Real-Time Visual Analytics for Patient's Health Monitoring

Analytique visuelle en temps réel pour la surveillance médicale de patients

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Abstract- The overflow of new technologies that enable live streams of big data has availed healthcare monitoring in real time. A massive amount of medical data generated by IoT wearable devices can be transmitted today in real-time to medical professionals. However, the high velocity and time sensitivity of such data make it difficult to include the analysis and processing to extract insights in real-time. This work presents an approach for patient health monitoring based on visual analytics to help collecting, processing, and visualizing medical data streams in real-time. A first prototype of this system was developed, and initial results are presented.

1.Introduction

Collecting different types of biomedical data has become consistently effortless due to the continuous growth of medical wearable devices. Thus, in the field of electronic health (eHealth), the prerequisites of patient monitoring can be fulfilled by the ability of these devices to perform distant transmission of the medical data [1]. During patient monitoring, sensors perform the capture of different health data variables and the IoT provides the storage and the transfer of these data allowing remote supervision of patients [2].
Due to the massive amount of data that can be generated by different sensors at the same time during the patient monitoring and its heterogeneity nature as well as its high velocity, it is challenging to process, analyze and visualize such data in real-time. These challenges cannot be handled using traditional current systems due to their limitations and time consumption [3].
Extracting insight from big data and making real-time decisions from visual representations can be provided using the visual analytics concept, which is essentially based on combining data analytics and interactive visualization. The application of visual analytics in patient healthcare monitoring could help to overcome the challenges raised using traditional methods.
This paper presents a new approach for real time visual analytics dedicated to patient's health monitoring and the initial implementation of a distributed framework is described.

2.Relatded work

Visual analytics is the concept of combining data analysis, visual representation, and human interactivity to extract insights and make decisions. Multiple disciplines are involved in the visual analytics process including data mining, machine learning and advanced graphic representations. Dynamic visual analytics is defined as "The process of integrating knowledge discovery and interactive visual interfaces to facilitate data stream analysis and provide situational awareness in real-time." [4]

The data can be massive, heterogeneous, ambiguous, and often conflicting in nature. Thus, several methods and models of visual analytics appeared depending on the requirements of each application domain. However, in the literature many taxonomies of visual analytics methods and techniques were proposed. Andrienko et al. defined a typology of tasks in exploratory data analysis based on data structure [5]. Analysis tasks were classified by involving the pattern notion into Behavior characterization, Behavior comparison and Relation seeking. Roth [6] presented a taxonomy of interaction techniques organized according to "three broad user goals motivating the use of the visualization": procure, predict, and prescribe. These goals can be considered as corresponding to the task 'assess', 'forecast', and 'develop options' [7].

In the medical field, visual analytics solutions started to be used increasingly last few years for monitoring, prediction of future health states of the patients and decisions making. KAVAGait is a visual analytics system allowing the storage and the exploration of complex data captured in clinical gait analysis [8]. Similarly, Preha is a novel application for precision rehabilitation that uses predictive visual analytics to process and visualize heterogeneous and multidimensional data [9]. Ghods et al. proposed an iterative visual analytics design for CIL (clinician-in-the-loop) that enables clinicians to monitor the patient behavior patterns obtained from smart home data and provides the potential to support self-management and chronic conditions [10]. to provide clinical decision support in managing glaucoma progression, Van den Brandt et al. designed a visual analytics tool that includes a prediction model. Their approach aims to assess reliability of a prediction, understand why the model made a prediction, alert to relevant features, and guide future scheduling of visual fields [11].

3. User requirements

Visual analytics has the potential for providing real-time data processing when integrated in live stream data workflow. However, the design of an effective visual analytics system that provides real-time patient's health monitoring is an elaborate work. Thus, such system design should take into consideration different requirements and challenges.

Using the triangle data-user-tasks defined by Miksch et al. [12], the most important requirements of such system can be specified as follows:

Data: In the real time patient health monitoring there are two types of data: stream data captured by specific wearable sensors and IoT and historical data stored from the previous health records. The data are numeric, time-oriented and characterized by its big volume and high velocity.

Users: The users are health practitioners such as doctors and physical therapists. These users need to have access to different data representations and interact with the visual dashboard.

Tasks: The main task of the health practitioner is to monitor and evaluate the patient's health conditions such as health vital parameters, symptoms of the evolution of pathologies, and for example, physical activities for Parkinson and post-stroke patients. The prediction of a patient 's health condition is crucial for taking immediate decisions and for planning the therapy program. Hence, there is a need for a distributed architecture that combines storing and stream processing of biomedical data.

4. Proposed approach

The proposed architecture of real-time visual analytics for patient health monitoring combines parallel workflow of data generated by the sensors worn by the patient fig .1.

The captured data is transmitted to an event hub which publishes data equally to:

- Persistent database to be used as a consistent training set to build reliable machine learning (ML) models,
- Stream analytics to process real-time data and apply specified ML models.

The resulting data is then redirected to a web visualization dashboard where the clinician has the possibility to interact with the system and readjust the monitoring features.

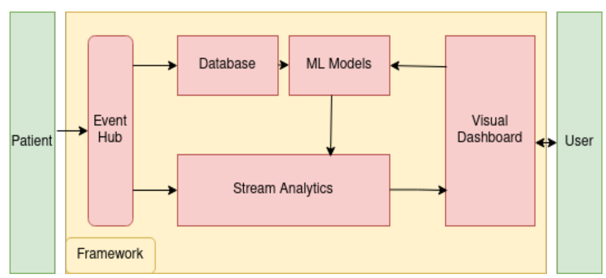


Fig.1 The proposed system architecture

4.1 Initial implementation

A first prototype of the proposed architecture was implemented on an Ubuntu 20.4 machine (Core i5 processor, 4GB RAM) equipped with Kafka 2.13-2.6.1 server, zookeeper and kafka manager. The system was developed using Spyder IDE 4.2.1 and Python 3.9.0.

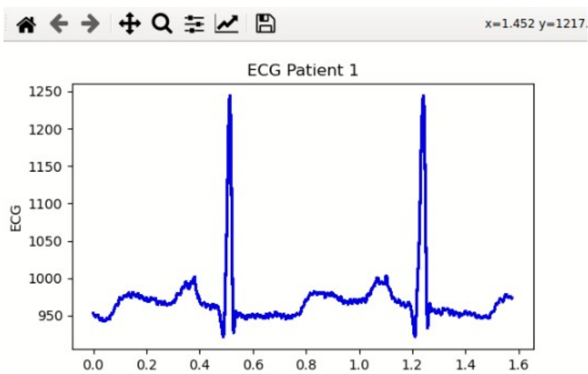
4.2 System Testing:

Using two existing datasets, the first dataset is obtained from an ECG and used to simulate the heart rate of the monitored patient [13]. The second dataset is of kinematics of hand during physical rehabilitation activities [14], they are used to simulate the data monitoring of the thumb flex angle during hand activities during medical rehabilitation exercises.

To develop a data generator, the ECG dataset of 1 second containing 3600 values and the thumb flex angle dataset containing about 600 values during 5 seconds were looped in time to simulate the real-time continuous dataflow.

The monitoring scenario is to capture and visualize the ECG data and the thumb flex angle data of a single patient during the execution of hand activity for lifting an object from a table and releasing it on the same table Fig 2.

(a)



(b)

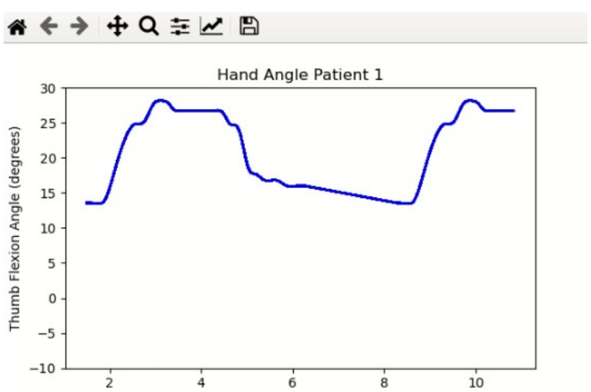


Fig.2 Example of real-time medical data monitoring. (a) ECG data. (b) Thumb flex angle during hand activity.

5. Results:

The latency of the data workflow increases with the number of patients monitored at the same time and the number of sensors used for data capture. This is due to the use of a single machine to embrace the different components of the proposed framework.

6. Conclusion and research perspectives

This paper proposed an approach of real-time visual analytics for patient health monitoring. A first prototype of this system was developed, and the initial testing showed the existence of data workflow latency. The future improvement of this system will be made using distributed machines to reduce the latency, which is crucial for patient safety and appropriate decision making. In the next step of the system development a cloud database and machine learning algorithms will be included to build prediction models of different medical data types.

References

[1] M. Muzny et al., “Wearable sensors with possibilities for data exchange: Analyzing status and needs of different actors in mobile health monitoring systems,” Int. J. Med. Inform., vol. 133, 2020, doi: 10.1016/j.ijmedinf.2019.104017.

[2] S. A. and D. U. Dahlia Sam1, S.Srinidhi2, V. R. Niveditha3, “Progressed IOT Based Remote Health Monitoring System Dahlia,” Int. J. Control Autom., vol. 13, no. 2, pp. 268–273, 2020.

[3] A. Ed-daoudy and K. Maalmi, “A new Internet of Things architecture for real-time prediction of various diseases using machine learning on big data environment,” J. Big Data, vol. 6, no. 1, 2019, doi: 10.1186/s40537-019-0271-7.

[4] P. C. W. John Dill, Rae Earnshaw, David Kasik, John Vince, “Expanding the Frontiers of Visual Analytics and Visualization,” 2554, [Online]. Available: http://library1.nida.ac.th/termpaper6/sd/2554/19755.pdf.

[5] N. Andrienko and G. Andrienko. (2006). Exploratory Analysis of Spatial and Temporal Data: A Systematic Approach. 10.1007/3-540-31190-4.

[6] R. E. Roth, “An empirically-derived taxonomy of interaction primitives for interactive cartography and geovisualization,” IEEE Trans. Vis. Comput. Graph., vol. 19, no. 12, pp. 2356–2365, 2013, doi: 10.1109/TVCG.2013.130.

[7] J. J. Thomas and K. A. Cook, “Illuminating the path: The research and development agenda for visual analytics,” IEEE Comput. Soc., p. 184, 2005, [Online]. Available: http://vis.pnnl.gov/pdf/RD_Agenda_VisualAnalytics.pdf.

[8] M. Wagner, D. Slijepcevic, B. Horsak, A. Rind, M. Zeppelzauer, and W. Aigner, “KAVAGait: Knowledge-assisted visual analytics for clinical gait

analysis," IEEE Trans. Vis. Comput. Graph., vol. 25, no. 3, pp. 1528–1542, 2019, doi: 10.1109/TVCG.2017.2785271.

[9] G. Bernold, K. Matkovic, M. Eduard Gröller, and R. G. Raidou, "preha: Establishing precision rehabilitation with visual analytics," Eurographics Work. Vis. Comput. Biol. Med. VCBM 2019, pp. 79–89, 2019, doi: 10.2312/vcbm.20191234.

[10] A. Ghods et al., "Iterative Design of Visual Analytics for a Clinician-in-the-Loop Smart Home," IEEE J. Biomed. Heal. Informatics, vol. 23, no. 4, pp. 1742–1748, 2019, doi: 10.1109/JBHI.2018.2864287.

[11] A. van den Brandt et al., "GLANCE : Visual Analytics for Monitoring Glaucoma Progression," 2020, doi: 10.2312/vcbm.20201175.

[12] S. Miksch and W. Aigner, "A matter of time: Applying a data-users-tasks design triangle to visual analytics of time-oriented data," Comput. Graph., vol. 38, no. 1, pp. 286–290, 2014, doi: 10.1016/j.cag.2013.11.002.

[13] S. Schellenberger et al., "A dataset of clinically recorded radar vital signs with synchronised reference sensor signals," Sci. Data, vol. 7, no. 1, pp. 1–11, 2020, doi: 10.1038/s41597-020-00629-5.

[14] N. J. Jarque-Bou, M. Vergara, J. L. Sancho-Bru, V. Gracia-Ibáñez, and A. Roda-Sales, "A calibrated database of kinematics and EMG of the forearm and hand during activities of daily living," Sci. Data, vol. 6, no. 1, pp. 1–11, 2019, doi: 10.1038/s41597-019-0285-1.