Comparative Visualization of Longitudinal 24-hour Ambulatory Blood Pressure Measurements in Pediatric Patients with Chronic Kidney Disease

M. Özmen¹, M. Y. Jabarulla¹, C. R. Grabitz², A. Melk², E. Wühl³, S. Oeltze-Jafra¹

¹TU Braunschweig & Hannover Medical School, Peter L. Reichertz Institute for Medical Informatics, Germany ²Hannover Medical School, Department of Pediatric Kidney, Liver and Metabolic Diseases, Germany ³Heidelberg University Hospital, Division of Pediatric Nephrology, Center for Pediatrics and Adolescent Medicine, Germany

Abstract

Pediatric chronic kidney disease (CKD) increases the risk of cardiovascular disease, stroke and other life-threatening conditions. Monitoring blood pressure in CKD patients is crucial to managing these risks. 24-hour ambulatory blood pressure monitoring (ABPM) is recommended for its comprehensive and accurate assessment of blood pressure over 24 hours. Analyzing and comparing 24-hour ABPM data of multiple diagnostic visits is a challenging task. Traditional methods involve comparing individual visits using paper printouts, which can be time-consuming and lacks a systematic overview of deviations over time. In this work, we present a dashboard visualization that allows clinicians (i) to assess the evolution of ABPM data over multiple diagnostic visits, (ii) to compare ABPM data of CKD patients with reference data of a healthy cohort, and (iii) to perform a detailed intra-individual comparison of the ABPM data acquired at two subsequent diagnostic visits. We demonstrate the dashboard in a case study of a patient with mild-to-moderate-stage CKD.

CCS Concepts

• *Human-centered computing* \rightarrow *Visual analytics;*

1. Introduction

Chronic kidney disease (CKD) in pediatric patients is characterized by the gradual loss of kidney function [BRMR16]. Hypertension is common in these patients since the kidneys help in controlling blood pressure, e.g., by producing specific hormones. Ambulatory blood pressure monitoring (ABPM) is hence, an important tool in CKD monitoring. It provides continuous blood pressure (BP) readings over 24 hours, detects BP changes, and helps in adjusting medication dosages and in treatment evaluation [SP04, SNF*12]. Physicians analyzing ABPM data of pediatric CKD patients face challenges due to the lack of normative data specific to this population and the lack of dedicated analysis software. Traditional methods of ABPM data analysis use paper printouts hampering a reproducible, structured overview of deviations over time [OPS*13]. To address these shortcomings, a visualization tool incorporating normative data is necessary to identify patterns, trends and deviations in longitudinal 24-hour ABPM data [TSK*21]. Many research works are dedicated to the visual analysis of time-series data [FXJ20]. A subset focuses on multi-variate time series and/or multiple time series visualization [TR09, GK15, LSS09, SBM*14, FKL*22]. Since none of the existing approaches has so far been tailored to 24-h ABPM data of multiple visits, we propose a novel dashboard for the comparative visual analysis of those data.

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2. Method

Dashboard Visualization. The dashboard visualization for assessing longitudinal ABPM data is shown in Figure 1. At first, a patient case is loaded based on patient ID, name (omitted here for privacy reasons), age, body height, and sex (Fig. 1,a). The dashboard is then populated with the ABPM data of all available diagnostic visits. The left panel provides an overview of the ABPM data in relation to the average ABPM profile of a body heightand sex-matched healthy sub-cohort (Fig. 1,b). One radar chart is drawn per visit. The systolic (red) and diastolic (blue) patient profiles are shown together with their respective healthy reference profile (green). The filled area representation shall convey the respective deviation from normal and enable clinicians to quickly identify large deviations. Next to the visit number, the respective age of the patient is shown. Moreover, the number of reference profiles available for computing the average reference profile is shown (green legend). The visual encoding of the right panel is similar (Fig. 1,e). Here, the transitions between two visits are conveyed by radar charts. For instance, the upper chart "Visit 4-5" superimposes the systolic and diastolic profiles of visit 4 (dashed line) and 5 (solid line). Again, the area between profiles encodes the deviation. In the left/right panel, the user can select two/a single radar chart (Fig. 1,c) causing the corresponding, detailed line charts to



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Figure 1: Dashboard for the visual analysis of single-patient 24-h ABPM data (details provided in the text).

be displayed in the center of the dashboard (Fig. 1,d). In the line plot, day and night time are emphasized since a nocturnal dipping of BP, for instance, is indicative for a normal profile. Finally, a table at the bottom of the dashboard shows some quantitative deviations between the visits with respect to a subset of study variables (Fig. 1,f). The therapy mode provides crucial information that may explain changes in BP due a specific associated medication. The development of our dashboard was carried out by utilizing pandas, numpy, matplotlib, and seaborn libraries of the Python programming language.

Average healthy profile computation. At each patient visit, the body height- and sex-matched healthy subcohort is determined (patient body height \pm 5cm and same sex). Since the corresponding subcohort profiles have different starting and end points as well as different temporal sampling rates, they need to be synchronized before averaging. At first, all profiles are aligned at noon. Then, artificial measurements are added for each ABPM profile if necessary at the earliest overall starting point and the latest overall end point in order to cover the same time span. As artificial measurement, the first and the last real measurement are simply propagated, respectively. Next, all profiles are resampled to one measurement value per minute. Thus, all profiles have the same length (number of measurement points) and the real measurements are kept. Finally, the average healthy profile is computed.

3. Case Study

Our CKD dataset contains 546 CKD patients and 825 healthy patients. The age range of the CKD patients is 5 to 25 and of the healthy cohort it is 5 to 20. The average number of visits per CKD patient is 3 and there is one visit per healthy child. Besides, the average number of measurements per visit for CKD and healthy patients is 63 and 65, respectively. Figure 1 shows the ABPM data of a 18-year-old (female) patient diagnosed with mild-to-moderatestage CKD, for whom nine 24-hours ABPM profiles were obtained during routine checkups between 2010 and 2018. Using our visualization tool, medical domain experts noticed a high BP in visit 4 compared to visit 2 and visit 3. This is due to the patient receiving kidney transplantation (TPL) before obtaining the visit 4 ABMP data. The high BP was caused due to the side effects of the immunization suppression drug given to the patient after transplantation. Medical domain experts verified this by comparing with the ABPM data of visit 5 where the BP was back to normal due to the proper medications given to the patient. Overall, performing such longitudinal visualization helps clinicians to prescribe and adjust necessary medications to maintain the patient normal BP.

4. Conclusion

Our dashboard visualization provides an overview of deviations in ABPM data over multiple diagnostic visits, allows for comparison with reference data of healthy patients, and enables detailed intraindividual comparison of ABPM data between subsequent visits. Our case study demonstrates the usefulness of the tool in analyzing ABPM data. In future work, we plan to integrate quantitative measures of profile dissimilarity and the visual highlighting of critical differences between profiles.

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