear, such effects can only be measured in perceptual studies. While we acknowledge these effects, we expect that our technique is still applicable to aspect ratios of up to 16:9.

5. Pooling-based Time Aware Color Smoothing

For some specific use cases, we observe adverse perceptual distortions, especially in the transition areas between primary color tones. For example, collective movements, as for which MotionRugs is originally intended, feature a strong focus on the group coherence. Yet, certain perceptual artifacts can occur in SpatialRugs, when a part of an otherwise homogeneous group of movers partially protrudes into another color area. Figure 1 shows such a case in excerpt 1, outlined in red, where most movers are in the green quadrant, with a few extending into the transition area to the blue quadrant, resulting in a salient blue line (outlined in the red box). Here, the perceived color distances appear larger than the actual distances of the blueish movers to the rest of the green group, possibly creating the false impression of two independent groups moving around. To mitigate such perceptual distortions, we propose a time-aware color smoothing technique. Our method regards the mover distribution of the current and subsequent steps to determine the color correction. If entities close to each other are located in different color areas, their respective color is corrected towards the majority.

Our method (seen in Fig. 3) consists of three steps (color collection, pooling, adaption) repeated for every pixel. During initialization (Fig. 3, Step 1), users adjust the pooling matrix, selecting three parameters: *neighborhood size*, *time frames* ahead, and *matrix shape*. Step 2 applies the user-defined pooling matrix around the target pixel and collects the colors of included pixels. In step 3, the collected pixels are ordered with a stable sorting algorithm (e.g., mergesort) on the RGB values. Outlier pixel colors will be sorted to both ends of the list, while more similar colors move to the mid. In Step 4, after the sorting, the median of the array yields the most prominent color value of the collected pixels, and the index pixel is corrected to the median. Based on the domain knowledge of the analyst on the dataset and task specifications, the analyst can modify the parameters in Step 1 to her needs. The neighborhood size parameter describes the spatial region around the focused pixel in the vertical axis. For analyzing movers of coherent behavior (e.g., fishes as opposed to monkeys), the analyst might adjust the neighborhood size so that stronger (or weaker for monkeys) relationships are incorporated. The time frames ahead incorporate the spatial movement into the future to smooth in the horizontal direction. For observations that include fast-changing movements, the analyst chooses to capture fewer steps in time ahead to be able to cover fast changes of color. Lastly, the matrix shape offers a way to reduce the neighborhood into the future to steer the importance of the developing spatial region. For movers who tend to behave more coherently over time, a matrix shaped (no steps) is recommended, while less overall coherent behavior requires a triangular matrix shape, focusing more on temporal than spatial coherence. Please refer to our supplementary material for alternative parameter variations. The code for the color smoothing is publicly available as Python notebook [Sch20].



Parameter	RMSE (TACS)	RMSE (Gauss)	MSE (TACS)	MSE (Gauss)	SSIM (TACS)	SSIM (Gauss)
TACS[9, 9] Gauss(3,0)	6,850	7,371	153867	158771	0,637	0,636
TACS[11,11] Gauss(4,0)	7,206	7,762	155231	159614	0,589	0,574
TACS[13,13] Gauss(5,0)	7,477	8,041	155774	160244	0,552	0,533
TACS[15,15] Gauss(6,0)	7,701	8,242	155915	160703	0,524	0,505
TACS[15,15] Gauss(7,0)	7,876	8,395	155922	161096	0,502	0,485

Figure 4: Comparing an unmodified SpatialRug(A) to a smoothed one (matrix size 15x15) (B) and gaussian blur (sigma y, x) (D). C provides a difference image between A and B and highlights the areas our smoothing focuses on in red. The table shows quantitative assessment results for time-aware color smoothing(TACS) versus standard gaussian blur(Gauss).

6. Results: Assessing Visual Outcomes

We next elaborate on preliminary results on the effectiveness of *SpatialRugs*, discuss color scale choice and smoothing method.
Color scale: In Section 4, we proposed an initial set of color maps using the work of Bernard et al. [BSM*15] and defined the tasks **I-III**. We further narrow down the selection of well applicable colormaps by visually investigating color space properties (see Figure 2). First, derived colors should be well distinguishable to relate them to an accurate spatial location, satisfying task **I**. The color maps of Bremm et al. 2 [BvLBS11], Steiger et al. [SBM*14] and Teuling et al. [TSS11] are clearly inferior to their competitors for this property. Second, task **II** states that the viewer has to maintain a mental map to associate particular colors with spatial positions. Here, the color map provided by Simula et al. [SA99] introduce a black/dark area between neighboring colors in the corners, impacting the perceptual continuity. The color regions by Ramirez et al. [RAGG12] and Bremm et al. 1 [BvLBS11] are also not linearly distributed. This leaves the colormaps by Ziegler et al. [ZNK07] and Guo et al. [GGMZ05] as candidates. Ziegler et al. anchors four distinctive colors, amongst them three primary colors, to the corners of the color space, creating a semantic notion of spatial orientation resembling the natural division of four cardinal directions. Guo et al. extend the color space radially around a white center. Both approaches scale well to different aspect ratios, satisfying task **III**. Guo et al. enable to encode the center area in white, as well. Yet, this could interfere perceptually if an additional feature should be encoded as modification of the color brightness. This only works if no black or white components are present. To leave this possibility open, Ziegler et al.'s approach is more suitable. In conclusion, we expect the color maps by Ziegler et al. and Guo et al. to fulfill our tasks. The choice between the two is use-case dependent.
Color smoothing: The time-aware smoothing aims to mitigate the effects of neighboring colors (outlined in red Fig 4 A) by including the temporal color distribution. In Fig. 4 A and B, we see that the methods reduce visible outliers while retaining the temporal structures. The difference image between (A) and (B) (see Fig. 4 (C)) provides preliminary evidence for the value of the applied smoothing method as it only affects the color transition areas, leaving the visual patterns still crisp and visible. In contrast, the Gaussian blur (D) creates a fuzzy impression, aggravating accurate interpretation of colors at a given point by blurring visual structures. A quantitative assessment of our color-smoothing (table in Fig. 4) shows results of applied quality measures by measuring the distance to the original, unsmoothed image. These measures include the root mean squared error (RMSE) [WMP14], the mean squared error (MSE) [WMP14] and the structural similarity index [Bov13] (SSIM). We compare our time-aware color smoothing (TACS) to a standard gaussian smoothing (Gauss). Similar reference area parameters are chosen to enable a better comparison of the smoothing methods. Lower RMSE and MSE values indicate better results, whereas a higher value for SSIM indicates better similarity between original and smoothed image. The results indicate that our pooling method outperforms the Gaussian blur even for small sigmas and large window sizes.

7. Conclusion and Future Work

SpatialRugs uses color mapping to allow users to perceive spatial relations through space-efficient designs. The intended use of *SpatialRugs* is in conjunction with other pixel-based movement visualizations by showing further features the user is interested in, enabling the relation of space and feature developments (compare SpatialRug and MotionRug in Figure 1). We compared several color spaces identifying advantages and disadvantages. Further color space comparisons and color smoothing results can be found in the supplemental material. We further discussed perceptual challenges derived by color scales, where movements appear more distant than in their physical space. To mitigate distortion effects, we proposed a time-aware color smoothing approach, which we illustrated in some examples and provided preliminary quality metrics. We expect that our approach can be applied to non-spatial 2D point distributions as well, for example, to projections of dynamic datasets.

SpatialRugs also comes with shortcomings: Perceptual limitations and color smoothing introduce spatial errors when trying to read precise positions, and balancing the parameterization of the color smoothing for specific use cases can be difficult. These aspects need to be evaluated, while guidelines for the correct parameterization have to be explored. In future work, we intend to quantify the viewer's perception of our technique and choice of color spaces. Also, the perceptual implications of our color correction process have to be tested thoroughly. Instead of using a single color map, we anticipate that *SpatialRugs* would benefit from an adaptive color map approach adjusted to the specific movement distributions and user task. Finally, we would like to support better detection of movements in semantically interesting regions by allowing users to place color anchors interactively according to semantic objects or areas.

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