Supporting Large-scale Pervasive Sensing via Distributed Edge Computing

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***Abstract*—This thesis is focused on investigating a better support for large-scale sensing platforms which are dedicated to inference of social interaction, among other aspects. The main expected outcome are mobile edge based mechanisms that can reduce latency and energy consumption of these platforms, by leveraging the network to best adjust to data computation requirements and to context.**

I. Introduction

Nowadays, mobile phones' usage is increasing as an integral part of the daily lives of billions of people [1]. Such mobile devices are today equipped with large storage capacity; a large variety of sensors; capability to transmit data directly between devices in the proximity.

Such novel features and in particular their sensorial capability are relevant in the context of monitoring quality of living and well-being aspects such as physical health conditions, personal management, personal behavior awareness [2]. In this context, there has been recently a surge of related work focused on the development of middleware and subsequent studies that can assist, in a less intrusive way, a better understanding of different dimensions of well-being.

Despite the fact that there seems to be a growing interest in the aforementioned context, today there is no clear understand on how to best develop such tools, which sensors are best applicable to which type of activity detection and/or recognition; which models best suit learning and inference, where and when on the network to capture and to handle data. Adding to this, there are computational aspects ranging from data capture, until data inference and visualization. These processes require heavy computation, which today is supported via cloud-based mechanisms.

Large-scale pervasive sensing environments are, however, people-centric, and usually based on devices that are carried by the user such as smartphones, smart watches, wristbands, or devices that are controlled by the user, e.g., specific *Internet of Things (IoT)* sets. Some, if not most of the data collected can be handled locally or in the edge of the network. This distribution can assist aspects such as data and user privacy. Edge-based computation can also assist in reducing overhead of these systems, as aspects such as calibration may be partially handled close to the end-user.

The focus of our work is therefore on contributing to a better support of large-scale pervasive sensing structures, via the development of algorithms that assist latency and energy consumption reduction based on mobile edge computing approaches.

II. Research Focus and Proposed Contributions

This thesis is focused on the reduction of end-to-end latency and energy consumption reduction in large-scale sensing environments via the development of mechanisms that can:

- Leverage networking architectures so that they better adjust to large-scale distributed sensing platforms, assuming highly mobile environments, and volatile data.
- Assist edge based data classification, providing the means for hierarchical classification, support of inference of human interaction, and to locally support aspects related with activity recognition, relevant in the context of human interaction behavior inference.

Our contributions are four-fold: i) to provide a better analysis on current sensors available, and how their captured data can be combined to perform different types of activity recognition and behavior; ii) to perform validation (based on living labs) of the potential for such tools to stimulate social interaction thus, for instance, improving communication and giving rise to higher levels of sociability; iii) to come up with new algorithms, heuristics, mechanisms that can assist in further developing sensing middlware in a way that allows pervasive sensing analysis to scale to large sets of users in close-to-real-time; iv) to validate our findings by building a framework prototype (proof-of-concept) that integrates our contributions.

III. Advancement Beyond Statement of the Art

A. Social Interaction

Large-scale sensing applications are expected to assist citizens in their daily activities, as well as to contribute to efficiency in the way resources are collectively consumed. There are several strategies considered to detect interaction with devices. Quantification of social interaction via sensing is a recent line of research, for which some aspects have already been addressed in related literature. Most work has been focused on distance estimation via sensing technology (Wi-Fi or Bluetooth) as well as the relation of distance and capacity to grasp real-world social interaction patterns [3].

Training personalized classification models can mitigate such problems. However, training a personalized model for each individual requires a large amount of individually tagged data. As a consequence, users are frequently forced to collect redundant training data which in fact a similar and nearby profile may have already collected, and such data is sent to the cloud.

According to Sofia et al. [4] social interaction provides an indication of how much device owners have interacted over time and space, derived from aspects such as the distance between these devices; the activity of sound level around the devices; the movement type of the devices. Such a capability is relevant to assist in a more accurate contextualization of proximity, of personal spaces and that can be applicable not only in a direct interaction context.

B. Inference and Estimation of Behavior Patterns

People-centric pervasive wireless systems usually recur to eager classification models that are normally fed by sets of data continuously collected from individual sensors (e.g., accelerometer, microphone, Bluetooth). Eager learner algorithms such as Decision Trees, Neural Network, construct general and explicit description of the target function based on the provided training examples and generalization beyond the training data is tried before receiving queries. Lazy learning algorithms, often applied in the context of wireless sensor networks, such as the k-Nearest Neighbour (k-NN) algorithm, store training data and wait until a query (test tuple) is performed [5].

Eager classification models present significant limitations to operate locally in mobile devices, such as smart phones, due to the amount of required resources (e.g., CPU, energy) and the need for continuous sensing strategies able to supply significant amount of data. To mitigate such limitations, researchers have been investigating methods to allow the deployment of people-centric sensing systems based on eager classification models by: reducing resources used in continuous sensing activities; relying on classification learning processes that run in cloud systems.

More relevant to large-scale sensing are algorithms that take into consideration prior learning, such as *Memory Based Reasoning (MBR)* [6], which is a lazy learning method that usually relies on k- NN to operate.

C. Context-awareness Network Aspects

Adequate network support to reduce resource consumption in large-scale pervasive sensing environments needs to take into consideration context aspects related with the end-user behavior for a specific purpose, for instance, to improve his/her well-being, to improve Quality of Experience, etc.. Context-awareness on the network should be derived from human interaction aspects, to best support data transmission and data computation. In proactive sensing systems, it is of great relevancy to know about people mobility profiles in order to analyse their impact on the collection and the use of the collected data in large communities.

Hence, it is important to devise metrics, algorithms, and mechanisms that take into consideration different aspects of a citizen routine to characterize specific contexts, e.g., well-being. Such contextualization is expected to be backed up by sensed data.

IV. Main Activities

This thesis work is on its first year of development, and has the following main activities: 1) Review on pervasive sensors and activity recognition (paper under submission); 2) Validation (based on realistic settings) of the potential of current tools to evaluate aspects of interaction; 3) Distributed Mechanisms, algorithms that can assist in supporting large-scale sensing frameworks. E.g., reduce energy consumption; 4) Framework prototype (Technology Readiness 4-6).

V. Status and Future Work

The current phase of work (first year) involves the analysis of the different concepts of edge computing, namely, fog computing, mobile edge computing, and cloudlet approaches in regards to large-scale sensing scenarios. For this purpose, we are starting to deploy a controlled Ambient Assisted Living scenario which is being worked upon in a local experimental IoT and wireless testbed, where specific middleware captures smart data such as interaction, sociability, interests, and exchanges it with other (trusted) devices. The middleware that we are currently considering for data capture is the open-source tool NSense [4], but our work is also being based upon data sets obtained via the Internet, as our core focus is not on data capture, but on mechanisms that reduce latency and energy consumption, derived from contextual information and local classification of such information. Based on this data, we expect to, in the future, develop heuristics that, based on local context, assist the network in understanding where and when to send, to storage, as well as to classify data.

In the future, and for large-scale experimentation, we shall recur to large-scale experimental environments, such as FIT-IoT and OpenLab.

References

[1] D. G. Blanchflower and A. J. Oswald, "Well-being over time in Britain and the USA," *Journal of Public Economics*, vol. 88, no. 7-8, pp. 1359–1386, 2004.

[2] K. Hänsel, "Wearable and ambient sensing for well-being and emotional awareness in the smart workplace," *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing Adjunct - UbiComp '16*, pp. 411–416, 2016. [Online]. Available: http://dl.acm.org/citation.cfm?doid=2968219.2971360

[3] N. Palaghias, S. A. Hoseinitabatabaei, M. Nati, A. Gluhak, and K. Moessner, "Accurate detection of real-world social interactions with smartphones," in *2015 IEEE International Conference on Communications (ICC)*. IEEE, 2015, pp. 579–585.

[4] R. Sofia, S. Firdose, L. A. Lopes, W. Moreira, and P. Mendes, "NSense : A People-centric , non-intrusive Opportunistic Sensing Tool for Contextualizing Nearness," in *2016 IEEE 18th International Conference on e-Health Networking, Applications and Services (Healthcom)*. IEEE, 2016, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/document/7749490/

[5] S. Dernbach, B. Das, N. C. Krishnan, B. L. Thomas, and D. J. Cook, "Simple and Complex Activity Recognition through Smart Phones," *2012 Eighth International Conference on Intelligent Environments*, pp. 214–221, 2012. [Online]. Available: http://ieeexplore.ieee.org/document/6258525/

[6] M. A. Alsheikh, S. Lin, D. Niyato, and H.-P. Tan, "Machine Learning in Wireless Sensor Networks: Algorithms, Strategies, and Applications," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 4, pp. 1996–2018, 2014. [Online]. Available: http://arxiv.org/abs/1405.4463{%}0Ahttp://dx.doi.org/10.1109/COMST.2014.2320099