

# Kaleidomap Visualizations of Cardiovascular Function in Critical Care Medicine

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## Abstract

*In this paper we consider how the use of Kaleidomaps can facilitate our understanding and interpretation of large complex multivariate medical datasets relating to cardiovascular function in critical care medicine. Kaleidomaps are a new technique for the visualization of multivariate time-series data. They build upon the classic cascade plot and use the curvature of a line to enhance the detection of periodic patterns within multivariate dual-periodicity datasets. Kaleidomaps keep user interaction to a minimum, facilitating the rapid identification of periodic patterns not only within their own variants but also across many different sets of the variants. By linking this technique with traditional line graphs and signal processing techniques, we are able to provide medical experts with a set of visualization tools that permit the combination of medical datasets in their raw form and also with the results of mathematical analysis.*

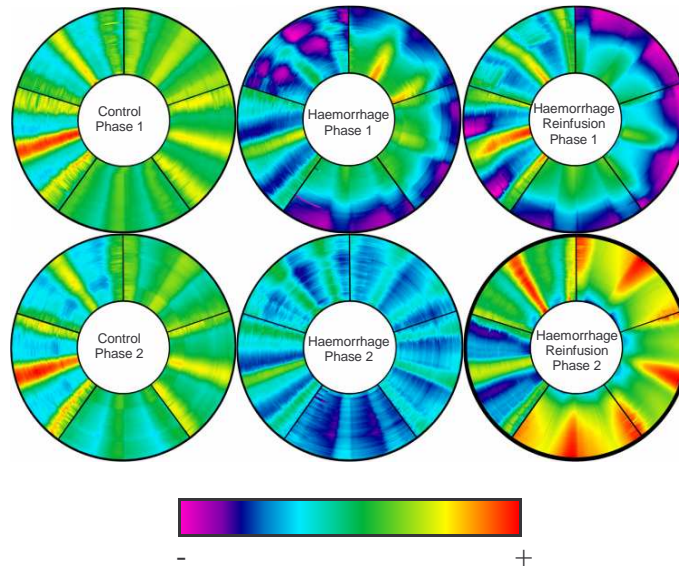
**Keywords:** *information visualization, multivariate time-series data, Kaleidomaps, data mining.*

## 1 Introduction

The BIOVASP (Biological, Visualization and Signal Processing) research group combines experts in visualization, signal processing and critical care medicine from Hull, Manchester and Bahcesehir in order to systemically uncover interactions between time, space and waveform morphology during the evolution and correction of acute haemorrhagic hypovolaemia (a state of low blood pressure caused by acute blood loss) We build upon previous work by Dark and Purdy [1,2]. Dark's thesis examines the pulsatile characteristics of the systemic arterial system during acute haemorrhagic hypovolaemia. In collaboration with Purdy, Dark was able to generate a nine-gigabyte multivariate dataset based on readings taken from sensors placed around the heart and within the arterial system. The dataset was generated from thirty subjects using six sensors. Three Codman catheter pressure sensors

[3] were used to measure femoral pressure, distal descending aortic pressure and ascending aortic pressure. Two Deltex Doppler ultrasound flow sensors [4] were used to measure distal descending aortic flow and femoral aortic flow. Finally, one electrocardiogram was used to monitor heart activity. All six sensors used a sample rate of 1.6 kHz and sampled data was cached and output to file every 20 seconds. The subjects were separated into three groups: control, haemorrhage and haemorrhage/reinfusion. Each subject was subjected to two 20 minute periods of experimentation. During these phases the control group was left untouched. The haemorrhage group was bled for the first phase and left untouched for the second. Finally, the haemorrhage/reinfusion group was bled for the first phase and then the removed blood was reinfused gradually over the second phase. Measurements were taken from all subjects throughout both phases resulting in 120x20 second wave samples per variant. Using wave averaging techniques provided by Purdy we were then able to reduce the 120x20 second samples into a singular wave average representative of each 20 second period. Whilst considerable analysis of the data had already been performed, the sheer size of the dataset has meant that much of the information, in particular the changes in morphology over time, have remained unexplored. Our task therefore was to provide a technique that would allow Dark and his colleagues to gain insight into the dataset and make accurate comparisons between not only the variants within each subject, but also across the series of subjects.

The visualization of time series data is not a new science and techniques for visualizing these datasets have been around for many years, dating back as far as the 18th century [5]. However, whilst sequence graphs, point graphs, bar charts and line graph paradigms are the most widely accepted visualization techniques for time-series data, their effectiveness at visualizing large or multivariate datasets (such as the medical data described above) is very limited. Indeed, in 2004, Johnson identified time dependent visualization as one of the top scientific visualization research problems facing us today [6]. Since these early days of time-series visualization many researchers have attempted to extend upon these early paradigms to accommodate for more complex datasets. Weber's Spiral Graph [7], similar in many ways to the line



**Figure 1 – Six Kaleidomaps showing the morphology of blood pressure and flow waves over two experimental phases**

graph, extends upon the original paradigm by replacing the straight time axis with a spiral form. This allows for far greater amounts of data to be displayed whilst also enhancing periodic patterns. Havre et al's ThemeRiver [8] paradigm extends upon the histogram, interpolating between bars using curves, providing a more intuitive method of viewing the relationship between both variables and time steps. Van Wijk [9] combines mathematical clustering techniques with 2D line graphs to provide the user with an efficient method of gaining insight into very large time-series datasets. Finally, Inselberg's Parallel Coordinate Plot [10] displays multivariate data as a series of parallel axes, joining values across axes to illustrate relationships. A more comprehensive review of current techniques can be found in Müller and Schumann's review of the field [11].

## 2 Kaleidomaps

Our visualization tools were developed specifically to provide a visualization technique that highlights the morphology of this large medical time-series dataset described above. We initially identified the following objectives for our visualization tool:

- Provide a single visualization suitable for quantitative dual-periodicity data;
- Support the visualization of large datasets;
- Support comparative reading of the dataset, to compare values in its neighborhood, across variants and across different sets of variants;

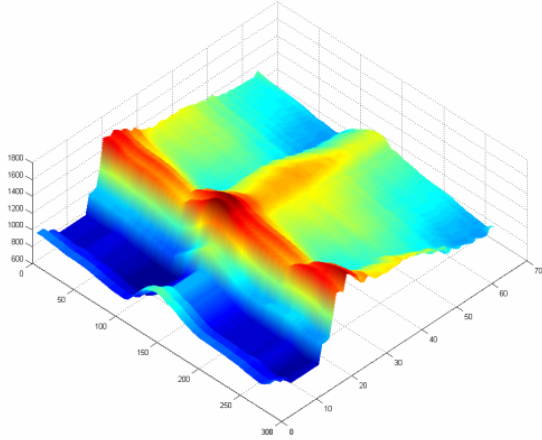
- Support the analysis of the dataset on the level of summary reading, whilst also providing the ability to identify periodic lengths;
- Allow for wave decompositions to be viewed in a similar format.

As we developed our visualizations, we noticed the similarity of the rendered output with the traditional children's kaleidoscope (an optical cylindrical toy that produced symmetrical patterns of constantly changing colours and shapes). We consequently named our visualization glyphs "Kaleidomaps" (Figure 1).

In order to develop an effective visualization we first looked at the problems encountered by previous techniques. The potential drawbacks of current visualization techniques are that:

- Three-dimensional techniques tend to require a high level of user interaction;
- Three-dimensional techniques tend to suffer from symptoms of occlusion;
- Geometrically complex visualizations are inclined to be more difficult to compare against similar representations;
- Many of the techniques require large amounts of screen estate.

With so many problems associated with three-dimensional representations of data, we decided to design a two-dimensional visualization, thereby reducing the level of user interaction required and furthermore eliminating any problems that might be caused by occlusion.



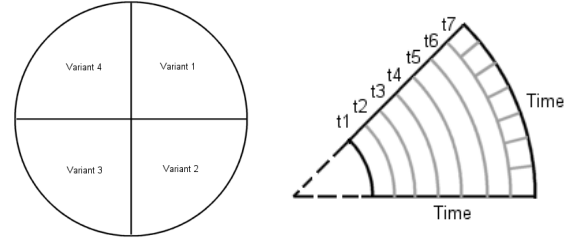
**Figure 2 – An example of a three-dimensional cascade plot used to visualize the morphology of a flow wave**

The cascade plot (Figure 2) has been proven to be very successful at visualizing sets of single variant time-series data. Cascade plots allow us to examine the morphology of sets of one-dimensional time-series data over time by dividing a one-dimensional set of time-series data into several subsets of equal period and plotting these subsets of data onto two time axes. Consequently we must consider each variant's data to be two-dimensional, so that it can be represented as a function of two time scales, for example  $f(\text{hour}, \text{minute})$ .

One of the objectives of the visualization was to provide a representation that could easily be compared against similar representations. To aid the comparison of representations, the visualization should take a standard and compact form. Whilst the cascade plot provides a very efficient and intuitive method of visualizing single variant time series data, if we wish to examine a large number of variants we must use multiple cascade plots. Due to the large amount of screen estate that these plots require, the amount of available screen estate quickly becomes an issue making comparisons difficult. By taking this paradigm and using colour to visualize the amplitude of the variant instead of the  $z$ -axis we are able to obtain a two-dimensional representation of the data where the  $x$  and  $y$  axis are used to represent time.

## 2.1 Creating the Kaleidomap

In its simplest form, a Kaleidomap can be described as a series of cascade plots, one for each variant, that are wrapped around a circle to form a ring. In doing so we preserve a continuous representation of time across the ring, so that a one-dimensional set of data at time  $t$  is at the same radial distance on one segment as it is on another.



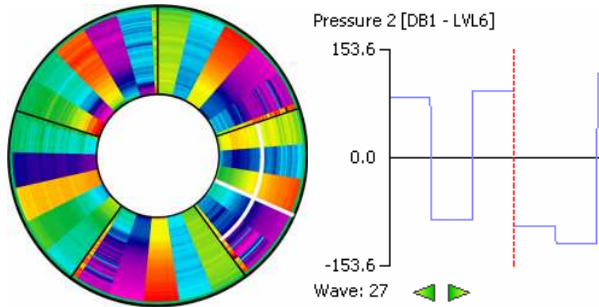
**Figures 3a (left) – An illustration of the layout of variants within the Kaleidomap**  
**Figure 3b (right) – An illustration of the layout of time within a segment**

To create a Kaleidomap, we begin by creating a circle segment or sector for each variant. Initially a circle is broken into  $n$  sectors of equal angle, where  $n$  is the number of variants within the dataset (Figure 3a). Each circle segment has two axes representing time, one along the radius and one along the arc of the sector. Time extends clockwise along the arc axis, whilst on the radial axis, time extends outward from the centre of circle. The arc is then broken down into a series of time bands. Figure 3b illustrates an example of this subdivision showing a sector that has been broken into seven time bands. Subsets of the dataset are plotted within the time band that is representative of the time at which they occurred. As the time bands approach the centre of the circle their area decreases. To prevent large quantities of data being mapped onto too small an area, we move the start of the radial time axis away from the centre of the circle. The exact distance from the centre will depend upon the sample rate of the data plotted along the arc. Whilst the start distance of radial time axis will be up to the visualization practitioner's judgement, we propose that the distance between the centre of the circle and the start of the time axis should increase with sample rate. As we are not using the third dimension, values are represented using colours.

## 2.2 Extending the Paradigm

We used Shneiderman's mantra of "overview first, zoom and filter, details on demand" [12] when designing our visualization tools. The Kaleidomap thus far provides an overview of the time-series data. Whilst this is useful for making high level analysis of the data, we must also provide further facilities to allow for an exploratory process to take place. The next stage in the process is to provide facilities to zoom and filter the data. We accommodate this by allowing the user to focus on a segment of interest by selecting it with a mouse. Upon doing so the other segments are hidden and the chosen segment fills the entire Kaleidomap. This creates a far larger area to plot the segment's data to, creating a much clearer representation of the data. Once an area of interest has been located, the user is provided with the ability to

highlight areas of interest using a set of markers (shown as a white cross on the Kaleidomap in Figure 4). The position of these markers is then repeated across all segments. Consequently, once an area of interest is highlighted, the user may return to the original view to see exactly how their area of interest relates to the data in the other segments.



**Figure 4 – An illustration of linking between line graph and the Kaleidomap**

We extend upon this idea of zooming by incorporating Focus & Linking into the Kaleidomap. Buja et al. [13] showed that by providing alternate representations of the detail data, it is possible to apply different, more effective techniques to the selected frame. As small features within each time band can be overlooked within the overview, an alternative more detailed view of these bands is required. We accommodate for this using line graphs that are linked to the selected area. Sliding a marker over a chosen time band enables us to see the data represented within a line graph. Any features held within this line graph representation can be highlighted using the mouse, and then if desired, upon the Kaleidomap itself (Figure 4).

Further interrogation of the data is permitted through the use of brushing. Brushing is an interaction technique which allows the user to specify an explicit focus within the visualization, providing additional information about the data within their selection. If the mouse is left to rest over a data sample within one of the Kaleidomap segments, a box will appear detailing the variant name, the point on each time axis, and the value of the data sample itself. This technique provides a very quick method of gathering detailed information about small areas within the Kaleidomap.

As noted in the previous section, as you approach the centre of the circle, the less area there is to plot data. This presents a slightly biased representation of the data, as data toward the edge of the sector will be clearer than it is in the centre. To address this issue we allow for the start of the time axis to scroll up and down the radius of each sector. This feature not only allows us to combat the issues created by the limited area to plot data, but by animating this

process we are able to see a moving depiction of how the data evolves over time.

Whilst the annular format reduces the problems of data being compressed into too small an area, it leaves the centre of the Kaleidomap free to represent individual variables such as Booleans or scalar values. For example, this area could be used to represent a patient’s breathing cycle, using black and white to represent inhaling and exhaling respectively.

### 3 Visualizing Cardiovascular Function

Whilst the Kaleidomaps provide a firm grounding from which to start the exploratory process, we decided to look toward the field of signal processing to provide a means of highlighting the less obvious information that might otherwise be overlooked. In many cases, the frequency content of a wave is of great importance. The frequency content can provide insight into the structure of a wave that would otherwise be very difficult to identify from the raw waveform within the time domain.

A wavelet is a waveform of effectively limited duration and has an average value of zero. Wavelet analysis uses these small waveforms and compares them against sections of the original signal to calculate a coefficient that represents how closely correlated that wavelet is to the original signal. By varying the scale of the wavelet, we can extract different frequency information: low scale wavelets will reveal rapidly changing details (high frequency), whilst high scale wavelets will reveal slow changing details (low frequency). However, calculating wavelet coefficients for every possible scale is a very time consuming task. By using a process called the discrete wavelet transform [14] we can extract the frequency information of the same accuracy using only wavelet scales and positions that are based on the power of two. Discrete wavelet transform is an iterative process, with each successive decomposition being decomposed in turn, so that one signal is broken down into lower-resolution components.

The main advantage of the discrete wavelet transform lies in its ability to preserve the time information. This means that features located within the decomposition will be located at the same point on the time axis as it is within the original raw data. By plotting the decompositions onto a Kaleidomap and comparing them against the original data, we provide the analyst with a far more accurate method for identifying and confirming features within the original data.

We began our exploratory process by taking one subject from each of the test groups; control, haemorrhage and haemorrhage/reinfusion, plotting each of the subject’s five sensor readings (two flow and three pressure) onto a Kaleidomap for each period.

A number of interesting observations were made when considering the three test subjects in Figure 1:



### Control Subject:

- Blood pressure and flow change very little over the two test phases.

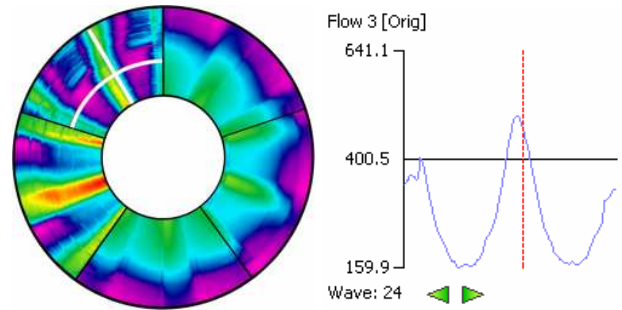
### Haemorrhage Subject:

- The amplitude of the blood pressure and flow waveforms gets steadily smaller toward the end of the first phase,
- The amplitude of the blood pressure and flow waveforms remain much weaker during the second phase, changing very little over the period.

### Haemorrhage/Reinfusion Subject:

- The amplitude of blood pressure and flow waveforms decrease toward the end of the first phase and is almost identical to phase 1 of the haemorrhage subject's Kaleidomap,
- The amplitude of blood pressure and flow waveforms steadily increase as time progresses through the second phase.

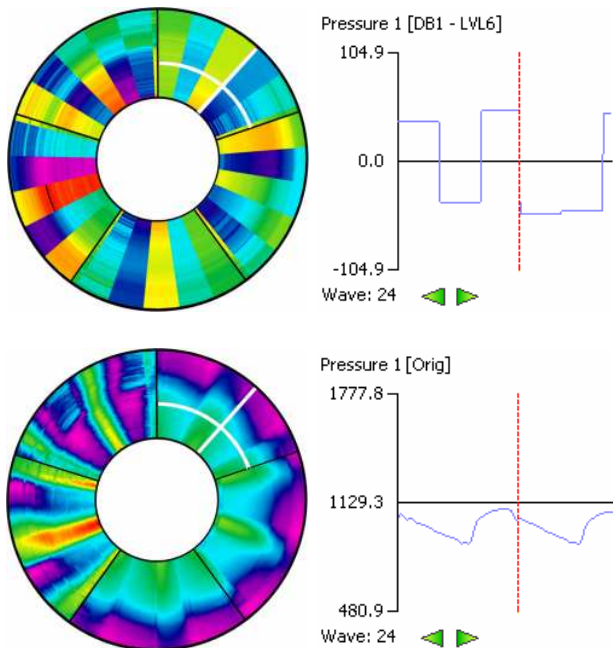
The aim of this project was to provide insight into the morphology of the waveforms over time. This initial analysis of the data shows us the morphology at a very high level. One of the relationships that Dark was originally interested in was how the diachrotic notch (a wave feature that represents the closing of the heart valve) related to the flow waveforms [15,16]. We therefore needed to examine the waveforms in more depth. We now consider an example of how we used Kaleidomaps to locate this feature and track its location in relation to the flow waveforms.



**Figures 5a (top), 5b (middle), 5c (bottom) –Illustrations of how wave features found within the decomposed Kaleidomap can be tracked back to the original raw data.**

Diachrotic notches can be described as a small but sharp turning point within a patient's blood pressure wave. As this is the type of feature that can be overlooked within the time-domain, we turned to wavelet decomposition to highlight this feature. Before continuing the exploratory process, all of the wave averages were decomposed using a Daubechies 1 wavelet [17]. The Daubechies family of wavelets was chosen for their ability to highlight turning points within waves. The process provided five levels of wave decomposition that highlighted the features held within a range of frequencies in the original data. The dataset and its associated decompositions were then examined by Dark and his colleagues.

Kaleidomaps showing decomposed wave data highlighted wave features as a banding across the circumference of the Kaleidomap. Dragging a marker (shown as a white cross within a segment) across a segment of decomposed data enabled the user to highlight features within the decomposition. This marker is linked back to the original Kaleidomap highlighting the point at which the feature occurs within the raw data. Taking the haemorrhage/reinfusion subject, we attempted to examine some of the smaller features of the wave. Firstly we located the most prominent step within the decomposed data and highlighted it with a marker (shown as a white cross on the Kaleidomap in Figure 5a). Tracing this marker back to the original Kaleidomap we were able to see exactly where that step occurred within the raw data (Figure 5b). However, whilst this provides an indication of its location it remains difficult to identify exactly how that step relates to the raw wave data. To address this issue we generate a line graph representation of the selected data (see right hand section of Figure 5). Each line graph shows the singular wave highlighted by the marker around the circumference, whilst the vertical marker on the line graph represents the point at which the two lines cross on the Kaleidomap. Plotting the data highlighted by the marker (shown as a white cross in Figure 5) within the Kaleidomap onto the line graph enables us to clearly see that the step in the decomposition relates directly to the



diachrotic notch in the pressure waveform. As markers are linked between Kaleidomaps and variants, locating the position of the diachrotic notch in relation to the flow waveforms is simply a matter of selecting the relevant variant and displaying its associated line graph (Figure 5c). Having located the diachrotic notch on the pressure wave and its relative position on the flow waveforms it was then possible to examine how the wave changed around that point by scrolling through the radial time axis. The positioning of the diachrotic notch in relation to the flow wave form has been an area of much discussion in the medical field. The Kaleidomaps have provided Dark and his colleagues with a means of examining this relationship across a very large dataset. Although the analysis of this data is still ongoing it is hoped that this technique will provide yet further insight into the relationships between these variants.

## 4 Conclusions

Our Kaleidomap visualization technique was developed specifically for the interpretation of a unique large-scale, highly complex time-series medical dataset generated by Dark and his colleagues. We have successfully compressed Dark's dataset into a series of static glyphs or 'Kaleidomaps' and provided the medical researchers with the tools that allow them to drill down in both time and frequency domains in order to uncover potential interactions between time, space and waveform morphologies (such as the relationship between the diachrotic notch and blood flow described in this paper).

Our tools have been well received by the medical research community at Hope Hospital, University of Manchester where they are currently being used to facilitate an in-depth study of the dataset. A full analysis of the dataset will require a further two years of analysis and the group's findings will be published in both medical and visualization journals.

## 5 Acknowledgements

This work is supported by the Engineering and Physical Sciences Research Council: Collaborative Immersive Visualization Techniques for the Interpretation of Cardiovascular Function in Critical Care Medicine GR/S82190/01(P). We thank the members of the SimVis research group at the University of Hull Computing Department especially James Ward, Dr Helen Wright and Dr Mike Brayshaw for their help and discussions related to this project.

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