PhilHumans

Conversational Interfaces for Personal Health

Abstract

Ruben Alonso[1], Sebastiano Battiato[4], Sergio Consoli[2], Giovanni Maria Farinella[4], Aki Härmä[7], Rim Helaoui[7], Milan Petkovic[5], Diego Reforgiato Recupero[6], Ehud Reiter[3], Daniele Riboni[6], and Raymond Sterling[1].

Abstract *Health self-management and home care are very important for future healthcare. The trend is driven by societal changes and the developments in technology. In this position paper, we give an overview of trends and opportunities in personal health services based on interactive cognitive interfaces and spoken dialog systems.*

[1]R2M Solution Spain SL, [2]Joint Research Centre, Italy, [3]University of Aberdeen, Scotland, [4]University of Catania, Italy, [5]TU Eindhoven, NL, [6]University of Cagliari, Italy, [7]Philips Research, Eindhoven, NL.

Introduction

01

Many chronic health conditions such as diabetes, obesity, substance abuse, and sleep disorders, can be helped by a lifestyle change. Passive health self-management services with a watch and a tracking app do not seem to be very effective for lifestyle change [12, 35]. Health counseling, on the other hand, is known to work [32, 22]. However, health counseling is expensive and do not scale well in a world with a growing deficit of healthcare workers [6]. One solution for personal health selfmanagement is automated counseling, AC. After 50 years of research, see, e.g., [5], the recent progress in dialog system technologies is finally making AC a realistic option. AC has also recently been shown to be effective in a controlled trial [13].

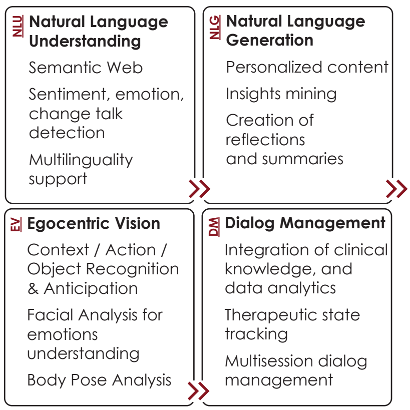

Fig. 1 Challenges in conversations technologies and applications for health self-management.

We believe that collaborative care management with a conversational agent will be central for future health self-management. The key element is the engaging dialogue which makes the user reflect own lifestyle choices and barriers, and find opportunities and motivation for a change [29]. This requires advances in sensing technology, model-based cognitive interaction technologies, and embodiments. Figure 1 lists enabling technologies that we believe are central for conversational interfaces in health self-management, but where also breakthroughs are needed.

Enabling technologies

02

Users may have a very different lifestyle and requirements, which requires highly adaptive solutions. In NLU, NLG, and dialog management [3, 18] there is a clear progression towards deep E2E solutions which provide flexibility over conventional rule-based systems [9, 19, 26]. However, in healthcare, it is very important to be able to combine data-driven learning with validated clinical knowledge [31], which is a challenge for many deep learning solutions. The system must understand what the words of the user mean in the desired clinical and therapeutic setting [8, 7], and how the output is expected to influence the user, and the goals of the counseling.

In order to lead a meaningful conversation about the lifestyle of the user, the system has to have a good understanding of it. This requires data-driven techniques for modeling of the lifestyle [21, 36], and situational intelligence, which can put the conversation in the right context [2]. In particular, wearable sensors and egocentric vision systems [23], together with cameras integrated into the dialog agent, seem to be necessary for human-level situational intelligence. Wearable computing has a long history [4, 28], it has become of more interest in the last years with the advancement of both hardware and software technologies [17]. The main applications of FPV systems in the context of assistive Computer Vision [25] is related to memory augmentation [1] and life logging [15, 20, 30]. Recent studies have also considered the FPV paradigm to recognize important objects observed by user [24] and to understand or to anticipate the actions and activities performed by the user [10, 14, 33, 34] or the next object to which the user is going to interact with [16]. A robotic embodiment for the conversational agent is another way to extend the capabilities of the agent. Robotic embodiments have proven to attract more interest and engagement from patients rather than other technologies. Different studies [27, 11] reported that both old and young adults preferred to interact with embodied robot over the non-embodied computer screen, and thus carebots may offer benefits over smartphones or tablets in delivering healthcare.

Acknowledgements

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The research leading to his paper/project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie training network PhilHumans[1] - Personal Health Interfaces Leveraging HUman-MAchine Natural interactionS under grant agreement 812882.

Beneficiaries

- Philips Research Laboratories in Eindhoven
- Technische Universiteit Eindhoven
- University of Cagliari
- University of Catania
- University of Aberdeen
- R2M Solution Spain

Partners

- University of Essex
- Bruno Kessler Foundation
- National University of Ireland Galway
- Philips Research North America
- University Paris Nord 13
- Zora Robotics N.V.
- Arria NLG
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- University of Pavia
- University of Tilburg

[1]https://www.philhumans.eu

PhilHumans Doctoral Projects

04

Eight industrial doctorate research fellowships are offered within the framework of PHILHUMANS.

1. Computational intelligence for behavior understanding

2. A conversational agent as a digital counsellor for automated therapy

3. Deep program induction for personal health services

4. NLP, semantics and setiment analysis from text

5. Scene understanding and interaction anticipation from first person vision

6. Face analysis and body language understanding from egocentric cameras

7. Natural language generation for personalised health communication

8. Business economics and robotics

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