Emotion Recognition in the Wild: Results and Limitations from Active and Healthy Ageing Cases in a Living Lab

Evdokimos I. Konstantinidis, Antonis Billis, Theodore Savvidis, Stefanos Xefteris, and Panagiotis D. Bamidis(✉)

Lab of Medical Physics, Assistive Technologies and Silver-Science Group, Medical School, Aristotle University of Thessaloniki, Thessaloniki, Greece
evdokimosk@gmail.com, {ampillis,bamidis}@med.auth.gr, teosavv@yahoo.gr, sxefteris@auth.gr

Abstract. The work presented in this paper relies on the recognition of emotions during pilot trials with elderly people in an ecologically valid living lab. The emotion recognition is processed by cloud based service and the photos for processing are captured from Kinect based on the skeleton presence and information. The Kinect publishes its information to a channel where the clients subscribe efficiently either to the skeleton or the RGM images channel.

Keywords: Emotion · Living lab · AAL · Elderly · IoT

1 Introduction

In the research field of Ambient Assisted living, a shift towards monitoring elderly people status remotely, providing the physicians with information not only on physical, but also the psychological health [1, 2] has been identified. The emerging trends are behavioral profiling and activity monitoring in the wild as parts of decision support implementations in AAL context [3, 4]. Face [5], body language and vocal cues [6, 7] are the dominant modalities for emotion recognition.

So far, in the unobtrusive emotion recognition domain, efforts are mostly made in "in-vitro" ideal set-ups while the real challenge is multimodal emotion recognition in the wild, in ecologically valid environments. Although a lot of facial expression recognition systems have emerged with good accuracy [8], emotion recognition in the wild remains a challenging problem due to diversity in scenes in the form of head pose, illumination, occlusion and background noise [9].

2 Materials and Methods

The work presented in this paper relies on the recognition of emotions during pilot trials with elderly people in an ecologically valid living lab. The emotion recognition is processed by cloud based service and the photos for processing are captured from Kinect based on the skeleton presence and information.

K. Giokas et al. (Eds.): eHealth 2016, LNICST 181, pp. 425–428, 2017.
DOI: 10.1007/978-3-319-49655-9_51

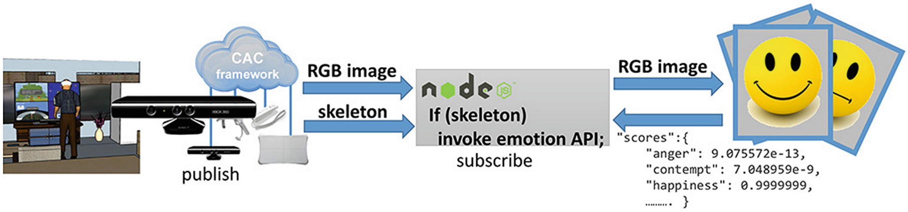

Fig. 1. Architecture of the emotion recognition approach exploiting the IoT infrastructure in Active and Healthy Ageing related pilots in living labs.

2.1 Architecture

The Controller Application Communication framework (CAC-framework) [10], based on the publish/subscribe messaging pattern in line with the IoT paradigm, is a cross device/application framework built on top of the Webockets. Design to support high throughput for real time streaming of information published from gaming controller, such as Kinect, Wii and Emotiv [11], JSON messages are exchanged among the devices and applications in the same session [12].

In the work presented in this paper (cf. Fig. 1), a NodeJs client subscribes to the skeleton information of the Kinect. Every time a skeleton is detected, the NodeJs client subscribes to the RGB image channel of the Kinect, gets the first streamed image and unsubscribes from this channel to avoid wasting bandwidth. Thereafter, the image is sent to the Emotion API of the Project Oxford[1] [13] and the emotion information is returned back. This information is then enriched with information pertaining to the skeleton position and rotation (from the body shoulders). The NodeJs application does not capture images more frequently than 5 s.

2.2 Experiment

Lab pilots ran in Thessaloniki, in the Active & Healthy Aging Living Lab (http://aha-livinglabs.com). There, a living room environment and a kitchen environment were set up in the same room and equipped unobtrusively with the necessary recording infrastructure, including the Kinect sensor. Each participant visiting the Living Lab was going through some daily activities [14], interaction with smart devices and exergaming play [15] for approximately 60–90 min (cf. Fig. 2). This study presents results of 6 sessions for 2 seniors. The CAC Playback Manager [16] was utilized to reproduce the experiment by playing back the recorded datasets.

[1] https://www.projectoxford.ai/demo/emotion#detection.

Fig. 2. The senior in the AHALL along with the skeleton detected information.

3 Results

In Table 1 emotions detected represents the number of images where at least one face emotion has been detected (along with the average value of three emotions) while the images analyzed is the total number of images sent to the Emotion API for processing. The max distance and body angle (shoulders rotation) are the maximum corresponding values of the skeleton when an emotion is detected.

Table 1. Emotions detected along with the seniors position and rotation

Actor#	Day#	Duration (mins)	Emotions detected	Images analyzed	Max distance (m)	Max body angle	Anger	Happy	Sad
1	1	87	334	667	2.42	41	0.005	0.008	0.017
1	2	88	252	665	2.5	68	0.004	0.024	0.003
1	3	124	350	1191	2.48	78	0.004	0.033	0.005
2	1	103	210	1035	2.44	39	0.009	0.100	0.051
2	2	135	347	1738	2.43	41	0.021	0.048	0.069
2	*3*	98	147	1305	2.54	42	0.012	0.070	0.033

4 Discussion

This work presents a first approach towards identifying the limitations of emotion recognition in the wild. Since the existing methodologies are far from perfect, a contextual approach to application should be considered. For example, since our findings indicate that existing algorithms perform better when the subject is less than 2.5 m away and with facing angle up to 70°, it follows that context aware emotion recognition could be more accurate in the IoT domain. On the other hand, the purpose of this work is to underline existing limitations and provide points on which we could focus our research for improving existing methodologies.

Acknowledgments. This work was supported in part by the UNCAP Horizon 2020 project (grant number 643555), as well as, the business exploitation scheme of the ICT-PSP funded project LLM, namely, LLM Care which is a self-funded initiative at the Aristotle University of Thessaloniki (www.llmcare.gr).

References

1. Xefteris, S., Baboshin, A., Tserpes, K., Androulidakis, A., Glickman, Y., Varvarigou, T., Haritou, M., D'Andria, F.: Enabling risk assessment and analysis by event detection in dementia patients using a reconfigurable rule set. In: Proceedings of the 4th International Conference on PErvasive Technologies Related to Assistive Environments, p. 47 (2011)
2. Haritou, M., Glickman, Y., Androulidakis, A., Xefteris, S., Anastasiou, A., Baboshin, A., Cuno, S., Koutsouris, D.: A technology platform for a novel home care delivery service to patients with dementia. J. Med. Imaging Heal. Inform. **2**, 49–55 (2012)
3. Xefteris, S., Andronikou, V., Tserpes, K., Varvarigou, T.: Case-based approach using behavioural biometrics aimed at assisted living. J. Ambient Intell. Humaniz. Comput. **2**, 73–80 (2010)
4. Billis, A.S., Papageorgiou, E.I., Frantzidis, C.A., Tsatali, M.S., Tsolaki, A.C., Bamidis, P.D.: A decision-support framework for promoting independent living and ageing well. IEEE J. Biomed. Health Inform. **19**, 199–209 (2015)
5. Ekman, P., Friesen, W.V., Ellsworth, P.: Emotion in the human face. In: Guidelines for Research and an Integration of Findings (2013)
6. Singh, S., Sharma, V., Jain, K., Bhall, R.: EDBL-algorithm for detection and analysis of emotion using body language. In: 2015 1st International Conference on Next Generation Computing Technologies (NGCT), pp. 820–823 (2015)
7. Martinez, L., Falvello, V.B., Aviezer, H., Todorov, A.: Contributions of facial expressions and body language to the rapid perception of dynamic emotions. Cogn. Emot., 1–14 (2015)
8. Song, K.-T., Lin, C.-Y.: Robust facial emotion recognition using a temporal-reinforced approach. In: 2014 14th International Conference on Control, Automation and Systems (ICCAS), pp. 804–807 (2014)
9. Dhall, A., Ramana Murthy, O.V., Goecke, R., Joshi, J., Gedeon, T.: Video and image based emotion recognition challenges in the wild: EmotiW 2015, pp. 423–426 (2015)
10. Konstantinidis, E.I., Antoniou, P.E., Bamparopoulos, G., Bamidis, P.D.: A lightweight framework for transparent cross platform communication of controller data in ambient assisted living environments. Inform Sci. **300**, 124–139 (2014)
11. Konstantinidis, E., Conci, N., Bamparopoulos, G., Sidiropoulos, E., De Natale, F., Bamidis, P.: Introducing Neuroberry, a platform for pervasive EEG signaling in the IoT domain. In: Proceedings of the 5th EAI International Conference on Wireless Mobile Communication and Healthcare - "Transforming Healthcare Through Innovations in Mobile and Wireless Technologies." ICST (2015)
12. Konstantinidis, E.I., Antoniou, P.E., Billis, A., Bamparopoulos, G., Pappas, C., Bamidis, P. D.: leveraging web technologies to expose multiple contemporary controller input in smart TV rich internet applications utilized in elderly assisted living environments. In: Stephanidis, C., Antona, M. (eds.) UAHCI 2014. LNCS, vol. 8515, pp. 118–128. Springer, Switzerland (2014). doi:10.1007/978-3-319-07446-7_12
13. Microsoft Project Oxford seconds that emotion: Biometric Technol. Today **2016**, 2 (2016)
14. Billis, A.S., Katzouris, N., Artikis, A., Bamidis, P.D.: Clinical decision support for active and healthy ageing: an intelligent monitoring approach of daily living activities. In: Pereira, F., Machado, P., Costa, E., Cardoso, A. (eds.) EPIA 2015. LNCS (LNAI), vol. 9273, pp. 128–133. Springer, Switzerland (2015). doi:10.1007/978-3-319-23485-4_14
15. Konstantinidis, E.I., Bamparopoulos, G., Bamidis, P.D.: Moving real exergaming engines on the web: The webFitForAll case study in an active and healthy ageing living lab environment. IEEE J. Biomed. Health Inform. (2016). Accepted
16. Konstantinidis, E.I., Billis, A.S., Bratsas, C., Bamidis, P.D.: Active and healthy ageing big dataset streaming on demand. In: HCI International 2016 (2016)