Performance Evaluation of Visual Analytics Framework for Monitoring Neuromotor Rehabilitation

Maryam Boumrah[1], Samir Garbaya[2] and Amina Radgui[1]

[1]*Centre d'études doctorales Télécoms et Technologies de l'Information (CEDOC-2TI)", INPT, Rabat, Morocco*

[2]*Laboratoire END-ICAP, INSERM UMR1179, Arts et Metiers Institute of Technology, CNAM, LIFSE, HESAM University, F-75013 Paris, France*

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Abstract: Remote rehabilitation of stroke patients reinforces in-person rehabilitation and enhances the regaining of neuromotor capabilities. However, monitoring stroke patients' rehabilitation from different locations and on a large scale requires a low latency and scalable approach. A real-time visual analytics framework for monitoring in-home rehabilitation of stroke patients based on fog computing is proposed. The objective of this paper is to evaluate the performance of the proposed framework in terms of latency and scalability. OpenTelemetry was used for the evaluation of the proposed framework. OpenTelemetry was chosen over simulation tools for its real-time observability features providing accurate comprehension of the distributed system behaviors in real-world implementation. Five scenarios were setup by progressively escalating the volume of data flow and the number of packets. These scenarios enabled a thorough examination of the framework's ability to handle higher workloads and scalability. The results of end-to-end latency of the proposed system were compared to the Cloud-only implementation. Compared to Cloud-only implementation, the findings of the evaluation showed that the latency of the proposed system was significantly low. Reflecting the scalability feature, the capacities of handling workload by the proposed system in terms of latency, throughput, processing, and resource utilization were stable across the first four configurations. However, the limitations noticed in the fifth configuration put in evidence the constraints of the experimental setup used in this research. Moreover, the scalability and efficiency of the system can be further enhanced in a distributed deployment in real-world conditions.

1 INTRODUCTION

The recent research in brain stroke focuses on in-home rehabilitation interventions that are having the most positive impact on functional, motor, and cognitive recovery outcomes of the patient's health. Remote patient monitoring (RPM) of in-home rehabilitation helps in reaching unassisted patients in different geographical locations and enhances patient-therapist communication (De Farias et al., 2020). In addition, RPM allows users to interact with therapy systems online and speeds up data transmission between different health stakeholders which improves the quality of healthcare and helps approach the in-home patients.

In all stroke rehabilitation systems, it is important to perform accurate assessments of physical recovery. The collected data from patients must be processed and presented to the therapist in a meaningful and useful way, especially for unsupervised systems. Furthermore, real-time information feedback provided by rehabilitation systems enables the therapists to take necessary and immediate actions. In order to provide the support to therapists in monitoring patients, the information must be visualized with simple illustrations. Real-time data analytics and visualization have the potential to perform as an informative decision-support tool for the therapists. According the literature investigations, few monitoring systems implemented data analytics but they did not include real-time data processing. Hence, real-time visual analytics is an important opportunity for the development of innovative rehabilitation systems.

The potential of RPM systems makes it play a crucial role in in-home neuromotor rehabilitation of brain stroke patients. However, the spatiotemporal nature of physical rehabilitation data and its massive volume make it challenging to maintain the real-time aspect of monitoring systems. The minimum latency

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is a crucial requirement that ensures the patient's safety and the accuracy of information transmission. The continuous increasing number of the stroke patients with different disabilities and the limited access to professional rehabilitation therapists imposes the necessity of monitoring multiple patients by each therapist. To fulfil these requirements, RPM systems need to be versatile and highly scalable.

The RPM systems are witnessing a proliferation of advanced technologies. Fog computing is a trending paradigm in healthcare systems for its scalability and low latency. However, existing RPM systems based on fog computing which have proved the ability to handle increasing workload and provide low latency were evaluated using simulation tools. While these tools, such as iFogSim (Gupta et al., 2017) are providing efficient modelling and simulating fog computing environments, they may fall short in providing real-time observability. In addition, their primary applicability is limited to experimental scenarios instead of real deployment conditions. On the other hand, as a relatively new paradigm, OpenTelemetry (OTel) (*Documentation | OpenTelemetry*, n.d.) is a unified opensource framework for generating, collecting, and transmitting telemetry data. OTel stands out for its real-time observability features providing more authentic operational insights.

In this paper, the performance of a proposed visual analytics framework for monitoring stroke neuromotor rehabilitation was evaluated using OTel. Based on fog architecture, this new framework approach was evaluated in terms of latency and scalability and compared with Cloud-only implementation. To the best of our knowledge, there is no research previous to the work presented in this paper that used OTel for evaluating the performance of fog-based RPM systems.

2 RELATED WORK

Fog paradigm provides computational resources closer to the data sources, such as IoT devices and their gateways. Challenges arise in monitoring the performance of the orchestrated services of this distributed infrastructure (Bonomi et al., 2012).

Mahmud et al.(Mahmud et al., 2018) presented an evaluation of performance of Fog-based IoT-Healthcare solutions through simulation studies using iFogSim (Gupta et al., 2017) in terms of service delivery, cost, energy usage and latency. They setup scenarios through simulations using the iFogSim simulator and the obtained results were analyzed in relation to distributed computing, reduction of latency and power consumption.

Similarly, Asghar et al. (Asghar et al., 2021) used iFogSim toolkit to validate the effectiveness of their fog based approach for health monitoring systems. They conducted five simulation scenarios for evaluating the latency and network usage of their approach while comparing it with Cloud-only implementation. Das et al. (Das et al., 2022) performed simulations using iFogSim to evaluate their approach about enabling green healthcare services using integrated iot-edge-fog-cloud computing environments. They used simulation-based analysis and real-time data analysis in Google cloud platform (GCP). They evaluated the metrics of stability, accuracy, latency, and energy consumption.

Saidi et al. (Saidi et al., 2020) analyzed the performance of their proposed Fog to Cloud computing solution in terms of latency and energy consumption using FogWorkflowSim simulator (Liu et al., 2019).

The existing approaches for evaluating the performance of fog-based solutions for healthcare monitoring are limited to the use of simulations toolkits such as iFogSim. Recently, the advancement of observability solutions such as OTel is growing. However, their applications in performance evaluation of healthcare monitoring solutions are still limited and not yet explored.

3 BACKGROUND

In-home neuromotor rehabilitation aims to regain neuromotor functionalities of patients and enhance the coordination of their body limbs after the stroke. The technology advancement opened opportunities for patients to practice rehabilitation exercises at home (Fig.1). These practices include activities of daily living, gait training, range of motion improvement, balance and strength exercises. The data collected from the stroke patient during rehabilitation is of multiple types. However, most of this data has spatiotemporal nature that makes it challenging in terms of processing and real-time visualization.

For monitoring in-home neuromotor rehabilitation of stroke patients, a visual analytics framework based on fog computing was proposed (Fig.2). The architecture of the proposed framework is based on a different approach from traditional fog-based architectures. The requirement for real-time visualization with minimal latency is crucial for patient safety and the accuracy of information displayed in the user interface. Thus, the streaming of the IoT data was split between real-time streaming and batch streaming. The real-time stream flows directly to the monitoring layer where the therapist dashboard is included without going through the Cloud. The batch stream is forwarded to the Cloud for storage and for complex data analysis such as the optimization of the medical information using deep learning algorithms. In addition, the proposed framework is integrally based on software microservices. Therefore, this allows the portability and versatility for different choices of devices and server capacities in real-world implementations.

For dynamic data visualization at the therapist dashboard, the implemented framework includes MQTT brokers at the Edge layer to facilitate the channeling of spatiotemporal data collected from motion sensors placed on patients' different joints during the rehabilitation exercises. The fog layer includes Apache Kafka for data ingestion and a streaming engine for real-time processing of patient data and its mapping with target data. The monitoring layer receives and displays advanced dynamic graphs using a dash server.

However, this new approach must be evaluated in terms of performance including latency, scalability, and resource usage. The objective of the performance evaluation of the proposed framework is to answer the following questions:

RQ1- Does the new approach of connecting the fog layer directly to the monitoring layer for real-time visualization provide a better latency than Cloud-only approach?

RQ2- By using the minimum of computing capacities, what are the limits of the framework latency, scalability, and resource utilization?

Answering these questions represents an important contribution to the optimization and real-world application of the proposed visual analytics framework.

Most of the existing works about the evaluation of the performance of fog-based systems used simulation tools notably iFogSim. While iFogSim is efficient for modelling and simulating fog computing environments, it may fall short in providing real-time observability. In addition, its main applicability is limited to experimental scenarios instead of real deployment conditions. On the other hand, as a relatively new paradigm, OTel stands out for its real-time observability features providing more authentic operational insights. It facilitates the collection of telemetry data and offers a standardized approach for different programming languages. The OTel instrumentation capabilities provide a detailed evaluation of multiple components of distributed systems, ensuring a holistic view of performance metrics, traces, and logs.

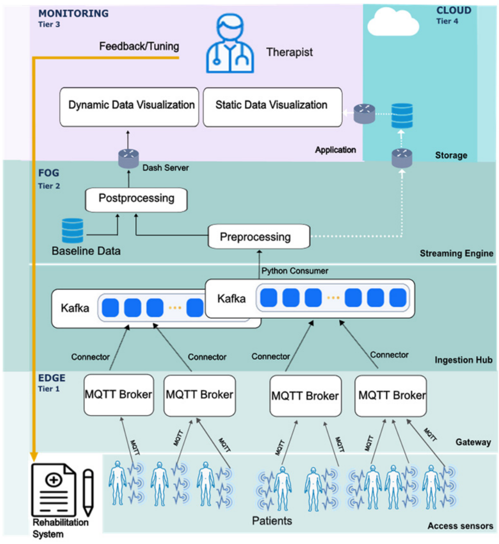


Figure 1: The architecture of Visual Analytics framework.

The preference for OTel over iFogSim in the evaluation of the proposed framework stems from the requirement for accurate comprehension of the system behaviours in real world implementations.

4 METHODS

4.1 Instrumentation with OTel (Testbed)

The implementation of holistic observability within the proposed framework implied the integration of OTel software development kits (SDKs) into the system codebase. This was accomplished by instrumenting the main components of the proposed fog-based architecture for capturing distributed traces, logs, and metrics. As shown in Fig.3, Tempo is a designated backend known for its scalability and cost-effective storage, it was used as a collector of the instrumentation traces from the codebase. While Loki was configured to aggregate and store logs, Prometheus was integrated to systematically provide metrics originating from Tempo traces. cAdvisor (Tolaram, 2023) was selected to acquire resource usage metrics on the container level within the Docker environment. This orchestrated integration required proficient visualization using Grafana for a comprehensive perspective on the behaviour of the evaluated visual analytics framework.

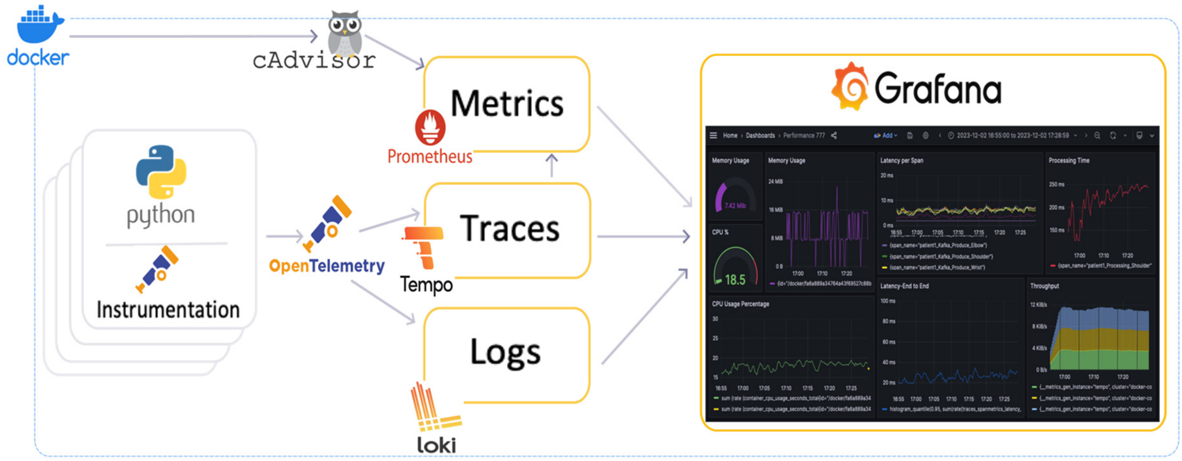


Figure 2: The structure of the testbed using OpenTelemetry instrumentation.

The instrumentation points are strategically placed to capture critical traces of the data flow within the system. These instrumentation points and their functionalities are detailed as the followings:

- **IMU** at Edge layer: This instrumentation point is used to evaluate the data acquisition from IMU sensors to the gateways.
- **MQTT** at Edge layer: The instrumentation encompassed both publishing and subscribing functionalities. MQTT publishing is used to write spatiotemporal data in MQTT broker while MQTT subscription is used to connect the data stream with the fog layer.
- **Kafka** at Fog layer: Kafka is deployed to facilitate efficient and scalable exchange of data streams. The instrumentation of Kafka includes Kafka producer and Kafka consumer. The functionality of Kafka producer is to transmit data acquired from the Edge layer to the Kafka Broker. On the receiving end, the Kafka consumer is employed to ingest the incoming data into the processing unit within the fog layer.
- **Processing Engine** at Fog layer: The instrumentation within the processing node includes preprocessing, mapping, and postprocessing to capture relevant metrics.

The Dash server at the monitoring layer displays data using callbacks with a predefined time interval. For displaying graphs that the human eye can comfortably perceive in real-time the common rate is ranging from 16 to 24 frames per second, which will imply a minimum callback interval of 41.7 ms. For this reason, the latency in the dash server was not included in the evaluation of the framework.

4.2 Key Performance Indicators (KPIs)

In order to evaluate the efficiency of the proposed framework and to offer valuable information about its different aspects, the following KPIs were defined:

- End-to-end latency: this metric is used to measure the time taken for a sensor's data packet to flow through the entire Edge and Fog layers. OTel enables tracking the duration of each span in instrumentation points detailed above,
- Processing time: reflects the duration taken by the execution of data processing in the processing engine of the evaluated system,
- CPU usage: indicates the percentage of the capacity of the CPU being consumed by the FastAPI application including the different code components of the framework. Monitoring CPU usage is important for the determination of computing resource requirements,
- Memory usage: Tracking memory usage reveals how much RAM is consumed by the system application. This metric helps for efficient memory management and the estimation of the required configurations for the optimization of the system performance,
- Throughput: quantifies the rate in bytes at which the system handles the stream of medical spatiotemporal data. It helps to

evaluate the efficiency of the system in handling increased workloads.

4.3 Experimental Setup

For implementing the designed evaluation testbed, a dockerized deployment was used due to the microservice nature of the distributed framework (Fig. 4). Docker Desktop v20.10.21 was used on a Mac operating system machine (Core i7 processor with12GB of RAM, with 2.9 GHz frequency). Using Pycharm v11.0.13 and Python 3, the different containers were running within the same Docker Engine. Docker containers encapsulated each element of the evaluation structure including the evaluated system application based on FastAPI. The following tools were used for testbed containers:

- HiveMQ broker v.4.21 for MQTT protocol,
- Zookeeper and Kafka v7.0.1,
- Prometheus v2.45.0,
- Loki v2.8.3,
- cAdvisor v0.48.0
-Tempo v2.1.1

The deployment using Docker Compose ensures the interconnection between the different containers reflecting real-world implementation. The gRPC (Google Remote Procedure Call) was used to export collected traces using tempo as a collector. The manual instrumentation was selected over the auto instrumentation due to the limitation of the available libraries for the components of the evaluated system.

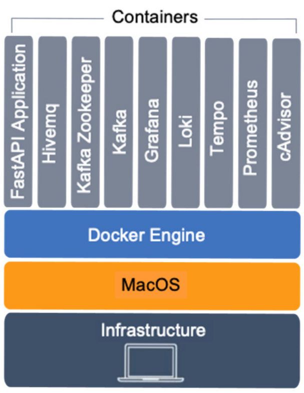


Figure 3: Docker deployment.

The proposed framework was mainly designed to monitor remote neuromotor rehabilitation of post-stroke patients. For this reason a dataset of stroke rehabilitation of the upper limb including spatiotemporal data of shoulder, elbow, and wrist during activities of daily living was used in the different test scenarios (Schwarz et al., 2020). Data were acquired using IMU sensors placed on the patient's upper limb as shown in Fig.5 (Averta et al., 2021).

To simulate real-world conditions, the data were looped and continuously ingested into the visual analytics system.

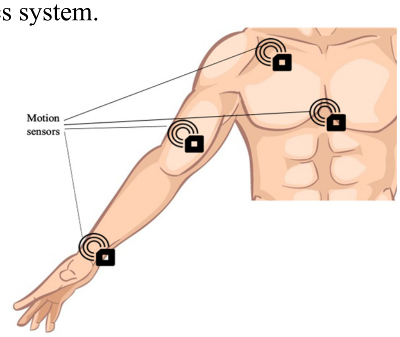


Figure 4: Motion sensors attached to the patient’s body for data capture.

The recommended minimum duration of a stroke rehabilitation session is one hour (Clark et al., 2017). For assessing the capabilities of the proposed framework in monitoring stroke rehabilitation sessions in real world conditions, five distinct configuration scenarios were set up for a duration of one hour each. During these scenarios, a single fog node was used to comprehensively understand the limitations and capacities of each node. The results will reflect the requirements for scalability in terms of the number of fog nodes in each use case. By progressively increasing the volume of data flow and number of packets, these scenarios enable a thorough examination of the framework's ability to handle higher workloads. The configurations used for the evaluation of the framework are shown in Table 1. The packet size used for the different scenarios is 232 bytes representing the size of a single spatiotemporal message. For real deployment conditions, the number of data streams is a multiplication of 3 which represents the number of sensors used to capture data from the patient’s upper limb.

5 RESULTS

The results of the evaluation of the performance of the proposed framework were displayed in a Grafana dashboard. Different graphs representing the defined KPIs were generated using PromQL (*Prometheus* Query Language) and TraceQL queries.

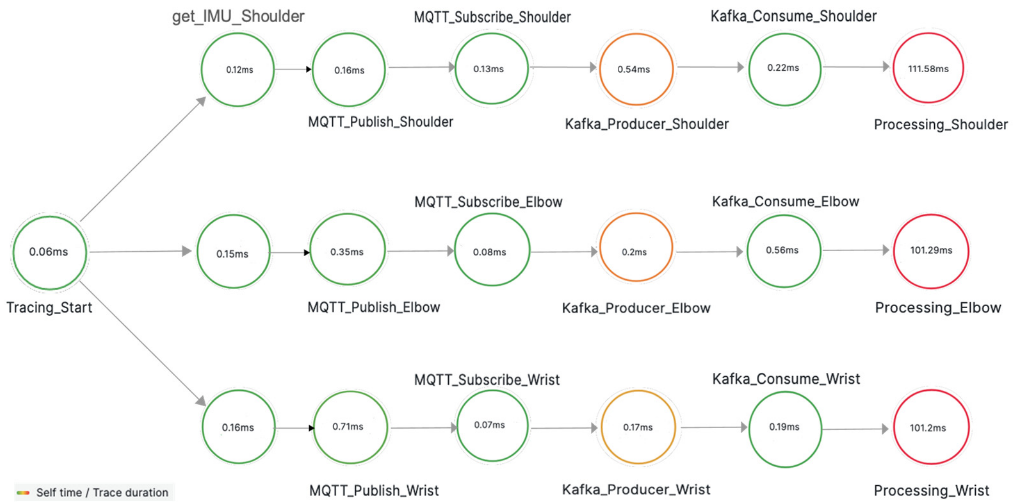


Figure 5: The node graph of the tracing propagation across instrumented points.

Table 1: Scenario Configurations (packet=232 bytes).

Configuration	Number of IoT streams	Number of packets/second
Config 1	9	600
Config 2	18	1200
Config 3	27	1800
Config 4	36	2400
Config 5	45	3000

For a primary overview of the instrumentation, figure 6 shows the node graph of the trace propagation throughout the instrumented points including parent span, MQTT publish/Subscribe spans, Kafka Producer/Consumer spans and processing spans. These traces were taken after ingesting 3 spatiotemporal data packets (collected from the movements of shoulder, elbow and wrist) into the system in a single packet for each data type. The upcoming results represent the measurements made during the execution of the testing scenarios described in the previous section.

5.1 Latency and Processing Time

The end-to-end latency of the proposed system is the total time spans of the instrumented points of the codebase. It represents the time taken by a data packet to travel across the system nodes. For a baseline comparison, cloud-only implementation was evaluated in terms of latency in which the flow of data is transmitted to the Cloud instead of the fog node. The End-to-End latency of the proposed system (Ls), and End-to-End latency of Cloud-only (Lc) are respectively defined as the following:

$$L_S = L_{get\_IMU} + L_{MQTT\_Publish} + L_{MQTT\_Subscribe} + L_{Kafka\_Producer} + L_{Kafka\_Consume}$$

$$L_C = L_{get\_IMU} + L_{MQTT\_Publish} + L_{MQTT\_Subscribe} + L_{Write\_Cloud}$$

Where:

L_{get_IMU}: Time to acquire IMU sensor data

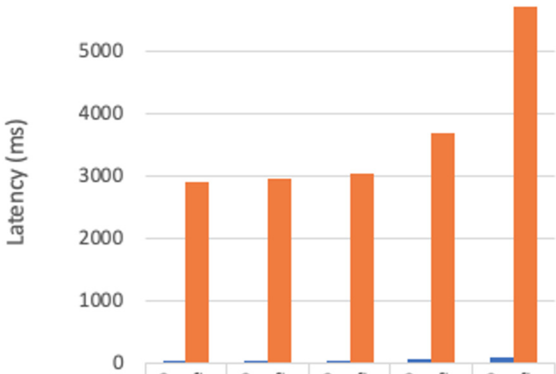
$L_{MQTT\_Publish}$: Time to publish data in MQTT broker

$L_{Kafka\_Producer}$: Time to send data to Kafka topic

$L_{Kafka\_Consume}$: Time to consume data from Kafka topic

L_{Write_Cloud}: Time to write data in Cloud storage

Figure 7 shows the End-to-End latency comparison between the proposed system and cloud-only implementation for the five configurations. It is noticed from the results that the latency in the proposed system across all configurations is significantly lower than in the cloud-only implementation. For further investigations, the proposed system latency was recorded for a duration of one hour to evaluate the capacities of handling increasing workload with a low latency (Fig. 8). PromQL function `histogram_ quantile` was used by quantifying the 95th percentile latency across various spans within the tracing service for in-depth understanding. The resulting End-to-End latency and per span latency were visualized in the graphs displayed in Fig.8, they provide a detailed distribution of latency values across the system. Each span of each data packet is represented by a different colour to illustrate the different trends. This diagnostic approach provided a detailed perception of the performance of the system in terms of latency under different workload conditions. It is noticed that for the configurations 1 to 4, the latency remained significantly low (less than 170 ms) and slightly increased with the workload. However, in Config 5, the latency starts scaling higher (up to 2 s).



	Config 1	Config 2	Config 3	Config 4	Config 5
Fog system	9.94	16.5	39.1	71.5	102
Cloud only	2910	2960	3040	3680	5700

Figure 6: End-to-End latency comparison between the proposed system and cloud-only implementation.

Using the PromQL query `traces_spanmetrics_latency_bucket` the processing time taken by each data packet was visualized in Grafana (Fig.8). Similar to the latency evaluation, the processing time remained reasonably stable (the average is less than 500 ms) for the four the configurations 1, 2, 3 and 4. However, the processing of data packets starts to slow down in the configuration 5 (1.5 s in average).

5.2 Throughput and Resource Utilization

The rate at which the data is successfully ingested through the framework is commonly used throughput in the performance evaluation of distributed systems. In this research work presented in this paper, the chosen throughput is the amount of data bytes handled per second. Across the five configurations, the throughput of the evaluated system was calculated using the PromQL query `traces_spanmetrics_size_total`. The results of the observations across the different scenarios are shown in Fig.9 in which different colours represent different data packets handled. The resource utilization metrics including CPU usage and memory usage were calculated using the following

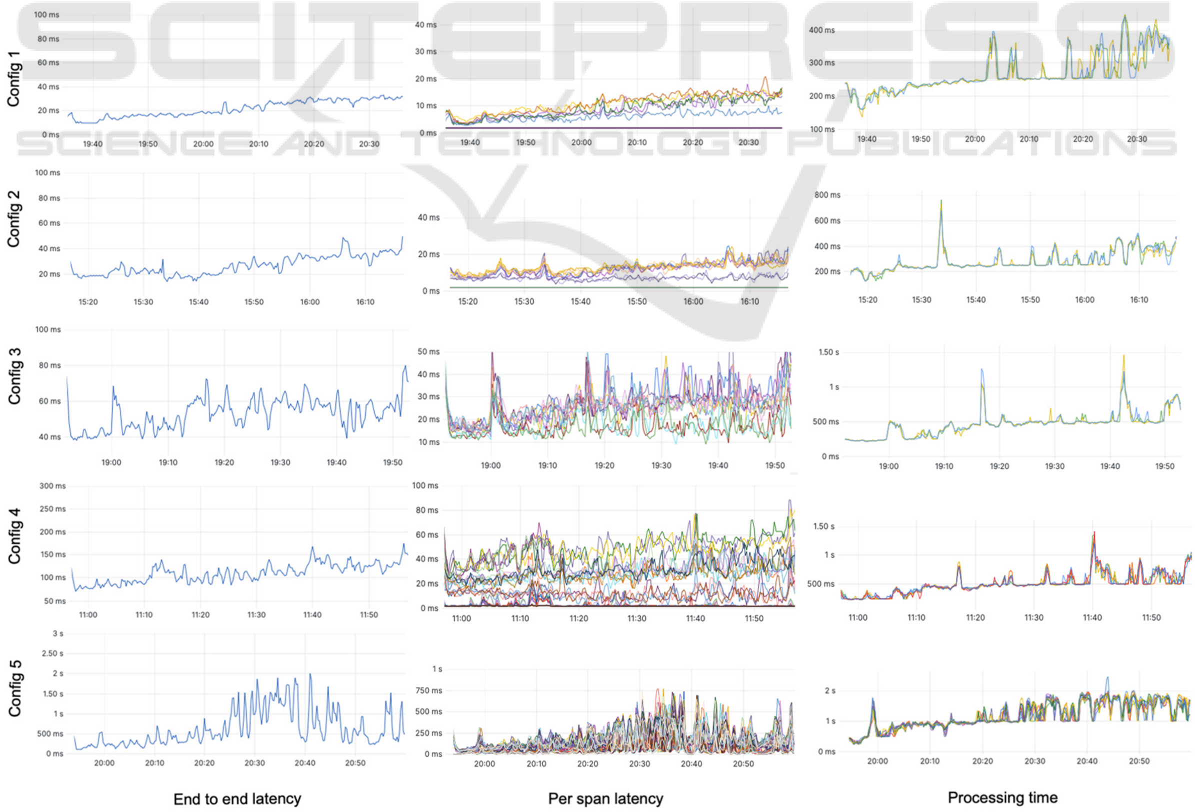


Figure 7: The End-to-end latencies, Per span latencies and processing time across the five configurations.

cAdvisor metrics: `container_cpu_usage_seconds_total` and `container_memory_usage_bytes`. The graphs displayed in Fig.9 show the percentage of the usage of CPU and Memory. Throughout the five scenarios, the CPU usage remained under 25%, while the memory usage did not exceed 24 MiB, which reflects a stability in the usage of resources by the system application. Table 2 Summarizes the diagnostics values of the system performance metrics across the five configurations. The included values are samples of the instrumented spans latencies and other metrics.

6 DISCUSSION

The performance evaluation of the proposed fog based visual analytics framework was carried out using OTel observability and performance metrics. The evaluation procedure provided deep understanding of the system's behaviour and capacity for handling different workloads. The analysis of the latency results across different configurations showed a significant trend of reduced latency in the proposed system compared to the cloud-only implementation. This confirms that the proposed system operates with a low latency despite the increase of the workload. It was also noticed that the latency in the configuration 5 was relatively increased but it remained limited compared to the implementation based on cloud. The individual latency per span showed that the time in the data flow tends to evenly be consumed by the different spans. The processing time is overall reasonable despite the nature of the computing infrastructure used for the evaluation. This indicated that the edge and fog nodes requirements in term of implementation devices are similar. The throughput was consistently maintained across the four configurations, but it has relatively decreased in configuration 5. This showed that the system's handling capacity decreased in the workload of the configuration 5. The results of CPU and memory usages highlighted the system's efficiency across all the defined configurations.

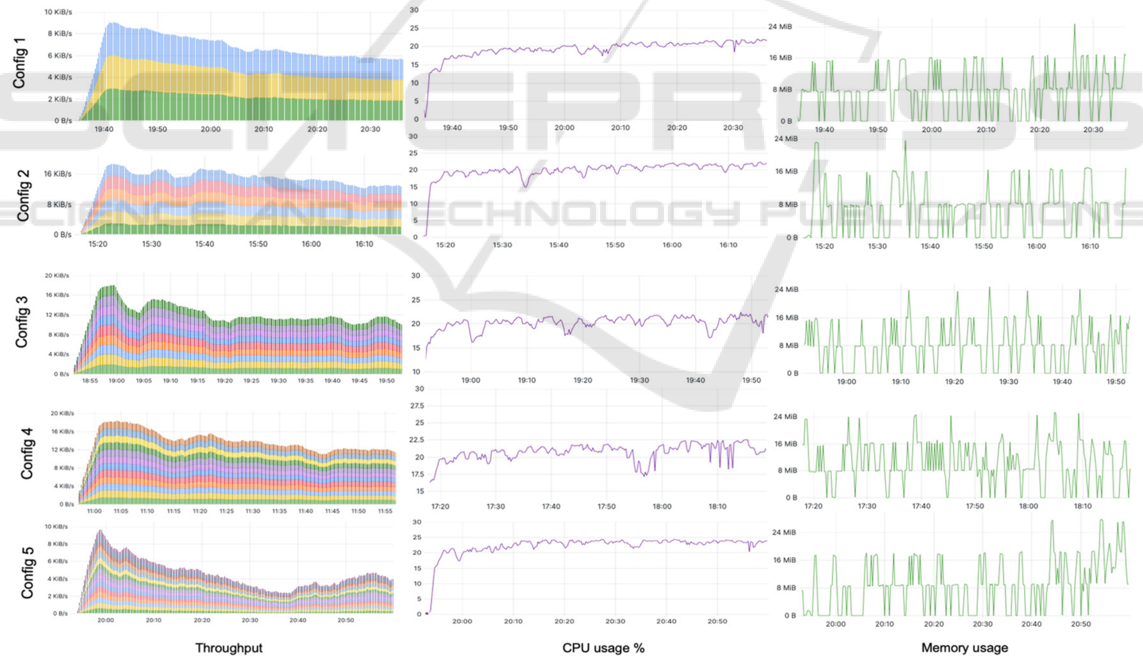


Figure 8: The Throughput, CPU and Memory usages across the five configurations.

Table 2: The metrics values across the five configurations.

Config	get_IMU ms	MQTT_Publish ms	MQTT_Subscribe ms	Kafka_Producer ms	Kafka_Consume ms	Processing ms	Throughput KiB/s	CPU %	Memory MiB
Config 1	1.90	2.75	1.90	3.07	1.93	154	9.12	13.4	7.44
Config 2	1.91	7.08	1.91	6.78	1.95	168	18.5	16.4	15.6
Config 3	1.93	14.5	1.94	14.5	1.98	226	18.1	17.7	15.9
Config 4	6.74	30.6	7.19	29.4	3.68	251	17.8	20.8	23.3
Config 5	30.8	57.1	61.2	90.4	59.3	289	9.8	24.1	23.9

The findings stemming from the analysis of the results was useful for the formulation of the following answers to the research questions set in this research:

RQA1: The direct data streaming from the fog layer to the monitoring layer without crossing the Cloud has significantly reduced the system latency compared to the Cloud-only approach. This perspective is evident across various configurations, showcasing the system's adaptability for real-time visualization.

RQA2: With minimal computing capacities on a macOS laptop and being accommodated with the whole OTel evaluation structure, the proposed framework showed stable performance in latency, processing, and resource utilization across the configurations 1, 2, 3 and 4. Thus, a capacity for workload scalability. The minor limitations noticed in the configuration 5 highlighted the experimental setup constraint caused by using a single machine for the whole system deployment. Furthermore, the scalability and efficiency of the system can be further enhanced in a distributed deployment in real-world conditions. Previous approaches did not address performance measurement using OpenTelemetry. The framework developed in this research showed lower latency despite the increase in streams. This was confirmed by the significant difference in the obtained latency compared to the results recorded by (Asghar et al., 2021b) for analogous configurations: 452 ms and 1082 ms vs 9.94 ms and 16.5 ms.

It is also worth of mentioning that the proposed framework was evaluated by conducting an experiment design including a System Usability Scale (SUS). The experiment provided qualitative and quantitative data from a group of rehabilitation experts and showed a good usability of the proposed visual analytics framework. However, the details of this study can be included in this paper due to the limitation of space.

7 CONCLUSIONS

The main objective of this paper is to evaluate the performance of visual analytics RPM framework dedicated to neuromotor rehabilitation of stroke survivors. The proposed framework is based on fog-computing with new approach of splitting the data stream into real-time and batch. The real-time stream skips the Cloud layer and flows directly to the monitoring layer, where the therapist interface for data visualization was included. This approach was evaluated in terms of latency and scalability. Common evaluation techniques of fog-based systems use simulation tools such as iFogSim. However, in this paper the evaluation was performed using observability and instrumentation through OTel. This unified opensource framework helps in generating, collecting, and transmitting telemetry data. Five configurations were used by escalating the workload for the evaluation of the proposed framework and for obtaining deep insight into the behaviour of its different components. The defined KPis for evaluation were End-to-End latency, throughput, processing time and resource utilization. The findings suggested that the latency of the proposed system was significantly low when compared to cloud-only implementation. The scalability of the system was reflected by its capacity of handling the increased workload across different configuration scenarios. Nevertheless, the minor limitations noticed in the fifth configuration highlighted the experimental setup's constraints imposed by using a single machine for the whole system deployment. In future work, the scalability and efficiency of the system will be further enhanced by the implementation of a distributed deployment in real-world conditions.

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