

VIDGA: A Visualization Interface for Detecting Gait Abnormalities in Humans

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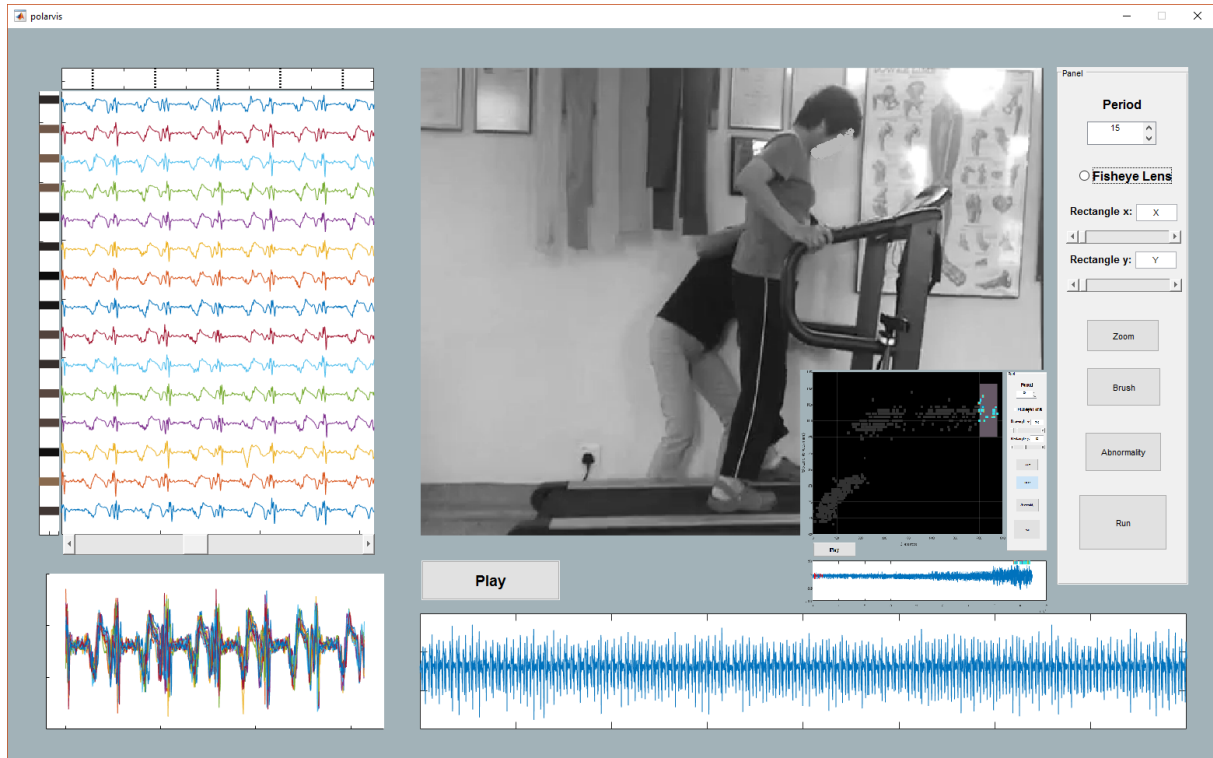


Fig. 1. A screen-shot of the VIDGA interface. VIDGA facets data into multiple views to help users to detect gait abnormalities in humans by comparing accelerometers signals attached to patients body.

Abstract—Emerging technology of wearable sensors facilitates generating a large data-set of human gaits for rehabilitation purposes. However, presenting this data by itself to physiotherapists can not provide very meaningful information, therefore still most of physiotherapists rely on visual observations for gait examinations. In this work, I present VIDGA, a new visualization interface for exploration of historical human gait data to diagnose abnormalities and ease making hypotheses for their causes. VIDGA is a visual analyzing system that connects the recorded data from sensors to observed gait features. By playing a recorded video of the patient walking or running during rehabilitation test or practice, VIDGA enables physiotherapists to locate the occurrence of anomalies in corresponding sensors signals. Later, faceting data across multiple views in VIDGA will help to find similar patterns in data-set and group labeling them, which can be further used to analyze the rest of gait cycles.

Index Terms—Human gait visualization interface, Gait abnormality, gait patterns

1 INTRODUCTION AND MOTIVATION

Physiotherapists use gait information to assess patients' performance for rehabilitation purposes. In many cases, they use visual observations to diagnose disorders or evaluate the prescribed treatment [3]. Growing number of patients and limitation of medical resources caused physiotherapists to play a more supervisory role instead of hav-

ing a one-by-one meeting, and respectively spend less time observing the performance of patient that reduces the quality of treatment. Meanwhile, advances in wearable electronic and sensor technology facilitate high precision, low noise gait data acquisition. Although this data is derived from physically meaningful variable such as joint angle and acceleration, it is difficult to extract useful information of gait features from plotted measurement data over time. In addition, to have more accurate analysis, many sensors might be positioned on different sites, for example, on the waist, wrist, and both ankles.

Because monitoring all these signals at the same time is very challenging, many recognition and classification systems are introduced to assist physiotherapists. For instance, a few software have been developed to help both patients and physiotherapists with a focus of home rehabilitation to reduce hospital visits by providing real-time feedback to patients and aid them to manage their chronic diseases [8][11]. However, due to large individual differences among patients

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which are determined by weight, limb length, type of stroke or injury, rehabilitation stage, and habitual posture, further studies are needed to increase the efficacy of these systems [9]. Consequently, my current options are either to increase medical facilities and number of physiotherapists to satisfy the ongoing needs or improve the recognition and classification systems. In this situation, a visualization interface—as is the focus of this project—can play a “medium” role by connecting the specialist’s observation to a classification system. Therefore I benefit from physiotherapists knowledge, by involving them in labeling the normal and abnormal data for each patient according to his/her conditions, and then the system can do the rest of process and detect anomalies. In this project, I introduce a new visualization interface to enable physiotherapists to detect anomalies in gait pattern by labeling a set of normal and abnormal behaviors and further visualizing them to monitor patients performance during the test or exercise.

2 RELATED WORK

2.1 Visualization of temporal data

Monitoring processes, verifying trends and predicting behaviors in future are among the main challenges that scientists, engineers, and businessmen are dealing with, which require analyzing data over the course of time. Visualization of temporal information has been extensively investigated and successfully used to address these problems. Survey papers on visualizing techniques of time-oriented data present the state of the art methods and categorize them with different perspectives. Aigner et al. [1] emphasis on visualization, analyze and task challenges of time-oriented data and provide a solution for different cases. For visualization part, they grouped different methods based on orthogonal design dimensions such as linear vs cyclic, time point vs time intervals and ordered vs branching vs multiple perspectives.

Exploiting the conceptual space-time cube, Bach et al. [2] explain various visualization methods by means of applying series of elementary operations. They break down this taxonomy of operations into five main groups: Extraction, flattening, filling, geometry transformation, and content transformation. These categorizations, however, are too broad and most often provide very general guidelines. Therefore, in order to have an effective visualization technique and benefit from the relevant studies, it is important to focus on natural characteristics of time series data which in our case is the occurrence of frequent patterns in a quasi-periodic manner. Temporal event sequence is a widely appearing problem in electronic medical records analysis [17] and a fundamental challenge in data mining [14]. Lifelines2 [15] lets users find hidden temporal patterns in electronic health records by aligning, filtering and ranking the results in order to find a causal relationship between events. For most of these techniques aligning similar patterns is the key to find similar records or to find the outliers.

On the other hand, Temporal data are normally large in term of a number of data items. There are many different tools that help users select their patterns of interests and filter through all the time series data. For example TimeSeracher 2 [4] which provide users with iterative multivariate pattern searching or VizTree [12] for discovering anomaly pattern and visually summarizing the structure of the data. By breaking down the data into labeled bins, VizTree employs a tree structure in which the frequency of patterns are encoded with thickness so that infrequent or potentially anomalous patterns have thin paths. VidX [18] suggests using Marey’s graph for identification of abnormalities in massive process control historical data. Users can label a set of normal processes and then the system can detect outliers based on them using label propagation technique which is a semi-supervised learning algorithm. One thing which is common in all of these techniques is that they all use the interactive identification of anomalies. However, in many of the mentioned techniques either the data have a simple pattern, for example processing time on each station or they use computational transformation such as symbolic aggregate approximation (SAX) to reduce the high dimensional data to a chain of character before running data mining tasks.

One of the main goals of this project is to foster the process of anomaly detection by providing group labeling of data without transforming it. The larger the labeled training data-set, the more accurate

the data mining and anomaly detection techniques will be.

2.2 Radial visualization for cyclic time-data

Among different representations of serial time data, spiral and radial layouts are considered to be effective for demonstrating periodic attributes of a dataset. These visualizations are mainly aiming for uncovering the previously known cyclic behavior of data. Detecting this periodic pattern can be supported by employing analytical methods or through user interaction with the system which relies on the human perception of detecting periodic patterns. However, for many phenomena, some irregularity in periodicity makes the radial approach less efficient. One approach to solving this problem is to use an event-anchored model which suits periodic dataset with different duration [5]. One nontrivial challenge of this method is to detect the event where period starts. However, resolving this problem is not the ultimate goal of this approach.

There are many studies on the benefits and drawbacks of radial visualizations. Although they are useful for periodic displays and for some aesthetic reasons, there are some limitations to them such as low rendering performance, interactivity, and navigation problems and difficulties in attaching detail information[7][6] compared to Cartesian coordinates which impose a careful consideration in the case of using them.

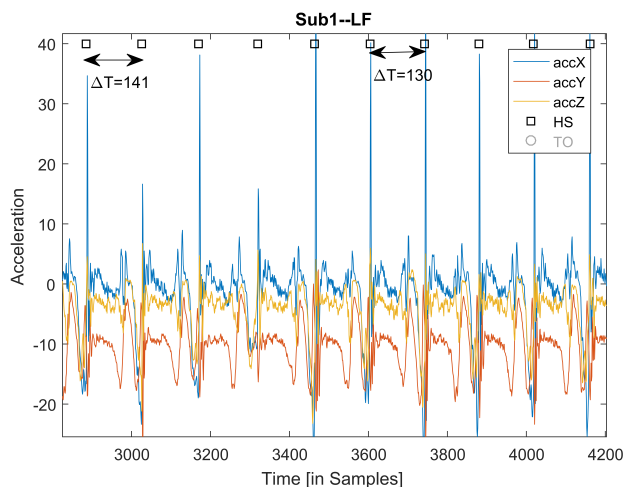


Fig. 2. Example of the accelerometer data placed on the right ankle, from the X, Y and Z axis. Two arrows show differences in gait periods.

3 DATA ABSTRACTION

In order to attain an effective visualization technique, it is necessary to exploit the specific features of data. Human gait signals are often periodic; however, since the sampling time is constant and users are changing their speed during the rehabilitation test or exercise, the frequency of these periods varies in time. Gait event detection algorithms use angle or acceleration data collected from controlled experiments with a predefined speed which is quite opposite to natural dynamic behavior of human gaits. In addition, there are cases that gait anomalies shows itself only in certain walking speeds and physiotherapists need to know them to determine the related disorders, for example, in one rehabilitation test, a patient feel more pain in his hip towards the end of exercise likely because of losing muscle strength which affects the gait periodic pattern [9].

In this project, I use MAREA (Movement Analysis in Real-world Environments using Accelerometers) gait database [10] comprises of X, Y and Z accelerometer logged data at a sampling frequency of 128 Hz for 20 healthy adults during gait activities (Walking and Running). As depicted in Fig. 2, the time interval between each gait cycle might vary in time especially during acceleration when a participant is transitioning from walking to running or contrariwise. The embedded

What: Data	Quasi periodic time series data with quantitative attribute. Key attribute of marked initiation of each cycle.
Why: Tasks	locate, identify and compare, produce by annotating.
How: Facet	Faceting into multiple views. Superimposed layers of data with distinguishable color.
How: Encode	Line charts (colored by partition number attribute), Scatter plots (using spacial encoding)
How: Manipulate	Selecting similar patterns and navigating
How: Reduce	Filter, Embed
Scale	Hundreds to thousand gait cycles.(100000 sample points)

Table 1. High level analysis framework, What-Why-How.

force sensitive resistors (FSRs) in the shoes of participant generate the ground truth values for the heel strike and toe-off events. I will use these values to mark each step and bin specific number of gait cycles accordingly.

To summarize this section, the most important properties of the data is the serial continuity and quasi-periodicity with defined upper and lower frequency bounds. In addition, this data has a quantitative attribute with bounded limits in amplitude with no large change across the time.

4 TASK ABSTRACTION

Observation of gait plays a key role in the diagnosis of abnormalities that gives useful information about the musculoskeletal and neurological conditions. Moreover, to have an accurate diagnosis of gait disorders, a good history of a patient along with detailed physical and neurological examination is required. Although many rehabilitation disorders can be diagnosed by observation, physical tests are also necessary to determine the strength of muscles and assessing the effects of therapy or exercise during the course of treatment. Since these effects appear gradually and might not be distinguishable by physiotherapists watching them, employing sensors can be a great aid by providing quantitative measures of patient movements. In addition, physiotherapists can evaluate the performance of patients on prescribed exercises remotely, which reduces the number of hospital visits. Fusing observational cues with recorded signal from sensors can profoundly help physiotherapists in their decision and consequently the result of treatment. Direct and real-time observation is not crucial in many cases especially during recuperation, instead, the physiotherapist can rely on a post hoc review of the recorded video to detect whether the gait behavior is normal or suspicious. Further, they can check the corresponding data of sensors to support their hypothesis. Obviously, the recorded signals should be synchronous with the video. To verify their decision and make sure that the phenomenon was not caused by an accident, they might be willing to search for similar patterns in data. Once they gain enough confidence in their diagnosis, they extend the result to the whole dataset to measure the quality of the therapy session or exercise.

From the visualization standpoint, I am making a tool that allows users to:

- **Search:** Discover and locate a normal or abnormal pattern in gait dataset. It highlights the selected gait cycle to show when and how it has happened. Regardless of having a specific target user should be able to explore the dataset.
- **Produce:** Enables users to annotate similar patterns. It assures that the selected pattern was not accidental and improve the reliability of diagnosis. It also increases the accuracy of any future classification tool by providing a larger group of labeled training dataset.

- **Query:** Supports predictive analysis to compare the rest of dataset with annotated patterns and then summarizes the results.
- **Analysis:** Filters the result of a query so that user can drive a subset of interest, according to the new data elements.

5 SOLUTION

5.1 Faceting and Multiple Views

Multiple facets are very common for exploratory data analysis [13]. Especially when the dataset is large and has multiple dimensions, encoding all the attributes in a single view is very challenging. For temporal data, this problem is even harder, since the serial ordering of time data might embed crucial causality relation between two adjacent sequences which should be considered by a visualization designer. Therefore, a timeline view is an indispensable part of many visualization techniques of time series data.

Moreover, by means of multiple views, vis designer can encode different attributes and features of a data as well. Similarly, in my design, I use the key features of faceting into multiple views, in particular, partition into views and superimposing layer.

5.1.1 Partitioning Layers

In this project, I use ground truth attributes to partition the whole dataset into different sectors. The aim of this partitioning is to align different sequences for better visualization of likeness and differentiation. As shown in Fig 3., machine selected color hues encode different sections of the partition. Since the speed of gait is hidden due to the alignment of sequences, I used color saturation on the side of each sector to show the average speed of the sequence. The dotted lines on the top of this view encode the type of the lens used over the plot. Here, equally distanced parallel lines means that no amplification method is employed. The time aspect and serial continuity of the signal are also maintained by spatial encoding of time. The time series data starts from bottom left and goes to the bottom right. So any event on the left side is happening prior to the sequence on the right side. In addition as one section ends in the right, the next point starts from the left side of the section above. Consequently, the last point of the data is on the top right.

5.1.2 superimposed Layers

Multiple line charts, derived from the partitioning section, are superimposed and presented in a same frame. The aforementioned partitioning can be considered as a juxtaposed view of this section. By overlapping different sequences as depicted in Fig 4. Users can visually compare the aligned sectors from partitioning section. Any outlier sequence immediately shows itself in the context of other normal behaviors. The color coding of different sectors eases the process of finding the outlier in the partitioning section. Moreover, if the user finds a group of sequence very similar, he/she can do a group labeling. There are two advantages with group labeling:

First, by verifying the detected abnormality with similar patterns, physiotherapists make sure that the event is not accidental.

Second, for a set of normal sequences, user can select them all together and then label them instead of doing the process one by one. Consequently, it provides a larger training dataset for future machine learning approach for abnormality detection.

By presenting both superimposed and partitioned views to the user, I made sure that users can carry out different abnormality detection tasks from local visual span to global level. [13].

The size of superimposed view of the platform shows that it needs less screen space to show the similarity between sequences compared to the partitioning view.

5.2 Focus+context: 1D Fish-eye lens

Fisheye lens enables user to see a small variation of data while maintaining the visual continuity of the pattern or image. In this project, the magnitude of acceleration attribute is much smaller than the time attribute of data. Therefore the need for zooming is only in the time axis. I employed 1D Fisheye lens in my partitioning view for simpler

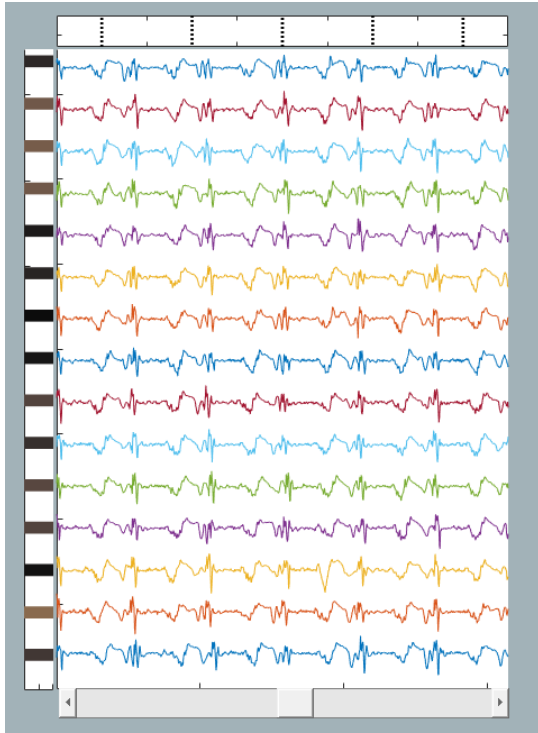


Fig. 3. Alignment and partitioning of the gait data based on the ground truth attribute. Speed of each sector is encoded with color saturation and depicted on the left side of the graph.

browsing in time. The main differences between 2D vs 1D Fisheye lens is the dimension of visual amplification. On the contrast of 2D Fisheye which has a single focus point, 1D has series of focal points which create a focus line. The implication of 1D Fish-eye lens in my system is to preserve the magnitude of the signal and just expand the sequences in time. To the best of my knowledge, this idiom has never been used for visualization of time series data. One reason could be the distortion of the signal which can change the shape of the pattern, however, in this project, since the focus of partitioning is to find similarity, all aligned sequences would have the same distortion which is acceptable for the similarity measurements. Fig 5. shows the application of 1D Fisheye lens in multiple parallel line charts.

Data is mapped into the polar coordinates with the radius of R and length of h . Dividing h to the number of sectors can give us the distance between each parallel line charts. The ratio of R over number of sequence in each sector implies the density of that sector. Even Fish-eye lens is limited to certain density of sequences in each sector which is larger than normal view.

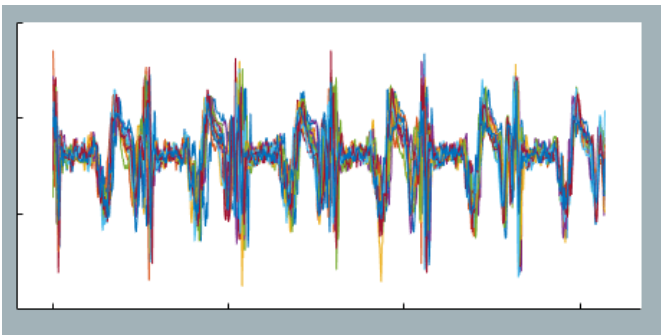


Fig. 4. The superimposed view of the gait data. Color hues encode different sectors of the data mentioned in partitioning section (5.1.1)

by placing a view of distance varying parallel lines on the top of this plot, I try to make sure that users are aware of the distortion in the data structure.

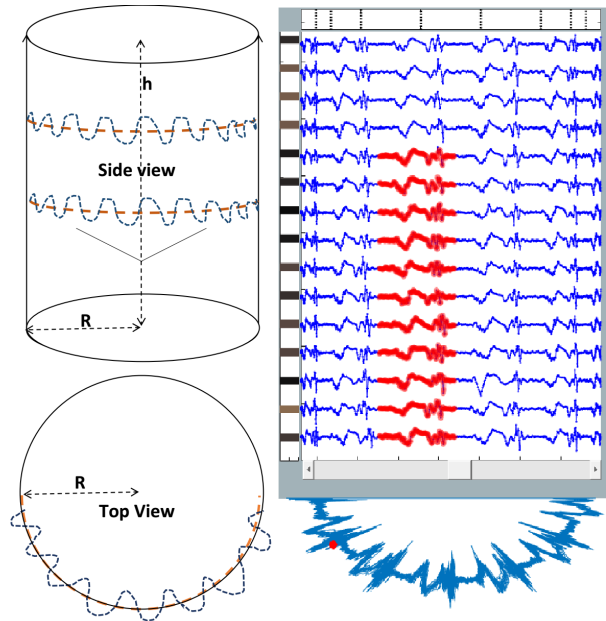


Fig. 5. 1D Fish-eye lens facilitates browsing task in the partition view by combining zooming and panning. By moving the focus line, user can change the zoomed view of column of sequences.

5.3 Filtering Abnormalities

According to the task abstraction part, one of the main goals of my proposed tool is to find abnormalities based on eliminating the normal patterns and just highlighting the unusual sequences through dynamic queries. In abnormalities visualizer part of my interface, I use spatial encoding of speed and distance in a scatter plot. The similarity measure is encoded as distance-like quantity on the x-axis and speed of each gait sequence is on y-axis. By making an area of interest zone, users can perform item filtering in the region of interest. This reduction can help users to narrow down the number of items to a specific subset of gait sequences with common feature.

I used color hue to encode filtered items. Since visualizing the entire data make the view too cluttered, I used the same color hue of the background and only change the color saturation for the rest of items. As a result, if not selected, items outside of area of interest, are hardly noticeable.

6 IMPLEMENTATION AND RESULT

I made my interface in MATLAB software to test different visualization design choices faster, and easily manipulate the data. Fig 1. shows the screen-shot of the VIDGA interface. This system consists of four main views and a control panel. These views include:

- **Video/ Abnormality visualizer:** Provides the observational cues by showing the video of patient walking or running on a treadmill/ By pressing Abnormality button the video will be displaced with abnormality view to show the result of similarity measurement.
- **Timeline:** Present the entire acceleration data over time. This timeline is linked with the Video.
- **Partitioned:** Present the partitioned version of Timeline as juxtaposed line charts
- **Superimposed:** Shows the superimposed layers of the Partitioned part.

The diagnosis process initiates by pressing the run button when VIDGA facets the data into multiform views. User can change the number of sectors by changing the period number in the control panel. Since the size of this view is limited, there is a trade-off between number of The Video starts by clicking on the play button. By observing the real video of the gait pattern users can analyze the behavior of the gait cycles. at the same time, on the Timeline, the color of the signal changes from blue to black according to the spent time. If the user observes a suspicious behavior then, he/she can stop the video. Immediately the signal's point will be marked in Partitioned and Superimposed views. To compare the the gait sequence, user might employ the 1D Fisheye lens. The sidebar underneath this plot can be used to place the highlighted gait cycle in the focal line of the lens. In addition, he/she can check the speed of each sector by looking and comparing the color hue of each sector. As shown in Fig 5. After detecting the abnormalities user can brush the selected items and label them. To check the validity of the decision, he/she might use the Superimposed view. By Pressing the abnormality button, system will run Dynamic time warping (DTW) to check the similarity between labeled data and the rest of gait sequences. DTW is a similarity quantity measure which finds the Euclidean distance of two signals.. Then it presents the data in abnormality visualizer as explained in 5.3. DTW is the only external library used in VIDGA.

For the post hoc analysis user can select the region of interest, by entering the minimum speed and distance. Then by means of sidebars he/she can change the dimension of the filtering zone. The results of filtered items will be marked in the timeline view.

6.1 Alternative visual designs

Helix is considered as an effective approach supporting intuitive navigation through a data set [16]. By transforming the time axis into a three-dimensional curve, data will be mapped into a spring-like format as depicted in Fig 6. This structure can support both superimposed and partitioned views depending on the perspective of the user. By looking from z axis to the x-y plane, we will see the superimposed layers formed in a circular shape. This is exactly similar to the radial visualization for cyclic time data as explained before. To make periodic sequences overlap correctly, the peach of helix ring should change according to the speed of gait. In my pilot design, I did not implement this feature.

Although radial graph has its own limitations, the main drawbacks of this design appear in partitioning section. From the Z-x view which is the side of the helix structure, we can see that the time axis forms a zigzag pattern. The tilted axes were not appreciated in my pilot test. A serious setback of this design is the mirroring of the sequence. As the axis rotates in a circular path, the sequences on the rear will be mirrored which is very ambiguous to users. As shown in Fig 6 the sequences on the red arrow are mirrored compared to the similar sequences on the black arrow. So the Helix design is best used for browsing only and not for similarity measurement.

7 DISCUSSION AND LIMITATIONS

Lessons Learned I think one of the strengths of this project is the use of 1D Fish-eye lens. I noticed that as the number of sequences increases in each partition, the 1D Fish-eye lens is more effective than the normal view, in providing fine details of each sequence. In addition, sliding left and right can ease the browsing task compare to zooming and panning. I also realized that there are two options in the implementation of Fisheye lens. In the first approach, the lens is fixed while a user can move the data dynamically and bring it to the focus line of 1D Fish-eye lens. For instance, if a user rotates the helix design, the part of the helix which is coming to the front view (at the center) is becoming larger and sequences on the sides shrink in size. In the other approach, the lens is trucking, similar to camera movement technique, by the user to an arbitrary position with defined upper bound and lower bound when the data is stationary. In this case, the minimum and maximum of the sliding of the lens are also clear and users know the exact location of the lens.

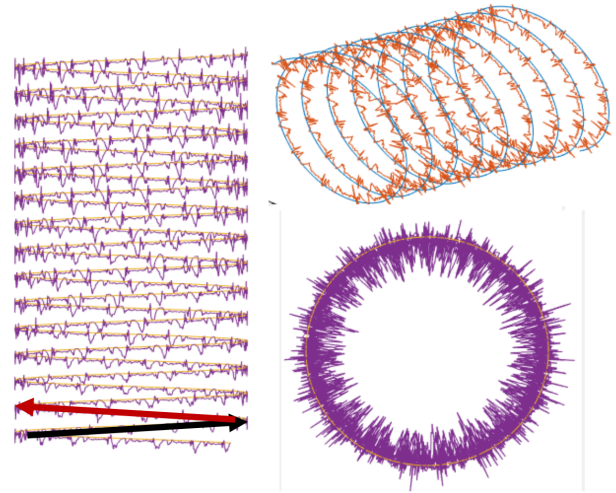


Fig. 6. Preserving the continuity of data in a 3D helix structure can facilitate browsing and provide more intuitive navigation through dataset. It can support both superimposing and partitioning depending on the perspective of the user. Tilted axes and mirrored sequence are the weaknesses of this design which make the similarity measurement hard to achieve.

Based on the result of my pilot test, I also find out that changing the linear axis of time to any 3D path such as helix is very confusing. Even presenting the data from 2D such as the x-y plane or the z-y plane was not easily conceivable by them. However, from the implementation side, it reduces the required effort for partitioning and superimposing by a straightforward mathematical transformation of data.

The last but not the least lesson that I learned is that, the juxtaposed partitioning and superimposing views can provide a powerful method to compare similarity and differences between gait sequences. The alignment and especially the same color coding in both views, enable users to find differences of overlapped layers in superimposed view and then find the corresponding sequence in partitioned view.

Limitations The dataset that I use in this project is only the acceleration in the z-direction of right ankle over time. However, many abnormalities might not appear only in one data for example in Hemiplegic gait, which is one of the most common gait disorders, the affected gait moves in a semi circle which is not visible in Z acceleration. Therefore, a more comprehensive analysis is needed on other dimensions of acceleration from one sensor (x, y). In addition, to have a more accurate diagnosis, we need to include data from other sites of the patient body such as waist or wrist.

Playing video is one of the key features of this interface. Current control system only offers to play and stop options which are clearly not enough, however, instead of adding more buttons we can link the video to the timeline so that users can move in time by dragging a cursor on the timeline.

MATLAB was not a good choice for linking data in multiple views, especially for brushing and annotating. Only in labeling abnormality, and filtering, I implemented the shared view and highlighting of selected data which can be extended to all the user interactions with data items. Better recognition and classification algorithm is needed to improve the accuracy of the system. One future work can be applying machine learning to gait analysis data and diagnose different gait deceases.

The last limitation is the scalability issue of the system. Despite the fact that it can perform well on the predefined task on the large dataset (approximately, 100000 data points), the visualization of data in partitioning section is not effective anymore. As the number of sequences in each partition increases, they become smaller and smaller

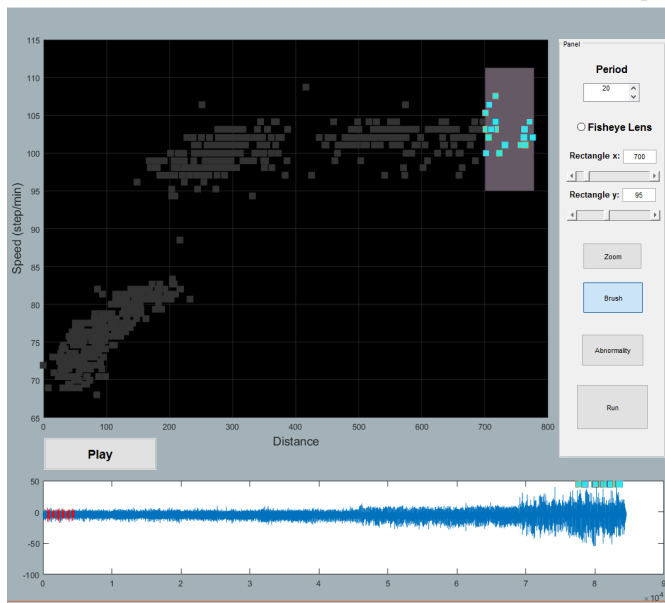


Fig. 7. Abnormality visualizer uses spatial encoding to show the similarity measures and speed through the entire sequences. Users can filter the area of interest to make a subset of sequences for further analysis.

and more compact until the user can not identify their similarity anymore. One solution to this problem is to enable the user to select part of dataset that is more relevant to study and perform the partitioning and superimposing on that and then extend the results to all sequences.

8 CONCLUSION

In this project, I propose a new visualization interface with application in rehabilitation domain. The built-in video player in the software enables physiotherapists to employ the observational cues for preliminary diagnosis. To have more robust detection and analysis of disorders, the system facets the data of accelerometers in multiple views. In particular, it uses partitioning and superimposing for similarity measurement and group labeling. Further by comparing the labeled data with the rest of gait cycles, it provides a comprehensive overview of the result for post hoc analysis. I believe that this system is a very promising start point to bridge the gap between conventional gait diagnosis and coming electronic technology. Further studies are required to press forward with wide range of application.

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