

# Gaining Insight from Physical Activity Data using a Similarity-based Interactive Visualization

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**Abstract:** This paper presents a new interactive visualization approach which aims to help and support the user in gaining insight over his physical activity data. The main novelty of the proposed visualization approach is the representation of similarities in the physical activity patterns in time using data clustering techniques, in addition to the continuous physical activity representation over a circular chart. This grouping of similar activity patterns helps identifying meaningful events or behaviors, combined with the periodicity highlighting circular charts. The user is able to interact with the visualization during the knowledge discovery process by changing the represented time-scale, time-frame and the number of clusters used for the user's physical activity pattern categorization. Additionally, the proposed visualization approach allows to easily report and store the insights gained during the visual data analysis process, by adding a textual description linked to the particular user tailored visualization configuration which led to that insight.

## 1 INTRODUCTION

Individuals have tracked their personal data historically with the objective to measure and improve specific behaviors (e.g. health, economy, sport performance) (Marcengo and Rapp, 2013). Traditionally, this personal data tracking has been carried out manually, or at most, with the support of basic informatics tool (e.g. spreadsheets) for storage and visualization purposes.

In recent years, the advances in self-monitoring technology, the availability of low cost and unobtrusive monitoring sensors (implemented in Smartphones or wearable devices), and the widespread adoption of the Smartphone and development of self-monitoring Smartphone Apps have led to a growth of the people engaged into the self-quantification through personal informatics movement (i.e. lifelogging or quantified-self). The research being carried out by quantified-self early adopters is of particular interest in the context of empowering people in the self-management of their health.

Personal physical activity is usually quantified as

energy expenditure (e.g. calories), or distance covered (e.g. step count). Those measures are obtained from different kinds of sensors, being the current trend to use the smartphone built-in sensors and commercial wearable devices (e.g. Fitbit<sup>1</sup> or Mi Band<sup>2</sup>) either separately or in combination.

Self-quantifiers draw meaningful inferences and realize causality through the collection and analysis of their personal data, following a self-reflection process (Huang et al., 2014). Self-reflection is achieved through the analysis of personal data using data visualization tools. However many Quantified-Selfers, are not visualization experts or data scientists (Choe et al., 2015).

The contribution of this publication is the proposal of an interactive visualization method which complements traditional chart visualizations with the automatic categorization of physical activity data patterns using clustering techniques. This interactive visualization method aims to assist individuals in their self-reflection process, by depicting visual cues to spot similar patterns, complemented with a data representation spatial layout which fosters periodic pattern identification.

<sup>1</sup><https://www.fitbit.com>

<sup>2</sup><http://www.mi.com/in/miband/>

In this paper, we first analyze the related work in the field of self-tracked physical activity visualization (Section 2). Section 3 presents our contributions, i.e., an approach for similarity based interactive visualization of self-tracked physical activity. In Section 4 we summarize the paper and present our conclusions.

## 2 RELATED WORK

Huang et al. (Huang et al., 2014) define and classify Personal Visualization (PV) as an interactive visual data representation process for the personal context, and Personal Visual Analytics (PVA), as visualization that involves the computer assisted analysis. Following this classification, in the first subsection we will first analyze the evolution of the personal visualization techniques considering the scope of personal data. Next, in a second subsection, PVA approaches, which integrate the computer assisted analysis with the visualization of the self-quantified data will be analyzed. The aim of the computer assisted analysis is to facilitate the self-reflection process and the identification of insights by the user.

### 2.1 Personal Visualization Techniques

In the prior works in the field, various approaches have been proposed for the visualization of self-quantified data, ranging from traditional statistical graphics, to representations in the form of abstract art. Although proposals of new visualization paradigms as informative art (Fan et al., 2012), living metaphors (Consolvo et al., 2009; Khot et al., 2015; Lin et al., 2006) or ambient display (Jafarainaimi et al., 2005; Rogers et al., 2010) have been defined, most of the tools for physical activity monitoring visualization at the consumer user level (e.g. Endomondo, MapMyFitness, ) still use charts (e.g. line, bar, diagram scatter, pie charts) and most-self-quantifiers use charts to represent and display their physical activity (Choe et al., 2015).

Recently, new approaches to visualize self-quantified data have emerged. A recent work (Larsen et al., 2013), presents a visualization technique for time series data in the form of a spiral structure visualization. This visualization technique aims to assist the user in identifying repeating patterns in self-quantified data, such as geographical location or physical activity.

The spiral-based representation is good at discovering recurrent patterns over a period of time.

The spiral visualization represents events with similar period aligned along similar angles of the arcs, resulting in aligned sections of the spiral (Carlis and Konstan, 1998; Weber et al., 2001).

A spiral is formed by a continuous line representing the time, so that “time’s continuity” concept is clearly represented. However, the represented time unit (i.e. hours, days, weeks etc.) is not always clearly identified. Say we have a visualization formed by a spiral of Archimedes that shows seven segments (representing days) per each rotation of 360 degrees. The primary time unit –a day- is obvious and easy to identify, nevertheless the secondary time unit –a week- is not so obvious and its boundaries are not always clear.

Our approach is based on circular maps. Spiral-based visualization and circular visualizations are similar in many ways, but the latter is unique in that each ring represents a temporary unit. This concept is similar to tree rings, where every ring represents a year. The rings closer to the center are the oldest and the external ones the newest. In addition, display can also be seen as an analog clock, in which the clock hands can have different number of positions depending on the time scale. For a week scale, the clock hands have 7 steps, one per day of the week. For a day scale the hands may have 24 steps, one per hour. And given position, all the rings crossed by the clock hand correspond to the same step/phase in the time scale (e.g. day of the week), that is, they are visually aligned permitting a clear comparison.

### 2.2 Personal Visualization Analytics Techniques

In the context of large data set exploration, it is generally a difficult task to recognize patterns or trends, even if a good visualization is provided. Furthermore, regarding personal data visualization and the tools available for that purpose, people may not dedicate much effort exploring the possibilities provided by those tools and may not have the skills or experience required to identify such patterns.

In the non-personal context, computer algorithms have been applied to visual analysis applications successfully (Gotz et al., 2014; Van Wijk and Van Selow, 1999). Here, Wijk et al. (Van Wijk and Van Selow, 1999) presented a job that uses a combination calendar and chart visualization combined with clustering techniques to facilitate the identification of patterns and trends in multivariate time series.

On a personal context, the use of computer algorithms to recognize patterns and trends can help users gaining insights into their behaviours and

reducing the attention required to explore personal visualizations.

In the research works (Froehlich et al., 2009, 2012; McDuff et al., 2012) the authors apply clustering techniques to PV. Froehlich et al. applied computer-based classification to improve the visualization of transportation usage (Froehlich et al., 2009) and water consumption (Froehlich et al., 2012). In the same way, McDuff et al. (McDuff et al., 2012) use a classification scheme to predict the emotional state of the user and provide a user interface to capture the user reflection.

Some other authors have investigated the use of computer algorithms to optimize the design of personal visualizations (Douma et al., 2009; Shen and Ma, 2008). Douma et al., (2009) use computer algorithms to maintain the design of integrated radial tree structure (involving graph structures) with balanced layout visualization. The development presented in (Shen and Ma, 2008) supports the temporal and semantic filtering through a time chart diagram and an interactive ontology. The aim of this development is to isolate subsets of data, for a detailed analysis.

Another usage of computer algorithms in PVA that has been identified is on texts analysis for visualization (Dork et al., 2010; Marcus et al., 2011). In the research of (Marcus et al., 2011), computational algorithms are applied to text analysis to automatically find peaks and high activity of tweets, and to significantly label them using text from the tweets themselves. Similarly, (Dork et al., 2010) use text processing in the context of the evolution of a conversation to visually represent what just happened and what is happening now.

Other uses for computer algorithms in PVA include the reduction of the data dimensions to allow users to visualize and navigate through them (Faridani et al., 2010; Preuveneers and Berbers, 2008). (Faridani et al., 2010) applied this approach to navigation through online comments and (Preuveneers and Berbers, 2008) did the same for the recognition of health states, to help users with diabetes, to take informed decisions about the daily dose, to achieve and sustain adequate levels of glucose in blood.

Finally, the last identified computer algorithms usage in PVA are data-mining techniques. Khovanskaya et al. used data-mining techniques to identify patterns in the personal context (Khovanskaya et al., 2013).

Grouping different data samples by similarity often facilitates the insight gaining process. This is why clustering techniques have been applied in the field of visual analytics as a way to emphasize differences and similarities between events or sequence of events (Van Wijk and Van Selow, 1999). In Wijk et al.'s work energy expenditure data is clustered in order to find similar day patterns along a year. Each cluster, -representing a day pattern- is assigned a color and, within the calendar, each day is painted with its corresponding cluster's color.

Our approach takes from (Van Wijk and Van Selow, 1999) the idea of grouping time series according to their similarity and identifying samples as members of the cluster they belong to, using colors. However, instead of using a hierarchical clustering algorithm as in (Van Wijk and Van Selow, 1999), our approach uses centroid-based clustering techniques. In addition, we have introduced the circular chart visualization instead of a calendar, thus providing better PVA capabilities.

### 3 MATERIAL AND METHODS

An interactive web-based user interface has been implemented enabling users to visually explore and analyze their own physical activity data.

We have used d3.js<sup>3</sup> as the primary chart generating tool of our interactive user interface. We have selected and combined some different visualizations such as circular chart, pie chart and multi-series line chart.

For the implementation of the unsupervised classification part we have utilized a clustering algorithm collection called *figue*<sup>4</sup>, since it provides a JavaScript implementation of algorithms such as k-means and fuzzy c-means amongst others.

Interactive web user interfaces have been built on top of Bootstrap<sup>5</sup> framework and jQueryUI<sup>6</sup> library. Those technologies allow following a responsive web design approach, thus providing an optimal viewing and interaction experience across different devices (e.g. smartphones, tablets, laptops).

#### 3.1 Activity Data

Although our work is generalizable to virtually any kind of univariate interval time series data, this work focuses on the analysis of physical activity data. To demonstrate the capabilities of our visualization tool,

<sup>3</sup><http://d3js.org/>

<sup>4</sup><https://code.google.com/p/figue/>

<sup>5</sup><http://getbootstrap.com/>

<sup>6</sup><https://jqueryui.com/>

we have built a dataset using raw physical activity data acquired continuously from Mi Band<sup>7</sup> devices. We have collected the raw data samples recorded by 5 different devices during a period of 4 months (over 170000 samples per person). The obtained raw data is composed of a per-minute measure of the following data:

- Timestamp
- Number of steps
- Activity (Sleep, Idle, Run, Walk)
- Walk Distance
- Run Distance
- Walk Calories
- Run Calories

Collected raw data has been processed in order to do aggregations of different granularity.

### 3.2 Clustering

Our ultimate goal is to group similar day activity patterns together, in order to show which group belongs each day. We also aim to show the shape of the average day of each cluster. For that purpose, we use machine learning based clustering techniques.

To apply cluster analysis techniques we divide our time series data into a collection of  $n$  elements, each representing a day,

$$X = \{x_1, \dots, x_n\} \quad (1)$$

An element consists of a sequence of  $m$  elements,

$$Y = \{y_1, \dots, y_m\} \quad (2)$$

Where  $y_i$  denotes the value of the single activity feature selected by the user (i.e. number of steps, caloric expenditure, run/walk distance). Depending on the time scale selected by the user,  $m$  can be either 1440 (per minute values) or 24 (per hour aggregation). This value along with period of time (i.e. start and ending dates), the clustering algorithm to be applied and the number of clusters ( $k$  value) can be specified by the user.

In this work we have used the well-known Fuzzy c-means (Bezdek et al. , 1984) algorithm as well as the widely used k-means algorithm, although other clustering algorithms may be used.

In fuzzy clustering –unlike hard clustering algorithms such as k-means- there is not a sharp classification of data elements into non overlapping groups. Instead, for every data sample the probability of belonging to each cluster is provided.

Thus, after applying the algorithm, we obtain not

only a list of  $c$  centroids,

$$C = \{c_1, \dots, c_c\} \quad (3)$$

But also a membership matrix,

$$W = w_{i,j} \in [0,1], i = 1, \dots, n, j = 1, \dots, c \quad (4)$$

Where  $w_{i,j}$  is a value between 0 and 1 which represents the degree to which the element  $x_i$  belongs to cluster  $c_j$ .

### 3.3 Similarity based Interactive Visualization

During the clustering process we obtain a collection of cluster centroids, which characterize each cluster and can be regarded as the average of each day's activity pattern. We also get a membership matrix where it is specified which cluster belongs each day. Finding a proper way of displaying this information could be a challenge.

As seen in Figur, we have designed a web-based user interface layout composed of 4 main elements, namely a) parameter selector area, b) day pattern and centroid area, c) circular map area and d) annotation area.

In the parameter selector area users can select the time range by specifying the starting and ending dates in a calendar. Users may also select which activity indicator should be used for the calculations. Choices are: i) run caloric expenditure, ii) walk caloric expenditure, iii) sum of run and walk caloric expenditure, iv) walk distance, v) run distance, vi) sum of walk and run distances and vii) number of steps. The time scale can also be specified in minutes or hours, along with the number of clusters for the categorization.

Last but not least, users can select whether to apply fuzziness or not. If fuzziness is set to false a standard k-means algorithm is used, otherwise fuzzy c-means algorithm is used and some additional functionalities are available within the resulting visualization (e.g. a pie chart showing the cluster-membership distribution is shown when the cursor is passed over a day).

Once the user has selected the values mentioned above, data is processed and a clustering process is triggered.

The *patterns of resulting clusters* are visualized in a typical line chart, where a color is assigned to each of them, as seen in Figure 1-b.

Days are represented using a circle chart and the color assigned the cluster they belong to. When the fuzzy c-means algorithm is utilized, the cluster with

<sup>7</sup><http://www.mi.com/in/miband/>

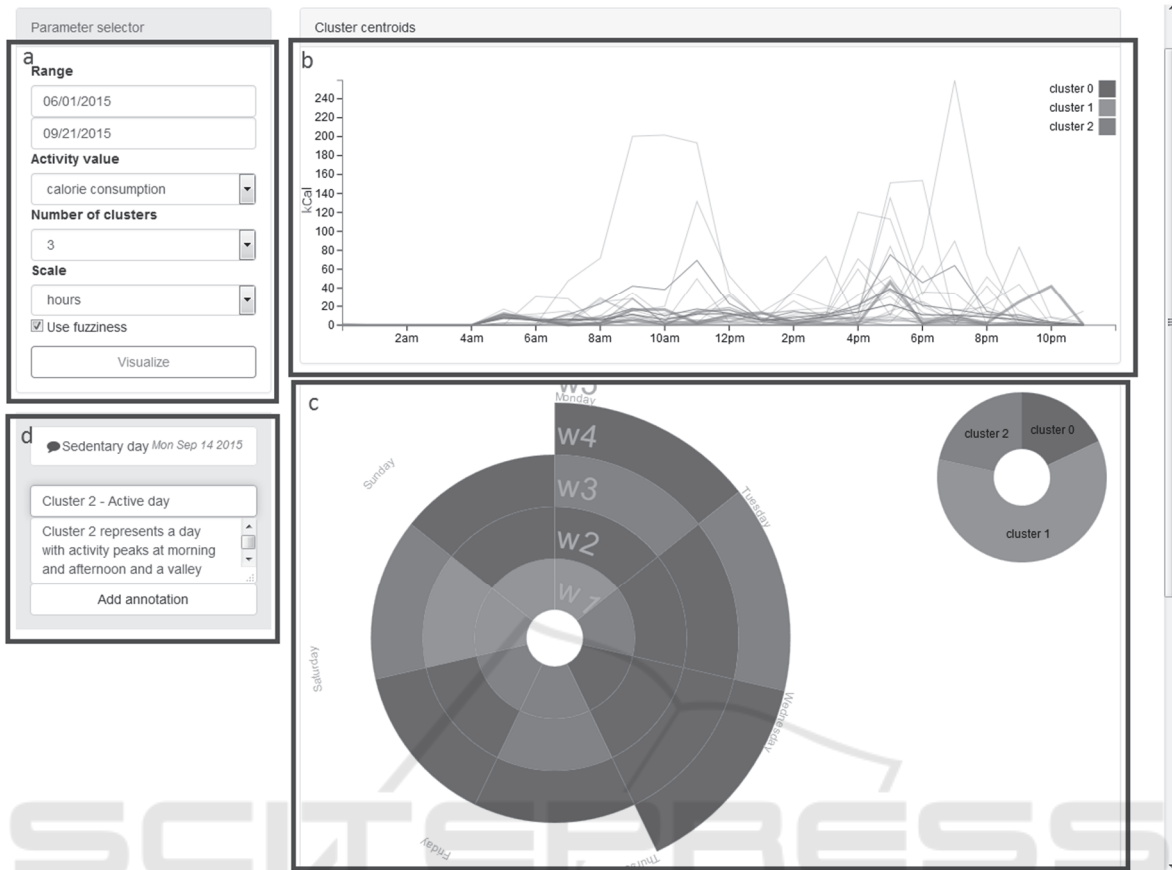


Figure 1: Web-based interactive visualization. a) Parameter selector area. b) View of the line chart showing day patterns (gray lines) and cluster centroids colored according to the legend. c) The user has placed the mouse over a certain cell of the circle chart, thus the pattern of that day is highlighted in the multi-series line chart (red line in the upper chart). Simultaneously a pie chart shows the membership distribution of the selected day. d) Insight annotation area.

the highest  $w$  value is selected for each day  $i$ ,

$$c_{max} = \max(w_{i,1}, \dots, w_{i,c}) \quad (5)$$

Although the color assigned for each day corresponds to the  $c_{max}$  value, we consider that the distribution of the cluster-belonging degrees provides valuable information that can enhance the exploration process. Hence, when the user selects a day by placing the mouse over a certain segment of the circle chart, a pie chart showing the cluster membership distribution for that particular day is shown in the upper right part of the canvas (see Figure 2). In addition, the activity pattern of that day is highlighted in the line chart. This makes it easy to compare a given day's activity pattern with its corresponding cluster's pattern.

The user can also have a detailed visualization of a particular day by clicking the corresponding segment of the circle chart.

Then, a new circular map is shown, where each segment represents the value of the selected parame-

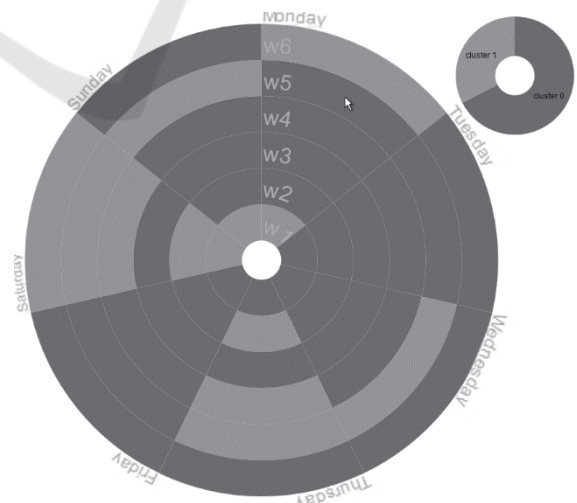


Figure 2: Visualization of 6-week caloric expenditure data. It can be seen that Saturdays (and Thursdays to some extent) are more likely to belong to cluster 1. This cluster groups days with higher activity levels in the afternoon.

ter of one minute (see Figure 3). The darker the color of the segment is, the greater the value (e.g. caloric expenditure) of that minute. Each ring represents a day, where the selected day is placed in the middle, surrounded by the three previous and next three days. This visualization aims to show the activity patterns in a more detailed way, as well as to better detect repeating patterns among days. Figure 3 depicts the circle heat chart showing the caloric expenditure patterns of a user during one week.

Finally, the user interface provides a simple yet useful tool for insight annotation. Users can annotate the discovered insights by inserting a title and a description. This self-reflection insight reporting functionality was added following (Choe et al., 2015) findings and their recommendation to support easy capture of self-reflection insights against specific elements of a dataset that may be associated with the insight, and access them both for exploration and for presentation purposes. Saved annotations are linked to the user-selected parameters, so that the associated visualization can be easily accessed in the future.



Figure 3: View of the circular heat chart. Each ring represents a day and is composed of 1440 cells (one per minute of a day) colored according to the calories expended.

## 4 CONCLUSIONS AND FUTURE WORK

We have presented a novel combination of well-established automated data analysis and visualization techniques which permits the user to interactively identify similarities in time-oriented data. This

approach has been implemented in the practical scenario of physical activity pattern visualization. The proposed visualization method is based on spatially arranging activity data in a given time period scale (e.g. day, week), automatically categorizing days into groups based on their activity pattern similarity and depicting similar activity days with the same visual representation. Thanks to this visual highlighting, repeating patterns can be easily spotted by the user. Moreover, combining this highlighting with the periodic arrangement of data that circular maps provide, periodic patterns can be easily recognized in different time scales (e.g. week or month). Both techniques are complementary in the sense that circular maps themselves don't permit a quick way to present similar items with the same visual representation, where each day's data cannot be summarized as an ordinal value, and on the other hand grouping days based on multiple features (and visually representing this categorization), without a proper spatial arrangement, doesn't permit an easy way to identify periodic patterns. Our approach takes advantage of the benefits of both visualization techniques, while avoiding their drawbacks.

Nevertheless, the authors are aware of at least a couple of limitations of this method: first, the day clustering technique is currently almost completely automatic, only the number of groups can be selected by the user, therefore lacking a fine tuning possibility for the visualization, considering for example different day similarity metrics. And second, the circular map is quite static, that is, information can only be arranged at daily and weekly time periods. Additionally, due to the characteristics of circular maps, older information has less visual impact, which for some scenarios might be useful, but not always.

Finally, this visualization method follows a top down interaction model, with an initial overview visualization combined with a following focused visualization for more in detail data review.

This visualization method closes the interaction loop by including the possibility to report insights and to link them to the visualization configuration which led to each of them.

We have performed some initial tests on a group of 5 volunteer subjects for a period of 4 months, regarding the usability of different visualization options and the insights provided by them. The subjects have shown interest in continuing with the self-monitoring and visual analysis process, as they perceive it as a quick yet useful tool to quantify their progress as well as to correct harmful behaviors.

Future work will include the validation of approach from the user interaction perspective, the

use of the clustering results to adapt the initial overview visualization and the exploration of hierarchical clustering methods, and alternatives such as latent class analysis (LCA).

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