A Social-driven Edge Computing Architecture for Mobile Crowd Sensing Management

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Abstract—The Multi-access Edge Computing (MEC) architectural model has fostered the development of new Human-Driven Edge Computing (HEC) frameworks that extend the coverage of traditional MEC solutions leveraging people roaming around with their devices. HEC is a well-suited architecture for human-centered technologies such as Mobile Crowd Sensing (MCS) as it allows to convey and distribute sensing tasks at the edges of the network, enabling also (local) sensing data collection from devices. This paper, through the joint use of HEC and MCS paradigms, introduces a new Social-Driven Edge Computing architecture based on incentives and centrality measures. The core idea is to add Social MEC (SMEC) nodes to complement the traditional edge nodes, i.e., the main actors of the middle-layer of the standard MEC architecture, acting as bridges between other devices and the cloud. The principle that underlies the SMEC selection is based on the attitude of the users in performing tasks and on their measures of centrality. In addition, we report extensive experimental results based on co-location traces and cooperativeness scores extracted from the ParticipAct living lab, a well-known MCS dataset based on data collected between 2013 and 2015 from 170 students of the University of Bologna, that show how the selection based on centrality measurements returns greater benefits than a simple selection based on cooperativeness scores.

Keywords—mobile crowdsensing; multi-access edge computing; human-driven edge computing; social mobility

I. INTRODUCTION

The widespread diffusion of mobile devices started at the end of the last century has experienced an exponential growth in recent years and we can assert that nowadays in developed countries, any person owns at least one mobile device. Such ubiquitous devices are typically equipped with sensors and both long-range and short-range communication interfaces. Sensors as accelerometers, gyroscopes, GPS, cameras, microphones, and so on allow to collect data in environments at any level of hostility. In addition, communication interfaces allow them to establish and maintain a continuous connection to the Internet, guaranteeing a potential communication channel with other devices spread all around the world. In this context, the synergistic use of all these functionalities has fostered the development of Mobile Crowd Sensing (MCS) that aims at leveraging this immaterial and highly sparse smart infrastructure to sense the real-world.

The Multi-access Edge Computing (MEC) is a recent paradigm presented as integral part of future 5G networks. It can be considered the direct evolution of the Mobile Cloud Computing (MCC) approach. The MEC support is based on platforms that host virtualized resources and that introduces an additional distributed tier made up of base stations (server proxies) between the more traditional cloud and device tiers. The proxies belonging to the intermediate MEC tier are physically deployed close to the devices they serve and typically offer multiple access possibilities. The general advantages that this type of infrastructure provides are low latency for end devices (e.g., because of local serving or cache hits by MEC nodes) and the facilitation of the edge nodes’ computation by moving data exchange close to them [1]. In the case of MCS, they can be leveraged to fasten the upload of sensed data by exploiting fast (local) wireless connections to increase the upload speed and save bandwidth on the core cellular infrastructure. More recently, an increasing number of relevant applications are exploring more collaborative MEC scenarios, also considering the join exploitation of MEC and MCS paradigms [2, 3, 4]. However, the limited case studies of which we are aware neither place people at the center of the attention nor carefully inspect social aspects characterizing the human mobility. The information exchange between devices in such a kind of networking scenarios must necessarily be conveyed by social interactions between individuals. In this context, the term social interaction implies kindship or friendship relationships, up to interactions with perfect strangers. Regardless of the type of link established, when users' devices stand in mutual Wi-Fi range for a relatively short period of time, they can exchange data. That real-time
information exchange between devices is realized at a personal level by neighbouring users [5] and the type of created network tends to assume a movement-based structure.

In our previous work, we presented the Human-Enabled Edge Computing Model (HEC) [6], a platform combining the potential of both MEC and MCS technologies. The HEC model enhances the MEC middleware layer by supporting the effective deployment of Fixed MEC (FMEC) proxies and by further extending their coverage through the introduction of impromptu human-enabled Mobile MEC (M^2EC) proxies temporary formed and maintained in high-density city hotspots (i.e., physical locality principle). The present work further extends our HEC model introducing also the concept of Social MEC (SMEC) proxies that aim at leveraging social ties (i.e., logical locality principle) between nodes taking part to the MCS process. The main idea is to evolve the standard MEC middleware layer by adding SMEC selected, according to incentives and centrality measures, as representative samples of people based on both their attitude to be cooperative and their representativeness, namely, their centrality position with respect to the other people in the group.

Eventually, good SMECs could act as substitutes of FMECs because of the economic benefits they can bring to the MEC architecture. In fact, high installation and maintenance costs constrain the number of FMEC that can be implant in a territory. In addition, FMECs can neither move within a city environments nor exchange data with devices far from their coverage range. Our proposal aims at improving the MEC performance, cutting down the number of needed FMECs by increasing the spatial coverage for information dissemination and data sensing at the same time.

To pursue our goal, we assessed the proposed HEC model through the ParticipAct Living Lab dataset, a well-known set of sensed data able to create any desired MCS test strategy [7]. Specifically, we select a one month’s sample of the dataset made up of individuals’ co-location traces, and we leverage the position of such individuals and their availability in performing tasks to select the most suitable ones to become social mobile edges. Our assumption is that selecting SMECs among more central nodes instead of those more collaborative, we improve the performance for our model. To support our assertion, we tested different SMEC selection strategies obtained by varying the percentages of centrality and cooperativeness computed for each node on the basis of a weighted average. The assessment of the performance for each SMEC selection is given in terms of latency and requests satisfied on a total of generated requests. Obtained results, based on a wide set of tests performed by varying the number of selected SMECs, support our assumption and show the benefits of HEC that allows a better social and spatial coverage of MEC-enabled environments.

II. RELATED WORKS

Without any claim to exhaustiveness, we briefly introduce the main works inherent MEC and MCS to give to the reader and the scholar an overview of their current state of the art, highlighting important, unresolved key-open issues. Finally, we introduce the initial works concerning our HEC architecture, achievements and challenges.

MCS is a well-known paradigm born by the convergence of participatory and opportunistic sensing [8]. Leveraging people roaming and the pervasiveness of their devices MCS opens to the opportunity of data collection and data dissemination without precedents. Through the installation of an MCS application, mobile devices can be enabled as parts of a large-scale immaterial smart infrastructure for crowd management. However, even if such devices are widespread all around a territory, there is always the possibility they may be unable to carry out certain tasks due to adverse conditions of the environments in which they are located (e.g. hostile territories with no cloud connection) [9]. Privacy and data integrity are other problems influencing the acceptance of this modern technology from users [10]. To guarantee an adequate level of privacy some feasible solutions have been proposed in [11]. Concerning reliability in data integrity in MCS campaign a good reference can be [7]. A more material problem is the fast battery consumption deriving from a continuous use of the MCS application which affects the involvement of people. To this problem, some interesting solutions can be found in [12]. Finally, in MCS campaigns there is the issue inherent the disinterestedness of the participants. Since the data harvesting is influenced by the number of MCS participants, users’ motivation is a non-trivial issue. To keep the participants’ level of involvement high some sort of incentives has been developed [13]. However, although various forms of incentive to encourage participants in visiting one area rather than another has been widely explored in theoretical and simulation studies, to the best of our knowledge none of them has been tested in a real MCS campaign with volunteering participants.

Concerning MEC, it is a Mobile Cloud Computing (MCC) distributed system in which computation resources are made available through Radio Access Networks (RAN) near mobile edge of the Internet [14]. Computing resources within mobile edges are virtualized and shared through APIs to be accessible to both the user and operator applications. The MEC model’s strengths are the reduction of the latency, the efficiency of network operations and data delivery services, and an overall improvement of the user experience as well [1]. However, only a very few works concentrated on
the opportunities of having cooperation between devices and the edges, also considering MCS as application scenario that could benefit from that. [2] and [3] propose to enhance the MCS process by leveraging intermediate MEC nodes, namely, FMECs, to boost data upload from mobile nodes to the infrastructure [2] and to provide more computing/storage capabilities closer to end mobile devices [5].

Our HEC model proposes to complement FMECs proxies, i.e., static base-stations which only act as intermediary between devices and the cloud, with M^2EC acting as FMEC at predetermined interval of time in logical bounded regions in which people tend to stay for a while. In our previous work [6], we showed that the monitoring of human movements leveraging MCS can eases the identification of these strategic hotspots where to install M^2EC and that the leveraging of local one-hop communications and store-and-forward principle enable the migration of data from FMECs to M^2EC and vice versa. A very recent and interesting work along this direction is also [4] that similarly to our effort aims at enabling more collaboration between entities co-located at edges. Both ours and this work, however, neglect humans and social/mobility effects. The present work intends to make an important contribution to the progress made so far by also considering social ties and a logical locality principle and, accordingly, introducing the new SMEC actor and proposing a highly innovative approach for a non-arbitrary selection of SMECs.

Please note that, being at the crossing and at the convergence of the MCS and MEC paradigms, the social-aware MEC paradigm inherits the intrinsic security and privacy issues and technical challenges belonging to the previous ones. In relation with MCS and MEC, these aspects have started to be addressed in the related literature [10, 11], but they are out of the specific scope of this paper.

III. A SOCIAL-BASED MOBILE EDGE ARCHITECTURE

A Mobile Crowdsensing platform implements a broad-range community sensing paradigm that consists of three components: individuals, devices and centralized, cloud-based servers. The individuals, who expressed their willingness to take part in the MCS platform and to its campaigns, wear mobile devices equipped with sensors, short-range communication interfaces and the MCS mobile application. The MCS mobile application can collect data autonomously through sensors or with the support of the user. Conventionally, data stored within devices’ memory is forwarded to a remote server for storage or for further processing in two possible ways:

• By broadband communication (e.g. 4G LTE or 5G) to directly connect the mobile device to the server on the cloud.

• Through Multi-access Edge Computing proxies (called herein FMECs) that may be present in the territory and that provide a middleware layer between the cloud-level and the access network.

It should be observed that, while the broadband communications are long-range and then usually available independently of the position of a mobile device (but they do have a cost for the users), the communications with the FMEC may instead rely on short-range communications (for example based on Wi-Fi, with a reduced spatial coverage) with no costs for the users. In a HEC architecture, a further set of mobile MEC (M^2EC) can be implemented by users’ mobile devices, carrying out the same functions of FMECs. M^2EC are selected from those carried by individuals and may collect opportunistically all the data produced by other devices that come in the range of their short-range radio interfaces. M^2EC are chosen to post a specific location and, similarly to FMEC, they have a spatial coverage that provides communication opportunities to the devices of other people that come in its communication range, in the geolocation where it is active. Details M^2ECs can be found in [6]. In this paper, we propose to further evolve our HEC model by introducing Social MEC (SMEC), that are proxies chosen among the users’ devices, based on their opportunity to meet other users’ devices during their travels. SMEC thus introduce a new dimension of coverage, that we call social coverage, and which is defined as the set of users’ devices met by a SMEC over a period of time. Note that the set of devices met by a SMEC depends on the meetings of the owners of the devices, either occasional or due to a social relationship between them. We refer the entire architecture including SMEC as Social-Driven Edge Computing.

The rationale of using SMEC as couriers between the cloud and mobile devices is the optimization of the data exchange in the MCS system, by finding a compromise to obtain the needed social coverage. In order to reach the largest possible number of devices, such couriers must be carefully selected. Social aspects related to human behaviours, as individual’s interaction or habits, are of fundamental importance for the mobile edges’ selection. In fact, based on individuals’ social spheres it is possible to properly select devices acting as mobile edges (electing them from among those more cohesive than others). Sociality, centrality and the availability of performing tasks are the metrics considered for the selection of our social mobile edges.

In our architecture the SMECs are thus a supplement to the existing infrastructure by extending its communication coverage by means of social coverage. The main advantage lies in the economic benefits they bring, since they do not have installation and maintenance costs, and they
may even contribute either to reduce the number of FMECs or replace them in entirely, thus further reducing the infrastructure costs.

To get an idea of what our study is about, let us give an example of application scenario. Let us imagine we are within a large area (for example a city) where a MEC architectural model has been deployed. Within this area a certain number of individuals, who participate in an MCS campaign, move establishing social relationships, performing daily routines (such as going to work, to the supermarket and so forth), and sometimes standing near people who are perfect strangers. During these routines, the MCS application opportunistically captures information from the environment through devices’ sensors or asks users to perform either individual or cooperative tasks, such as go to an event and take a picture or record an audio track at the location where they stand. Data stored within devices’ memory is routed to the cloud either through SMECs encountered along the way. Figure 1 depicts our reference scenario showing FMEC, M2EC, SMEC, and cloud servers as layer entities (i.e., FMEC, M2EC, and SMEC nodes). Leveraging the SMECs movement capability, we have the opportunity of reaching city environment locations unattainable by FMECs/ M2ECs, thus expanding the potential number of reachable devices. As we will discuss in the next sections, this will open to the opportunity of replacing the number of needed FMECs entirely, keeping the same overall coverage.

IV. SMEC SELECTION STRATEGY

The role of SMECs is taken by personal mobile devices of users of the MEC platform that, for a period, accept to offer storage and communication services to other users’ devices. For this reason, we transform the standard MEC middleware layer by replacing FMEC with SMECs, selecting them within a sample of people based on the attitude of the users to be cooperative (possibly upon incentives). Even though conflicting, another important aspect is that the SMECs have to offer opportunities of communications to other devices as much as possible. For this reason, we also select the SMECs based on social aspects of their owners. It should be observed that we intend social relationships in a broad way, since we also include cases in which a person remains close to a stranger for a period (for any reason, for example they take the same bus daily), since also this fact gives the opportunity of two people’s devices to communicate and exchange relevant information for the MCS. More specifically, we identify potential SMEC candidates of the MCS based on the social relationships among pairs of individuals, that is, within the sample we identify a small number of users that have stronger and more frequent relationships with other users by using the betweenness centrality measure. The betweenness centrality measure fit well to our case study because indicates how frequently a node lies along the pathways of other nodes in a network [15], and this is a good indicator of the trade-off between characteristics as sociality and mobility. In addition, in order not to limit the SMEC selection to a single parameter, which could be discriminative towards more cooperative nodes, we decided to use the sensitivity of a node in performing tasks as well. In detail, we use both centrality measure and the attitude of a node in performing tasks. First, because nodes that are more central than others tend to meet other nodes more frequently encouraging the exchange of data among these devices. Second, because individuals who are likely to perform tasks also tend to be better conveyed than others in uncovered areas of a territory.

In order to test the effectiveness of SMEC selection based on the trade-off centrality-cooperativeness measures we perform different kind of selection strategy by using an alpha parameter. Specifically, each node is associated with a centrality value (computed with betweenness) and a cooperativeness score (assigned on the basis of the tasks performed); the alpha value shifts the importance of the weights associated with centrality and cooperativeness from a normalized scale of values. In this way, the SMEC selection strategy algorithm focuses on both sociality and cooperativeness and works as follows. For each node of the sample is computed both the betweenness centrality measure and the
cooperativeness score. Since these two sets of values differ in the calculation procedure, in order to compute the weighted average of them, we perform a normalization procedure to bring such values in the range [0,1]. Once obtained the normalized values, we compute the weighted average with respect to the alpha parameter, also selected in the range [0,1], which determines whether to give more importance either centrality or cooperativeness of a node. Afterwards, we sort the results in ascending order. Based on this ranking we perform three different tests for eleven different alpha values by incrementing, for each test, the number of SMECs selected.

V. EXPERIMENTAL RESULTS

To test our model, we used the ParticipAct Living Lab dataset [7]. ParticipAct is a real-world MCS experiment carried out by roughly 170 University students of the Bologna city (Italy) in the timeframe of 18 months, from 2013 to 2015. The result is a dataset of information collected by students’ devices, including their mobility traces. In details, each ParticipAct volunteer was equipped with an android smartphone device running an MCS application. Such app, through Google APIs, was able to track volunteers’ locations in a fixed sampling interval of 2.5 minutes. Data gathered were forwarded to an MCS backend for further elaborations as users' locations interpolation and filtering.

The fact that during the summer holidays universities lose their liveliness leads us to choose a spring month as reference for testing our model. Particularly, the period that goes from April to June 2014. In this period the semester is still running, lessons are held, and students are preparing for the exam sessions, increasing the number of contacts they establish with each other.

To test the effectiveness of the different SMEC selection strategies defined above, a series of requests (in the number of 5000) are generated by random nodes at various times. Such requests are to be understood as the need for a device to communicate data gathered to the cloud. Once a request is generated, it has a week’s time to be resolved by a SMEC. After this period, the request is automatically resolved by the cloud.

Our simulation work considers typical applications of long-term crowdsensing campaigns, which do not have specific time constraints, like applications that aim at collecting data for off-line statistical analysis (for example aimed at collecting statistical data about pollution, or at obtaining data for the optimization of mobility flows in a smart city) or even applications for the optimization of opportunistic and participatory communications among devices. We use the time limit of one week as maximum delay for each request (before it is served reverting to a direct broadband communication device to the cloud) because this limit has been considered an appreciable time interval for observing as social relations affect the delay in communications among devices (note that, even with this upper bound, most communications were completed much earlier). The current delay depends on the selection of the SMEC, and our results show that selecting the SMEC without considering users’ sociality degrades the performance results significantly. Based on these quantitative observations, it is possible to trade the latency with the efficiency of the solution in a specific deployment environment and depending on specific application requirements.

We perform three different tests by increasing the number of SMECs each time. For the first test, we limit the selection to 4 SMEC. For the second and the third one, we use 8 and 12 SMECs respectively. The average latency is computed by considering the summation of the time interval of all requests satisfied by SMECs plus all requests satisfied through broadband communication, all divided by the total number of requests.
First results show that SMEC selected using only the measure of cooperativeness report better performance than those selected using only the cooperativeness score. Specifically, SMEC selected using the highest alpha value, namely, giving the utmost importance to the cooperativeness factor, solve the highest number of random requests, performing a better total average latency in the resolution of such requests as well. At the opposite, the SMEC selected using the lowest alpha value that is choosing the SMECs considering only their cooperativeness scores, returned the worst performance of all other.

Concerning latency, we observe that there is a progressive decrease with the increase of both the number of SMEC and the alpha parameter. From an initial latency of more than 50 percent performed by 4 SMEC selected from those more cooperatives, we achieve a decrease of more than 25 percent with 12 SMEC selected among those more central.

Figure 4 shows the cooperativeness score with respect to the betweenness values of nodes for one month’s observation. Based on the preliminary results and in line with the above, SMECs selected among nodes on the right side of the histogram report a better performance than those selected from the left one. On the x-axis the plot reports node labels. Labels with larger values are associated to nodes with higher values of cooperativeness. Vice versa, labels with smaller values are associated to nodes with higher values of cooperativeness.

VI. DISCUSSION AND CONCLUSIONS

The synergistic use of MCS and MEC paradigms has given life to our Social-Driven Edge Computing architectural model. In this article we discuss the effectiveness of using centrality measures and cooperativeness scores of nodes to obtain an efficient social mobile edge selection. SMECs are evaluated based on the speed in responding to a non-arbitrary number of requests generated by nodes acting in a MCS scenario and based on the total number of nodes’ requests they are able to satisfy. Several tests have shown that the selection of SMEC, considering the cooperativeness score only, does not return appreciable results in terms of requests satisfied and latency. Whereas, if the selection of SMEC is made by considering only the centrality value of a node, performance related to satisfied requests and latency increase considerably.

All percentages support our assumptions that the selection of SMECs among those that are more central brings more benefits than using SMEC selected on the basis of their cooperativeness scores.

Although MCS and MEC are entrenched paradigms and the scientific community has faced several issues for both, the joint use of these technologies is still a largely unexplored field of study. A very open related research direction is about the acquisition of high-quality data on users’ mobility and sociality, in order to take more accurate and robust decisions in the SMEC selection process. In fact, currently, the sociality aspects are investigated as simple co-presence of users in a limited space, while it could be treated considering other factors, as the users’ meetings frequency or their habits. In addition, there is the recognized need to work on extensive performance evaluation of different clustering algorithms for identifying communities in dynamic graphs. Other aspects that deserve further research are those concerning privacy and security in the management of the data acquired to optimize the MCS and the MEC platforms; finally, the lack of a standardized HEC platform, on which to perform reproducible tests for data validation, is a non-negligible limitation to experimentation and result sharing.

In these tests we perform the SMEC selection strategy by using as sample a specific period of time within a precise interval. However, we are more than convinced that the introduction of an effective community detection mechanism in the SMEC selection strategy can bring benefits in terms of both latency and number of requests satisfied. Finally, these encouraging results in favour of centrality measures with respect cooperativeness scores drives us to investigate more deeply the social aspects related to human behaviour. The social sphere of a person is as important as its mobility and can be the starting point for devising more efficient strategies of SMECs selection.
REFERENCES


BIographies

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