New Frontiers for Pervasive Telemedicine: From Data Science in the Wild to HoloPresence

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ABSTRACT

Telemedicine has been regarded as the natural application of information and telecommunication technology to health and healthcare. But until now its application has been limited, and mostly focused on specialized environments. The evolution of ubiquitous sensors and the pervasiveness of mobile devices, including the growing capability to sense remote parties, is opening up new exciting opportunities pioneered by mHealth applications on our mobile devices. Coupling advances in real-world sensing with multimodal signal processing and machine learning techniques is equipping us with 'super powers' that enable understanding of health-related data in real-time, opening up new opportunities to embrace 'Data Science in the Wild'. On the other side, exciting advances in augmented and mixed reality are enabling immersive experiences that are paving the way for the next generation of telemedicine through wearable see-through augmented reality displays. We believe that the intersection of these two exciting technologies currently represents one of the cornerstones for Pervasive Telemedicine. We contextualize the sensing-intervention-visualization continuum in pervasive health, by illustrating two examples from our research in terms of (i) remote assessment of stroke through multimodal pervasive sensing, and (ii) immersive mixed reality tele-surgery and holopresence. The goal is to stimulate conversation around opportunities and limits of these technologies for pervasive telemedicine.

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords

Pervasive Health; Telemedicine; Data Science; In-the-Wild studies; Holograms; Augmented Reality; Mixed Reality

INTRODUCTION AND BACKGROUND

Mobile devices are increasingly pervasive and ubiquitous. Market penetration in the US is rapidly reaching the totality of the population. In 2015, 95% of US citizens owned a mobile phone with nearly 2/3 owning a smart phone [36, 31]. The number of worldwide mobile phone users is forecasted to reach 4.77 billions in 2017 [37] and the number of connected devices worldwide will reach 47 billions in 2021, doubling the 2016 numbers [13]. Moreover, estimates suggest that 38% of the US adult population used their mobile devices for health information [25], and over 250,000 mobile health or mHealth apps are listed in online catalogues for a range of mobile devices (e.g., iPhones and Android devices) [34]. Those apps have been developed to monitor or intervene with a variety of health-related conditions [7, 12, 15, 22, 30], often in conjunction with wearable health devices, which according to recent reports reached 44 million units shipped in 2013 [1], and will reach 97.6 million in 2021 [27]. Wireless health sensors, including smart pedometers, activity trackers, blood pressure monitors, pulse oximeters, blood glucose monitors, and Wi-Fi weighing scales are increasingly popular for continuous health monitoring and assessment of key physiologic, psychological, and environment variables.

These numbers reflect the astonishingly rapid onset of the growing pervasive technology era also on research, where scientists can now objectively measure sedentary and active behavior using a wearable accelerometer sensor [35, 21], stimulate memory using a wearable camera [42, 14], or monitor mental health using smartphone capabilities [39, 40]. Likewise, researchers can mine social media communications to predict disease outbreaks [10, 11], inform the risk of contracting a disease [38], or track geographic location to contextualize health behaviors [19].

Sensing, however, is only one side of the equation. When we think about how to support people — both patients, and clinicians — in the healthcare space, the representation or visualization of the information, as well as the way users can interact with it, becomes crucial. The advent of mobile devices made it possible to access and visualize data in a pervasive way, and the advances in interactive information visualization, especially on the web [6], made it possible to explore data in many different ways, which mainly enabled self reflection, as evident in the Quantified-Self (QS) movement [9]. However, when we pair this shift in visual data exploration with the ad-

PervasiveHealth '17, May 23–26, 2017, Barcelona, Spain

ACM ISBN 978-1-4503-6363-1/17/05…$15.00
https://doi.org/10.1145/3154862.3154912

vancement of visualization and interaction capabilities recently enabled by both Virtual Reality and Augmented Reality [5], we see a clear opportunity for a paradigm shift in the design of human-computer interaction systems. The complexity of these systems previously required specialized prototypes, but newly available commercial products like the Microsoft HoloLens[1] make the technology more available also in the context of Health and Healthcare [17].

While in this new era of advanced technology we see an emergence of applications and technology aimed at exploiting pervasive sensing for health and healthcare, we also see some sort of disconnection with the application of mobile health to more traditional medicine and clinical work. Many of the technologies and approaches described above could be used as a support for traditional diagnosis or treatment, but clinicians are not yet routinely employing these tools in their daily interaction with patients. On the other side, telemedicine has been historically regarded as the natural application of new information and telecommunication technology (ITC) to health and healthcare. But until now its application has been limited, and mostly focused on specialized situations and environments, such as overcoming distance barriers and providing services through remote consultation in distant communities. In the remainder of this paper we reflect on the opportunities that new technologies are creating, specifically in the context of three focal elements: sensing, intervention, and visualization. We discuss these elements by contextualizing them around future application to telemedicine, specifically in terms of *Data Science in the Wild* and the opportunities offered by *HoloPresence*. We do this by discussing two examples from our research in the context of remote assessment of stroke and immersive tele-surgery.

DATA SCIENCE IN THE WILD

In the same way as they enable novel mHealth applications, pervasive sensing technologies now allow us to better understand situated real-world activity. In our work we demonstrated how the deployment of situated cameras and remote sensors in healthcare environments [41] enables rich understanding of the observed activity at a variety of levels, and informs the advancement of computational models to understand behavior. While multimodal pervasive sensing enabled us to engage in rich sense-making through the introduction of Computational Ethnography [44], new advances in multimodal signal processing and machine learning techniques, such as deep learning [23] are equipping us with 'super powers' that enable understanding of health-related data in real-time. This opens up new opportunities for embracing the concept of what we call 'Data Science in the Wild': we believe that continuous sensing paired with real-time multimodal data analytics in the healthcare environment will allow us to capture rich data at high frequency, and develop interactive and interventional systems that will represent the new wave of telemedicine. We illustrate this concept through our ongoing and future work on UbiStroke, a Multimodal Sensor-Based Assessment of Stroke Deficits.

UbiStroke: Computational Remote Assessment of Stroke

In the area of acute neurological disease diagnosis and treatment, speed and accuracy are both incredibly important. This is especially true in the case of stroke. The drugs and procedures used to treat stroke often carry very high risks related to internal bleeding (especially in the brain). Therefore, diagnosis of stroke is only made by highly trained and specialized neurologists, before treatment can be administered. Unfortunately, experts are frequently not available, or remote, and current solutions rely heavily on support staff to triage and prioritize patient evaluations. This often leads to stroke not being treated on time, with only 5% of acute strokes treated with the standard medication (rt-PA), mainly due to the narrow therapeutic time window for intervention [18].

Recent work explored classic telemedicine approaches to support acute stroke diagnosis in remote locations [3], as well as specialized mobile stroke units that can perform more accurate diagnosis outside of the hospital [43]. Our work takes inspiration from these approaches, but focuses on multimodal computational assessment of stroke through machine learning, employing a Microsoft Kinect camera[2] to detect body movements, and other behavioral and physiological clues. We are studying how to computationally characterize stroke features by observing patients' multimodal behavior [32, 33].

Currently, we are collecting behavioral data from patients while they are assessed by neurologists (see Fig. 1, top); as the

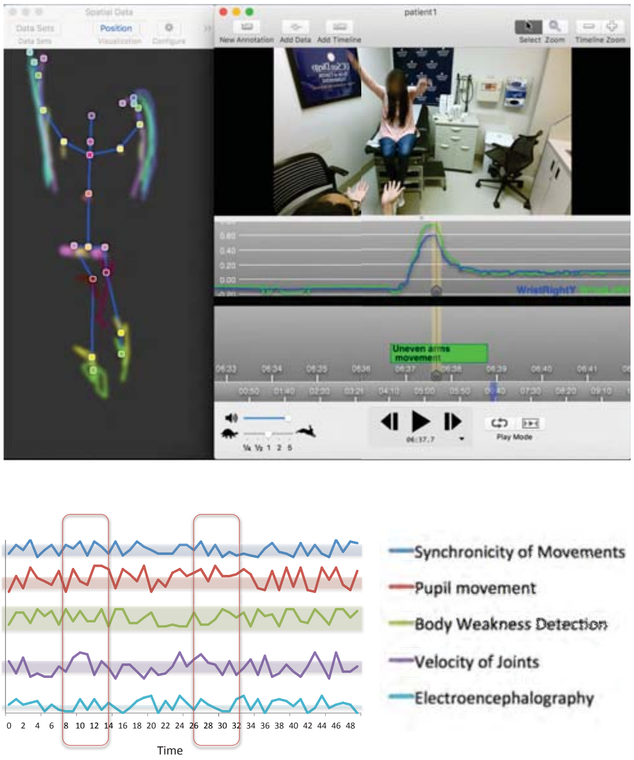

Figure 1: Top: Body tracking data collected from a patient during a neurological assessment visualized in the multimodal analysis tool ChronoViz [16]. One of the arms of the patient was abnormally asymmetric during analysis, indicating higher likeliness of stroke conditions. Bottom: envisioned characterization of problematic moments in time, across modalities

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[1] http://microsoft.com/hololens

[2] http://developer.microsoft.com/kinect

patients run through a battery of speech-based, motor-based, and coordination-based tasks and tests to assess neurological condition. We isolate features indicative of positive and negative stroke diagnosis, with the ultimate goal to provide tools that help to augment doctors' diagnostic abilities.

Beyond our initial work that looks at synchronicity of movements [33] and hemipareis [32], we envision the integration of a variety of machine learning algorithms that will lead to the design and deployment of a system which can autonomously and remotely (i.e. using Telemedicine) aid triaging through *sensing*. Our broader aim is to integrate these algorithms and techniques beyond the outpatient rehabilitation clinic and beyond the current modalities. By simply placing a Kinect camera in front of a patient bed or in the waiting room in the emergency department of a hospital, we envision diagnosing a variety of stroke-associated symptoms while a patient is waiting for a neurologist to come in. We aim to integrate current detection techniques [33, 32] with other reliable methods that allow clinicians to characterize stroke in a real-time, emergency settings. In particular, our goal is to deploy a multimodal system, which analyzes and integrates these signals in such a way that they can provide a real-time *signature* of stroke. Moreover, we also believe that integrating body motion and posture analysis with the characterization of visual field deficits that can be achieved using computer vision on one side, and mobile non-invasive EEG monitoring that can extract abnormal signals and link them to specific pathologic brain waves pattern on the other side, will lead to a robust system that will perform well beyond the current stroke evaluation techniques.

In summary, we envision our multi-modal detection system to enable quick, objective, and accurate diagnosis of stroke, without the presence of an experienced neurologist. If a neurologist cannot immediately be seen, patients can first engage with our tools, which will interactively guide them through a basic battery of tasks previously been found to elicit the strongest signals for stroke diagnosis. This, in turns, will be providing just-in-time support to clinical staff through reports highlighting the positive and negative signals detected (see envisioned chart in Fig. 1, bottom), and potentially inform *intervention* in terms of the administration of the right medication, while reducing the time to diagnosis. By diagnosing stroke as soon as possible after its inception in such emergency settings, we hope to be able to increase the number of accurate administrations of the rt-PA, including in remote locations where neurologists are not available.

AUGMENTED REALITY IN SURGERY AND SIMULATION

Although the concept of Virtual Reality (VR) and Augmented Reality (AR) is not new, recent developments in this technology have paved the way forward, creating a different kind of augmented reality, commonly referred to as Mixed Reality (MR). MR allows for the seamless integration of virtual objects into the real world. Deeply grounded in physical reality, these computer-generated entities behave and react in accordance with user actions as though they themselves were real world objects. These objects blend in with a user's own reality, enabling them to integrate with and to anchor themselves onto real objects, mixing the virtual with the physical.

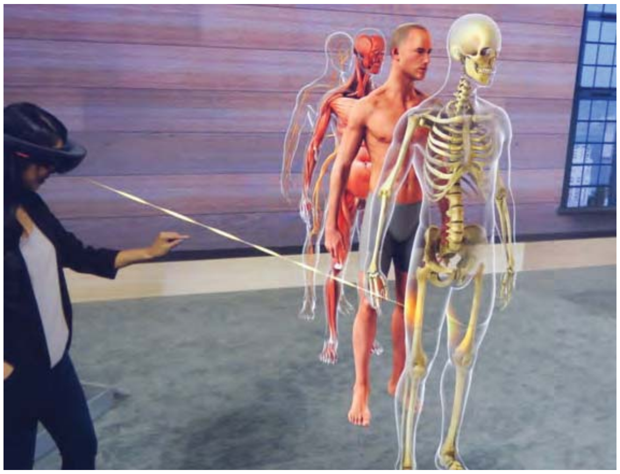

Figure 2: Microsoft HoloLens' user interacting with the projected hologram of a body (source: Microsoft Demo)

What makes wearable MR compelling in medicine is that it enables physicians to work with both virtual and real at the same time: detecting important features with the naked eye [2] while going further within the body without the need to look at an external monitor [4]. By making use of new Augmented Reality devices such as the Microsoft Hololens it is possible to provide a more realistic means for interaction with the simulation world. Information and visualization are provided at the location where it is relevant and needed, rather than on remote displays and screens which require effort to transform the information from the digital realm to the physical. Figure 2 shows an example of a holographic representation of a body, floating in front of a HoloLens' wearer.

In our work with expert surgeons we are exploring how Mixed Reality and HoloLens can be integrated as part of the next generation of surgery and support enhanced capabilities in different situations [17]. We summarize here the potential of this technology for remote and augmented surgery.

Remote Surgical Guidance and HoloPresence

The intent of tele-mentoring systems in surgery is to provide visual instruction to a local surgeon during specific operations. We envision remote surgeons using mixed reality teleconferencing clients to have access to a view of the local surgeon's point-of-view, and be able to directly engage with the surgery field in an interactive way. This will create virtual spaces around a body to be operated and remote surgeons can use these spaces to mark places on the body, guiding local surgeons in terms of *where* to operate, similar to [8].

Remotely located surgeons that have a specialization in certain kinds of operations can guide novice surgeons during particularly challenging operations. Guiding would be achieved through annotations on the 3D space, allowing the physically present surgeon to focus, operate and act based on the locations marked in the virtual space, extending the work on telestration [26] to augmented and mixed reality environments.

Figure 3: Mixed Reality training though immersive imaging. Left: CT Scan image integrated within the body of a mannequin during a simulation training with medical students. Right: Ultrasound imaging projected into the body of a mannequin.

In order to make the remote experience more realistic we envision this interaction to be supported by a remote virtual reality system (e.g. using HTC Vive[3]) connected to the local MR environment (e.g. using HoloLens). The remote surgeon could then be projected into the real world space through HoloPresence or HoloPortation [29].

Augmented Reality Training and Immersive Imaging

Besides the real-time HoloPresence, mixed reality could also be used to record a surgery from the perspective of the surgeon, creating a 3D video of the operation that could be letter used for teaching or evaluation. This could be also used in training to guide a novice surgeon to perform a simulated surgery, *following the example* of the experienced surgeon.

Analogously, we are exploring how augmented reality can be employed as an in-place display for imaging scans (see Fig. 3). The source can be sonograms [24, 20], CT scans, MRI, or the infrared light reflected by indocyanine green [28]. Mixed reality could help here by allowing the surgeon to focus on the patient, while the images are directly displayed on his/her body, and avoid the artificial interaction with a separate display. Ultimately this could help supporting a better visualization of important structures — such as organs, vessels or tumors — or enabling a greater accuracy in dissection or resection.

In summary, we believe that introducing augmented and mixed reality in surgery, especially when coupled with pervasive sensing and augmentation of the environment, will enable more effective just-in-time feedback and guidance, whether this occurs while skills are taught in simulation or during actual surgeries. Leveraging augmented reality in this setting will support the design and deployment of means for visually augmenting various surgical procedures and enabling the effective evolution of telemedicine to an immersive experience.

DISCUSSION AND CONCLUSION

In this paper we shortly introduced the emerging potential of new technology for sensing, intervening and visualizing in the healthcare setting. Specifically we presented two areas and two specific examples that make use of cutting edge technology based on situated sensors and machine learning on one side, and augmented and mixed reality on the other side. We believe that both of these paradigms will be key contributors to the future of telemedicine.

With the advent of mobile health and wearable devices, more and more sensing and computation will be done remotely at the patient's location, and pervasive devices and sensors will be able to collect incredible amounts of information. We envision a new kind of data science that will be performed in real-time and directly in the field, as one of the key element of the next generation of telemedicine. Instead of deploying specialized medical infrastructure in remote locations, or relying on (low-quality) video conferencing, our own devices will become the eyes and ears of the clinicians in the field. Telemedicine will therefore be supported by a new stream of interpreted data that will flow back to specialists in the hospital, and that will inform faster and more specific interventions. In the case of stroke, we envision emergency responders to be able to use a wearable version of UbiStroke that will allow them to collect data on-site about possible indicators for stroke and reach a diagnosis — either stand-alone or with the collaboration of a remote neurologist — through a direct interpretation of the stroke signature that UbiStroke will generate.

On the other side, the new wave of visualization and interaction that augmented and mixed reality technology is enabling, will allow the explosion of remote assistance, as well as better integration of data visualization in the medical field, which will benefit both experts and novices. We envision the next generation of surgeons to be able to collaborate through combined virtual and mixed reality interfaces, where telepresence will become HoloPresence, and remote experts can be projected into the surgical field and be instrumental for guiding complex procedures. Furthermore, we expect the next generation of telemedicine to embrace the integration of mixed reality with pervasive sensing and their potential to interpret the current patient medical context (i.e. recognizing the heart rate variability, or the breathing pattern of a patient). This will lead to a future where augmented reality will become part of every medical procedure, and even be integrated in the future first aid kits as a way to help novices or non-trained individuals to save a life.

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[3] http://www.vive.com

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