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Cloud Platform using Big Data and HPC Technologies for Distributed and Parallels Treatments

Olivier Debauche[a,b,*], Sidi Ahmed Mahmoudi[a], Saïd Mahmoudi[a], Pierre Manneback[a]

[a] *Computer Science Unit, Faculty of Engineering, University of Mons, 20 Place du Parc, B-7000 Mons, Belgium*

[b] *Biosystems Dynamics and Exchanges Axis, Biosystem Engineering Department, ULiège Gembloux Agro-Bio Tech, University of Liège, Passage des Déportés 2, B-5030 Gembloux, Belgium*

Abstract

Smart farming is one of the most diverse researches. In addition, the quantity of data to be stored and the choice of the most efficient algorithms to process are important elements in this field. The storage of collected data from Internet of Things (IoT), existing on distributed, local databases and open data needs particular infrastructure to federate all these data in order to make complex treatments. The storage of this wide range of data that comes at high frequency and variable throughput is particularly difficult. In this paper, we propose the use of distributed databases and high-performance computing architecture in order to exploit multiple re-configurable computing and application specific processing such as CPUs, GPUs, TPUs and FPGAs efficiently. This exploitation allows an accurate training for an application to machine learning, deep learning and unsupervised modeling algorithms. The last ones are used for training supervised algorithms on images when it labels a set of images and unsupervised algorithms on IoT data which are unlabeled with variable qualities. The processing of data is based on Hadoop 3.1 MapReduce to achieve parallels processing and use containerization technologies to distribute treatments on Multi GPU, MIC and FPGA. This architecture allows efficient treatments of data coming from several sources with a cloud high-performance heterogeneous architecture. The proposed 4 layers infrastructure can also implement FPGA and MIC which are now natively supported by recent version of Hadoop. Moreover, with the advent of new technologies like Intel® Movidius™; it is now possible to deploy CNN at fog level in the IoT network and to make inference with the cloud and therefore limit significantly the network traffic that result on reducing the move of large amounts of data to the cloud.

Keywords: GPU; FPGA; MIC; CPU; TPU, Cloud; Big Data; parallel and distributed processing; heterogeneous cloud architecture

* Corresponding author. Tel.: +32(0)65-374-059 ; fax: +32(0)71-140-095.
E-mail address: olivier.debauche@umons.ac.be

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1. Introduction

According to Superuser [13], 75% of High Performance Computing (*HPC*) centers worldwide are used to perform deep learning and artificial intelligence. Today thanks to the high-performance networks and the using of Single Root I/O virtualization (*SR-IOV*), HPC is now available in a cloud environment [5]. The actual trend is the Shifting to hyperscale [13].The data of the Internet of Things is dynamic: very diverse in term of origin, amount and speed. The throughput and quality of data depend on the use case which are unlabeled [1]. Indeed, data can be transmitted continuously, at certain frequency or by burst that applies large and fast throughput.

For example, in phenotyping and 3D images are particularly consuming in processing and storage [6]; in smart farming, data can arrive at very high speeds close to real time (100 Hz) [7] [10]; or arrive massively from connected objects that transmit them at a fixed frequency [8] [9]. In the case of monitoring landslides, the data burst as soon as anomalies are detected [11]. Moreover, users of cloud infrastructures are increasingly asking for response time to request made on data close to real time. Scientists need to process data such as images arriving with velocity (tens of MHz) which must be treated at real time [2].

Data is not available under the form of data feeds but also in local and distributed databases, open data, firehose, and structured files in which are stored raw and results of treatments from external processes, applications, etc. These information are under construction; because, they are not in relation with other data to achieve more pertinent analysis. Crossing this data is necessary to handle complex events and make better decisions. But for this, the data must be previously processed and stored in a form that ensures their crossing, aggregation and exploitation. Moreover, deep learning models are traditionally trained in the cloud with a supervised method which requires tremendous amount of training data labeled by humans. However, in the case of IoT, raw data are coming from a large number of nodes. All these IoT big data are difficult to label and consequently the traditional supervised training is not suitable, which require an unsupervised method to really exploit the potential of big raw IoT data with reduced data movement [1].

This result leads to think about a new way to design cloud computing architectures for the Internet of Things. It becomes crucial to reconsider how data is stored and how it is processed to maintain performance regardless of increase of data volume to ensure response times of less than one second. The use of high-performance computing (*HPC*) architectures for the distribution of treatments coupled with the use of Many Integrated Core (*MIC*), Field-Programmable Gate Array (*FPGA*) and multi Graphics Processing Unit (*GPU*) allow today to process tremendous amount of raw data quickly. In addition to the data from the connected objects the processing infrastructures are also brought from other data sources, private distributed database and open database.

In this paper, we propose a cloud architecture which combines the use high-performance computing, FPGA, MIC, TPU and Multi GPU to treat distributed big data coming from multitenancy and multi-sources. With this approach, treatments are distributed between GPU and parallelized in each GPU to ensure a high efficiency.

2. Related Works

Currently, three trends emerges: (1) the increase of power and complexity of modern HPC systems in order to build exascale class machines, (2) the increase use and sophistication of commercial and open cloud infrastructure, (3) the increase functionality and the use of Big Data in conjunction of HPC [3]. Several authors have already used heterogeneous architecture based on GPU and/or FPGA to accelerate the processing of large amount of data. Among its authors we quote the most important contributions.

Fox et al., 2017 [3] propose the integration of HPC and Apache Big Data Stack (*ADBS*) in order to offer usability, functionality and sustainability that is not available in the HPC ecosystem. They mention also that an implementation of HPC-ABDS is provided in the SPIDAL project [12].

Napoli et al., 2014 [2] have developed an GPU Architecture using parallel and distributed treatments to process and interpret tremendous amount of data at real-time of tens of millions of raw images. They use dynamic adjusting of number of hosts because the performance of data processing that cannot be predicted and the throughput of data can variate while time goes. The using of solution such as MPI cannot adapt dynamically the number of process once the execution has begun.

Song et al. 2018 [1] have proposed a novel framework and an architecture based on the principle of fog computing to train the Deep Learning locally with the aim of reduce data movement, speedup model update and by consequence contribute to energy saving. This approach addresses the problem of transfer of all data on the cloud needed to train Deep Learning statically models but they can not handled with high accuracy raw IoT data which are dynamic and unlabeled.

Lu et al. 2016 [5] have studied the impact of choosing network technologies on the HPC Cloud. They propose an architecture based on Hadoop multi-protocol aware to take advantage of Reliable Connection (*RC*), Unreliable Datagram (*UD*), hybrids protocols for InfiniBand (*IB*) and RDMA over Converged Ethernet (*RoCE*) that provides Remote Direct Memory Access (*RDMA*) to provide high bandwidth, latency and the throughput for Hadoop RPC and HBase communication.

Salaria et al, 2017 [4] has compared performance between the latest generation of HPC-like cloud and a HPC for Graph500[1] which is a well-know Big Data benchmark and shown than Cloud HPC can provide good compute performance with low variability.

Sood et al., 2017 [14] have proposed an architecture in 4 layers from bottom to the top: (1) the IoT layer (*IL*), (2) the Fog Computing Layer (*FCL*), (3) the Data Analysis Layer (*DAL*) and (4) the Presentation Layer (*PL*). The IL organize the social collaboration and energy saving of IoT devices. The FCL achieves on one hand the routing of data from IoT devices to cloud computing using multiple network devices and on the other hand the pre-processing or the prediction of data on enodes or gateways. The aim of this layer is the reduction of the latency of the system by sending calculated values on the cloud computing. The DAL contain any big data based smart system. It is also responsible of collecting, storing, mining and data analyzing to obtain results. Finally, the PL is the user views of the system in which results can be attained after processing of all the information.

3. Proposed Architecture

Our architecture is composed of 4 layers as proposed by sood et al. [14] from bottom to the top: (1) The sensing layer (*SL*) is constituted by sensors and microcontrolers which acquire physical measures of their environment. A primal treatment of data (Edged computing) is also achieved on capable sensors to send only valuable data. (2) The Fog Computing Layer (*FCL*) is composed of enodes, gateways able to achieved more important treatments than the SL and mobile GPU and FPGA used for the incremental deep learning training [1], (3) the Data Analysis Layer (*DAL*) aim to collect data from IoT sensor on one hand and from external sources such as local and distributed databases, open data, etc. Finally, (4) the Presentation layer allows to users to view results of treatments (Fig. 1).

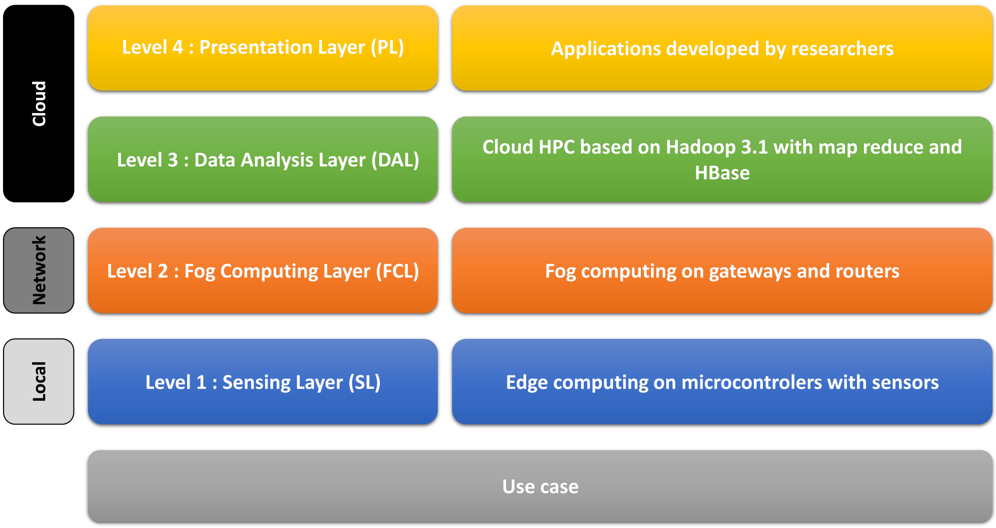

Fig. 1. Proposed Architecture

[1] http://www.graph500.org/

3.1. Data collection

The collect of data is operate at sensing layer by means of sensors connected to a node. A node generally controls several sensors which make physical measure of their environment. The Edge computing is used to pre-process data and to send only relevant data to limit the data sending that is energy consuming and thus improve the life of the nodes that control the sensors. However, the use of edge computing cannot be done on the older nodes that are more limited in memory, processing capacity and storage than the most recent nodes. The data is then sent to gateways and hubs that are capable of performing heavier processing (Fog Computing) and therefore limiting data sending and processing in the cloud. This process limits the use of bandwidth and brings the management of privacy issues back to the data producers. The Edge and the Fog computing are respectively implemented in the first two layers.

3.2. Data management

Data coming from IoT sensors via the second layer and other external sources such as Local, distributed database, CSV and TSV files, open data, messaging services, etc., are collected and treated before to be stored in the distributed database (HBase). A specific framework has been developed to retrieve open data in XML, RDF and CSV file format and store them in HBase. The centralization of all these data is needed to enrich analytics and make better decisions.

3.3. High Performance computing

Stored data on HBase are processed with Hadoop 3.1 which support natively GPU and FPGA. We have modified the support of GPU for the use of Multi GPU by using Map Reduce to ensure the distribution between GPU where data are processed in parallel using tools like Cuda[2], OpenCL[3], etc. In this new release of Hadoop, Erasure Coding which provides significant improvement in data access speed on HDFS. The exploitation of GPU allows also to train Neural Networks in order to use Machine Learning and Deep Learning using tools like TensorFlow[4], Keras[5], OpenAi[6], etc. on stored data.

3.4. Exploitation of results

Finally, applications and models developed by researchers exploit the results analysis achieved by the heterogeneous cloud HPC on base of data stored in the big data.

4. Conclusion and future work

In this paper, we propose versatile architecture in 4 layers for Smart Farming able to collect, store and treat data coming from IoT Nodes and integrate external data from other sources such as local and distributed data, messaging services, open data, etc. This architecture offers at same time the possibilities to achieve the using of different kinds of Deep Learning supervised algorithms.

In future work, we will collect real data and test this architecture on real data in a future research project that will be start in January 2019. Other format of open data will be implemented in order to increase the amount of data which can be matching with IoT data.

[2] https://developer.nvidia.com/cuda-downloads
[3] https://www.khronos.org/opencl
[4] https://www.tensorflow.org
[5] https://keras.io
[6] https://openai.com

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