OWLS: Observational Wireless Life-enhancing System (Extended Abstract)

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ABSTRACT

Socially assistive robotics technologies for individuals, who have been affected by age-related disabilities and similar types of disorders, have become popular options for facilitating natural independence and uninterrupted mobility. 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, called OWLS, where multiple wearable sensors, software agents, robots and health analysis technology, have been integrated into a single personal therapy solution (SPTS). Our system uses a reinforcement learning algorithm to make decisions about the user's current health conditions, and to take appropriate actions, as necessary (i.e, contacting outside parties). We show that the approach of non-invasive monitoring, when combined with an alert system, makes this a desirable SPTS in future health care.

1. INTRODUCTION

There is an increasing need for the personalized care to allow people with physical limitations or disabilities to continue functioning independently.Robotic systems have been used for various therapies such as movement training, wrist and arm rehabilitation, and others [3]. Recently, wearable sensors, have been used to also assist humans to monitor health conditions [4] and to enable proactive and ubiquitous personal health management. In this paper, we present an *Observational Wireless Life-enhancing System*, which we call OWLS, composed of multiple robots, sensors, and software agents, to provide uninterrupted personalized monitoring of a user's current health in his or her own environment. Similar to an owl who watches uninterruptedly in the wild, by unintrusive observation, the robots and sensors in our system collect data to ascertain the general health conditions and well-being of the user. A reinforcement learning algorithm is used to decide on the condition of the monitored user and take an appropriate action. At regular intervals, the OWLS prepares a compiled report of all the processed information to keep a person's caregiver (i.e., doctors, family, etc.) informed of any changes in the health status of the monitored individual. If an analysis of the user's well-being determines a form of threat or the likelihood of a threat in the future (developing illness, worsening conditions, etc.), then the system is equipped to immediately notify the appropriate caregivers. The experimental results show that OWLS is accurate in determining the user's condition and taking an appropriate action. Reinforcement learning algorithm used by OWLS is also shown to outperform a baseline algorithm used for comparison.

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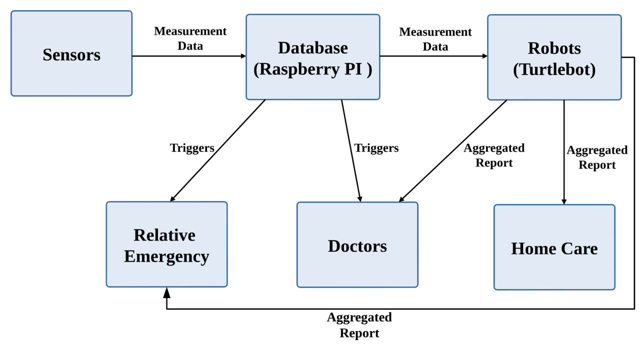

Figure 1: The diagram of the OWLS interactions.

2. REINFORCEMENT LEARNING-BASED MONITORING ALGORITHM

Figure 1 shows the interactions between various components of our system. A person employs multiple wearable sensors 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. The robots monitor the person's movements and motion using a technique similar to [2].

The algorithm used by OWLS for the decision making in our system is the reinforcement learning using Q-learning technique. This learning paradigm relies on agents choosing an action and then receiving a scalar reward based on how the state of the environment changes. In our system, the state of the environment correlates to the condition of the monitored user. Each individual robot collects data from its own observation of the user and also collects the latest raw sensor data from the database. For the data that is competitive, where the same type of data is collected by both the robot and the sensor, the robot uses Kalman Filter [1] to aggregate it. The complementary data is also processed to extract relevant information to be added to the report. The robots then use simple decision rules to take all of the aggregated data and obtain a current observation value.

During reinforcement learning, one of four policies is chosen to maximize the potential reward. These policies are designed to apply a simple change to the action to produce the anticipated next state. The expected reward is calculated for each policy, and the policy yielding the most favorable reward is chosen along with the corresponding action. By using the reward-based learning process each agent incorporates feedback from its own historical experience through the local observation and also from the other agents' by considering the global observation value when calculating the reward. By maintaining historical data on the reward given for each action performed, we can design our robotic agents to seek the most optimal reward possible based on both short-term and long-term goals. This type of agent learning was chosen due to the lack of existing monitored data for the scenarios tested in the scope of user health monitoring. Without such reference data, we needed a way to determine the validity of each robot's decision; and reinforcement learning provided a reliable solution to the problem.

3. EXPERIMENTAL RESULTS

We conducted experiments using two Turtlebot II robots, and several wearable sensors using Flora - wearable electronic platform, including GPS, accelerometer, compass, gyroscope, temperature sensors, among others. Turtlebot II robots use a 3D Kinect sensor to monitor and record the movements of the person, including the distance that the person travels. 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.

The information generated by the robots is related to a user's movement and motion data (i.e. the distance, altitude, magnitude and the acceleration of user movement in a 3D space). Each robot determines its observational value based on the aggregated sensor data and its own data, which is sent to the central computer, where OWLS aggregates (averages) the robots' observational values and selects an action 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). 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 1 hour, 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. Our experimental results have shown that the reinforcement learning algorithm developed with our system allows the robots to accurately detect immediate signs for the correct determination of the health conditions in monitored users.

We also compared our reinforcement learning techniques with multiple robots and sensors to a decision-making method without a multi-robot system present. In our baseline comparison technique, the action chosen by the system was purely dependent on the data produced by wearable sensors. The same simple decision rules were used as the ones used by OWLS. Table 3 shows the accuracy percentages, which were calculated by comparing the calculated observation values and chosen actions by the two techniques against the manually recorded "events" (e.g. the time step at which the drastic fall or temperature rise occurred). Overall, our comparison experiments supported that OWLS, which utilizes both a multi-robot and a multi-sensor system, performed better than a basic multi-sensor system.

State	Baseline	OWLS
Normal	90%	99%
Slightly abnormal (notify caregiver)	87%	93%
Abnormal (notify doctor)	92%	96%
Very abnormal (emergency)	95%	100%

Table 1: Accuracy of the OWLS vs. the baseline technique that utilizes only sensor data.

We also noted that the final observation values, obtained using 3 and 4 robots, were similar to the previous results and therefore, these results have not been included in this paper. In summary, we conclude that our multi-robot, multi-sensor system with learning support is able to efficiently learn the conditions of its users to be able to make the necessary notifications regarding their well-being.

4. CONCLUSION

In this paper we have described a single personal therapy solution (SPTS) that uses reinforcement learning based multi-robot and multi-sensor well-being monitoring system, called OWLS. Our experimental results have shown that the reinforcement learning algorithm developed with our system allows the robots to accurately detect immediate signs for the correct determination of the health conditions in monitored users. OWLS, using multiple robots and wearable sensors was able to outperform the system that only relies on the wearable sensor data. In the future we plan to conduct more experiments with our system for more complex and continuous health monitoring tasks. In particular, we plan to use more medically relevant sensors, such as a blood pressure and sugar level detecting sensors. We also plan to do statistical comparison of our results with other commonly used learning methods.

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