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Towards an Interactive Learning Ecosystem: Education in Power Systems

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Abstract. In this paper, it is presented the ongoing work on developing an Interactive Learning Ecosystem for power systems education and training. Opportunities to employ low-cost human computer interfaces for creating an Interactive Learning Ecosystem based on intelligent Human-Computer Interfaces are presented. Then, an Interactive Learning Ecosystem framework is shown. The ongoing work integrating these interfaces within Virtual Reality systems that compose a power systems education ecosystem are presented and discussed.

Keywords: interactive learning ecosystems, human-computer interfaces, big data, data science, power systems education.

1 Introduction

E-learning technologies have taken a major role in education, from traditional academic setups to corporate training, these have become part of most individuals everyday learning. These technologies range from isolated platforms such as Learning Management Systems (LMS) or Virtual Reality (VR) environments, to Learning Ecosystems (LEs) which integrates one or more technologies such that users' information is standardized, shared, and exploited between the LE components [4, 10]. In particular, designing e-learning technologies through the lens of LEs is indispensable in today educational landscape, due to the large amount of systems that need to exchange and maintain educational information in formal and informal settings [4, 5].

A key aspect of LEs is that these are principally shaped by Big Data (BD) and Data Science (DS) technologies. Loosely speaking, BD refers to large heterogeneous data, generated at fast speed, and which is too large to process or store using a single machine [11]. DS on the other side, can be comprehended as a new paradigm that unifies theory, experiments, and software, for developing methods to support new scientific discoveries through the analysis of large data amounts [13]. In fact, these two are becoming major players in the e-learning field. Even now governments are reporting a) how BD&DS contribute in the assimilation, ingestion, storage, information exchange, and exploitation of students trace data from heterogeneous systems, and b) conceptualizing how these technologies shall be incorporated into educational areas hereafter [11]. Likewise, BD&DS powers Machine Learning (ML) algorithms in areas such as Face Recognition, Emotional and Gestural Recognition from facial, body, and textual expressions, Natural Language Processing (NLP) [2, 7, 14, 16], to mention a few.

On the other hand, advances in the aforementioned ML areas and the fast-paced hardware improvements, have allowed to develop reliable devices that provides more natural Human-Computer Interfaces (HCIs), which are already prepared to be integrated into LEs. These range from *Do-It-Yourself* (DIY) low cost sensors networks based on open-source platforms such as Arduino™or Raspberry Pi™, to highly sophisticated plug-and-play robots such as Pepper™which are already equipped with touch sensors, light sensors, 3D cameras, Emotional Recognition, and so on [12].

Hence, in this work it is discussed the ongoing work to develop a framework namely *Interactive Learning Ecosystem* (ILE), which integrates HCIs into a LE to provide more natural and individualized HC interactions. In particular, it is discussed HCIs which allow to a) estimate an student affective state, b) control applications through hand and fingers gesture recognition, and c) control applications and provide personalized support through voice commands. These HCIs are examined at different interaction levels within the ecosystem, from navigation controls in a specific VR application, to higher level individualized assistance. Moreover, it is analyzed how data generated from such interactions shall be streamed, standardized, and stored for its subsequent exploitation. Therefore, this work is organized as follows: in Sect. 2 it is presented the HCI devices and the proposed ILE framework; in Sect. 3 the ongoing work regarding the integration of HCIs into a ILE to be used for power systems education; in Sect. 4 a discussion is elaborated regarding the current ILE state and the future work to be delved.

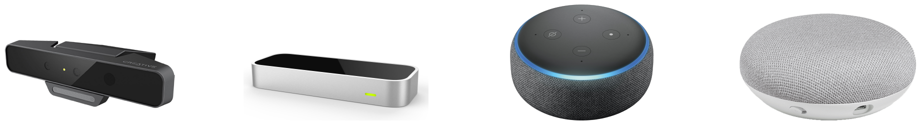
2 Materials & Methods

Nowadays the amount of *intelligent* HCIs is huge. These are *intelligent* in the sense that can carry out one or more human functions by themselves, e.g. inferring the affective state of a person by its facial expressions. Together they form a network of sensors, which in fact, can be considered as devices of the Internet of Things (IoT). As such, these require an standardized protocol to gather interaction data from heterogeneous systems for its future exploitation. The e-learning specification namely, eXperience API (xAPI), offers a solution to this issue [11]. Any interaction coded as a xAPI learning experience is then delivered to a BD infrastructure where interaction messages are streamed, ingested, stored, and analyzed using Learning Analytics (DS applied to educative data).

2.1 HCI Devices

Devices such as Intel RealSense™RS300 camera, the Leap Motion™(LM) hand gesture tracking, Alexa Echo Dot™(AED) and Google Home™(GH) Mini virtual agents, are examples of gadgets improvements brought by BD&DS. For the time being, these four devices are considered and evaluated as part of the ILE due to its low cost and high compatibility; these are shown in Fig. 1. An important aspect of these devices is that, while the RS300 camera and the LM can work offline given that they are already provided with embedded systems, GH and AED require internet access to provide its NLP services.

Tracking devices such as LM or RS300 are 3D cameras which are capable of gesture tracking, face recognition, and estimate affective states by using skeleton, head, facial, hands and fingers landmarks to generate motion data features. While the RS300 device is capable to identify an individual facial expressions, affective state, and track body and hand gestures, the LM device is specific for hand and fingers gesture tracking [6, 15]. These two devices can work independently to capture different data or in a redundant fashion to improve fidelity by integrating multimodal and multiple-sensors data.

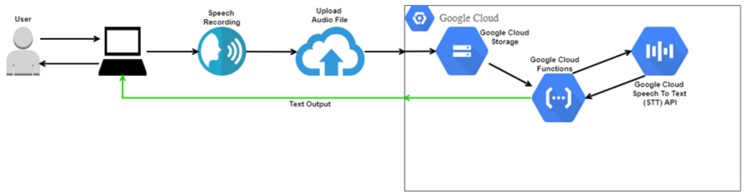


(a). (a) **(b).** (b) **(c).** (c) **(d).** (d)

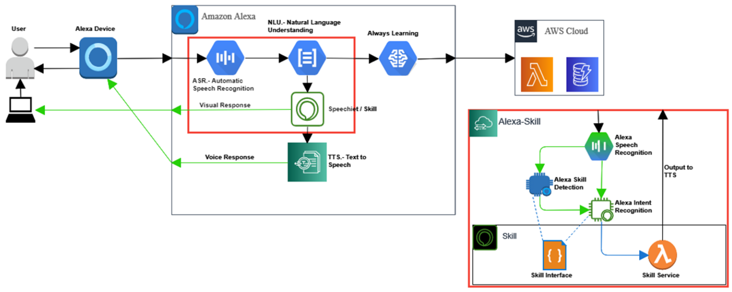
Fig. 1. HCIs considered in the ILE: (a) RS300 camera, (b) Leap Motion, (c) Alexa Echo Dot, and (d) Google Home Mini.

On the other hand, GH and AEO are considered Intelligent Virtual Assistants (IVAs), although these are known by many names [3, 9]. An IVA is any software agent that provides aid and services to an individual commands in an personalized fashion. These commands are in the form of speech (i.e. Spoken Dialogue Systems) or text (i.e. Chatbots). IVAs provide a wide range of spoken dialogue applications, from controlling home appliances with voice commands (i.e. Domotics) to tracking personal activities such as physical excercise, productivity, and so on. Loosely speaking, most spoken dialogue IVAs follow the following process: Speech is converted to Text (S2T), then text is mapped into an action (Natural Language Understanding -NLU-) namely *Skill*, if the skill exists the corresponding action is carried out, result is then synthesized into a natural language expression, and given to the user by converting it from Text to Speech (T2S) [3, 9]. For instance, GH and AEO dialogue system schemes are shown in Figs. 2a and 2b, respectively. Both systems are designed to work for dedicated devices [3], however, Google Speech API as well as Amazon API now can be integrated with a plethora of devices. Likewise, both APIs provide advanced deep learning models to carry out the Automatic Speech Recognition

(ASR) necessary for the S2T process and NLU to recognize *intents*, words that triggers an skill. Nevertheless, while Alexa enables developer to build skills, the GH is constrained to prefabricated built-in skills.



(a). (a)



(b). (b)

Fig. 2. IVAs speech dialogue processing. On (a) Google Cloud Speech API, on (b) the Alexa Voice Services components for NLU.

2.2 Interactive Learning Ecosystem

Using the aforementioned HCIs, we now proceed to describe the proposed ILE framework. Fig. 3 presents the overall data flow, and ILE components. These ecosystem is composed by several systems such as a Virtual Reality Training System (VRTS), a LMS, Social Media, etc; generate data from these is then validated, ingested, processed, stored, and exploited by a big data infrastructure [11]. It is worth mentioning that, HCIs interactions will conform a multi-modal data that will be required to be parsed into learning experiences by the message broker.

In this ILE, HCIs interactions can be discussed at two levels: single applications and personalized support. For the first lets consider a VRTS, the RS camera is used to recognize facial expressions and affective states during a training session. During these sessions the VRTS is controlled with the LM and AEO: the former to navigate and interact with the environment, whereas the latter to ask details and information about the virtual environment.

While these multimodal data can be used for improving training in the VR application, a higher level of personalization can be achieved by integrating Alexa third party skills. This means that, during the training session, an individual may request information to web search engines, track productivity, or even perform domotic actions such as turning off the washing machine. These information will be gather by the ILE to obtain a broader scope of an individual such as his/her health, activity schedules, interests, and so on.

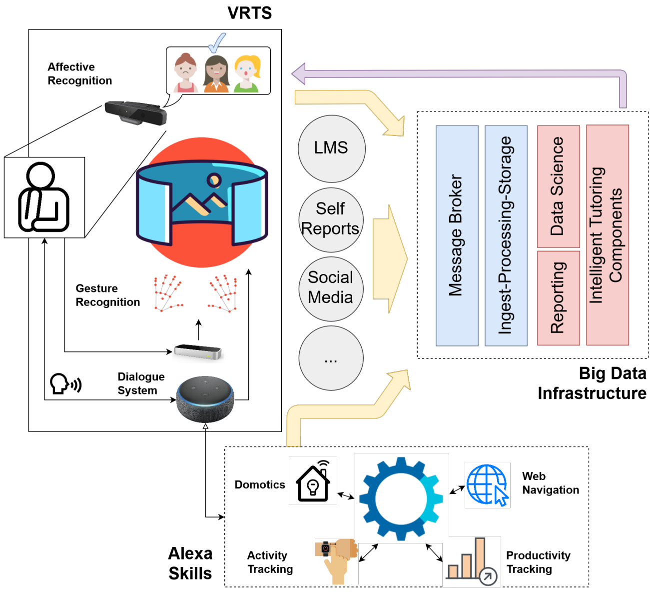


Fig. 3. Proposed Interactive Learning Framework.

3 Ongoing Development in Power Systems Education

Education for electrical power systems range from electricity and physical theoretical concepts to practical maintenance courses. These courses may consist in the usage or management of specialized software for electrical engineering, the proper operation of maintenance tools, equipment, and protective hardware, to mention a few. In the following it is described how two virtual systems belonging to a power systems LE, integrates HCIs such as LM and AED.

3.1 Robotic Operated Vehicles for Underwater Inspection and Maintenance of offshore Facilities

Underwater offshore facilities such as the required by wind power turbines or oil extraction platforms are inspected, maintained, and cleaned by human divers.

Yet, underwater operations are inherently dangerous due to oceanic conditions such as water flow velocity and wave height. Fortunately, underwater Remotely Operated Vehicles (ROVs) are now replacing the physical presence of divers in these undependable conditions. This does not only provides a safer environment for workers, but also lowers inspection and maintenance costs of offshore facilities. Nevertheless, ROVs are expensive vehicles which utilities and oil companies cannot afford to damage or lose.

Therefore, ROV pilots require to be trained properly in the operation of these vehicles previously to be allowed to carry out maintenance in the field. SimRov is a VRTS used to train ROV operators in underwater operations and the operation of the ROV itself [1]. For this, the student operates a virtual ROV equipped with two arms, video cameras, and thrusters to move around. However, the typical HCIs used in this type of VRTS are joysticks and keyboards. In particular, these are unnatural in the operation of robotic arms, and it has been proposed to use LM to replace joysticks to control the robotic arms in a more amenable form [8]. Therefore, LM is integrated to the SimRov VRTS to improve the manipulation of the robotic arms, Fig. 4 shows the ongoing work regarding the development of such interface.

Fig. 4. ROV for offshore underwater maintenance controlled by LM.

3.2 Virtual MicroGrids (μG) for Power Systems Education

Climate change has increased the urge to employ renewable energy sources and the development of resilent networks. Among the technologies to address these issues stand MicroGrids (μGs). These are small scale networks restricted to a specific geographical area, which are powered by traditional plants, renewable energy sources, and stationary energy storage systems. μGs satisfy several roles, from prosumers which sell energy to the power network, to the satisfaction of the electrical demand in rural regions.

The development of such frameworks have lead into the creation of new job opportunities which require prepared professionals to satisfy the labor demand. This, has lead into the development of training systems that must ensure teaching effectiveness that allows students to carry out experimental activities. In this sense, the Virtual μG (VμG) has been developed. This is a VRTS that aims to train professionals in the operation and maintenance of microgrids. For achieving this the user operates an avatar which is situated into a virtual μG, where he/she must carry out maintenance and operation maneuvers.

Navigation and interactions within the virtual environment are performed using a keyboard to fulfill maneuvers steps. Additional information requested by the user regarding the maneuver steps, the maneuver objective, and μG components are provided by a proprietary Alexa Skill through the AEO. Fig. 5 shows the ongoing work regarding the development of this VRTS.

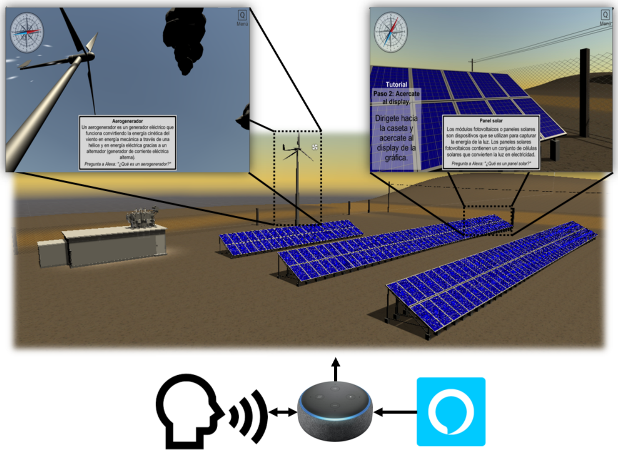


Fig. 5. Virtual μG integration with Alexa Echo Dot. The devices provides information about navigation and items around the VR environment.

4 Discussion

In this work it is presented a proposal for building an ILE for power systems education. This goes towards generating a standardized system for storing HCIs interactions as learning experiences within a BD infrastructure. To date the development have focused upon the tools for building the ILE. Resulting VRTS systems and their integration with the LM and AEO are encouraging, thus, the next steps involve polishing HCIs integration with VRTS, the integration of a multimodal dataset coming from HCIs interactions, and the experimental design for assessing improvements in learning by students.

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