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An Architecture For Cooperative Mobile Health Applications

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Abstract Mobile health applications are steadily gaining momentum in the modern world given the omnipresence of various mobile or WiFi connections. Given that the bandwidth of these connections increases over time, especially in conjunction with advanced modulation and error-correction codes, whereas the latency drops, the cooperation between mobile applications becomes gradually easier. This translates to reduced computational burden and heat dissipation for each isolated device at the expense of increased privacy risks. This chapter presents a configurable and scalable edge computing architecture for cooperative digital health mobile applications.

Keywords Digital health · Edge computing · Mobile computing · Mobile applications · Cooperative applications · Higher order statistics

Mathematics Subject Classification (2010) 05C12 · 05C20 · 05C80 · 05C85

1 Introduction

Mobile smart applications for monitoring human health or processing health-related data are increasing lately at an almost geometric rate. This can be attributed to a combination of social and technolgical factors. The accumulated recent multidisciplinary research on biosignals and the quest for improved biomarkers bore fruits in the form of advanced bisignal processing algorithms. Smartphone applications are progressively becoming popular in all age groups, albeit with a different rate for each such group and, moreover, mobile subscribers tend to be more willing to provide sensitive

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health data such are heart beat rate, blood pressure, or eye sight status to applications for processing. Thus, not only technological but also financial factors favor the development of digital health applications.

The primary contribution of this chapter is a set of guidelines towards a cross-layer cooperative architecture for mobile health applications. The principal motivation behind them are increased parallelism, and consequently lower turnaround or wallclock time, additional redundancy, which translates to higher reliability, and lower energy consumption. All these factors are critical for mobile health applications.

The remaining of this chapter is structured as follows. Section 2 briefly summarizes the recent scientific literature in the fields of edge computing, mobile applications, mobile services, and digital health applications. Section 3 presents the proposed architecture. Finally, section 4 recapitulates the main points of this chapter. The notation of this chapter is shown at table 1.

Table 1 Notation of this chapter.

Symbol	Meaning
$\triangleq$	Definition or equality by definition
$\{s_1,\ldots,s_n\}$	Set comprising of elements $s_1,\ldots,s_n$
$\lvert S\rvert$ or $\lvert\{s_1,\ldots,s_n\}\rvert$	Cardinality of set S
$\mathrm{E}[X]$	Mean value of random variable X
$\mathrm{Var}[X]$	Variance of random variable X
γ_1	Skewness coefficient

2 Previous Work

Mobile health applications cover a broad spectrum of cases as listed for instance in Sunyaev et al. (2014) or in Fox and Duggan (2010). These include pregnancy as described in Banerjee et al. (2013), heart beat as mentioned in Steinhubl et al. (2013), and blood pressure as stated in Logan et al. (2007). Using mobile health applictions results from increased awareness of the digital health potential as Rich and Miah (2014) claims. A major driver for the latter is the formation of thematically related communities in online social media as stated in Ba and Wang (2013). Another factor accounting for the popularity as well as for the ease of health applications is gamification as found in Lupton (2013) and Pagoto and Bennett (2013), namely the business methodologies relying on gaming elements as their names suggest - see for instance Deterding et al. (2011a), Deterding et al. (2011b), or Huotari and Hamari (2012). Gamification can already be found at the very core of such applications as described in Cugelman (2013).

The processing path of any digital health may take several forms as shown in Serbanati et al. (2011). For an overview of recent security practices for mobile health applications see Papageorgiou et al. (2018). Path analysis as in Kanavos et al. (2017) play a central role in graph mining in various contexts, for instance in social networks as in Drakopoulos et al. (2017). Finally, the advent of advanced GPU technologies can lead to more efficient graph algorithms as in Drakopoulos et al. (2018).

Finally, although it has been only very recently enforced (May 2018), GDPR, the EU directive governing the collection, processing, and sharing of sensitive personal information, seems to be already shaping more transparent conditions the smartphone applications ecosystem is adapting to. In fact, despite the original protests that GDPR may be excessively constraining under certain circumstances described in Charitou et al. (2018), consumers seem to trust mobile applications which clearly outline their intentions concerning any collected piece of personal information as Bachiri et al. (2018) found out.

3 Architecture

This section presents and analyzes the proposed cooperative architecture for mobile digital health applications. Figure 1 visualizes an instance of a mobile health application running on a smartphone and a number of peers which can be reached either by WiFi or by regular mobile services.

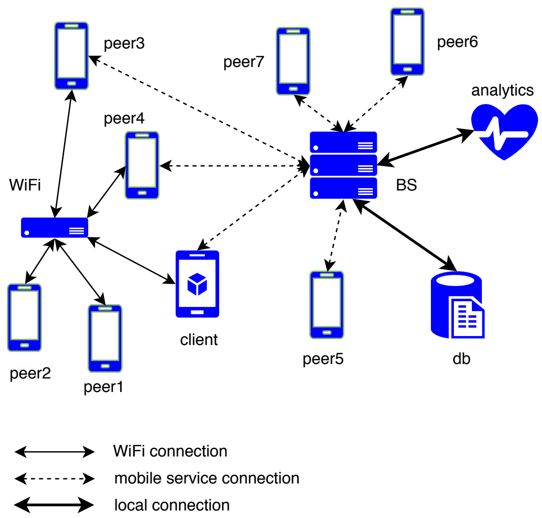

Fig. 1 Instance of a mobile application surrounded by peers.

As with the majority of mobile architectures, the proposed architecture is conceptually best described with graphs, as concepts such as connectivity and community structure can be naturally expressed. To this end, the cell phones, the base stations, and the WiFi access points are represented as vertices, each device category being represented as a different type. Moreover, connections between these are represented as edges, where each edge is also of different type depending on the connection. These can be easily programmed in a graph database like Neo4j.

The general constraints that will be the basis for the subsequent analysis are as follows:

- Assume that a mobile health application monitoring a biomarker or a biosignal must deliver results every T_0 time units, usually seconds. Additionally assuming that the required computation can be split into $n+1$ parts to be distributed to the available n neighbors, then:

$$T_a + T_p + T_s + 2T_c \leq T_0 \tag{1}$$

  Where T_a, T_p, T_s, and T_c denote respectively the time required for analysis, namely breaking down the computation and assigning each neighbor a task, processing, namely the time of the slowest task, synthesis, namely assemblying the solution of each task to create the general solution, and communication. The latter term counts twice as the data and the task need to be communicated and then the results need to be collected.
- In mobile communications is of paramount importance the minimization of the energy dedicated to a single task. In general the relationship between a given task and the energy spent for its accomplishment is unknown. However, given that tasks have a short duration, it is fairly reasonable to assume that the same function $f(\cdot)$ links the task and the energy at each neighbor. Then the following inequality should also be satisfied:

$$\begin{aligned} (n+1)f(T_p) + f(T_a) + f(T_s) + 2(n+1)f(T_c) \;\leq\; f(T_0) \;\Leftrightarrow \\ \frac{f(T_0) - f(T_a) - f(T_s)}{f(T_p) + 2(T_c)} - 1 \;\geq\; n \end{aligned} \tag{2}$$

Given the fundamental constraints (1) and (2), let us estimate the key parameter T_c, since T_a, T_s, and T_p depend on the problem and T_0 is a constraint.

Let $e_{i,j}$ denote the communication link between vertices v_i and v_j has a given capacity $C_{i,j}$ as well as a propagation delay $\tau_{i,j}$. Then, the number of bits $b_{i,j}$ which can be transmitted over edge $e_{i,j}$ in a time slot of length τ_0 is, assuming the variables are expressed in the proper units:

$$b_{i,j} \;=\; C_{i,j}(\tau_0 - \tau_{i,j}) \tag{3}$$

If the link delay $\tau_{i,j}$ is expressed as a percentage $0 < \rho^{\tau}_{i,j} < 1$ of the time slot τ_0, then:

$$b_{i,j} \;=\; C_{i,j}\tau_0\left(1 - \rho^{\tau}_{i,j}\right) \tag{4}$$

Note that the case $\rho^{\tau}_{i,j} = 0$ represents a near physical impossibility, whereas the case $\rho^{\tau}_{i,j} = 1$ denotes either a useless link or a misconfigured network protocol.

In a similar way, if C_0 is the maximum capacity, then each $C_{i,j}$ can be expressed as a percentage $0 < \rho^C_{i,j} \leq 1$ of the former. Thus:

$$b_{i,j} = C_0 \tau_0 \rho^C_{i,j} \left(1 - \rho^\tau_{i,j}\right) = B_0 \rho^C_{i,j} \left(1 - \rho^\tau_{i,j}\right) \tag{5}$$

Note that in this case $\rho^C_{i,j}$ can be 1, unless C_0 is an asymptotically upper limit. Therefore, if for the given task $B_{i,j}$ bits must be transmitted, then the total number of slots for that particular link is:

$$T_{i,j} = \left\lceil \frac{B_{i,j}}{b_{i,j}} \right\rceil \tag{6}$$

At this point, we can estimate T_c as:

$$T_c \stackrel{\triangle}{=} \mathrm{E}\left[T_{i,j}\right] \tag{7}$$

Furthermore, we can use the distribution of T_c to determine whether a big task should be subdivided to smaller tasks. Assuming τ_0 is constant, then it can be used as a reference point to consider the frequency distribution of $T_{i,j}$, which can be treated as a probability distribution.

For any random variable X is possible to define the skewness coefficient γ_1 as:

$$\gamma_1 \stackrel{\triangle}{=} \mathrm{E}\left[\frac{X - \mathrm{E}[X]}{\sqrt{\mathrm{Var}[X]}}\right] = \frac{\mathrm{E}\left[X^3\right] - 3\mathrm{E}[X]\,\mathrm{Var}[X] - \mathrm{E}[X]^3}{\mathrm{Var}[X]^{\frac{3}{2}}} \tag{8}$$

In equation (8) $\mathrm{E}[X]$ and $\mathrm{Var}[X]$ stand for the stochastic mean and variance of X respectively. In actual settings these can be replaced by their sample counterparts and they can be updated as new measurements are collected. In the derivation of the right hand side of (8) the following properties were used:

$$\begin{aligned} \mathrm{E}\left[\sum_{k=1}^{n} \alpha_k X_k + \alpha_0\right] &= \sum_{k=1}^{n} \alpha_k \mathrm{E}[X_k] + \alpha_0 \\ \mathrm{Var}[\alpha_1 X + \alpha_0] &= \alpha_1^2 \mathrm{Var}[X] \end{aligned} \tag{9}$$

The skewness sign indicates the shape of the distribution. When γ_1 is negative, then X takes larger values with higher probability, whereas when γ_1 is positive, then X is more likely to take lower values. Finally, in the case where γ_1 is zero, then the distribution of X is symmetric, as for instance in the case of the binomial distribution.

Therefore, positive values of the skewness coefficient γ_1 for the distribution of T_c of the channel delays indicate that it is more likely more time to be available for useful information transmission.

The proposed methodology is summarized in algorithm 1.

Algorithm 1 The proposed scheme.

Require: Knowledge of T_0, T_s, T_a, and T_p.
Ensure: A cooperative computation takes place.

repeat
  update estimates for $\{T_{i,j}\}$
  if equations (2) and (9) are satisfied **then**
    break the problem into tasks
  end if
  communicate tasks
  compute tasks
  collect results
  compose answer
until true

4 Conclusions

This chapter presents a probabilistic architecture for cooperative computation in mobile health app settings. It relies on a higher order statistical criterion, namely the skewness coefficient of the number of slots which are suitable for communication, in order to estimate whether a computation can be broken into smaller tasks and communicated to neighboring smartphones over WiFi or the ordinary cell network. Once the tasks are complete, the results are collected back at the controling smartphone and an answer is generated using a synthesis of these results.

In order to find the hard limits of the proposed architecture and to assess its performance under various operational scenaria, a number of simulations must be run in addition to theoretical probabilistic analysis. Additionally, more conditions should be added to the architecture, for instance what happens when a neighboring smartphone stops working or is moved out of range. Moreover, conditions for duplicating certain critical computation must also be created.

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