IoT Based People Detection for Emergency Scenarios

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***Abstract*—First generation Internet of Things (IoT) based systems have focused on Cloud based remote asset monitoring, device management etc. The next-generation IoT systems are utilized to accomplish massive IoT and mission critical business cases. This work presents a real time people detection framework for emergency scenarios and its integration into EURECOM IoT Platform. Due to real time requirements, the Edge Server of the Platform has been extended to perform people detection and streaming the processed video to an IoT Client.**

***Index Terms*—Edge Server; IoT; People Detection.**

I. Introduction

Fire brigades are always on the look for new enabling tools to improve their operational management in rescue missions and increase their situational awareness, thus to ensure the safety of human lives in emergency situations. Thermal imaging cameras were first used by the State Fire Service enabling the firefighters to see through smoke and dust. However, thermal cameras were extremely costly which prevents fire departments to deploy them extensively and limits their use in risky environments. A major interest in thermal technology has grown since their first use in civilian applications. Consequently, such cameras have evolved to become affordable and user friendly. With the wide adoption of IoT across vertical industries, emergency responders are also exploring how IoT can assist in real time people detection for rescue missions. Some previous works exist in this area. Utilization of connected devices (e.g. sensors, actuators) along with inexpensive communication and computing power has paved the way for smart environments around us. Emergency management and situational awareness support systems are benefiting from IoT. The authors of [1] exploited IoT and crowd-sourced smartphone data for emergency situations and recommendations for a safe and quick evacuation. Another detailed study about emergency situations management in Smart Cities is found in [2]. This paper relies on sensor networks for the five steps of emergency management - preparedness, mitigation, prevention, response, and recovery. Privacy is often overlooked in emergency contexts. But the authors of [3] developed a privacy conscious architecture for the same in a Smart City context. The key ingredients of the architecture include a community Cloud system for emergency response, where participating organizations have pre-built trust relationships and compliance with privacy laws. Evacuation management from indoor and building contexts are considered in [4]. Indoor localization is important for calculating the evacuation paths for individuals. Unmanned Aerial Vehicles (UAVs) are also being used in path planning for such scenarios aided by IoT technologies [5]. A face detection system using IoT is presented in [6]. The authors utilized cameras connected to Raspberry Pi devices which acted as IoT gateways. They employed cascade classifiers for face detection and spatial correlation for improving the detection. To best of our knowledge, we do not find any research that exploits MEC and IoT for people detection in fire related emergency situations.

In this paper, we demonstrate an IoT system for emergency situations exploiting MEC technologies. The novel aspect of our work is in integration of the real time people detection framework into a MEC server of the EURECOM IoT Platform. Our work is positioned as an architectural and technical improvement through Digital Transformation of handling of fire related emergency use case.

II. Integration of People Detection into IoT Architecture

This section describes our people detection framework and its integration in the IoT Platform.

A. People Detection Framework

We assume that emergency responders are equipped with a wireless camera that can stream live video to the operation station where it is processed and then broadcasted across the emergency rescue team. To accomplish the rescue mission, we have relied on thermal cameras that enable to see through smoke and dust in order to be able to detect people in case of a burning or a collapsing building. There are numerous algorithms for human body detection and body pose estimation adjusted for visible images [7, 8, 9]. However, to the best of our knowledge, there are only algorithms that are able to detect standing/walking people in thermal spectrum as it is the case for pedestrian detection. These algorithms tend to fail in detecting people when they are presented in a more complex pose. Considering the real life emergency scenarios that may occur, it is less likely to find a person in a standing position, but rather in lying, sitting or curled up position. Therefore, we opt for anatomical keypoint detection algorithm of the human skeleton.

1) OpenPose: The people detection solution is based on OpenPose, the first library for real-time multi-person keypoint detection [10]. This system contains two main blocks: the detection of body keypoints and their association of the joint parts. The detection of body keypoints is performed by generating confidence maps that are 2D representations of the probability that each pixel of the image belongs to a particular part of the body. Ideally, if only one person appears in the image, a single peak should exist in each confidence map if the corresponding part is visible. if there are several people, there should be a peak corresponding to each visible part for each person. Given a set of detected body keypoints, the association of each pair belonging to the same person is done by a non-parametric representation called Part affinity fields. This representation is a 2D vector field, illustrating each member of the body by its location and orientation. Each member is allied to an affinity field joining the two members of the body associated with it.

The people detection architecture is based on a neural network composed of two branches, each branch is a convolutional neural network. The first CNN is designed to generate a set of detection confidence maps, and the second a set of part affinity fields. The OpenPose model is trained on COCO database [11].

2) Experiment and results: The OpenPose system has achieved very high performance for the detection of human body keypoints on visible spectrum data. To evaluate this system on thermal spectrum data, a database of paired data acquired in the visible spectrum and the thermal spectrum was collected. The data acquisition was performed using the dual sensor camera FLIR DUO R. The visible imager has a 4000×3000 pixel array and the thermal sensor has 640×512 pixel array. The pair of frames stream was downsampled to 320×256 pixels. For the data collection, we have considered two sessions with different scenarios. First session was recorded in constrained conditions with clear vision where the volunteers have performed various body poses. Second session was collected by firefighters during a fire experiment, where there was smoke and poor light conditions.

We report, in Table I, the performance of Openpose based people detection algorithm on visible and on thermal spectrum in the two aforementioned scenarios. We note that in constrained conditions we obtain better performances on visible spectrum when compared with the thermal spectrum. This is mainly due to the fact that OpenPose model is trained solely on visible data, besides in thermal spectrum human body parts are not easily discernible due to lack of textural and geometric information. However, when employed in real-life emergency scenarios where the vision is altered by smoke and/or poor light conditions, performances reported on thermal spectrum are higher than the performances obtained on visible spectrum. This can be justified by the fact that thermal imagery enables the vision through smoke and in darkness, while the information is missing or even absent in visible spectrum. We illustrate an example of people detection when employed in darkness in Fig. 1. We note that the detection fails in the visible spectrum while it has been successful in thermal spectrum.

	Clear		Smoke	
	VIS	TH	VIS	TH
Detection rate	92.15	76.87	68.16	83.17
False alarm rate	0.58	18.92	9.68	8.05
Miss detection rate	7.85	23.13	31.84	16.82
Accuracy	91.66	65.18	73.95	85.62
Precision	99.42	81.08	95.21	96.37

TABLE I: Performance evaluation (%) of OpenPose algorithm on visible and thermal spectra.

(a) (b)

Fig. 1: OpenPose based people detection (a) Visible spectrum (b) Thermal spectrum.

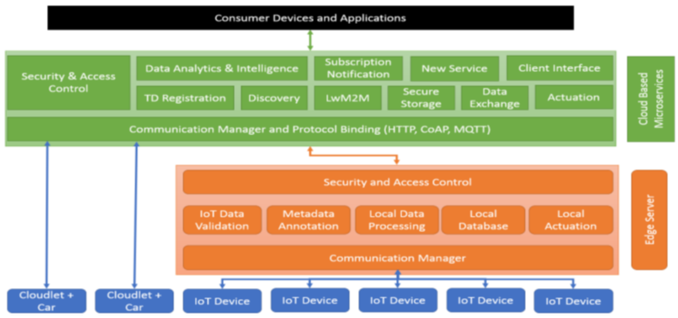

Fig. 2: Full stack EURECOM IoT Platform.

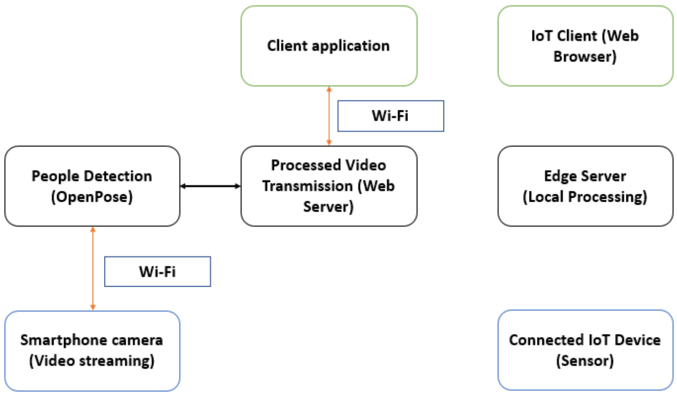

Fig. 3: Experimental setup for IoT based people detection for emergency scenarios.

B. Integration with IoT Platform

The novel aspect of the work is in integrating the above framework into the Cloud based, full stack EURECOM IoT Platform depicted in Fig. 2. Its capabilities are exposed through web services using north and south interfaces. The south interface of the Platform connects to IoT devices and an Edge Server. The north interface interacts with IoT clients. The Edge Server is actually a MEC node providing local data validation, metadata annotation using Sensor Measurement List[12], local data processing, storage, and local actuation capabilities. Due to the real time nature of emergency situations, the OpenPose based people detection framework (i.e. local data processing) have been integrated into the the Edge Server of the Platform. This web server also streams the processed video with people detection performed to any IoT Client (i.e. a web browser) connecting to it. The client is connected to the Edge Server, Wi-Fi is utilized in this experiment. The browser presents the available cameras (i.e. thermal, visible) and the emergency responder can select the necessary camera. Then the web browser will receive the processed video frames over HTTP. This integration is depicted in Fig. 3. The right side of this image denotes the layers in the overall solution.

III. Conclusion

In a nutshell, this paper demonstrates an IoT system for real time people detection for emergency services. Our novel aspect is the integration of people detection module in the Edge Server of the IoT Platform.

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