Alleviating the Master-Slave Distance Limitation in H2M Communications through Remote Environment Emulation

Elaine Wong
Dept. of Electrical and Electronic Engineering
University of Melbourne
VIC 3010, Australia.
ewon@unimelb.edu.au

Sourav Mondal
Dept. of Electrical and Electronic Engineering
University of Melbourne
VIC 3010, Australia.
s.mondal@student.unimelb.edu.au

Lihua Ruan
Dept. of Electrical and Electronic Engineering
University of Melbourne
VIC 3010, Australia.
ruanl@student.unimelb.edu.au

***Abstract*— In the past few years, we have seen communication networks evolve from predominantly supporting content-centric traffic under the Internet paradigm to increasingly serving machine-centric traffic under the Internet-of-Things paradigm. We are also currently in the throes of the next evolutionary leap in communication networks, under the new paradigm known as the Tactile Internet. Human-to-machine communications is central to TI, empowering humans (masters) to immersively interact with remote environments. Predictably, traffic in a TI is dominated by control and haptic feedback data that have strict reliability and latency requirements on the communication network. Consequently, the strict latency requirement of H2M communication places a limit on the distance that can be deployed between the master and slaves domains. This paper will explore a new approach that facilitates remote environment emulation to alleviate the master-slave distance limitation and decouple this limitation from the perceived latency.**

***Keywords*— AI-embedded cloudlet, Human-to-machine communications, remote environment emulation, Tactile Internet.**

I. Introduction

Human-to-machine (H2M) communication that is central to Tactile Internet (TI), empowers humans to immersively interact with remote environments through "feeling" and "controlling" real and virtual machines/robots. The immersive experience of humans through remote machines has significant economic and societal impact, cross-cutting sectors from proactive healthcare, industrial automation, intelligent transport, surveillance for defence and disaster management, to edutainment [1]-[4]. A TI can be decomposed into three distinct domains: a master domain comprising a human operator controlling a master interface, a slave domain comprising remotely-controlled slave machines/robots, and a network domain that supports bilateral H2M communication between the master and slave domains [3]. Predictably, traffic in a TI is dominated by control and haptic feedback signals that have strict reliability and latency requirements on the communication network.

A recent report by the IEEE 1918.1 working group [5] stated that the communication network of a TI can be a combination of shared/dedicated, wired and/or wireless networks, as long as strict latency and reliability requirements are met. Unsurprising, research in TI has been heavily focused on the radio access network segment. While it is true that ultra-low latency communication between local master-slave pairs residing within the same wireless coverage area can be readily supported by advanced wireless technologies, communication between remote master-slave pairs will need to traverse optical front/back-haul segments [4]. In fact, future cellular networks are expected to adopt a converged model of fixed optical and mobile wireless access to better deliver both fixed and mobile applications [6]-[7]. Fig. 1 illustrates such a converged communication network which combines a capacity-centric optical backhaul with mobility-centric cellular and wireless local area networks. Naturally, there are three types of optical network units (ONUs) that connects masters to slaves: the first serving fixed users (ONU), the second integrated with WiFi access points (ONU-AP), and the third integrated with cellular network base stations (ONU-BS).

The support of H2M traffic (both control traffic from master to slave and haptic feedback traffic from the slave to master) places significant demands on the network. Since the communication network completes the human-slave control loop, its latency affects system stability and impacts quality-of-experience. To date, revolutionary capabilities and technologies to support H2M communications on these converged networks remain in their infancy and technology challenges are yet to be resolved.

For one, the strict latency requirement of H2M communication places a limit on the distance between the master and slave domains. A possible solution to overcome this distance bottleneck is through remote environment emulation whereby, for example, the physical environment at the remote slave domain is emulated near the master domain. This way, realistic immersive experiences can still be conveyed to the human operator even though the distance between the master and slave is large [3]. The paper outlines our recent work on using AI-embedded cloudlets to achieve remote environment emulation.

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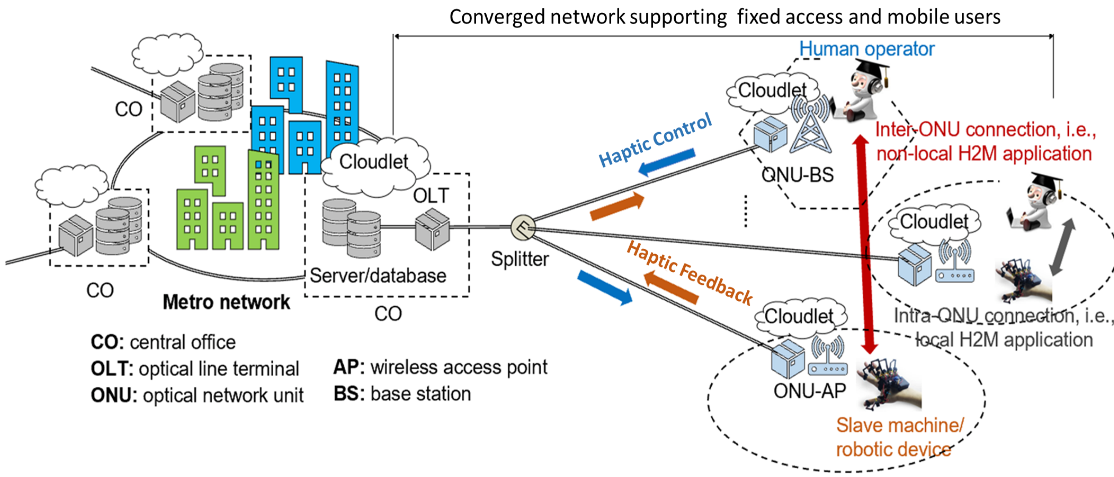
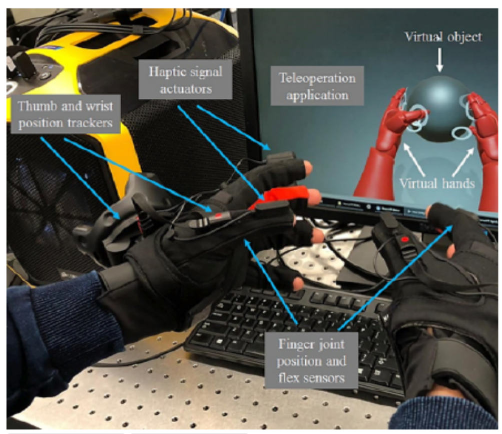


Fig. 1. Converged optical and wireless network with AI-embedded cloudlets for remote environment emulation



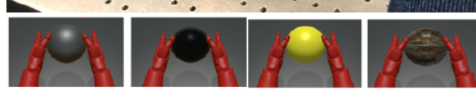
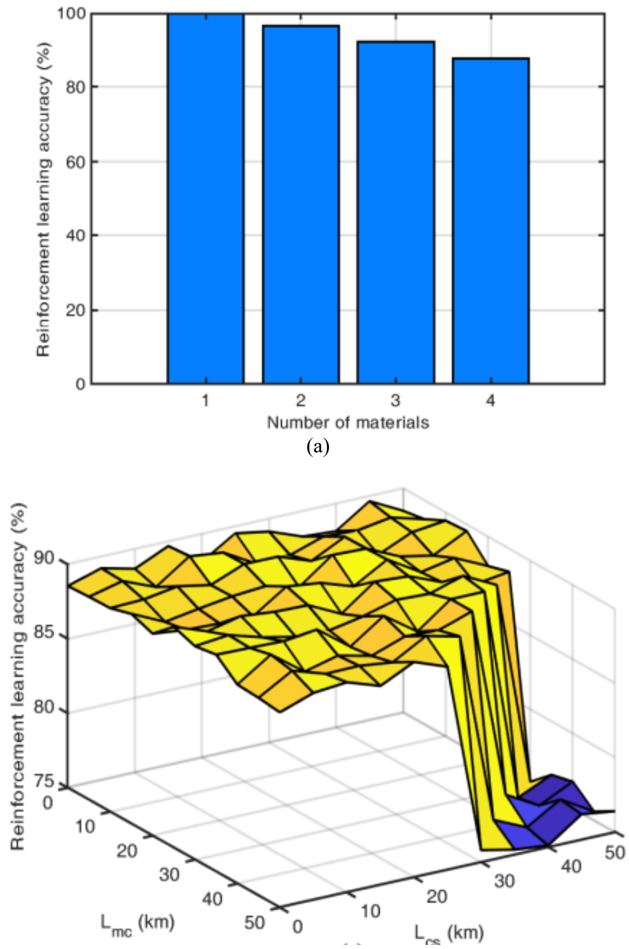


Fig. 2 Master (VR gloves) and slave (virtual ball) of H2M experiment with virtual ball of different materials: Metal, wood, plastic, foam.

II. Principle of Operation

To realise remote environment emulation, AI-embedded cloudlets where H2M servers are located, are expected to first forecast haptic feedback from slaves, and then deliver these predicted feedback to the human operator [3], [4], [8], [9]. The delivery of the haptic feedback from slaves is therefore expedited to the human operator as compared to the round-trip trip of the master-slave distance. Consequently, the master-slave distance will no longer have influence on the perceived latency thereby enabling H2M applications with high dynamicity to be deployed over large distances. Cloudlets are distributed computing/storage resources placed close to end-users to relieve computation/storage pressures of their mobile devices while maintaining satisfactory quality-of-experience for users [10]. In our investigations, we used a Virtual Reality (VR) based teleoperation setup as shown in Fig. 2 whereby the human operator (master) operates a pair of VR gloves to touch a virtual slave ball on a computer running a VR application. The material of the virtual ball can be either metal, wood, plastic or foam. Upon touching the virtual ball, the VR application sends different haptic feedback samples back to the haptic actuators on the fingers of the VR gloves worn by the human operator.

For the first time in [7], we showed that forecasting and delivery of haptic feedback from slaves are feasible through a novel Event-based Haptic SAmple Forecast (EHASAF) module which consists of a 2-stage AI model. The first stage comprises a series of artificial neural network (ANN) units that facilitate touch event detection. An ANN is established for each finger and it implements a supervised learning algorithm on control signals received from the human operator. It acts as a binary classifier to either proceed with forecasting (if touch is detected) or no forecasting (if touch is not detected). The second stage of EHASAF is a reinforcement learning (RL) unit to forecast and deliver haptic feedback to the master within the expected quality of experience (QoE) time. The RL unit will randomly choose a material out of up to 4 possible materials when a touch event detection is affirmative in the ith timeslot



(a)

(b)

Fig. **3** Forecast feedback accuracy of the reinforcement learning (RL) unit of EHASAF vs. (a) number of materials of virtual ball; and (b) distance between H2M server and master, L_{mc} and between H2M server and slave device L_{cs}.

and forecast the first haptic feedback sample. The RL unit will then compare this to the actual haptic feedback sample from the slave device received after a certain time period and compute the reward which is the normalized error. The RL unit will then use this reward value to update its probability distribution for choosing a haptic material in the *i*+1 timeslot.

III. Results and Discussion

Through the setup shown in Fig. 2, up to 800 instances of both control and haptic data from touching the virtual ball of different materials with random fingers of both hands, were captured. 70% of that was used to train ANNs (2 hidden layers of 10 and 5 neurons respectively), each corresponding to a different finger. Half of the remaining data was used for validation, and the other half for testing. Results indicate an ANN touch event accuracy of ~99%. Subsequently, in operation, when the ANN has successfully detected a touch event, the RL then starts to generate haptic feedback samples. Results in Fig. 3(a) highlight a 100% forecast feedback accuracy of the RL unit when only one option in material is tested. This accuracy decreases to 87% with 4 different material options to choose from.

Finally, the role of master-slave distance on the forecast feedback accuracy of the RL unit with 4 different material options, is plotted in Fig. 3(b). The distance between the master and H2M server, L_{MC}, and that between the H2M server and the slave, L_{CS}, were varied from 0 to 50 km. The accuracy is above 87% except for when the sum of L_{MC} and L_{CS} is ~80 km and beyond. For aggregated distances > 80km, the actual haptic feedback samples from the slave are delayed to the H2M server and the RL algorithm's performance degrades. Our current efforts are focused on extending this emulated master-slave distance.

IV. Summary

We have discussed our recent proposal of the 2 stage AI-based EHASAF module. When deployed near the master domain, it is able to forecast and expedite the delivery of haptic feedback traffic from the slave to the master. With this powerful approach, haptic feedback samples reach the master much quicker, thus decoupling the latency from the master-slave distance. Preliminary investigations using objects of 4 different materials yield a touch event accuracy and forecast feedback accuracy of 99% and 96%, respectively.

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