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Radial Visualization Model in Health Care: A Survey

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ABSTRACT

One of the main focuses of research in health care involves the processing of large amounts of data accumulated in Electronic Health Records and their communication in an interactive, understandable, and adequate way to the needs of each user, either health care professionals, patients, or care givers. One way of conveying the information to all of them is in a graphical way. There are, traditionally, two types of graphic models for data presentation: Cartesian/linear models and radial models. From literature one can observe that there is an increasing interest in radial models to analyze and present large amounts of data. In this paper an exploratory study is presented aiming to understand how radial visualization model evolved throughout history, as well as its importance and relevance in data visualization with a particular interest in clinical data. The methodology used is focused on case studies found in literature, collecting all the relevant references about the radial visualization model and conclude on their weaknesses and strengths.

Keywords: Radial visualization, Electronic health records, Health care

INTRODUCTION

In recent years, as a result of computerization and technological advances, we have witnessed an exponential increase in electronic databases in different areas of society. In health care field it is not different, the increasing digitization of health records (clinical histories, imaging, genetics, laboratory results, among others) has exponentially expanded the medical information available electronically (West, 2013). This escalate is based on the explicit benefits of electronic health records (EHR) compared to paper records such as cost, readability, accessibility, storage, and security (Jin, 2016). Despite the well-known advantage of EHR, some recent studies have shown that EHR-based systems hardly improve the ability of healthcare providers to make better decisions (Abdullah, 2020). Their volume, heterogeneity and complexity may overload the user, leading to interpretation errors or overlook vital data (Abdullah, 2020) (Aigner, 2012) (Ledesma, 2019) (Martignene, 2020).

Therefore, currently, one of the main focuses of research in healthcare is related with processing and communicating large amounts of information in an interactive, understandable, and adequate manner to the needs of each user (Filipov, 2021). With better clinical decision-making tools, that health professionals may use, the data becomes more amenable to visualization. The refinement of the models in association with biomedical illustrators, and a more intuitive and dynamic interface can assist clinicians to treat patients instead of spending hours reading computer screens. Nonetheless, the development of data visualization in healthcare is in its beginning (Boyd, 2017). One of the first paper on this area was published less then 3 decades ago (Plaisant, 1996). Since then, several interfaces were developed, such as LifeLines (Plaisant, 1996), KNAVE-II (Goren-Bar, 2004), TimeLine (Bui, 2007) HARVEST (Hirsch, 2015), OutFlow (Wongsuphasawat, 2012), Care Pathway Explorer (Perer, 2015), EventFlow (Monroe, 2013) offering to the user a better comprehensive view, making it easy to detect temporal associations. Most of these interfaces used a linear model to present their data, however, over the last decade we have witnessed the development of tools for analyzing patient clinical data that replace more traditional linear graphics with radial models (Jin, 2016) (Joshi, 2012) (Zhang, 2013) (Hu, 2014) (Baytas, 2016) (Ledesma, 2016) (Senathirajah, 2017) (Kaushal, 2017) (Ha, 2019) (Abdullah, 2020).

Radial Models Importance for Data Visualization

One of the most effective ways of communicating information based on large datasets is through graphical visualization. As there are different graphic models to represent data, various communication contexts require distinct types of graphics to deliver an informative and meaningful visualization for a given problem.

Among the different graphic models there is the radial model. Draper et al. (2009) refers that radial visualization is not a panacea for all information visualization problems. However, there are many situations where this type of graphics is the most appropriate way to promote the data relationship and effectively communicate the information. Radial models come in different shapes such as circular, elliptical, or spiral form (Diehl, 2010), typically using polar coordinates instead of Cartesian coordinates, used in linear methods. There are situations where radial models present the data in a more comprehensive form and therefore convey important messages that in other type of graphics wouldn't be evident or not properly emphasized. Indeed, although linear methods are generally considered easier to read, more accurate and faster, there are some upsides in using radial models, namely their more natural shapes, more appealing aesthetics. This aspect is also considered important in certain applications since they may drive to a more positive attitude, improve the engagement, the availability to learn and explore, and better explaining historical narratives (Filipov, 2021). Time-related data is an example of a dataset that will have a good representation using a radial model. As Aigner (Aigner, 2008) stated, there are many natural processes that are cyclic/periodic and therefore will have a better visualization with radial models. Other feature where radial models are good is in addressing the display fragmentation issue. This feature mitigates the need to access different displays to see the information, avoiding the need to retain information in memory while other information is researched (Senathirajah, 2017) (Senathirajah, 2020). Radial models are more visualization-space efficient and easing the comprehension and interaction of the user, with the capability of providing valuable insights from the data (Maças, 2018). Another aspect of this type of model that can be very powerful, when used for the right purpose, is the fact that can be easier to memorize. For instance, when the most important dimension is represented as sectors it enhances the memorization (Diehl, 2010). Radial models are particularly interesting for focusing on a particular dimension (Maças, 2018), or when depicting two dimensions that are not equally important (Diehl, 2010), or even to represent periodical patterns (Maças, 2018). When there are several categories related to the same object that have a dimension in common, you can quickly apprehend information from a radial graphic, whereas in a linear graphical you would have to visit several displays, several times, to come to the same conclusion. This principle can be seen, applied to a set of clinical events (categories) over time (common dimension) for a patient (object) (Bastardo, 2021).

Radial Models Evolution in Health Care

Historically the term radial view model was introduced by Hoffman et al. in 1997 (Hoffman, 1997), although radial representations date back to the beginning of the 19th century, in the field of mathematics and statistics, with pie charts. The works of William Playfairs, “The Statistical Breviary”, and Florence Nightingales are considered the first examples of the use of radial methods (Hoffman, 1997).

Drapper et al (Draper, 2009), propose a classification of radial visualizations into three main design patterns: “Polar Plot”, “Space Filling” and “Ring Pattern”. The “Polar Plot” is divided into 2 subpatterns: “Tree” and “Star”. In both the center of the graph has some special meaning. In the “Tree Pattern”, the origin of the graph is located at or near the center of the graph. From the center, segments of lines radiate outwards, and these segments may present ramifications. This type of pattern is mainly used for visualization of hierarchical structures, as well as visualization of the relationship between disparate entities. The “Star Pattern” is like the previous, where the origin of the graph is equally in the center, from which linear segments come outwards, however, unlike the “Tree Pattern” these segments do not have ramifications. They are mainly used for ranking search results as well as visualizing the relationship between disparate entities. In the “Space Filling”, also known as “Radial Space Filing” (RSF), as in the “Polar Plot”, the center of the graph also represents the origin, however instead of the information being dispersed in lines from the center to the outside, it is arranged in the form of concentric circles (“Concentric Pattern”), spirals (“Spiral Pattern”) or spatial clusters (“Euler Pattern”). These types of patterns are used especially for visualizing sequential, periodic and time-oriented data. In the “Ring Pattern”, unlike the other radial patterns, the center of the graph is not very relevant. As the name implies, the data is presented in the form of different rings. There are 2 sub-patterns, the “Connected Ring Pattern” and the “Disconnected Ring

Pattern". The purpose of both is to find points of relationship between different sets of data. In the first, a point is placed on one of the rings and then edges are drawn between common points of different rings. In the second subpattern, instead of lines joining common points from different datasets, the relationship is established through colors, shapes, labels, or both. This way the confusion created by the lines in the middle of the graphic of the previous pattern is avoided. The last decade has shown a growing interest in applying this type of model in Medicine field, with the development of several tools for analyzing patients' clinical data (Jin, 2016) (Joshi, 2012) (Zhang, 2013) (Hu, 2014) (Baytas, 2016) (Ledesma, 2016) (Senathirajah, 2017) (Kaushal, 2017) (Ha, 2019) (Abdullah, 2020). Some of these radial models were developed to analyze specific clinical conditions of patients (Joshi, 2012) (Hu, 2014) (Ha, 2019) (Abdullah, 2020), while others aim to map the general clinical situation of the patient (Jin, 2016) (Zhang, 2013) (Ledesma, 2016) (Senathirajah, 2017) (Kaushal, 2017), or populations (Baytas, 2016).

Joshi and Szolovist (Joshi, 2012) developed a radial "starburst" interface to assess the condition of critical patients in Intensive Care Units and provides prognostic previews of patient's clinical conditions in real-time. To reduce the complexity of data represented by over 100-dimensional space, the model use machine learning to group similar clusters of patients characterized by eight physiological foci (general, lung, cardio, liver, kidney, hematology, acid-base, electrolytes). The radial axes capture organ severities from 1 (being normal) to 8 (being the worst). Different colored lines depict different time points during the patient's ICU stay. The "Five W" model (Zhang, 2013) is based on the journalistic concept of describing each occurrence based on answering the five basic questions: who, what, where, when and why. In this interface, the who is the patient, the where is the patient's body, and the when, what, and why is a reasoning chain which can be interactively sorted and brushed. Using the patient's body as a radial map, the display captures all medical events that have occurred in the past and present, serving as a quick overview for the doctor who is evaluating the patient, always answering the five basic questions.

OmicCircos, a tool to analyze large-scale genomic data collection, can be used to generate high-quality circular plots for visualizing genomic variations, including mutation patterns, copy number variations, expression patterns, and methylation patterns (Hu, 2014). Jin et al (Jin, 2016) present an interactive system to illustrate health information in an intuitive way, centering their tool on a two-dimensional image of the human body to support body-centered data layout. The user can explore the different locations of the human body to see different symptoms. By selecting these symptoms, the user can easily add, enter and update information. Furthermore, to provide a better layout of the health records, a timeline and color coding are integrated to distinguish different components.

Phenotree is a hierarchical, and interactive phenotyping interface, that permits users to participate in the phenotyping process of large-scale EHR cohorts. This visual analytic tool that allows physicians to interactively explore EHR cohorts, and generate, interpret, evaluate, and refine phenotypes by building and navigating a phenotype hierarchy. Specifically, given a cohort or sub-cohort, PHENOTREE employs sparse principal component analysis to identify key clinical features that characterize the population (Baytas, 2016).

Ledesma et al. (Ledesma, 2016) developed hFigures, an open-source library for visualizing a complete, accurate and normalized graphical representation of health data. The idea is based on the concept of the hGraph, developed earlier by MITRE Corporation (Follett, 2012). The hGraph design consists of a circular space with an area defined by two circumferences. The area represents the minimum and maximum recommended values for a given measurement. The values are distributed in a circular space. A graph is formed by joining the data points around the circular area. This polygon or graph reveals a pattern, and its shape provides a quick overview of the general situation of all the values and how they deviate from the recommendations. The hGraph shows a static overview of a person's wellness. Disease and wellness are processes that change over time. Thus, in addition to a static snapshot such as in hGraph, hfigures provides additional key features, including a comparison of multiple health measurements over time. It makes an emphasis on multiple graphs, or figures, in order to provide a graphical representation of evolution of the data over time (multiple snapshots of the data at certain points in time).

MedWISER tool, consists in a "Sunburst" type visual system, in which the patient's clinical data are represented in different rings. These rings are subdivided into the different medical categories of the patient (lab results, clinical notes, images, among others). These categories are subdivided into more specific subcategories as the rings become more exterior. There is also a color code to identify clinical elements that belong to the same category. In addition, one of the main features is that the user can select the categories he wants to view in each case and simultaneously, which avoids the problem of fragmentation, as repeated browsing and viewing other displays are not necessary (Senathirajah, 2017).

Patient Journey Visualizer (PJV) is a tool that helped visualize patient journeys, from sickness to recovery, using Parallel Coordinates, Sankey, and Sunburst charts. Parallel Coordinates are used to visualize multivariate data concerning patient journeys at the individual level. Sankey charts assist in visualizing the flow of patients between various phases of patient journeys. Sunburst charts provide a representing hierarchical relationship between diagnoses, procedures, and prescription medications (Kaushal, 2017). Ha et al. (Ha, 2019) developed RadVIS a 3D radial model to assist psychiatrists in evaluating multidimensional data from groups of patients with dementia. It allows the user to get a better understating of the characteristics of patient cluster and analyze the variable values of data comprising each cluster at the same time. The user can choose the number of clusters for segmentation after selecting either a foggy cluster or a random cluster algorithm. A patient with dementia is represented by a single node in this visualization. RadVis also supports a multi-filtering function through parallel coordinates plot to assign different conditions for a more comprehensive analysis. VISA_M3R3 is a system designed to help clinical researchers to identify medications and medication combinations that can be associated with a higher risk of acute Kidney injury (AKI). By integrating multiple regression models, frequent itemset mining, data visualization, and human-data interaction mechanisms, VISA_M3R3 allows users to explore complex relationships between medications and AKI. The analytics module of VISA_M3R3 performed a single-medication analyzer that focus on finding associations between each medication and AKI. Also has a multi-medication analyzer that purposes to identify the medication combinations that are associated with AKI. (Abdullah, 2020).

DISCUSSION AND CONCLUSIONS

As shown in this paper, there has been an intensive discussion around what is the best graphic way to represent big amounts of data so there is a better communication to the users. A better communication consists of capturing the most important messages for a given use in an efficient and timely way. This characteristic is mostly important in the healthcare sector where frequently decisions must be made based on a big quantity of different types of data in a very short period. Radial models can play an important role in this context. Not being a "one-fits-all" solution it proves to be most suitable to many situations in health care. The different case studies use diverse graphic approaches: radial (Joshi, 2012) (Zhang, 2013) (Baytas, 2016) (Senathirajah, 2017) (Kaushal, 2017) (Ha, 2019) (Abdullah, 2020); human-body based (Jin, 2016) (Zhang, 2013) and circular plots (Hu, 2014) (Ledesma, 2016). The radial models further divide in radial (Abdullah, 2020), radial tree (Baytas, 2016), radial sunburst/starburst (Joshi, 2012) (Senathirajah, 2017) (Kaushal, 2017) and 3D radial (Ha, 2019). In the healthcare sector this kind of graphics is used for different goals. There are some used for analytic purposes, such as (Hu, 2014) (Baytas, 2016) (Abdullah, 2020). Others are used in clinical environments. Of these some are dedicated to patient's overview (Joshi, 2012) (Zhang, 2013) (Follett, 2012) (Senathirajah, 2017) (Kaushal, 2017) (Ha, 2019), and one explores the prescription medication (Kaushal, 2017). This survey shows that the radial model is used in many situations related with healthcare, providing a variety of options that cover a wide range of applications, proving that Information Visualization research plays an important role in shortening the distance between users and their own health data.

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