Context-Aware MAS to Support Elderly People (Demonstration)

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ABSTRACT

This paper presents a context-aware, multiagent system for care of the elderly. The system combines state-of-the-art sensor technologies to detect falls and other health problems, and calls for help in the case of an emergency or issues a warning in cases not needing urgent attention. When deployed at the home of an elderly person it provides them with 24-hour monitoring. Consequently, the elderly may live alone at home, even at an advanced age. The health problems are detected with six groups of agents processing the sensor data and augmenting the data with higher-level information, such as the posture of the person, his/her activity and the context of the situation's environment. The system has been tested in several live demonstrations, where it achieved an excellent performance in complex situations. The system is based on the set of agents observing the elderly person from various points of view, and combining the location and inertial sensors to provide context awareness.

Categories and Subject Descriptors

I.2.1 [**Artificial Intelligence**]: Applications and Expert Systems - medicine and science

General Terms

Algorithms, Measurement, Design, Verification

Keywords

Elderly health care, fall detection, general disability detection, ambient intelligence, ambient assisted living

1. INTRODUCTION

The number of elderly people is increasing rapidly in developed societies. Many of them require assistance with everyday activities. Institutional healthcare already enables monitoring of the elderly and provides help when needed in special facilities or at home. However, the resources for healthcare are insufficient and the presence of care personnel is therefore quite limited. Ambient-assisted-living systems that monitor elderly people at home may be able to effectively cope with this problem.

Our main objective is the development and integration of innovative technologies to build a care system for the detection of health problems on three time scales: (i) the short-term detection of critical events, such as falls; (ii) the mid-term detection of unexpected behaviors that may be related to health problems, e.g., limping; and (iii) the long-term detection of deviations in behavior that may indicate a disease or a deterioration in the person's health.

There are many commercial and research solutions for fall detection, mainly based on inertial sensors. They typically report nearly 100% performance in laboratory settings. However, when deployed in real-life situations, they often face high false-alarm rates and generally decreased performance. This paper presents a multiagent system[1] to help the elderly. Its novelty is in exploiting the context in problem detection, and in combining inertial and location sensors. The agents are arranged hierarchically, providing increasingly more abstract situational awareness. The system is also able to adapt to each specific user as well as to learn false alarms. The results of the fall-detection experiments show that context-dependent reasoning can detect complex scenarios [3] that might be misinterpreted by inertial-based systems. The exact use of the context is the subject of an ongoing patent application. This paper and demo desribe the functional performance of the Confidence system in complex scenarios.

2. THE CONFIDENCE SYSTEM

The system is designed as a classical hierarchical multiagent system where agents are implemented as task-dedicated heterogeneous procedures with agent properties, i.e., they trigger at a specific pattern and provide one of many opinions or actions. The agents are organized into groups at a specific level of abstraction and coordinated by another, hierarchically higher-level agent. Each agent can be easily modified or replaced and new or redundant agents can be incorporated. The MAS architecture [2] is illustrated in Figure 1. This figure shows the main groups of agents and their interactions indicated by arrows. The agents share the data through direct acquisition using three types of messages. The first type is a measurement message that is created when a new measurement is obtained by the sensor agents. At the initial stage the message contains only raw sensor data. The message is later augmented by other agents with additional interpretation data, e.g., filtered/derived data, posture information, etc. The second message type is an action mes-

[1]The system is the result of the Confidence project, http://www.confidence-eu.org

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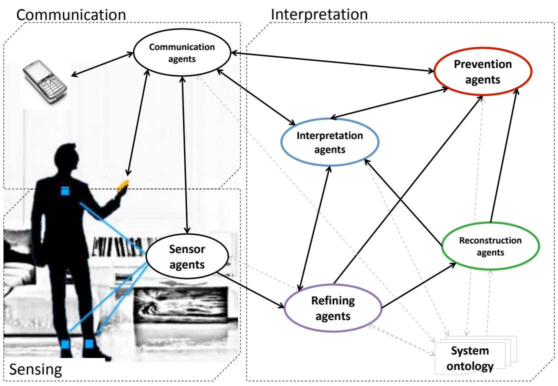

Figure 1: MAS architecture.

sage that is generated when an agent or an agent group requires a service from another agent or group. A typical scenario is when a group of agents detect a fall and require an alarm action from the communication agent group. The last message type is a status message that is used to pool or post the agent state.

At the lowest layer, an arbitrary inertial and location hardware system can be employed. In our case it was the combination of Ubisense[2] and XSens[3]. Sensing agents read the raw sensor data (every 1/10th of a second), and serve them in the form of measurement messages. The sensor agents can also report other information, for example, a status message "low battery" is sent to the communication agent group, which forwards the message to a user-friendly interface. The refining agents filter the noise, compute the derived attributes and map the raw data to a human-body model.

The reconstruction agents aim to determine the posture of the person in the environment. The group consists of classification agents based on machine learning (Random Forest) and expert rules [4]. When all the classification agents provide their label for the posture, a meta-classification agent (Hidden Markov Models) merges the labels to the final posture classification.

The interpretation group of agents detects whether a person is in a dangerous situation. Consider the following situation as an example: an agent detects that the user is *not moving*, the reconstruction agents indicate that the posture of the user is lying, and the refining agents give the location as the *kitchen*. The interpretation agents, implemented with data-driven (Support Vector Machine) and knowledge-driven approaches (expert rules), classify this situation as risky, since it is very unusual and most likely related to a health problem, e.g., the person might have lost consciousness, and inform the communication-agent group.

The prevention-agent group monitors how the person moves on various time scales. It consists of several agents that observe a variety of statistics, e.g., gait characteristics, activity characteristics, daily dynamics, etc. [1, 5]. Each agent pulls the relevant measurement messages from other agents and builds its own behavior model (implemented with outlier detection). When an agent detects a deviation, it notifies the group coordination agent, which decides whether to notify the communication agents.

The last group consists of communication agents that are dedicated to user interaction, for example, the agents that alert the user with a reply demand, make a phone call to relatives or help center, graphically display the state of the system, etc.

The performance was evaluated on a scenario recored by 10 helathy voluteers (five times by each), which included nine different complex fall-detection situations (e.g., fainting, tripping followed by standing up quiclky, quickly lying down on the bed, etc.). The average fall-detection accuracy is 94.7% when using four sensor boxes (neck, belt, both ankels), and 90.1% with one sensor box (neck) only, while the best inertial-based fall-detector was able to achieve the accuracy of 81.8% [3]. To the best of our knowledge, the proposed solution is the only one that: (i) integrates behavior monitoring on several time scales; (ii) incorporates various types of context; and (iii) achieves significantly better performance than inertial-based solutions for fall detection in complex real-life scenarios.

3. DEMO

This demo[4] shows the usability of the system in the following scenarios: (i) complex fall-detection scenarios in which falls can be correctly recognized using the context and (ii) scenarios demonstrating the detection of unusual behavior on two time scales. The fall-detection scenarios include three cases. In the first, a person is lying on the floor and moving. The sequence before the lying posture is crucial to understand the context of the situation and decide whether the situation resulted from a fall or some other activity. The second case shows an example in which the person misses the bed while lying down, which triggers an alarm since the person is not lying where he/she should be. The third case shows the person sitting on a chair and leaning to one side, e.g., due to a heart attack. In this case, the sitting in an unusual posture on the chair raises an alarm, while this posture would not raise an alarm in the bed. Unusual behavior detection is presented with scenarios showing (i) limping detection as a change in the person's gait and (ii) unusual daily dynamics such as frequent toilet visits (or other long-term statistics).

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[2] Ubisense location system, `http://www.ubisense.net`

[3] XSens inertial motion tracker, `http://www.xsens.com`

[4] Demo video: `http://dis.ijs.si/confidence/aamas2012.html`