Monitoring the Well-Being of a Person Using a Robotic-Sensor Framework

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Abstract

Applications of robotic and wearable sensors based systems for human assistance or health monitoring have been gaining popularity in recent years. Among its diverse applications, therapeutic robotic systems have been utilized in the muscular physiotherapies for movement training, wrist and arm treatment for injuries and overexertions, and other therapies. Applications of wearable sensors for human assistance or health monitoring have been also gaining popularity in recent years. Wireless wearable sensor systems enable proactive personal health management and the ubiquitous monitoring of vital signs to keep an active watch on immediate health conditions.

In this paper, we develop a system that consists of multiple wearable sensors, software agents and robots, where a robot has the intelligence to process its own observed data, the collected wearable sensor data, and to aggregate the information into a single compiled report. Our system is also able to detect severe abnormalities with the well-being of the monitored individual as detected by the sensors and to create immediate alerts. Our preliminary experimental results show that our system is accurate in detecting and monitoring basic human conditions. We posit that the approach of non-invasive monitoring, when combined with an alert system, will make this a desirable personalized well-being monitoring system in future health care.

Introduction

With the growing special-needs and aging (baby boomer) populations there is an increasing need for the personalized care to allow people with physical limitations or disabilities to continue living independently. Socially assistive robotics technology for the members of special-needs populations has been outlined as one of the key areas in robotics that can be instrumental in facilitating independence and mobility associated with those who suffer from disability and aging-related disorders (Christensen et al. 2013). Robotic systems have been used for various therapies such as movement training, wrist and arm rehabilitation, and others (Krebs et al. 2007; Lum et al. 2002; Nef and Riener 2005). In (Fasola and Matarić 2012), for instance, socially assistive robotic systems were designed to engage elderly people in physical exercise.

Recently, wearable sensors, have been used to assist humans to monitor health conditions (Pantelopoulos and Bourbakis 2010) and to enable proactive and ubiquitous personal health management. Additionally, wireless sensor networks have the potential to greatly improve the study of diseases that affect motor abilities. Small, wearable sensors that measure hand or foot movements, posture, and physiological conditions can provide quantitative data for the better understanding of disease to develop more effective therapies. Wearable sensor platforms have already been developed in motion analysis for the treatment of neuro-motor disorders, (i.e., Parkinson's Disease, epilepsy, and stroke (Lorincz et al. 2009). Wearable sensors are also able to take vital measurements (i.e., temperature, blood pressure and etc.), which could be used to monitor health and the person's general well-being (Pantelopoulos and Bourbakis 2010). However, wireless sensor networks have limited capabilities in terms of their computation, storage, and the ability to send information. Additionally, each sensor generally monitors its local environmental conditions from a two-dimensional setting. Able to perform high computational tasks, robotic systems allow us to overcome these challenges when they are fitted to work in tandem with wireless sensors.

In this paper, we present an overview of a system, composed from multiple robots, wearable sensors, and software agents, to provide uninterrupted, unintrusive and personalized monitoring of a user's current health in his or her own environment. Our system contains autonomous mobile robots and wearable sensors (WSs), in which each sensor is equipped to collect the necessary data to monitor a person's health conditions. In our system, robots share tasks of monitoring user's movements and they are able to communicate with each other to make changes to their tasks if necessary during the monitoring. Since suffering a fall or a stoke will accompany strict changes in behavior, working collectively as a unit to process the user's behavioral and health information, the robots are able to more aptly determine any abnormal trends to signal the warnings of potentially life-threatening conditions. At regular intervals, the multi-robot system prepares a compiled report of all the processed information to keep a person's caretaker (i.e., doctors, family, etc.) informed of any changes in health status. If the system determines that there is a threat (i.e., a developing illness or other abnormality), then the system is equipped to immediately warn the caretaker.

Related Work

Over the last two decades wireless sensor networks have been popular in applications for environmental monitoring tasks. Sensor networks have been used to monitor habitats (Mainwaring et al. 2002), the moisture level of the soil (Cardell-Oliver et al. 2004), conditions in and around building (Jang, Healy, and Skibniewski 2008). Unlike regular wireless sensors, wearable sensor systems, comprising of various types of small sensors that can be warn on the person, allow for mobility. Wearable sensor systems have been identified as a potential low-cost solution for continuous, ubiquitous, all-day and omnipotent health, mental and activity status monitoring (Pantelopoulos and Bourbakis 2010). Many of the current wearable systems are able to provide reliable vital signs measurements that can be used to monitor a person's well-being (Pantelopoulos and Bourbakis 2010). Wearable sensor systems have also been developed in motion analysis research for the treatment of neuro-motor disorders, such as Parkinson's Disease, epilepsy, and stroke. In (Lorincz et al. 2009), a wearable sensor network platform, called Mercury, is discussed that is able to monitor patients with Parkinson's disease and detect epileptic seizures during long-term studies. Individual sensors in Mercury compute high-level features from the raw data, while a base station performs data collection and adjusts sensor node parameters based on energy availability, radio link quality, and application specific policies. Accidental falls is a serious problem in the aging population and for people suffering from seizures, thus the early detection of fall is very important to rescue the subjects and avoid the incorrect prognosis. Zhang *et al.* (Zhang et al. 2006) propose a fall detection technique based on the support vector machine algorithm.

Robots have been used for health related problems, such as therapies involving movement training, wrist and arm rehabilitation, and others. For example, in (Nef and Riener 2005) a new robot, ARMin, for arm therapy is presented, which can be used in patients' daily activities in clinics. ARMin has a semi-exoskeleton structure with six degrees of freedom, and is equipped with position and force sensors. Krebs *et al.* (Krebs et al. 2007) developed a robot for wrist rehabilitation, providing three rotational degrees-of-freedom. Their experimental results with 200 stroke survivors showed a reduction of impairment in movements confined to the exercised joints. Researchers (Lum et al. 2002) have also compared the effects of robot-assisted movement training with conventional techniques for the rehabilitation of upper-limb motor function after stroke. Their experiments conducted in the Department of Veterans Affairs rehabilitation research and development center with 27 participants with chronic hemiparesis, show that the robot-assisted movements had advantages in terms of clinical and biomechanical measures. In (Fasola and Matarić 2012), a socially assistive robot (SAR) system was designed to engage elderly users in physical exercise. The results of SAR validate the system approach and effectiveness at motivating physical exercise in older adults according to a variety of user performance and outcomes measures. The results also show a clear preference by older adults for the physically embodied robot coach over the virtual coach in terms of enjoyableness, helpfulness, and social attraction, among other factors.

Robotic systems can also be used in applications where mobility is important and thus the usage of the stationary wireless sensors would not be possible. In (Dhariwal, Sukhatme, and Requicha 2004) a simple, yet novel, approach based on a biased random walk is proposed to locate and track gradient sources such as temperature, light, PH and salinity. The proposed approach is validated through experiments involving one robot in a phototaxis experiment. Jadaliha and Choi (Jadaliha and Choi 2013) develop a scheme for the problem of monitoring an environmental process in a large region by a small number of robotic sensors. They test their approach by monitoring the temperature of an outdoor swimming pool, as sampled by an autonomous aquatic surface robot. Robotic systems can be viewed as mobile wireless sensors that can be used in cooperation with the stationary wireless sensors. Tekdas *et al.* (Tekdas et al. 2009) develop a system that integrates mobile robots with wireless sensors. The authors utilize autonomous robots as data mules that visit static sensors within their communication range, get the data from the sensors, and return to a remote base station to offload the collected data. One of the benefits of this approach is that a sensor-based system saves on energy consumption which prolongs the lifetime of the sensor network.

In many monitoring applications, robots need to make decisions about how to interpret their sensing, what kinds of information to communicate to other robots, and how information obtained from other robots and sensors should be aggregated. Although, robotic systems have been applied to environmental monitoring problems, they have been generally used as data collecting and measuring agents. When applied to tackle health related problems, only single robotic systems have been proposed for specific tasks. In this paper, we develop a multi-robotic solution, which works in collaboration with the wearable sensors.By using multiple robots and multiple sensors, our system produces fault tolerant and accurate results.

A Cooperative Robotic-Sensor System

Figure 1 shows the interactions between various components of our system. A person employs multiple WSs to collect data regarding his or her activity levels or other vital conditions (i.e., temperature, heart rate, altitude, magnitude, angle, etc.). This data is then stored in a database, which contains triggers for emergency situations. For example, if a dramatic fall or a dangerous spike in temperature is detected during the analysis of sensor data, then the database trigger sends a warning via connected software agents, to remote systems located at the users home and to systems which are accessible by relatives and doctors. In addition to the wearable sensors, mobile robots provide an external view of the user and his or her environment. To determine the user's movements and motions mobile robots utilize a technique similar to (Machida et al. 2012). The benefit of using multiple robots for monitoring a person's well-being lies in

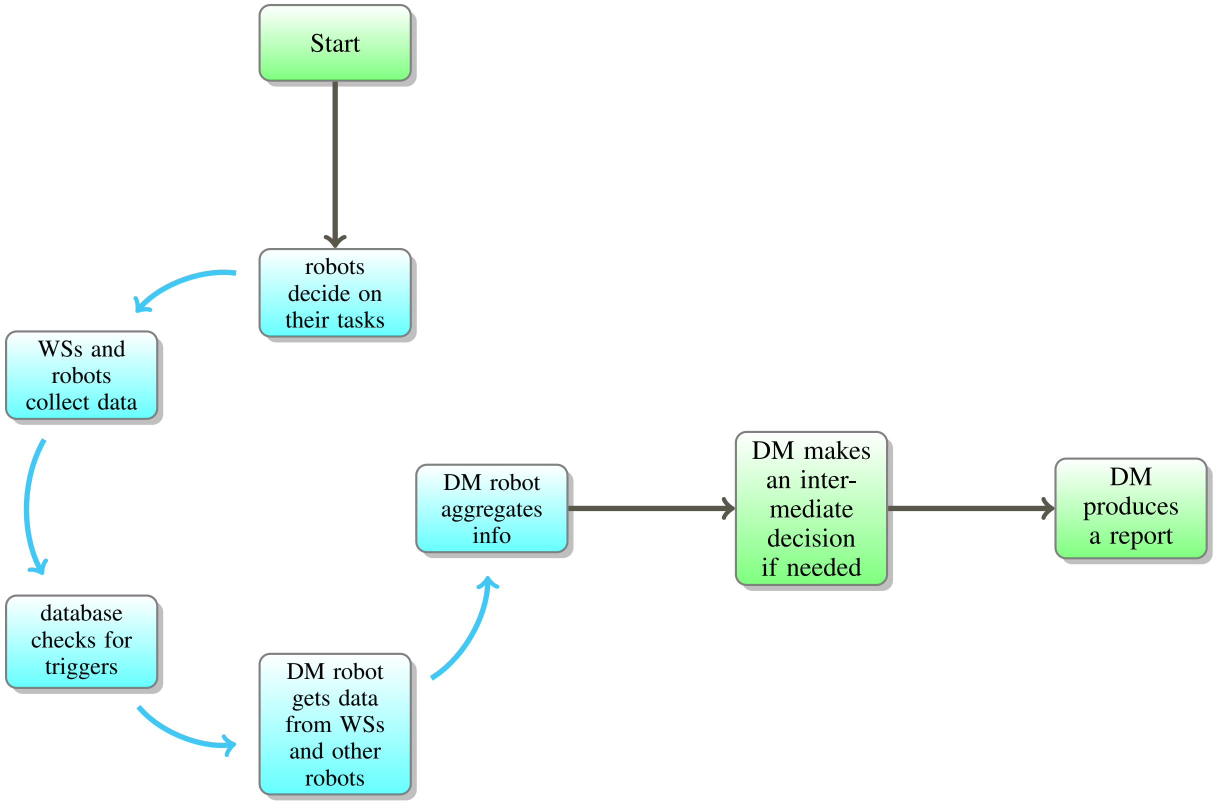

Figure 2: Flowchart showing the systematic methodology of our system

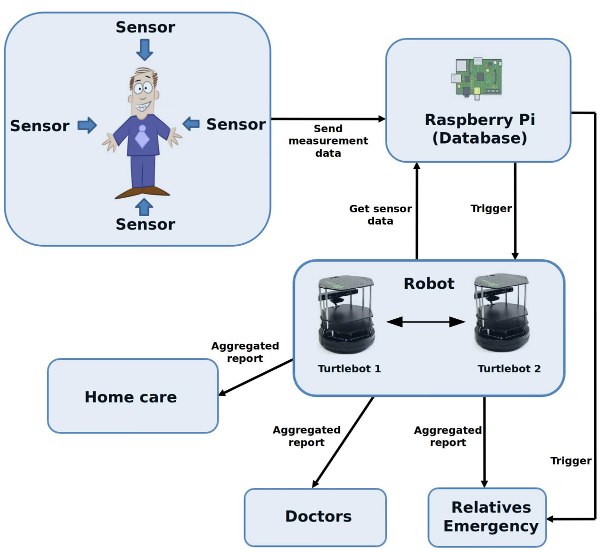

Figure 1: The diagram of our system interactions.

their capability to accomplish complex tasks in a cooperative manner. For example, multiple robots are able to share tasks such as tracking of the person, aggregating information and compiling the report, or confirming an emergency situation. In addition, if one robot needs to recharge, it can do so, without the interruption to the continuous monitoring. Each mobile robot in our system is intelligent, with a software agent that participates in a cooperative task sharing and decision making process. At regular intervals, our system prepares a compiled report of all the processed information to provide a monitored person's caretaker (i.e., doctors, family, etc.) information regarding any changes in health status. If the system determines that there is a threat (i.e., a developing illness or other abnormality), then the system is equipped to immediately warn the caretaker, either through the database triggers or, if that fails, directly through the system.

Figure 2 shows the flow of our developed system. Since the focus of our paper is to illustrate that integrated multi-robot and wearable sensor system is possible, accurate and useful, we utilize existing state-of-the-art techniques for task allocation and data aggregation, and we omit the details of those techniques in this paper. The tasks in our system include following the monitored user and collecting user movement and motion data, obtaining the sensor data from the database, aggregating the data and making a decision on what to include in the final report, or if an emergency alert should be sent. The tasks have priorities, which may change during the monitoring task, and the robots are sequentially assigned the tasks starting with the highest priority task. We classify the robots in our system as *monitoring* robots and *decision making(DM)* robots. One or more monitoring robots have to follow the user and monitor its motions and movements. In the case when the monitoring robot has lost track of the user, it creates a new task enabling another robot to be called for help and then both robots proceed to navigate the environment until one of them reinstates contact with the user. DM robot can participate in the monitoring task, but is also responsible for aggregating all of the sensor data and compiling a report or creating an emergency alert. Allowing the system to perform all of the computation (aggregation, decision making and taking an action) in a mobile manner on a robot, allows our system to be easily deployed to any user's environment and to adopt to a new environment if necessary.

In particular, DM robot needs to obtain and aggregate data from wearable sensors and from the other robots and then it has to choose the appropriate action (i.e., what to include in the report or if an emergency alert should be sent). We note that some of the data is complementary (different sensor measurements) and some is competitive (same measurements from different sensors). We use the current popular technique for the competitive data aggregation, known as Kalman filter, and utilize a very simple decision making approach. Once the competitive data is aggregated, the DM robot analyzes the data by comparing the current aggregated observation data and previous recorded aggregated data from the database to determine whether the user has an abnormal condition. The difference between two datasets can help the system to determine the user's well-being condition such as the difference between user's current position and previous position, current temperature and previous temperature, etc. The difference between these two datasets must stay in the range of some thresholds value. Otherwise, the system will think the user has an abnormal status and needs to do create an emergency alert to help user. For example, for the temperature change, $|T_{pre} - T_{cur}| <= t$, DM agent determines whether the temperature change between previous observation and current observation is irregular, by checking if the current temperature, T_{cur}, has changed significantly from the previous temperature, T_{pre}, where t is the threshold value for the temperature change. However, since it is possible that factors like user exercise or hot outdoor temperature could cause his or her body temperature to rise, our system also checks the complementary sensor data to prevent accidental emergency report issued by the system. Finally, the aggregated competitive data and complementary data is combined into a single report.

Experimental Results

We implemented our system using two Turtlebot II robots and several WSs using FLORA - wearable electronic platform, including GPS, accelerometer, compass, temperature sensors, among others. Partial set up of the sensor system is shown in Figure 3. Flora wearable sensors were sufficient for our proof-of-method experiments as they provide a diverse number of sensors that are easy to integrate. The database, containing the sensor data, is stored on a Raspberry Pi B computer, which can conveniently fit into a pocket along with the sensors. At the beginning of the experiment, the robots are sequentially (robot 1 and 2) assigned the two main tasks. One robot follows the person and records the person's movements (changes in altitude, direction, distance traveled, etc.), while the other robot at specified intervals collects the sensor data from the database and gets the data from its team-member robot. If a monitoring robot needs help (confirming an emergency situation or locating the user), it calls its team member for help. The Turtlebot II robots use a Kinect sensor to monitor and record the movements of the person, including the distance that the person travels. The robots utilize a technique similar to (Machida et al. 2012) for motion analysis using a 3D Kinect sensor. The robots and sensors are tasked with monitoring a person's behavior over a period of time. This simple experiment allows us to test our model in a controlled environment.

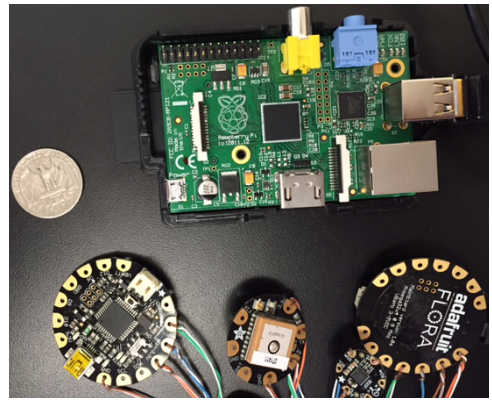

Figure 3: Wearable sensor system used in our experiments.

In order to acquire the sensors data, we used different hardware components and software packages. For our system, we employed the Raspberry Pi ran a Raspbian Linux OS with a MySQL version 5.5.46 and Python 3.2. To collect the data, we first programmed the FLORA main board, using Arduino-1.6.4, to return all of the sensor values in 1 second cycles (i.e. 1 second = 1 time step). A Python program was then run on the Raspberry Pi to connect it to the Flora main board to handle the returned sensor values. The returned values were then stored in a local MySQL database. Our data collection, performed by a Python program runs continuously: collecting and storing the sensor data until it is terminated. A sample collected sensor data is shown in Table 1. When the database has exhausted the Raspberry Pi memory, the data (stored in the database) is automatically sent to the user's computer, and the Raspberry Pi can then overwrite the previous sensor values in its local database.

In our experiments, we restricted the possible aggregated observational values to the set $\{0, 1, 2, 3\}$, corresponding to the following actions, {"just send the report for a normal situation", "notify the caregiver", "notify the doctor", "emergency"}. We ran the experiments for two hours, with data readings each second, where one of the co-authors wore the sensor system and imitated various situations, including sitting, standing, walking, quick fall, slow fall, running (slow and fast). To vary the temperature, an ice packet and then a heat wrap was applied to the user to imitate the decrease and increase in temperature, correspondingly. Figure 4 shows the results for when the observation value changed from 0 to 2 and then to 3 (i.e. from the normal situation, to a doc-

Table 1: A sample data produced by the sensors.

ID	Date	Time	Accelerator (x,y,z)	Magnitude (x,y,z)	Gyro (x,y,z)	Temp
1	15/11/2015	20:29:40	1.10, -8.53, -4.83	-2.62, -1.69, 0.24	2.18, -2.19, -8.35	15.63
100	15/11/2015	20:30:32	1.17, -8.40, -4.80	-2.62, -1.43, 0.56	2.67, -2.68, -8.44	19.62
800	15/11/2015	20:45:17	6.58, -11.78, -4.88	0.11, 0.19, -0.01	33.94, 22.12, 22.98	37.87
1200	15/11/2015	20:48:29	5.97, -8.13, -1.40	0.37, 0.18, -0.20	-55.21, 5.94, -17.70	41.87

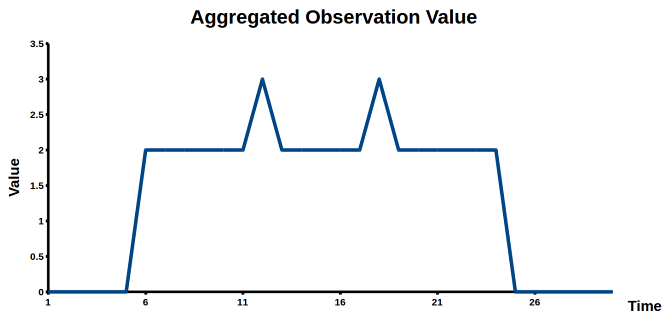

Figure 4: The aggregated observation value for the snippet of the experiments corresponding to a three level change in observation value.

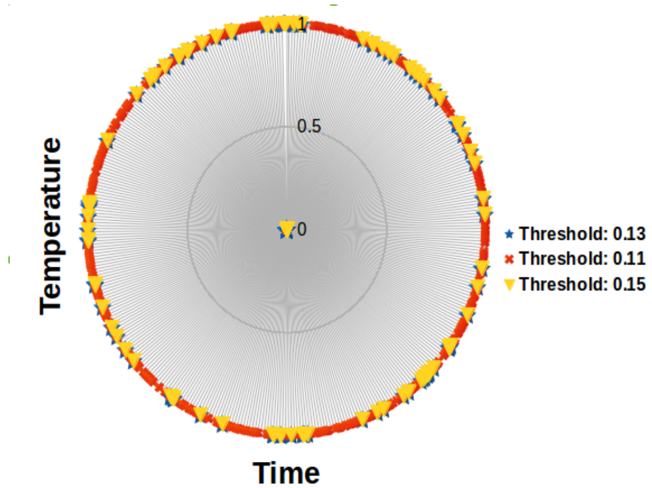

Figure 5: The threshold value.

tor's notification and then to an emergency notification. This part of the experiment corresponded to an increased heart rate followed by a drastic fall in the initial 15 time steps, indicating the need to initially notify the doctor of a fall and then to contact emergency personnel for the increasing seriousness of the fall. During the next 15 time steps, the heart rate returns to normal, changing the observation value to 2, but then the temperature drastically changed, prompting an emergency notification again.

At each time step, DM robot conducts data processing that goes through the sensor data in the database and aggregates it with its own data. The information generated by the robots concerns a user's movement/motion data (i.e. the distance, altitude, magnitude and the acceleration of user movement in a 3D space). DM robot determines its observational value based on the aggregated wearable sensor data and the robot sensor data, and selects an action (what is included in the report) based on this analysis. The report is then sent remotely to three different machines: the user's own machine, the doctor's machine and that of the caregiver (or relatives). A partial sample report is shown in Table 2.

Threshold parameter for each type of data is an important parameter for our simple decision making technique. We ran experiments with various values of the thresholds. For example, for the temperature data set, a lower value for the threshold is not very accurate. This can be seen in Figure 5, where a lower threshold value of 0.11 is misaligned with the other two compared threshold values. This result was also confirmed when accuracy values for various threshold values were compared. In our experiments we chose tested threshold values that produced the highest accuracy for each type of data.

Table 3 shows the overall system's accuracy percentages, which were calculated by comparing the calculated aggregated observation values and chosen actions by our technique against the manually recorded "events" (i.e., the time step at which the drastic fall or temperature rise occurred). Since incorrectly estimating the emergency notification observations is more costly than the normal observations, the decision rules prefer to choose actions for notifying the doctor or the emergency personnel. Therefore, the accuracy for those states was higher than for the normal state.

Table 3: *Accuracy of our preliminary system*

Condition	Accuracy
Normal	93%
Slightly abnormal (notify caregiver)	94%
Abnormal (notify doctor)	97%
Very abnormal (emergency)	100%

Conclusion

In this paper we presented a preliminary, but a robust and a coherent system with the potential of improving the quality of lives through monitoring a user's health for the early detection of abnormal behavior. Our system combines a multi-robot system with a wearable sensor technology for a more comprehensive monitoring of the user's well-being.

Table 2: A sample report produced using our method.

Date	Time	Movement Status	Distance Traveled	Temperature Status	Heart Rate
15/11/2015	17:18:32	Normal Movement	Normal Distance	Normal Temperature	Normal Heart Rate
15/11/2015	08:34:16	Abnormal Movement Altitude changed by 200 cm	Abnormal Distance Total of 0.1 miles	Normal Temperature	Low Heart Rate 60 beats per minute
15/11/2015	16:35:59	Normal Movement	Normal Distance	Abnormal Temperature Temp increased by 2C	Normal Heart Rate
15/11/2015	23:20:10	Abnormal Movement High changes in acceleration	Abnormal Distance Total of 5.2 miles	Normal Temperature	High Heart Rate 102 beats per minute

We are currently working on an implementation that, additionally to our current system, uses the sensors that can take vital measurements. We are also working on developing more sophisticated learning techniques for aggregation and decision making. In the future, in addition to the monitoring a person's conditions, we will implement a solution for the multi-agent robotic system to provide motivation for cognitive and physical exercises to the user by considering the history of the user's daily tasks and coaching the user to fulfil the appropriate tasks. Our multi-robot system will also be able to interoperate with existing systems, such as person's medical records from the doctor and in-home stationary sensors to create and process supplementary statistics to further the user's medical care.

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