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What's Hot in Intelligent User Interfaces

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Abstract

The ACM Conference on Intelligent User Interfaces (IUI) is the annual meeting of the intelligent user interface community and serves as a premier international forum for reporting outstanding research and development on intelligent user interfaces. ACM IUI is where the Human-Computer Interaction (HCI) community meets the Artificial Intelligence (AI) community. Here we summarize the latest trends in IUI based on our experience organizing the 20th ACM IUI Conference in Atlanta in 2015.

At ACM IUI, we address the complex interactions between machine intelligence and human intelligence by leveraging solutions from machine learning, knowledge representation and new interaction technologies. Although submissions focusing on only Artificial Intelligence (AI) or Human Computer Interaction (HCI) will be considered, we give strong preferences to submissions that discuss research from both AI and HCI simultaneously. Typical IUI topics include intelligent input technologies (e.g., interpretation of speech, gesture, eye gaze, posture and physiological signs), smart data presentation technologies (e.g., visualization, text summarization and multimedia content generation), adaptive and personalized user interfaces, intelligent assistant for complex tasks, interactive data analysis (e.g. interactive machine learning and information retrieval), and intelligent interfaces for ubiquitous computing, wearable computing, affective computing, human robot interaction and recommender systems. In the following, we present some recent advances and main challenges in IUI.

New Trends in IUI

Since the topics in IUI are quite diverse, here we only highlight a few recent trends.

Sensor-based New Interaction Paradigms

Previously, the primary modes of human-computer interaction include voice, keyboard, GUI, simple gesture on touch screens, and eye tracking. With the recent advancement of build-in sensors that support high definition image and audio processing, motion detection, location detection and gesture detection, innovative sensor-based interaction paradigms have emerged. For example, at IUI 2015, conductive hair extensions were used to send messages, record conversations and control cameras (Vega, Cunha, and Fuks 2015) (Figure 1). Also, the availability of new body-tracking devices such as Microsoft Kinect have contributed significantly to the development of Natural User Interfaces that use touchless hand gestures (Erazo and Pino 2015). Ambient sounds captured with a wrist-mounted device were used to detect the type and amount of food consumed for dietary self-monitoring (Thomaz et al. 2015). Surface electromyography (sEMG) signals were used to capture subtle gestures to improve the accessibility of mobile devices for users with visual impairments (Costa 2015). In addition, sensors built in commodity smartphones were used to recognize gestures (Zhang et al. 2015), and detect physiological signs (e.g, heart rate) (Fan and Wang 2015).

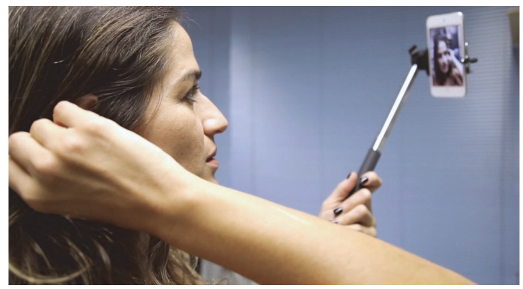

Figure 1: Take a Selfie with Hairware

We expect this trend to continue. Recently, Google has teamed up with Levis to announce Project Jacquard, an effort to create clothing items that can alert wearers of weight gain. The sensors used are so thin that they can be directly woven into garments. Users can use body gestures such as leg crossing, swiping and lifting to interact with devices (e.g., smart phones).

Human-Centered Data Analysis

While significant advances in machine learning and data mining continue in improving the accuracy and efficiency of data analysis algorithms, another equally important goal has garnered less attention: usability. For example, many data analysis algorithms are difficult to understand, hard to use and unable to adapt. The performance metrics used to evaluate these algorithms (e.g., perplexity) are not always consistent with human judgement.

To make data analysis more user-friendly, smart interaction techniques such as interactive data visualization are often used. At IUI 2015, we continue to see the coupling of data analysis and information visualization. For example, visualizations were used in supporting interactive text analysis (Dinakar et al. 2015) , event analysis (Malik et al. 2015), graph analysis (Pienta et al. 2015) and structured data analysis (Lallé et al. 2015).

Recently, a trend has emerged in which new machine learning algorithms were developed to directly address the usability issues in data analysis. For example, (Yang et al. 2015) proposed a new constrained topic modeling algorithm for document analysis. The new algorithm can avoid the inconsistency and instability problem in the classic topic modeling algorithm LDA (Blei, Ng, and Jordan 2003).

Finally, instead of treating machine learning algorithms as blackboxes, better explanation of the inference process was proven to be more effective in increasing participants' understanding of the learning system and their ability to correct system mistakes than using a traditional learning system (Kulesza et al. 2015).

Pervasive Affective Computing

Affective computing is a component in developing intelligent user interfaces that are capable of detecting and responding to the affective needs of users. Since human emotions are often expressed via speech, facial expressions, body postures and physiological signs (e.g., skin conductivity, pupillary dilation and heart rate), detecting and responding to human emotions often require sophisticated signal processing technologies (e.g., computer vision, speech processing and machine learning). So far, affective computing has been adopted in social interactions such as video sharing (Kwok et al. 2015) and in tutoring systems to detect and respond to student's emotional states (e.g., boredom, confusion, delight, engagement, and frustration)(Bosch et al. 2015).

With the recent advancement of distance sensing devices such as Google glass and up-close sensing devices (e.g., wristband), affective computing becomes increasingly pervasive. For example, with Google glass, a computer system can now detect the emotional and physiological state of people accurately.

Main Challenges in IUI

Since IUI is a multidisciplinary area, solutions to typical IUI problems often require close cross-disciplinary research collaborations. For example, to enable human-centered data analysis, we need researchers from machine learning (ML), data visualization and HCI to work closely together. Currently, in the analytics community, there is a lack of awareness of the importance of developing ML algorithms that take human factors into consideration. Moreover, in terms of pervasive affective computing, it is unclear how this will impact our privacy since it is possible for anyone wearing a Google glass to detect our emotional and physiological states accurately during social interactions.

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