An Intelligent Energy-driven System for Mobile Health Management

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***Abstract*—Pets have difficulties in communicating with their owners or veterinarians on healthcare problems. Mobile sensing can consistently detect their health problems and deliver the problems to their owners, so the owners can help them out. Data transferring and battery usage are two major challenges in mobile sensing, especially when continuous and long-term data transmission are needed if pets get lost. In this paper, we develop an intelligent energy-driven system for conditional data analysis and transferring, so sensing devices can work longer and more efficiently without recharging. Our system can be applied to the sensing devices used in other agents, such as babies, animals, and patients.**

Keywords–Mobile sensing; Healthcare monitoring; Energy aware system; Feature embedding.

I. INTRODUCTION

In mobile sensing field, data transferring and battery consumption are major issues to continuous data tracking and uploading [1] [2], especially when devices are in the wild without charge stations. That is why most of mobile sensing-based health data tracking are mainly operated under experimental environment where humans intensively control the sensing devices [3]. The sensing data transmitted to the cloud are usually raw data, which can consume large amount of transmission resources with low efficiency. However, unlike human beings who can manually adjust sensor devices and watch out for battery usage [4] [5] [6], pets (and monitored animals) are agents who have communication difficulty and cannot operate devices, especially when they get lost in the wild without power charge stations.

Most of people can communicate with families, friends and doctors when they are not feeling well. But pets cannot directly tell their owners when they are sick or in danger. In some situations, pet owners cannot stay with their pets all day long because they have to work or travel to other places. However, pet owners want to make sure the safety of their pets when they are not around.

As far as we known, there is limited work on developing an intelligent energy aware system to efficiently transfer sensing data based on real time battery level and help find the lost pets in the wild [7]. In this paper, we use pet as the agent example, but our methods can be applied to any agents that have communication difficulties, including but not limited to babies, wild animals, patients, etc.

After this introductory section, in Section II, we explain a framework to help find lost pets using energy aware mobile sensing. In Section III, we introduce an energy-driven mobile sensing system for pets.In Section IV, we further go through how the model is automatically trained and optimized through feature embedding on the cloud end and then be applied to the agent device.

II. FINDME: A MODEL TO FIND LOST PETS BY ENERGY AWARE MOBILE SENSING

With the prevalence of mobile devices using worldwide, mobile sensing are widely applied in different areas varying from GPS tracking [8], activity recognition [5], sleep quality measuring [9], daily social media usage [10] to personality traits [6], working performance evaluation [11], and mental health detection including depression [12] [13], anxiety [14] [15], and schizophrenia [4] [16]. Sensor equipped devices are also applied to monitor the health of pets, such as dogs and cats [17]. But all sensing based devices can not avoid one essential issue on saving battery and dealing with large raw data uploading and computing, which is a challenge to continuous data tracking and recording. This issue will be even more profound when the pets get lost without power charger. Once battery is out, there are limited ways to help owners find their pets. Based on real situations, we want to answer the question: How to prioritize battery consumption and data processing of mobile sensors in the wild?

1) Sensors applied in the system: Sensors in our system can be put into two groups: personal sensors embedded in a device and environmental sensors equipped at home. Personal sensors refer to thermometer, pulsimeter, sphygmomanometergravity sensor, GPS, Bluetooth, photoplethysmography, electrocardiogram, etc. Environmental sensors include beacon, camera, microphone ambient light detector, etc. With these two kinds of sensors, we can record and track agent behaviors both at home and in the wild, when the agent carries the device.

2) FindMe function applied in different situations: Figure 1 shows the functions of a FindMe model applied in different situations, at home and in the wild. A wearable device with integrated sensors will capture pets GPS locations and record their sound and environment features as well as their health conditions. When pets are at home, environmental sensors, such as beacon and camera are also included. When a beacon detects that a pet is getting into danger, such as standing beside an open window, it will send an alarm directly to the owner's phone. When a camera combined with health sensors detects that a pet's health is at risk, such as bleeding or in pains at home, it will also send warning to the owner. In the wild, if the sensors in a pet's device detect that the pet is getting lost

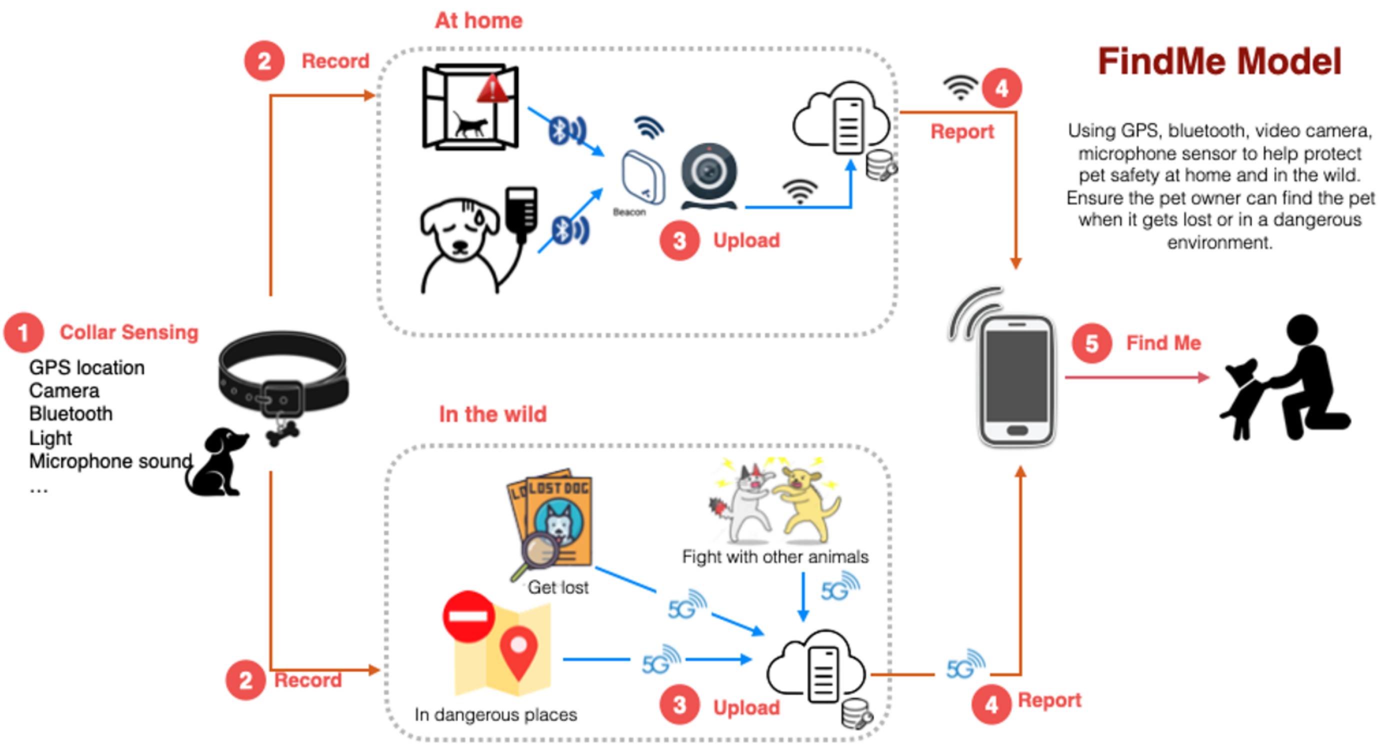

Figure 1. The FindMe model applied in the sensing system

or reported lost, the device will report to the owner about the pet's location and provide timely updates of the pet's safety.

III. An energy-driven mobile sensing system for pets

Regarding the FindMe model discussed in Section II, energy consumption is a challenge especially when the agents are in places without power chargers nearby. Unlike human-beings who can speak with each other and ask for help, pets cannot speak human languages or ask for help as easily as us. Instead, they are very dependent and not able to control the devices manually. A system with energy-driven adaptive data analysis and upload that can improve battery life of mobile sensing devices is essential to help these agents get back home safely.

A. The battery level

Different batteries have different voltage decreasing rates. They have different discharge curves for real battery test [18]. To develop an energy aware system to save battery intelligently and automatically, we need to first understand their voltage rate during consumption by time. And what we can do here is that the battery level can be defined into a lookup table in the device ROM. We can use lookup table to know battery consumption and control sensors according to battery levels. Taking the battery consumption into consideration, the battery usage is not likely to be decreasing in a linear trend but a sharp drop after it reaches a certain level. However, with the lookup table written in the device ROM, a system will get timely updates about its battery usage rate and make adjustment to current working sensors.

B. An energy-driven system design and development

In order to prioritize tasks, when the battery level decreased, a system should reduce data processing to save power, i.e., the lower the battery, the less unimportant conditions should be processed. Let a_i be a parameter showing if data of sensor i can be processed, i.e., $a_i = 1$, depending on battery level. Assuming a device has m battery levels, the higher the level, the more power left. Let $b_i = 1, ..., m$ be the cutoff battery level of a sensor, which is predefined for each sensor. Note that the higher the cutoff level, the less chance a sensor will work when battery level is low, i.e., a sensor will only work when the battery level is higher than its cutoff level. Let b_t be the battery level at time t, H be the Heaviside function, and

$$a_i = H(m - b_i) = \begin{cases} 1, & if\ b_i < b_t \\ 0, & if\ b_i >= b_t \end{cases}$$

Note that a_i will be normalized based on the available sensors in the integration process, the green rectangle in the figure. The goal of using a_i is to only process the important conditions when battery level is low, Figure 2.

In Figure 3, another innovation of this system design is about using Long Short-term Memory (LSTM) to automatically learn the time-series data continuously from the multiple sensors. Facilitated by the deep learning model of LSTM, this system can intelligently react to the battery level by opening or shut down certain sensors to save energy and make the device working longer. Usually, some less important sensors with high data transferring demands will be shut down or decreased usage when the battery is running out in the wild. Not like the manually controlling and decision making of which sensor

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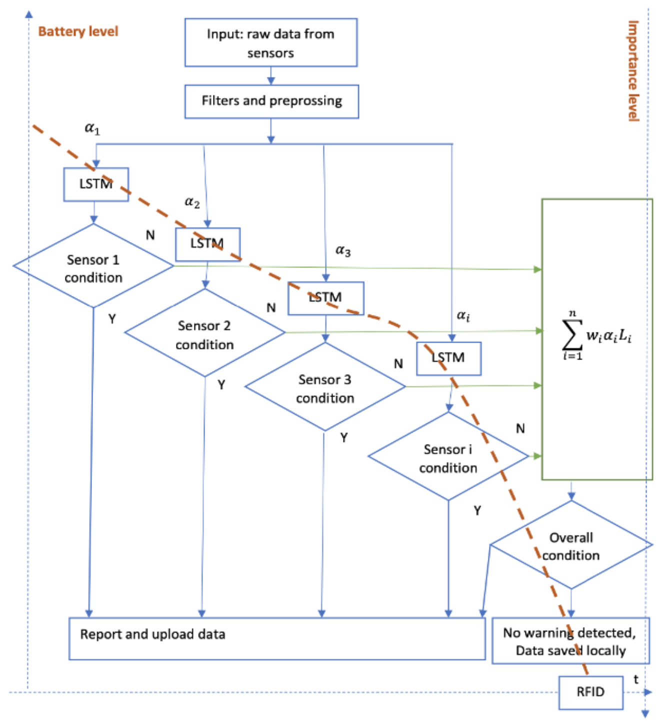

Figure 2. An energy-driven system for adaptive data profile and upload

should be first shut down or decrease usage frequency to what extent, our system aims to automatically learn from the data and making intelligent decision from the sensors, environment and battery level. This could be very helpful and essential for lost pets or agents to get more support and protection in the wild.

In our model, LSTM network is applied to track the changes in sensor data. Other machine learning methods can be applied to this modal too. Because each agent is different, so not only the values but the value changes are important features to tell how an agent's conditions change. Thus, a machine learning method that can track changes will help track the conditions of an agent.

IV. Feature Embedding On The Cloud-End

How could our system automatically learn when to lower the frequency or shut down certain sensors? On the agent's device, we utilized feature embedding trained on the cloud service and then applied to local end (agent's device) after a fine-tuned model is achieved. Feature embedding [19] is an emerging research area which intends to transform features from the original space into a new space to support effective learning. A generalized feature embedding algorithm (GEL) can learn feature embedding from any type of data or data with mixed feature types [20]. Specifically, multi-modal sensor data (i.e., time-series data from various sensors) are uploaded to the cloud where a feature embedding encoder can be trained based on the data from all devices. Note this step can be unsupervised that does not require any user input. Eventually, we obtain feature embedding algorithms for each sensor (or a combination of several related sensors), where a time series data can be represented as a special point in a multidimensional space. Similar time series (that most probably have similar semantics) will be mapped to close areas in the space. Such embedding algorithm are updated online and synced to the portable devices regularly.

Once the edge has downloaded the embedding algorithm from the cloud, it can generate features for its own sensor data using the model. In this way, it utilizes the patterns learned from the cloud. Locally on the edge, a customized decision tree model is trained using the embedded features and user labels. The owners or doctors can label some period as risky, so that the model can learn local thresholds for sensor data to classify risky behavior in the future.

V. Conclusion

Mobile sensing is important in health management. The FindMe model facilitates timely monitoring and health warning to owners when agents are in danger or get lost. To extend battery life and achieve intelligent sensing in the wild, we design an energy-driven system for conditional data analysis and transferring, so sensor device can work longer and more efficiently. This system can be utilized in devices for agents with communication difficulty. Agents, such as infants, toddlers, seniors or patients with dementia and Alzheimer's disease are vulnerable and dependent to caregivers and medical devices. Our model will make sure that these devices provide seamless cares to agents. In addition, our system and methods can extended to IoT scenarios, such as machine-to-machine(M2M) communications as well as edges and cloud nodes with communication challenges.

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