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A Matrix-Based Visual Comparison of Time Series Sports Data

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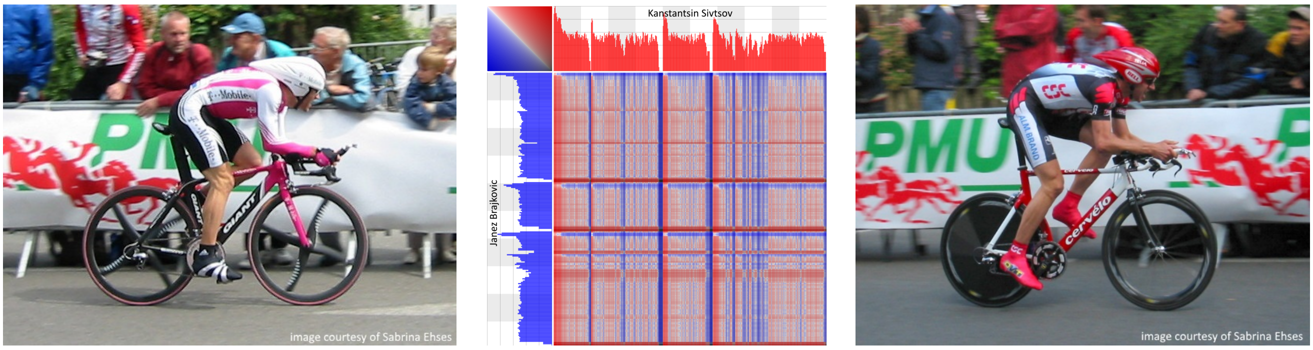

Figure 1: *Matrix-based visualization technique for comparing the time-varying performance of two athletes in time trials (e.g., road cycling).*

Abstract

In sports, large amounts of data are measured and stored with the help of modern sensors and electronic devices. In particular, for endurance sports events, time-varying data are recorded and can be used to analyze the athletes' performance. Finding patterns and issues can help better understand results in sports competitions, which is of interest for the athletes, sports managers, and trainers alike. In this paper, we introduce a matrix-based approach to visually compare similar and dissimilar periods in performances of athletes. We differentiate the performances and visually encode these differences as color-coded matrix cells. The strengths of our approach are illustrated in a case study investigating the performances of two riders in the prologue of Tour de France 2012.

1. Introduction

Sports events have become a popular form of entertainment and, with the progress in technology, more and more data about the participating athletes can be measured, recorded, and stored. Typically, sports events span a predefined period of time or require to do a certain task as fast as possible—in either case, analysis involves time-varying performance data of the athletes. Visualization is particularly suitable to support analysts in an explorative inspection of such data sets because precise goals of the analysis might not be known in advance and questions can be multi-faceted. For the athletes themselves, their trainers, and managers, visualization could help react to possible problems either during the event or in retrospective analysis.

While it is already interesting to analyze the performance of a single athlete, this perspective sometimes lacks a reference to judge the performance and to reveal potential for improvement. Providing a static, absolute standard, however, is difficult because the athlete's performance is time-dependent. A better criterion could be to take another athlete's performance as a reference. A comparison like that might tell what one athlete does better than the other or could reveal different tactics they use. While there often exist straightforward ways to just overlay or juxtapose standard diagrams reflecting the performance of different athletes, developing visualizations explicitly designed for comparison could even provide more powerful tools. Also, temporal data alignment between inputs and data inconsistencies are challenges that often play a role in the practical application of such approaches for sports data.

In this paper, we introduce a matrix-based visualization approach to compare time-varying athletes' performance. To the best of our knowledge, the approach is novel and extends the state of the art (Section 2). As an underlying concept for the visualization, a performance difference is used as a difference measure (Section 3). The resulting differences are depicted in a color-coded matrix representation where the axes represent the time lines for two athletes to be compared, or for two repetitions of the same challenge for a single athlete (Section 4). Performance, in the context of this work, can be regarded as a quantitative measure of the behavior or state of the athlete, such as the traveled distance, velocity, acceleration, and the like; the approach is applicable to many sport disciplines, in particular, endurance sports. Our technique is illustrated by a case study investigating time series data for cyclists acquired during the prologue of Tour de France 2012 (Section 5).

We see our main contributions in applying a matrix-based visualization approach—a well-studied and effective technique—to the novel application of time series comparison. The application in sports analytics serves as a first, promising example where the technique can be leveraged to support athletes, trainers, as well as sports managers and researchers. However, its applicability potentially reaches to all scenarios where two time series need to be compared. In contrast to other time series comparison techniques, ours allows for comparing arbitrary points in time and does not require uniform sampling or temporal alignment of inputs.

This paper is based on an unpublished contribution to the SportVis workshop at IEEE VIS 2013 [BBW13].

2. Related Work

Analyzing the performance of athletes is an active research discipline in sports science [McG09, NAH08]. For endurance sports, for instance, factors can be identified to predict performance [AN01] or the variation of performance of single athletes across different races can be studied [HH01]. While these questions are typically answered applying statistics, we suggest a more explorative approach. Instead of extracting results generalizable to larger groups of athletes, our goal is to gain insights into performance of an individual athlete. We are not aware that this is already sufficiently supported by results and tools of statistical sports analysis or by domain-tailored visualization approaches.

Visualization of temporal sports data is not limited to athletes' performance. For instance, SoccerStories [PVF13] visualize temporal trajectories of soccer players on the field. *À Table!* [PVF14] shows the evolution of team ranks in soccer rankings along time. MatchPad [LCP*12] represents real-time statistics and events of soccer and rugby matches on a time line. TenniVis [PYHZ14] encodes the evolution of scores in tennis matches in a matrix-like representation. In our approach, however, we purely focus on athletes' performance as it can be measured in all sorts of endurance sports.

Generally, not limited to applications in sports, there are various **visualization techniques to represent time-varying data** [AMST11]. Dynamic quantities are a simple form of time-varying data because only one variable is changing over time. Visualizing such data is intuitive by just plotting the points at each time step in a Cartesian coordinate system and possibly connecting two subsequent points by a line. In literature, such diagrams are referred to as line plots [Tuf92]. Comparing several dynamic quantities, line plots are oftentimes aligned and plotted into the same coordinate system; different colors or stroke styles can be used to distinguish a small number of those lines. Alternatively, avoiding the overplotting of lines, a so-called ThemeRiver visualization [HHWN02] represents time series as river-like shapes stacked on top of each other. However, it becomes difficult to compare quantities over time. As evaluated by Cleveland and McGill [CM86], a common baseline aligning the quantities is missing. Krstajic et al. [KBK11] therefore propose CloudLines where each river has its own baseline to circumvent this problem. TimeEdgeTrees [BW11] use a similar concept encoding multiple time series embedded into a hierarchy. Those techniques working with small multiples, however, require jumping back and forth between the diagrams to conduct a comparison; in particular, comparing the exact same positions in time becomes difficult.

Only few approaches explicitly encode the **comparison of time series**, that means, compute a comparison and visualize the result of this [CMR07, GHWG14, HKF16, KPBG13, LS09, SLKS12]. According to the taxonomy of Gleicher et al. [GAW*11], an explicit encoding is one of three main approaches of visual comparison; the other techniques described above can be mostly classified either as superposition (overlay) or juxtaposition (small multiples). A simple explicit encoding for the visual comparison of time series would be to compute the difference of the time series and visualize the resulting difference time series, for instance, as a line plot [GAW*11] or bar charts [KPBG13]. Kehrer et al. [KPBG13] discuss several approaches how to compute meaningful differences based on absolute and relative references. Others, for instance, compute and show relationships between time series based on temporal changes and trend [LS09] or summarize multivariate time series [CMR07, GHWG14]. Haroz et al. [HKF16] compare paired time series in connected scatterplots.

Matrix-based techniques have been used for the visual comparison of data. Most related to our approach, DiffMatrix [SLKS12] uses a matrix for time series comparison, but compares n (temporally aligned) time series with each other, employing line-based difference encodings in the cells of the matrix. Other data types can also be compared in matrices. For instance, bioinformatics researchers work with dot plot matrices [GM70] for comparing DNA or RNA sequences. Matrix representations are also employed for comparing vertex sets in graphs plotting the vertices to the axis of the matrix and marking adjacencies in the cells of the matrix [ABZD13, BD13]; similarly, the cells could represent evolving edge weights [BN11, SWS10, YEL10]. Also, the comparison of hierarchies can be implemented by marking cell areas of a matrix while having the two hierarchies attached to axes of the matrix [BD13, GK09]. However, we are not aware of any matrix-based approach directly comparable to ours.

3. Data Model

In the context of this work, we model a time series S as a finite sequence of n data points

$$S := ((t_1, v_1), \ldots, (t_n, v_n))$$

where t_i represents a point in time with $t_i < t_{i+1}$ and $v_i \in \mathbb{R}^+$ a data value. Depending on the sports events, the time series can represent different kinds of performance data of a single athlete. Multiple aligned time series of the same length representing different measures might be available.

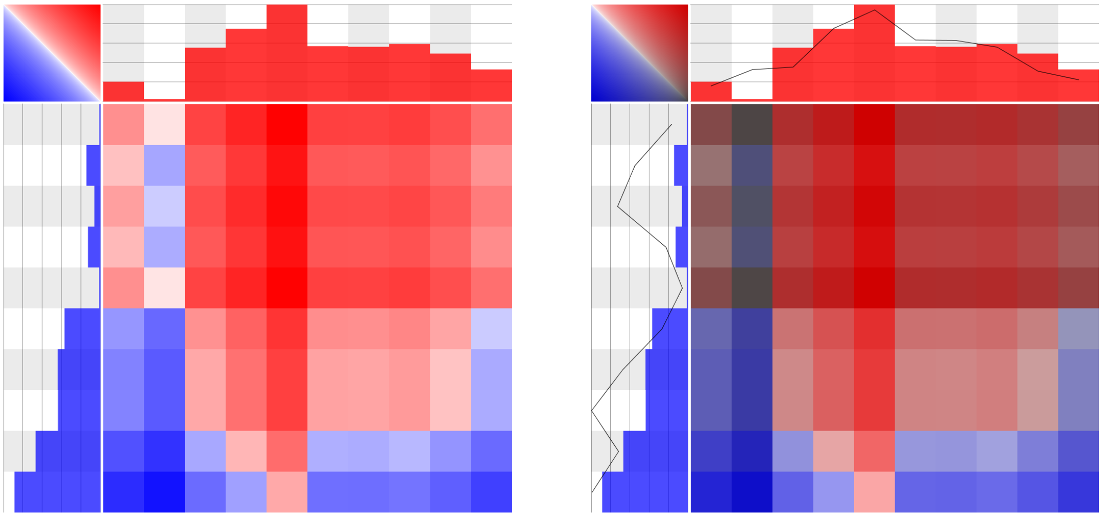

Figure 2: *Small sample data set visualized with the basic time series comparison technique (left) and the weighted time series comparison technique plus line plots (right).*

The approach is able to compare two time series

$$S^1 := ((t^1_1, v^1_1), \ldots, (t^1_n, v^1_n))$$

$$S^2 := ((t^2_1, v^2_1), \ldots, (t^2_m, v^2_m))$$

of lengths n and m. The two time series could either represent the performances of two different athletes or repetitions of performances of the same athlete—in either case, the underlying sports challenge should have been equivalent for the sake of fair comparison. Please note that time series S^1 and S^2 might not be aligned, could be gapped, or may result from different sampling rates.

For contrasting any two data points v^1_i and v^2_j of two time series S^1 and S^2, a difference measure $\delta : \mathbb{R}^+ \times \mathbb{R}^+ \longrightarrow \mathbb{R}$ is required. This function allows comparisons between arbitrary data points; the result will be explicitly encoded in the visualization. The most straightforward definition of the difference measure is $\delta := v^1_i - v^2_j$, which we use in the following. Additionally, we introduce a function $\sigma : \mathbb{R}^+ \times \mathbb{R}^+ \longrightarrow \mathbb{R}^+$ that does not reflect the difference of the compared data points but their aggregation; its easiest definition is $\sigma := v^1_i + v^2_j$. This aggregation measure σ will be used in the visualization as an additional augmentation of the difference measure δ for a weighted comparison approach. This combination of both measures allows the analyst to judge both absolute quantities and differences. Exploring other difference and aggregation measures will be part of future work.

4. Visualization Technique

Our proposed visualization technique is based on a matrix view with the time series attached to the axes. Both time series start in the upper left corner; while time series S^1 is aligned horizontally and ends on the right, time series S^2 goes vertically to the bottom of the diagram. The matrix in the middle provides a visual comparison of the two time series. The visualization technique employing a basic visual comparison approach is illustrated in Figure 2 (left), which compares two time series each having ten data points; in addition, Figure 2 (right) shows the same data based on an extended comparison approach.

4.1. Time Series Visualization

The two time series visualizations attached to the matrix are standard bar chart plots, however, one of them not aligned from left to right but from top to bottom. Two colors, red and blue, are used to consistently discern the two diagrams from each other. The length of the bar, encoding a value v^1_i or v^2_j of the series, follows the same scale in both diagrams (i.e., the same length encodes the same value). While all examples in this paper use linear scales, logarithmic or other scaling could be applied as well.

The decision to use filled bar charts instead of line charts for encoding the time series was motivated by several reasons: first, bars better reflect the discrete nature of the sampled time series than continuous lines; second, the bars intuitively show the orientation of the horizontal axis in the rotated time series plot (i.e., values increase from right to left, not vice versa); and third, the quantity of colored screen space increasing with the values of the time series provides a metaphor that can be further exploited for encoding differences as explained in the following.

4.2. Basic Time Series Comparison

The matrix in the center of the diagram encodes the comparison of the two time series, as shown in Figure 2 (left) for the basic comparison approach. Each cell in the matrix represents the comparison of two data points: the data point in the respective column of time series S^1 (red diagram) and the data point of the respective row of time series S^2 (blue diagram). In the basic comparison approach, only the difference measure δ of the two data points is reflected in the color: red represents positive values of δ (higher value in the red diagram), blue negative values (a higher value in the blue diagram), and white balanced values around $\delta = 0$. The color scale is normalized by the maximum data value across both time series $\max_{i,j}(v_i^1, v_j^2)$. Transitions between colors are continuous, but non-linear to have a higher color resolution for more frequently occurring small difference values (in particular, a root function). The color scale is provided in the left upper corner of the diagram as a static color legend; the scales of the bar chart diagrams are aligned with the two axes of the legend, i.e., two values from both diagrams can be intersected in the legend and resolved to a color. Since different combinations of values map to the same value of δ, those combinations will have the same color in the visualization.

Since we potentially handle long time series, we need to discuss visual scalability. Following the proposed approach, it can be possible that multiple cells of the matrix are mapped to the same pixel on screen. Generally, there are two ways of dealing with this issue:

- **Blending:** Data values are processed and drawn in their temporal order, potentially overplotting previous values that fall into the same pixel. Blending approaches mix the colors proportional to their overlap with the respective pixel so that not only the latest data value is visible. The resulting blended colors might slightly deviate from the color scale.
- **Aggregation:** Aggregation of data points implies that we first look up all data points that fall into the same pixel. All candidates are taken into account for computing a specific color. Several ways of aggregation might be used: the maximal value, the average value, or the sum.

The current implementation of our approach uses the standard subpixel rendering (floating point coordinates) of Java 2D as a blending techique.

The encoding of the difference values in the matrix allows us, in contrast to standard overlaid line charts, to compare data points or subsequences of the time series independently of shifts in time: without changing the image, just by looking at different areas of the matrix, the first data points of S^1 can be compared to the first data points of S^2 as well as to last ones of S^2. The visualization also supports the balancing of different scaling in the two compared diagrams, which just requires analyzing a non-quadratic, rectangular region of the matrix. As a consequence, it is not a problem if the time series have different lengths ($n \neq m$), the sampling rate varies, or the time series are not aligned properly. The matrix comparison encodes all possible $n \times m$ comparisons, whereas overlaid line charts only depict $\min(n,m)$ direct comparisons (additional indirect comparisons are possible in a certain spatial neighborhood of the data points).

4.3. Weighted Time Series Comparison

Although the values of the time series can be retrieved from the attached bar charts, it would be helpful being able to directly estimate the values from the matrix: for instance, it could make a considerable difference for the interpretation if a balanced difference is caused by two small values or two large ones. As a weighted comparison approach illustrated in Figure 2 (right), we vary the brightness of color coding to additionally encode the absolute values based on the aggregation measure σ. Mapping σ to a brightness scale and applying that to the previously described color scale makes the resulting color unique for every combination of values. For instance, a bright red color then indicates a high value of S^1 and a medium one for S^2 or a dark gray color represents two balanced but low values in the two time series. A non-linear mapping (again, a root function) of values to the brightness scale is applied because it is difficult to discern colors of very dark colors. Again, the color scale, now varying in two dimensions, is provided in the upper left corner of the visualization and can be read as before.

The design of the visualization technique allows for easy encoding of additional information such as further time series. To implement that, we propose plotting the time series as line plots and overlaying these on the bar charts as demonstrated in Figure 2 (right). The different chart styles (bars and lines) clearly indicate the different roles of the time series: while the *heavy* bar charts form the basis for the comparison, the *light* line charts just provide additional information. Although multiple line charts can be overlaid at the same time and discerned by color, we just use examples with one additional time series because the diagram can quickly become overloaded with information when adding more data.

4.4. Multiple Comparisons

The technique can easily be extended to the comparison of more than two time series: Instead of attaching one time series at each side of the matrix, we can add a set of time series. This creates a matrix (*meta-matrix*) of time series comparisons, where each matrix cell contains a matrix-based comparison of two time series as introduced above (*comparison matrices*). An example is given in Figure 3, where four time series on the horizontal axis are contrasted to the same set of four time series on the vertical axis. While a symmetric layout like this might be a good default approach for a comparison of multiple time series, asymmetric layouts using different series on the horizontal and vertical axes are possible as well. Increasing the number of time series, of course, decreases the size and readability of the individual comparisons within the matrix cells. However, we consider the meta-matrix only as an overview that allows us to find interesting pairwise comparisons, and then, enlarge and analyze those one-by-one.

5. Case Study: Cycling Time Trials

For this case study, we investigate the example of cycling time trials. In particular, we analyze data of two riders from the prologue of the Tour de France [TdF]. The prologue is a short time trial race where all riders are sent on the track separately, one after the other, and slipstreaming (which can have a big impact in road cycling) is forbidden. The 2012 prologue of Tour de France was carried out in Liège, Belgium, on a 6.4 km track without any relevant ascents. Fabian Cancellara, a Swiss time-trial specialist from Team Radioshack-Nissan, won the stage in 7' 13".

For this stage, Peaksware, a company that sells analytics software for cycling professionals called TrainingPeaks, recorded performance data of a small number of riders. We compare the performance of Kanstantsin Sivtsov, a Belarusian rider from Team Sky Procycling, against equivalent data of Janez Brajkovic, a Slowenian member of the Astana Pro Team (the two riders shown in Figure 1 are other cyclists; pictures were taken at the prologue of Tour de France 2004, which also happened to be situated in Liège, Belgium). While Sivtsov finished 63rd out of 198 cyclists, 0’ 25” behind the winner Cancellara, Brajkovic was ranked 32nd with 0’ 22” time difference to the winner. The provided data for the two riders are recorded with a sampling interval of one second for Sivtsov and two seconds for Brajkovic. Including not only the race, but also race preparation (with gaps), the data sets span 148’ 25” (5,522 data points) for Sivtsov and 284’ 01” (3,304 data points) for Brajkovic, i.e., the actual race is only a small subset of the data.

The case study is based on three visualizations comparing the performance measured as the power used for pedaling of the two cyclists: Figure 4 provides an overview of the complete data sets including the race preparation and race (no preprocessing or alignment was applied). Figure 3 focuses on the four training laps of Kanstantsin Sivtsov. Finally, Figure 5 shows details of the race periods in larger resolution. To create space-efficient visualizations, time periods without recorded data are skipped and the progress of time is presented as an additional line plot to mark the gaps in Figure 4; since there were no gaps in recording during the training laps and race periods, this additional encoding is not necessary for Figure 3 and Figure 5. When comparing two riders (Figure 4 and Figure 5), we counterbalanced for the different sampling rate by scaling the visualization to have the same temporal scale on both axes.

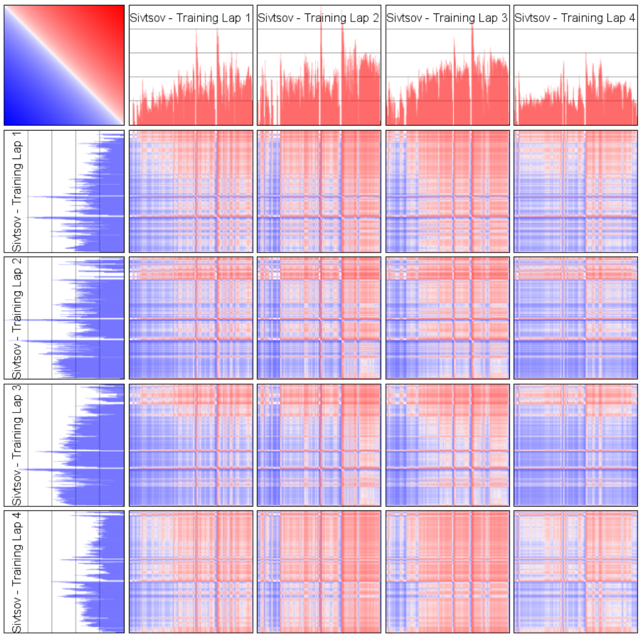

Figure 3: *Comparing the four training laps of Kanstantsin Sivtsov to each other in a grid of matrix comparisons.*

5.1. Race Preparation

Analyzing the complete data sets in Figure 4, we can confirm from the visualization that the race itself, which can be easily detected as a period of high and constant performance values, covers only a short time span at the end of the time series. This can either be detected by looking at each time series individually (A1, A2) or by searching for the brightest area within the matrix (A3). This area actually conforms to what is depicted at a higher resolution in Figure 5 and will be discussed below. Figure 4 is more suitable for analyzing and contrasting the race preparation strategies (and follow-up activities) of the two athletes.

For both riders, the preparation phase falls into two parts indicated by larger jumps in the additional time series as well as by different patterns in the bar charts and matrix. We assume that the first part (B1, B2) was recorded while the riders cycled on the road because the performance values are varying more: while being on the road, the cyclists have to slow down for bends or obstacles like other cyclists, cars, or pedestrians, that can be still on the track during race preparation. The comparable, repetitive patterns of similar length within the time series of the two riders (bar charts) as well as in between of the riders (matrix) further indicate that both drove four laps on a similar track. Comparing those laps to the race period in the matrix (B3, B4) even suggests that this track was the later race track: the matrix shows quite homogeneous red or blue areas at the intersections of the early preparation phase and the race, i.e., the athletes’ performances follow the same pattern but just on a consistently lower level. The dominating red color at the upper left corner of the matrix shows that first Sivtsov trained harder for the first three laps (B5); the last lap, however, Brajkovic powered more as indicated by blue color in the matrix (B6).

The second phase of the preparation is dominated by more regular patterns (C1, C2) that can hardly be achieved when cycling on the road, but require a more controlled environment as probably provided through bicycle rollers (i.e., a training device similar to a stationary bicycle but that can be used with the road bicycle). Brajkovic trained multiple intervals of constantly increasing intensity; a sudden drop in intensity marks the beginning of a new interval (C1). Indicated through diagonal patterns in the matrix (C3), a similar pattern can be observed just once for Sivtsov, who spans this single interval, however, over a much longer period. Sivtsov used the second half of this controlled training phase for constant intensity training with three extreme but short peaks at the end. These peaks are reflected in isolated vertical red lines in the matrix (C4)—equivalent blue horizontal lines indicating similar peaks for Brajkovic are not detectable. In total, Brajkovic spent more time on this second preparation phase than Sivtsov, but including a shorter period of relative inactivity directly before the race (C5, C6).

After the race, Brajkovic seemed to continue with some training on bicycle rollers (regular pattern in D1), while the recording for Sivtsov ends shortly after the race (D2).

5.2. Training Laps

Further analyzing the four training laps of Sivtsov, we demonstrate how we can make use of the comparison of multiple time series. To this end, we cut the first half of the recordings of Sivtsov into four parts, estimating the ends of the individual laps. This creates a set of four time series that are compared to each other in all combinations, which is shown in Figure 3.

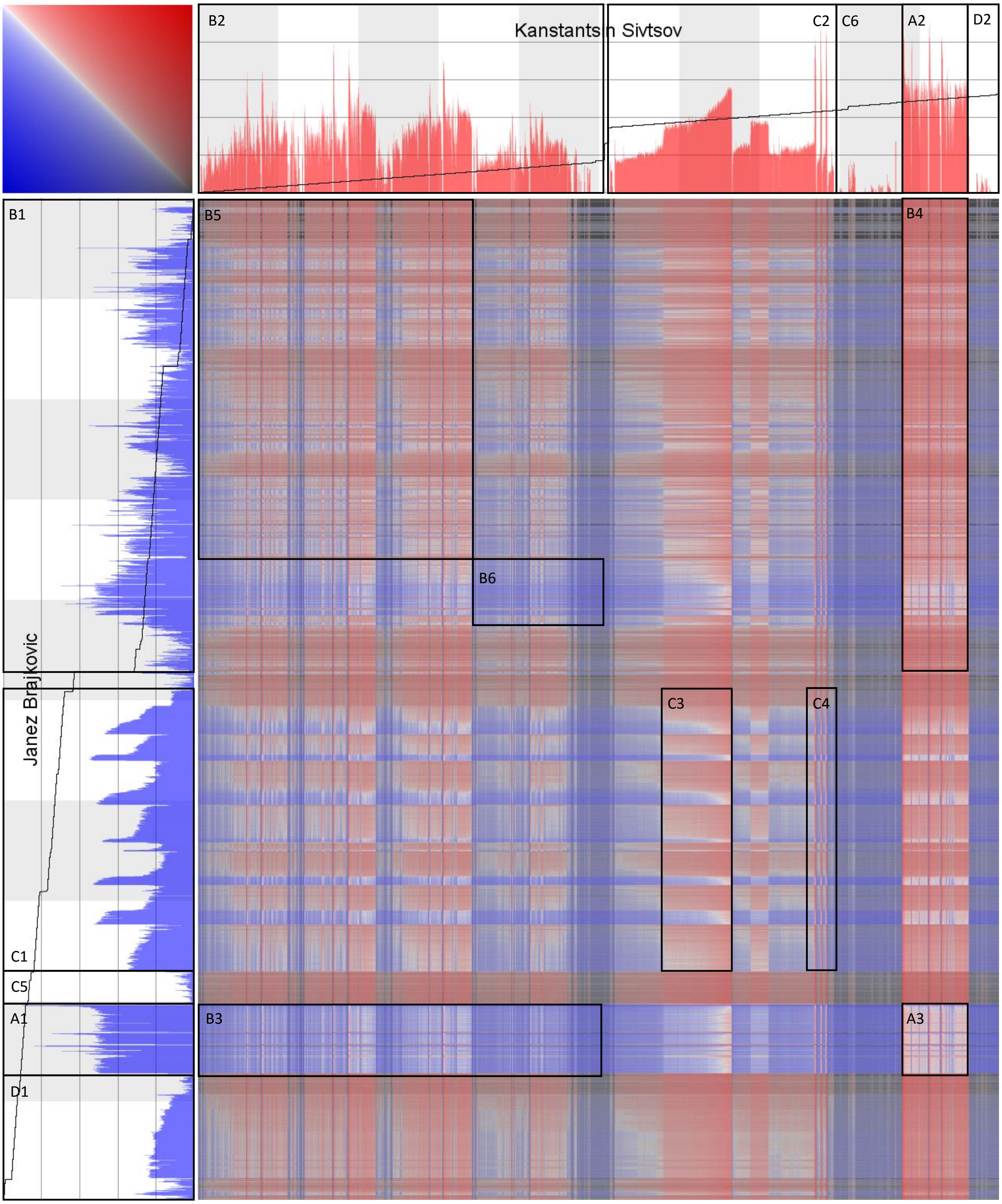

Figure 4: *Comparing the performance (power) of Kanstantsin Sivtsov (red) against Janez Brajkovic (blue) in the prologue of Tour de France 2012 including their preparation period for the race; the additional line chart reflects the progress of time and indicates gaps in measurement.*

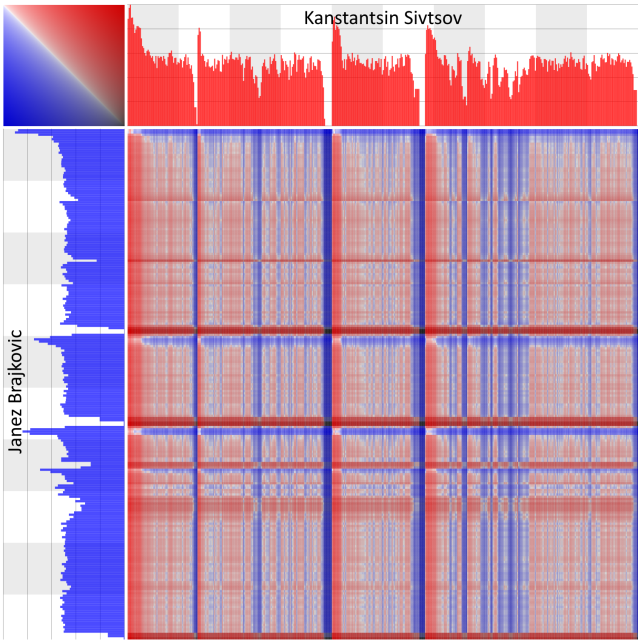

Figure 5: *Focusing the data of Figure 4 on the actual race periods.*

While the comparison matrices on the diagonal are necessarily symmetric, we partly observe largely symmetric comparison matrices, also off the diagonal, which indicates high overall similarity between the time series. In particular, Laps 1–3 follow a very similar pattern, whereas Lap 4 shares less characteristics, resulting in non-symmetric comparison matrices compared to all other laps. Analyzing the first row of the meta-matrix (i.e., comparing Lap 1 to Laps 2–4), we also find that in Laps 2 and 3 Sivtsov increased his efforts (overall, red is dominating over blue), while Lap 4 was considerably slower (overall, blue is dominating over red). Investigating in more detail, we notice that these differences mostly derive from each the second parts of the laps: while the balance between blue and red is about the same in the upper left quadrant of all comparison matrices of this first row of the meta-matrix, there are reasonable changes in the balance in the lower right quadrant.

5.3. Race

The race itself can be best analyzed in Figure 5, which compares the two race periods of the two riders in an enlarged version. The matrix showing the comparison is dominated by two vertical and two horizontal color-intense lines and is divided by these into regular squares. The lines are caused by two sudden drops in power at the same time of the race for both riders. These parallel short phases of rolling hint at sharp bends in the track—looking at the map of the course, we find indeed two 180° bends at about the middle of the distance. Further, weaker horizontal and vertical lines, symmetrical for both cyclists, indicate weaker bends or other obstacles on the track. The first drop of power and the following climb, however, are stronger for Sivtsov than for Brajkovic as the more intense vertical than horizontal lines show; Sivtsov hence may have had more problems at the first obstacle.

In general, the whole matrix area of Figure 5 is colored in a bright mixture of blue, red, and white, only with exceptions of the already discussed color-intense vertical and horizontal lines. Neither blue nor red is dominating: none of the riders seems to have performed consistently better. This can be confirmed by looking at the total time difference between the two athletes, which was only 0' 03" at the finish line. Since there can be many reasons that explain the small difference, it might be too ambitious trying to name the reasons just through the use of visualization. Nevertheless, our visualization reveals subtle differences between the riders that could have influenced the total time: high-frequent vertical stripes in the matrix are somewhat more distinguished than equivalent horizontal ones, which shows that the performance of Sivtsov is varying more than the performance of Brajkovic. In particular, after the second 180° bend, Sivtsov's performance has a more irregular pattern than Brajkovic's. These observations together with observations from the race preparation might point to potential issues and could help the athlete and trainer improve the athlete's performance beyond just trying to increase overall fitness.

6. Discussion and Limitations

We are aware that our matrix visualization has limitations. Moreover, we only applied our visualization to time series from sports applications and scenarios from other domains may cause additional challenges for our visualization approach.

- **Data Selectability:** A matrix-based visualization on pixel-based visual granularity is suitable to represent long time series, but the interactive selection of individual points becomes a difficult task. Hence, we argue that more region-based selection concepts have to be applied before selecting single points as a details-on-demand feature.
- **Visual Scalability:** Visually encoding thousands of data points leads to the problem of either aggregating certain time periods or of showing only one representative of all the contained ones in a time period. In either case, some information is lost in the visualization, which may cause misinterpretation of the visualized data.
- **Perceptual Scalability:** We use color coding as the major visual feature to distinguish data values in the matrix representation. The human visual system is not able to distinguish that many colors, i.e., if similar color hues are placed far apart from each other in the display, those might be taken one for the other although they are not exactly the same [War10]. Even a change in color scale cannot solve this problem reliably.

7. Conclusion and Future Work

In this paper, we illustrated how time series can be visually compared by using a matrix representation. The novel concept of showing comparisons of data points as color-coded matrix cells is simple, yet powerful: in contrast to overlaid line plots, our approach allows for the comparison of any shifted and scaled periods within a single static diagram because all pairwise combinations of data points are represented. This advantage may come at the costs of a less intuitive representation and a more difficult comparison of concurrent data points. We extended the approach to $n \times m$ comparisons. The case study illustrates the applicability and utility of the visualization approach in the area of sports visualization. Although being only tested on data from a bicycle time trial, it is likely that the visualization will also be suitable for analyzing other kinds of endurance sports. In particular, the visualization revealed different preparation strategies for the race of the two compared athletes as well as subtle differences in race performance. As part of future work, we plan to explore the usefulness of the approach in other areas of application, study how interaction techniques could support the analysis, and evaluate the tool against traditional comparison techniques for time series data.

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