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Edge Computing and Artificial Intelligence for Landslides Monitoring

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Abstract

Landslides are phenomena widely present around the world and responsible each year of numerous life loss and extensive property damage. Researchers have developed various methodologies to identify area of high susceptibility of landslides. However, these methodologies cannot predict 'when' landslides are going to take place. Indeed, Wireless Sensors Network (WSN), Internet of Things (IoT) and Artificial Intelligence (AI) offer the possibility to monitor in real-time parameters causing the triggering factors of rapid landslides. In this paper, we suggest a real-time monitoring of landslides in order to precociously alert population in dangerous situation by means of a warning system. The novelty of this paper is the coupling of wireless sensors network and a multi-agent system deployed on an edge AI-IoT architecture by means of Kubernetes and Docker.

Keywords: Landslides susceptibility; Internet of Things; Artificial Intelligence; early warning system; landslides monitoring

1. Introduction

Landslides are phenomena widely occurred around the world causing numerous deaths and extensive property damages every year. Landslides are movements by the gravity of soil, rock, or both slopes down, which can be caused by the combination of multiple factors. This latter can be climate characteristics, geology structure and/or topography of certain areas predisposed to a greater risk of landslides. To these factors are added the anthropic footprints linked,

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in particular, to deforestation, the over-exploitation of land that highlights the risk of land movement. In addition, the modification of the water regime related to climate change in certain parts of the world has further accentuated these phenomena. Moreover, many human lives and properties have been destroyed by these natural phenomena each year that have led researchers to develop methods to map the susceptibility of areas where landslides could occur. The variety of landslides, their kinematics, and their triggering factors pushed us to the development of several methods. The performance of these techniques is directly impacted by the quality of available data which itself influenced by the robustness of our results.

In this paper, we propose a real-time monitoring of landslides in order to precociously alert population in case of danger. In the subsequent paragraphs our paper will be organized as follow: Section 2 describe our background in terms of Internet of Things (IoT) and Artificial Intelligence (AI) at edge level of the network. Then, we list the main susceptibility and monitoring methods. Afterwards, we aims to develop more specifically ANN works achieved to monitor landslides. In section 3, we describe our contribution based on WSN, IoT, and AI at Edge Level in collaboration with the cloud. In section 4, we experiment our proposition, and then we discuss our findings. Finally, we conclude in section 5 and we give an overview about our future works.

2. Literature review

This section is structured in two parts. The first part summarizes our past developments and contributions in term of Edge IoT and AI Architecture, Cloud Architecture that are validated on various use cases. The second part gives an overview about WSN applied to landslides field.

2.1. Background

In our previous works, we have progressively developed our proposition of Edge Internet of Things and Artificial Intelligence Architecture[23] through diverse use cases: patients and elderly monitoring[24], smart poultry real-time monitoring[19], cattle behavior[20], smart irrigation[13][17], and urban agriculture[2][21]. We have also proposed a system of landslide monitoring using LoRaWan and a Wireless Sensors Network (WSN) to monitor soils parameters causing ground movements[41] that we aim to improve in this paper. Additionally, we have also developed a HPC cloud architecture [29] and a Lambda cloud architecture on various use cases: bee health[30], elderly and patient monitoring[24], smart campus[12], smart home[16], smart city[18], smart building[27], cattle behavior[15][26][14][20], phenotyping[25][28], urban gardening[2], climatic enclosure[22], and smart bird[1].

2.2. Related Works

Plethora of study are dedicated to the evaluation of landslide susceptibility area by diverse methods such as Support Vector Machine (SVM), Particle Swarm Optimization (PSO), Logistic Regression (LR), Frequency Ratio (FR), Analytical Hierarchy Process (AHP), Bivariate Statistics (BS), Kernel Logistic Regression (KLR), Multi Criteria Decision Making (MCDM), Logistic Model Tree (LMT), Frequency Ratio (FR), Decision Tree (DT), Weights of Evidence (WoE), Random Forest (RF), Classification and Regression Tree (CRT), Boosted Regression Tree (BRT), and Artificial Neural Networks (ANN)[47][8][48][36][49][34][40]. Many of these techniques are also combined to develop more complex approaches.

These methods allows us to produce maps indicating areas with their susceptibility of landslides; in other terms their level of risk to have a major mass movement. Behavior of mass movements are determined based upon their type and triggering factors. In fact, areas with an important level of susceptibility must be followed, however, the parameters to monitor are controlled by the type of landslides. When human lives and/or economic issues are threatened, early warning systems are used to alert people as soon as possible and recommend their evacuation.

The Table 1 shows a synthesis of traditional approaches of monitoring used for each kind landslide. The analysis of this table shows that parameters that are classically triggered landslides are seismicity, rainfall, lithology, geotechnical characteristics, and ground water level.

Table 1. Comparison of monitoring approaches - Synthesis of Literature review

Technique	Triggering	Parameters	Type	Characteristics	Location	Authors
Geocube	Rain Slope Hydrology	Micro-seismicity Seismic Waves	Landslide	0.005 to 0.03 m.day^{-1} 100m to 1 or 2km	Southern French Alps	Benoit et al., 2015[6]
WSN	Sedimentary deposit Slope	Vibrations	Landslide	Undefined	Nusa Tenggara Timur	Kotta et al., 2011 [37]
EWS	Geologica Formation	Rainfall	Rockslide	182,000 m^3	Torgiovannetto, Italy	Intrieri et al., 2012 [35]
GB-InSAR	Limestone formation Slope	Rock wall	Rockfall	0.30 m^3	San Leo Rock Cliff, Italy	Casagli et al., 2018[10]
SAR[1]	Rainfall	Undefined	Translation Landslide	a 100m high, 90m wide	Santa Trada Landslide, Italy	Casagli et al., 2018[11]
GB-InSAR	Topographic, Geologic formation	Rainfall	Rockslide	30Mm^3	Valfurva, Italy	Casagli et al., 2018[9]
TIAMS	Environment and severe conditions	Undefined	Landslide	Undefined	Coastal Slope of the River Yenissei	Ginzburg et al, 2018[32]
UAE	Undefined	Meteorological Conditions	Landslide	Undefined	Russia–Turkey Gas Pipeline	Ginzburg et al, 2018[33]
SANF	Rainfall Slope movements	Rainfall	Landslide	Undefined	Italy	Rossi et al., 2018[44]
KLO	Precipitation groundwater changes Earthquakes	Geodetic, Hydrological and geotechnical charachteristics	Landslide	32Mm^3	Zagreb, Croatia	Arbanas et al., 2018[3]
Remote Sensing Photogrammetry GPS	Topography Geologic Formation	Geodical and geotechnical characteristics	Landslide	3Mm^3	Grohovo,Croatia	Arbanas et al., 2018[4]
EWS	Rainfall	Rainfall	Debris Flow	10 Mm³	Mt. Merapi volcano Indonesia	Fathani et al., 2018[31]
CLLS	Earthquakes Anthropogenic Activities Naturals ones	Groundwater levels in boreholes, angles of slope, and litho-dynamics	Landslide	1500, 500, 700m^3	Tsar's Palace and Livadia Palace, Ukraine	Trofymchuk et al., 2018[45]
LEWIS	Rainfall	Hydrological and Geotechnical Characteristics	Landslide Debris Flow	Undefined	Southern Italy	Versace et al., 2018[46]
TLS	Sliding rotational	Rainfall, Groundwater level	Landslide	Undefined	Pisciotta, Italy	Barbarella et al., 2012[5]
UAV	Topographic	3D dense point cloud	Landslide	Undefined	Hollin Hill, UK	Peppa et al., 2016[43]
D-InSAR	Topographic	Topographic	Landslide	Undefined	Three Gorges region, China	Liao et al., 2012[38]
VSN	Slope	Vibration	Landslide	Undefined	Uttaradit province, Thailand	Biansoongnern et al, 2016[7]

Legend: CLLS = Central Livadia Landslide System; D-InSAR = Differential interferometric Synthetic Aperture Radar; EWS = Early Warning System; GB-InSAR = Ground-Based Interferometric Synthetic Aperture Radar; KLO = Kostanjek Landslide Observatory; LEWIS = Landslides Early Warning Integrated System; SANF = National Early Warning System for rainfall-induced landslides; TIAMS = Topsides Induced Acceleration Monitoring System; TLS = Terrestrial Laser Scanner; UAE = Unified Automatic Equipment; VSN = Vibration Sensor Network; WSN = Wireless Sensor Network

More recently, new approaches have been tested to improve the capabilities to detect landslides at earlier stage. Among these approaches we can mention the following major contributions such as: Luo et al. have tested tree expressions of programming and artificial bee colony [39]. In addition, artificial intelligence has been used to produce more accurate susceptibility map. Among majors contributions, we can cite Nguyen et al. who have developed a new hybrid approach using multiboost based naïve bayes trees tested on 248 landslides and fifty parameters [42].

3. Our contribution

In this paper, we propose an adaptable and distributed landslides monitoring system able to monitor several kinds of landslide based on Multi Agent System (MAS) deployed on an Edge heterogeneous cluster composed of Odroid N2 and Nvidia Jetson Nano previously described in [23]. In order to limit the use of the cloud for training artificial intelligence models, we have added an NVIDIA Xavier to perform training locally at the edge.

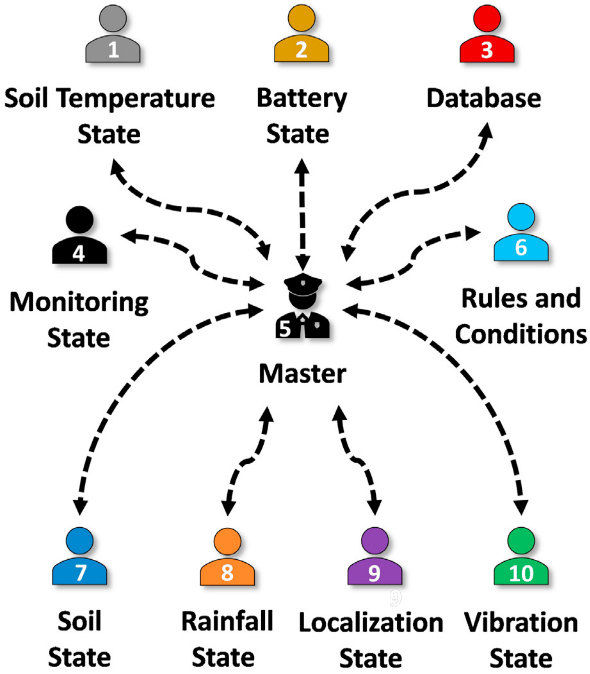

Fig. 1. Detailed View on Multi Agents System (MAS)

The Figure 1 shows the different agents composing the MAS playing following roles:

(1) The **Soil Temperature State** agent assesses the state of drought, normal functioning or freezing of the soil. Indeed, it implies a runoff of all precipitation; however, a desiccated soil accentuates the vertical infiltration of water in depth.

(2) The **Battery State** agent follows the level of battery of each sensor.

(3) The **Database** agent stores states of soil and air temperature, soil moisture, rainfall, localization, and vibration states. This data is useful for Rules and Conditions (4) to detect anomalies and launch an early warning alert.

(4) The **Monitoring State** agent detects failed sensors.

(5) The **Master** agent plays a role of coordination between all independent agents composing the system.

(6) The **Rules and Conditions** agent makes decision on base of the state of following parameters: soil, rainfall, localization, vibration, and soil temperature.

(7) The **Soil State** agent identify the soil moisture state, which means the available amount of water contained in a terminated volume of soil.

(8) The **Rainfall State** agent evaluates the maximum intensity of the rain and the volume of precipitation. This is a major landslide settlement.

(9) The **Localization State** agent measure the displacement on specific points of the landslide susceptibility area. Low displacement or deformations may occur.

(10) The **Vibration State** agent analyses earthquake signal to detect pattern announcing event likely to trigger landslides.

Our system, allows to monitor wide panel of different type of landslides without questioning the monitoring system operation mode. In addition, it is scalable to monitor numerous landslides at once and can easily accept new monitored parameters to address specific situations and use case.

4. Experimentation and Discussion

The Figure 2 gives an overview about the different implemented components of the system. To experiment our architecture, we have used a weather node and several ground nodes implemented at chosen point of the landslides. These nodes have been completely described in our previous paper [41]. All these nodes use LoRa RF protocol to transmit data to a LoRa gateway connected with our Edge AI-IoT Cluster [23] which is linked to a cloud computing infrastructure and an alert system. The database is store on the master node which is equipped of SSD.

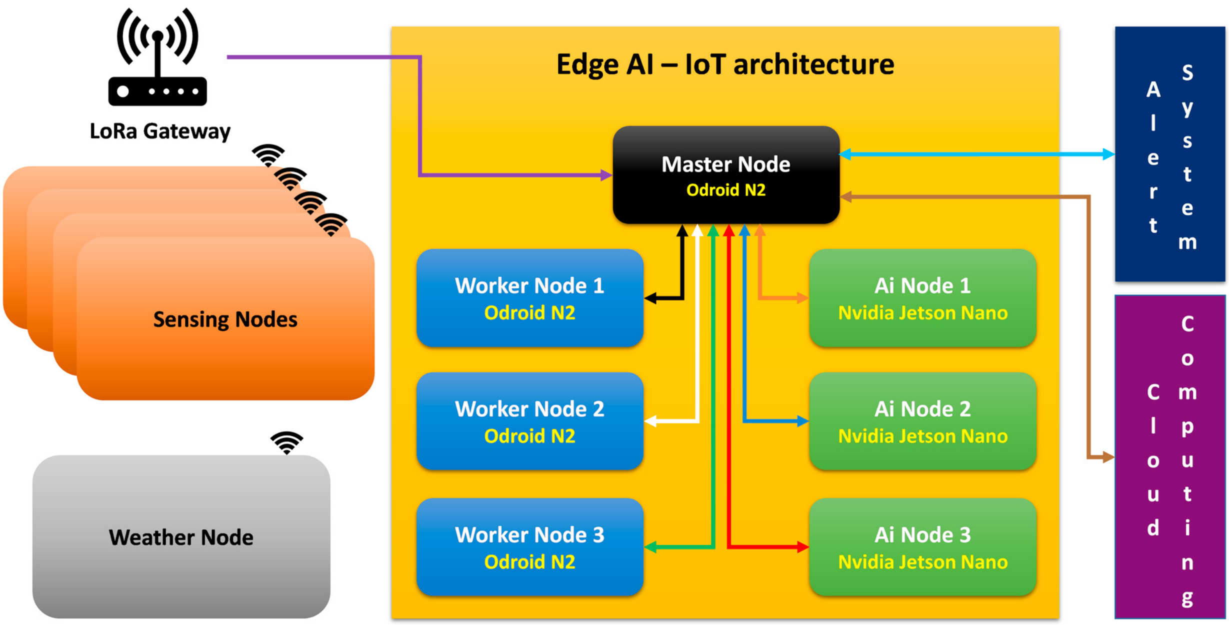

Fig. 2. Overall scheme of the experiment achieved

The Edge AI-IoT architecture uses Kubernetes and Docker to deploy multi-agent system on the heterogeneous cluster composed of an association of Odroid N2 and Jetson Nano that provides its computing power and AI capabilities. The cloud computing punctually assists the edge architecture by providing it with additional computing power when necessary. All data are also archived on the cloud in order to reevaluate regularly rules and conditions of landslides detection.

The Table 2 presents mean results obtains by comparison with our previous paper [41].

Table 2. Performance comparison between cloud and edge approaches.

Metric	Cloud centric approach [41]	Edge centric approach (this paper)
Network latency	208ms	53ms
Processing time	2.06s	12s
Mean bandwidth	2.63Mbits	249.5Kbits
Data transferred to the cloud	1180.06 Mb	112 Mb

5. Conclusion and Future Work

In this paper, we have adapted our previous work [41] to implement Artificial Intelligence algorithms and better detect patterns of landslides on basis of measures achieved by means of connected things. Most of the treatment has been displaced from cloud to the edge to limit the bandwidth, improve the latency, and obtained a reduced time of reaction. The data processing a the edge of the network hardened the system against network outage. Our in-situ experimentation has shown a reducing of the latency from 208 ms in the previous configuration to 53 ms with the edge architecture. While mean bandwidth has been reduced from 2.63 Mbits to 249.5 Kbits and the amount transfer to the cloud has decreased from 1180.06 MB per hour to 112 MB per hour. The processing time at edge level has increased; because, computing power of our edge AI-IoT architecture is more than the cloud. At this stage, the whole of our proposed architecture has not been tested yet; because, there are no landslides' occurrence until the present moment.

As a perspective, we would like to monitor, mainly, active landslides whose nature and kinematics are based on diverse triggering factors in order to completely validate our proposal, and collect numerous data to be able to train our artificial intelligence models.

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