Inferring Human Behavior by means of Multimodal Context Mining

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Abstract. Changing human behavior is a societal priority to lessen the actual prevalence of lifestyle diseases. To identify unhealthy routines and promote beneficial behaviors a precise and seamless monitoring and description of people conducts is required. Although many digital applications and systems are increasingly available for the collection and analysis of behavioral data, current solutions are certainly insufficient to cope with the complexity of human behavior characterization. This work presents a more sophisticated approach combining multiple context-awareness technologies to cope with the analysis of people's conduct from a holistic perspective. Activity recognition, emotion identification and location discovery techniques are integrated together with ontological mechanisms as part of a novel framework to comprehensively infer human behavior. The foundations and main architectural components of this framework are introduced in this paper.

Keywords: Human behavior, Context-awareness, Activity Recognition, Location Tracking, Emotion Recognition, Semantics, Ontologies

1 Introduction

Lifestyle choices can have a tremendous impact on people's health and wellness [13]. Avoiding unhealthy habits is nowadays a priority, and to achieve this goal, individuals' awareness and more solid expert knowledge are required. Data collected during doctor visits and traditional self-report mechanisms normally fail to fairly represent people's conduct [11]. A variety of digital monitoring systems have been proposed to date to automate this process and increase the level of precision while detecting human behavior [8, 10, 6, 7, 3]. Not only research prototypes but also commercial systems have recently arisen in this context to overcome the limitations shown by traditional approaches [14, 5, 4, 9]. However, most existing solutions are domain-centric and technology-dependent, thus fundamentally supporting the detection and logging of primitive context information by using a limited set of sensing devices. This work briefly introduces a Multimodal Context Mining framework intended to infer human behavior in a more holistic fashion through mining heterogeneous person-centric data. This framework is the core of "Mining Minds" [1, 2], an innovative digital platform to enable the provision of personalized healthcare and wellness support.

2 Multimodal Context Mining Framework

The framework is composed by two main modules, namely, Low Level Context Awareness (LLCA) and High Level Context Awareness (HLCA). LLCA is in charge of converting the wide-spectrum of data obtained from the user interaction with the real and cyber-world into low-level contexts or categories, i.e., activities, emotions and locations. To that end, the heterogeneous sensory data coming from the user monitoring devices is first processed by the Sensory Data Router. This component is in charge of identifying which low-level context recognizer(s) may operate on the incoming data, thus distributing it accordingly. It is worth noting that different recognizers may leverage the same data or combinations of data, e.g., the same video data can be used to recognize the user's activity and the user's emotion, which constitutes a key advantage with respect to standard domain-specific context-aware systems. Different machine learning models are used for the identification of the user low-level context, which are here named according to the sensing modality they build on, i.e., Inertial/Video/Audio Activity Recognizer, Physiological/Video/Audio Emotion Recognizer and Inertial/Video/Geopositioning Location Detector. The decisions delivered by each of these models are fused for every context category through the Activity Unifier, Emotion Unifier and Location Unifier respectively. Every time

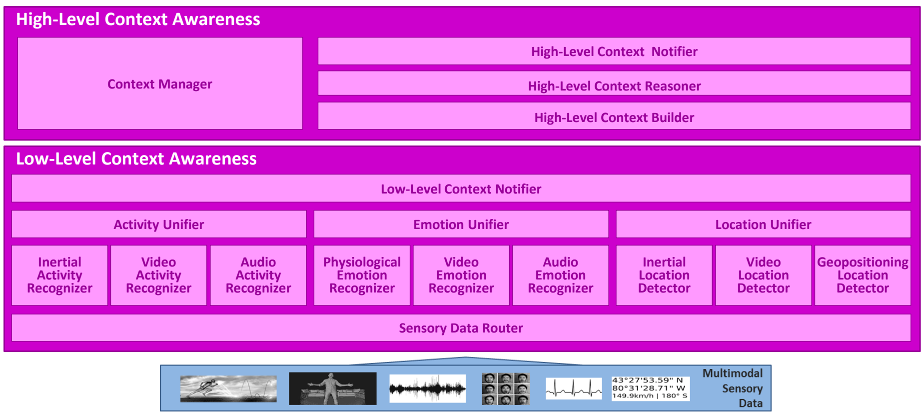

Fig. 1. Multimodal Context Mining Framework.

a new low-level context is identified, for example, a new activity is performed by the user, the Low-Level Context Notifier provides the potential subscribed applications or consumers with this information.

Activities, emotions and locations are valuable information for neatly describing the user's behavior. However, some more elaborated and comprehensive contextual descriptions can be obtained out of them. Accordingly, the detected low-level context categories are served to HLCA for further analysis and mining. First, the High-Level Context Builder semantically interprets the low-level context categories or labels, i.e., activity (e.g., `sitting`), emotion (e.g., `boredom`) or location (e.g., `office`), and maps them into ontological concepts according to the Context Ontology model [12]. The Context Ontology models diverse high-level contexts as combinations of the three considered low-level context categories. Once a given low-level context is mapped, e.g., an activity, the concurrent low-level values for the other two categories are sought, in this case, location and emotion, and then combined into an instance of high-level context. This instance is input to the High-Level Context Reasoner, which uses the Context Ontology and reasoning techniques for its classification. Thus, for the above example (`sitting`&`boredom`&`office`), the identified high-level context would be `office work`. Finally, as for the low-level context information, the High-Level Context Notifier informs the subscribed applications whenever a change in the high-level context is identified for a given user.

3 Conclusions

A novel approach to holistically identify context information for behavior tracking has been presented in this paper. The proposed system combines low level context-awareness models devised to recognize activities, emotions and location primitives from multimodal person-centric data. This information is further considered to sophisticatedly infer high-level context categories by using ontological reasoning techniques. The framework has been implemented and validated, and it is currently under evaluation. The outcomes of this evaluation and more specific details of the implementation are planned to be included in an extended version of this paper.

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References

1. Oresti Banos, Muhammad Amin, Wahajat Khan, Muhammad Afzal, Taqdir Ali, Byeong Kang, and Sungyoung Lee. Mining minds: an innovative framework for personalized health and wellness support. In *Proceedings of the 9th International Conference on Pervasive Computing Technologies for Healthcare*, 2015.

2. Oresti Banos, Muhammad Amin, Wahajat Khan, Maqbool Hussain, Muhammad Afzal, Byeong Kang, and Sungyoung Lee. The mining minds digital health and wellness framework. *Biomedical Engineering Online*, 2016. Online.
3. Francesco Calabrese, Laura Ferrari, and Vincent D Blondel. Urban sensing using mobile phone network data: a survey of research. *ACM Computing Surveys*, 47(2):25, 2015.
4. Fitbit Surge. Available online: https://www.fitbit.com/surge (accessed on 29 Aug 2015).
5. Garmin Vivofit. Available online: http://sites.garmin.com/en-US/vivo/vivofit/ (accessed on 29 Aug 2015).
6. Ozlem Durmaz Incel, Mustafa Kose, and Cem Ersoy. A review and taxonomy of activity recognition on mobile phones. *BioNanoScience*, 3(2):145–171, 2013.
7. Andrea Kleinsmith and Nadia Bianchi-Berthouze. Affective body expression perception and recognition: A survey. *IEEE Transactions on Affective Computing*, 4(1):15–33, 2013.
8. Oscar Lara and Miguel Labrador. A survey on human activity recognition using wearable sensors. *IEEE Communications Surveys Tutorials*, PP(99):1–18, 2012.
9. Misfit Shine. Available online: http://www.misfitwearables.com/products/shine (accessed on 29 Aug 2015).
10. Oluwatoyin Popoola and Kejun Wang. Video-based abnormal human behavior recognition-a review. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 42(6):865–878, 2012.
11. Robert Shephard. Limits to the measurement of habitual physical activity by questionnaires. *British Journal of Sports Medicine*, 37(3):197–206, June 2003.
12. Claudia Villalonga, Oresti Banos, Wahajat Ali Khan, Taqdir Ali, Muhammad Razzaq, Sungyong Lee, Hector Pomares, and Ignacio Rojas. High-level context inference for human behavior identification. In Ian Cleland, Luis Guerrero, and Jose Bravo, editors, *International Work-conference on Ambient Assisted Living an Active Ageing*, volume 9455 of *Lecture Notes in Computer Science*, pages 164–175. Springer International Publishing, 2015.
13. WHO. Global status report on noncommunicable diseases 2014. Technical report, World Health Organization, 2014.
14. Withings Activité. Available online: www.withings.com/eu/en/products/activite (accessed on 29 Aug 2015).