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A Smart Range Helping Cognitively-Impaired Persons Cooking

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Abstract

People suffering from a loss of autonomy caused by a cognitive deficit generally have to perform important daily tasks (such as cooking) using devices and appliances designed for healthy people, which do not take into consideration their cognitive impairment. Using these devices is risky and may lead to a tragedy (e.g. fire). A potential solution to this issue is to provide automated systems, which perform tasks on behalf of the patient. However, clinical studies have shown that encouraging users to maintain their autonomy greatly help to preserve health, dignity, and motivation. Therefore, we present in this paper a new smart range prototype allowing monitoring and guiding a cognitively-impaired user in the activity of preparing a meal. This new original prototype is capable of giving adapted prompting to the user in the completion of several recipes by exploiting load cells, heat sensors and electromagnetic contacts embedded in the range. We currently own a provisional patent on this new invention, and we completed a first experimental phase.

Introduction

Cognitively-impaired persons, such as elderly people with Alzheimer's disease or young people with brain injuries, suffer from a loss of autonomy. This deficit induced by their condition limits these individuals in performing their essential Activities of Daily Living (ADL), such as bathing or cooking [1]. These people generally have to routinely perform tasks, in their home, using devices designed for healthy people, which do not take into consideration their cognitive deficit. These devices are not adapted to their conditions, and they often come with unacceptable risks (e.g. fire) [2]. Nevertheless, a vast majority of cognitively-impaired people want to remain in their home as long as possible, where they feel safe and autonomous [3]. With the growing problem of aging population, the governments also want to postpone the institutionalization of these people for social and economic reasons. Consequently, smart technology presents itself as a viable avenue of solution, carrying a lot of hopes [4]. One potential approach to solve this issue is to develop efficient automated systems, which perform tasks on behalf of the resident. However, clinical studies have shown that encouraging users to maintain a certain level of autonomy greatly helps to preserve health, dignity and motivation [5]. In that sense, automated systems had the inconvenience of entirely removing the autonomy of the user. An alternative approach consists in developing assistive systems (instead of automated systems) that are able to track an activity of a cognitively-impaired user in order to identify his erroneous or risky actions, and that are able to give adequate prompts (hints, suggestions or reminders) thus increasing the probability of a desired behavioral outcome [3]. The aim of these systems is to provide appropriate guidance to the user to allow him to complete, by himself, his ADL safely.

In this paper, we present such a new assistive system, which takes the form of a smart range prototype allowing monitoring the cooking activity of a cognitively-impaired user and to give adapted guidance [1] in the completion of a recipe. Our system is also able to detect risky situations (e.g. a dangerous state that may lead to fire) and is able to take preventive actions accordingly. The originality of the device is to combines, in real time, the inputs coming from load cells, heat sensors and electromagnetic contacts embedded in the range in order to infer the current state of an on-going activity. The system also identifies the main types of errors characterizing cognitively-impaired users [6]. The artificial intelligence (AI) model of the prototype relies on a stochastic representation of each activity with a state-transition model [7], which is included in a knowledge base. We recently obtained a provisional patent covering North America on this invention. A first experimental phase has been conducted on the prototype, giving promising results that will be presented in this paper, showing the interest of this device.

Related Works

In the last several years, many research teams proposed new assistive systems aiming to help disabled people performing their everyday tasks [8, 9, 10, 11, 12]. One of the most well-known of these systems is certainly COACH (**C**ognitive **O**rthosis for **A**ssisting with a**C**tivites in the **H**ome) [9]. This system aims to actively monitor an Alzheimer's patient attempting a specific bathroom task, for instance, hand washing, and to offer assistance in the form of guidance (e.g. prompts or reminders) when it is most appropriate. It uses a camera to obtain as observations a set of state variables, such as the location of patient's hands, in order to determine the completion status of the task according to a handcrafted model of the activity. If a problem occurs, such as an error being made or the patient seeming to be confused, the system computes the most appropriate solution to finish the task, using a probabilistic approach based on Partially Observable Markov Decision Processes (POMDP), and then guides the person in the completion of his activity. Hence, this approach is an adaptive system that learns how to guide, in the best way, the user by using POMDP. Clinical trials conducted with the COACH system, including Alzheimer's patients and therapists, have shown very good results in monitoring a single pre-established activity and in providing adequate assistance at the right moment [9]. Nevertheless, an important limitation of this prototype is that it relies on a complex and very sensitive sensor: a single camera. In practice the task of extracting features from such rich low-level representations has proven to be very challenging and not very robust when generalized [13]. For instance, the camera is sensible to many changes, such as fluctuation in brightness, color, form of the objects, etc. Moreover, the presence of a camera in the bathroom affects the privacy of the user and causes ethical issues. Finally, COACH does not address the fundamental task of cooking at home.

Another well-known former prototype is the Autominder system [8]. It provides reminders to a user for ADLs completion using three key components: a plan manager, a client modeler and a reminder module. The plans are modeled with a symbolic approach as disjunctive temporal problems (DTPs). The reminder module reasons about inconsistencies between what the user is supposed to perform and what he is currently doing, and determines what reminders to issue through an iterative refinement process. Thus, the Autominder system is able to take into account situations where the user performs multiple activities, thanks to multiple sensors installed, and to prompt reminders when some erroneous behaviors, mainly temporally related, are detected. This system has been deployed in a prototype form on a mobile robot assistant in order to assist elderly individuals with mild cognitive and physical impairments and to support nurses. Nevertheless, this system presents several constraints. For instance, it is complex and expensive to manually specify the rewrite rules and evaluation function, because to accomplish the goal of personalization, they would have to be redesigned for each user. In addition, this prototype is limited in the fact that it does not distinguish the type of cognitive errors committed by the users, for which it is important to adapt the prompting strategy.

The Independent LifeStyle Assistant (I.L.S.A.) by K.Z. Haigh *et al.* [10] and the company *Honeywell*, is also a well-known initiative. It presents a multi-agents system integrating a unified activity detection model, situation assessments, response planning, instantaneous response generation and machine learning. This prototype main focus is on monitoring the taking of medication and the mobility of elders to issue alerts and information to family caregivers through communication technologies. The ADL model exploits the Geib *et al.* [14] hybrid hierarchical plan recognition model for its task tracking component. However, it should be noted that the hardware of I.L.S.A. is complex and requires many hours of testing and active debugging as well as multiple visits onsite to deploy.

More recently, Afridi *et al.* [12] worked on a project focusing on the mobile social computing to offer assistance to enhance the care for elderly. The cares are divided into three categories: physical needs, emotional needs and task or functional needs. These needs are supported through social media and software (e.g. applications on mobile, robots, etc.) and ubiquitous care software information. This technology has been developed in order to make easy the relation of elderly with their family and to ensure the collaboration of family members to take care of them despite the distance and the lack of time. However, this system has some weakness. First, it can be difficult to protect the privacy of the family using social networking technologies. Secondly, the elders do not necessary feel comfortable with social networking. More importantly, the issue targeted here can be seen as secondary or higher-level needs. The cognitively-impaired people have more basic needs, related to fundamental ADLs (cooking, bathing, etc.), requiring to be addressed first.

There are other similar examples in the literature of prototype systems aiming to assist people with disabilities. The vast majority of them suffer from the same limitations: using complex or non-robust enough sensors, not taking into account the type of cognitive errors performed by the user, hard to deploy, etc. Moreover, there are very few systems specifically addressing the issue of assisting a cognitively-impaired user in cooking tasks. In the next section, we will present our new automated cooking assistant that we developed, taking the form of a patented prototype of smart range.

A New Assistive Prototype to Help Cognitively-Impaired Users Preparing a Meal

A schema of our prototype is presented on Figure 1. As we can see, it is made with a standard range on which we installed several sensors: 4 load cells, 2 infrared sensors, 5 heat sensors, and 1 electromagnetic contact. Each sensor is used in the detection of the actual state of an ongoing activity. The chosen sensors are all industrial types. The load cells are used to estimate, with signal analysis [15], the position and the nature of the objects placed on the stove. The infrared sensors, combined with the load cells, are used to detect fire. Heat sensors are used to estimate the appropriate cooking time of an item, to anticipate situations that may lead to a fire, etc. Finally, the electromagnetic sensor allows knowing when something is put inside the oven.

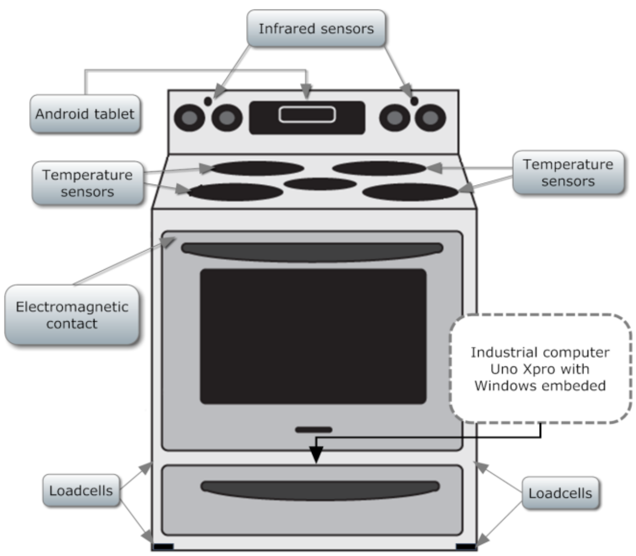

Figure 1. Schema of the smart range

On the top, an Android Tablet has been embedded to replace the frontal control panel of the appliance. This tablet provides, a touch screen menu to allow the user selecting one or more recipes that he wants to perform. The tablet is also exploited to send guidance, in the form of audio and video prompting, when an error is committed of when a risky situation is detected. In the bottom drawer, an industrial Uno PC has been installed. The inputs for all the sensors are sent to this PC to be analyzed by the artificial intelligence module. This module can send prompts to the user when it is appropriate by using the tablet screen. The PC and the tablet communicate with a wireless link.

The price building this prototype was 3178$ Canadian dollars (including the cost of the basic range), and we estimated that we can optimize it to reach a building cost of approximately 1500$ per unit. At this time, we just obtained a grant to conduct a complete large-scale market analysis of the potential of this new patented invention.

Implementation of the System

The system is implemented as follows. Sensors and actuators are connected with wires to a programmable APAX-5570 automaton located in the bottom drawer (see Figure 2). The APAX automata harvests information in real time from all sensors and sent it to the Uno industrial computer, also located in the drawer. These heterogeneous inputs are formatted by a small software module, and they are then sent to a Microsoft SQLServer database installed on the Uno. From there, the AI module fetches all the sensing data from the database at each 200 milliseconds to proceed to an inference cycle. In this cycle, the actual state of each ongoing monitored recipe is inferred. The system also analyzes the user's behavior through time to recognize different type of errors (e.g. forgetting a step, inversing two steps, boiling for two long, etc.). Also, the AI infers if the range is actually in a potential risky state. If so, a preventive action (such as cutting the power) can be taken.

Figure 2. Implementation in the range drawer

The Android tablet replacing the usual control panel of the range provides a graphical interface to the user (see Figure 3). On the left part of the figure, we can see the menu for selecting a recipe that we want to perform. As we can see, the user can select simultaneous recipes. On the right, we can see that the touch screen interface offers the standard buttons for controlling the range temperature, plus a menu indicating the actual state of the monitoring process. A particular attention was devoted to keep it simple and easy to use.The artificial intelligence can take the control of the tablet at any time, using the wireless link, to send prompts.

Figure 3. Graphical interfaces for the user

Tracking Objects on the Stove

An important part of our smart range is the AI module that handles the tracking of objects placed on the stove or directly in the oven. This functionality is mainly based on the four load cells installed under the prototype and exploits recent methods from the field of signal processing [15]. We chose to exploit load cells for two important reasons. First, these sensors are very robust and for the most important part of the system it is a crucial characteristic. Second, they are cheaper than many alternatives, but enable us to get a lot of information. The main idea is to analyze the variation of weight and its distribution on the stove. When the system is launched for the first time, the module calibrates itself to adapt to a floor that is on an angle or simply to a new type of sensors. Thereafter, it is easy to determine the total weight on the stove since it is the total difference from the calibration.

The tracking is performed by analyzing how the weight is evolving. It keeps track of how much objects were put at each spot on the stove; four lists for the hubs and one for the oven. For example, let us suppose that the user put a new object on the stove. The object is first detected. Then, let us assume that the module determines that the weight has increased mostly in the front on the left side of the stove. Therefore, the object is added to the corresponding hub. An object will be added to the oven list if the new weight is well divided among the load cells and if the door has been open. We still check if the weight is on the center since the user could have open the door by mistake and then put an object right after that on one of the hubs.

		0.45kg	1.13kg	4.5kg
Hubs	1 object	20/20	20/20	19/20
	2 objects	19/20	20/20	16/20
	3 objects	19/20	20/20	10/20
	4 objects	13/20	15/20	3/20
Oven	Only	5/5	5/5	5/5
	+ 1 hub	4/5	5/5	5/5
	+ 2 hubs	3/5	4/5	4/5

Table 1. Success rate of the object tracking

The tracking module was first tested separately of the rest of the system in our laboratory. To proceed, we used three weights of respectively 0.45kg, 1.13kg and 4.5kg. Then, with each of them, we placed one to four objects on each hub. Thereafter, we placed objects inside the oven and on the hubs. The table 1 shows the success rate of the tracking for each series of tests. As you can see, up to three objects, the tracking module is very accurate whether the objects are placed on the hubs or in the oven. However, we had some troubles with the heaviest object, which was often recognized as two objects put on the same hub. The reason is mostly because it takes more time to place an object that is very heavy. Thus, it can be seen as two consecutive objects. In fact, the most difficult situation for the tracking module is to deal with objects of a very different weight. In kitchen activities, however, such discrepancy between weights is infrequent.

Passive Monitoring

A fundamental concern of the smart range is the security enhancement. While we aim to create a prototype that helps people in the completion of their recipes, we also want them to use the stove safely. That is why few AI modules always run in the background to detect any risky state. For instance, it will detect and act if the user forgot to turn off a hub or the oven. The actions chosen by the system depend on how dangerous the situation is and can go from a simple warning (e.g. a beep) to a complete shutdown of the stove. It should be noted that cutting the power of the stove do not shut down the AI.

Another example of background services is the fire detection module. This module exploits the infrared (IR) spectrum by analyzing its variation in time. Also, to ensure the IR are not emanating from an uncovered hub, the module combines the information with the object tracking information. We also tested this particular service separately. The table 2 shows the success rate.

Sensitivity / Flammes	Very sensitive	Sensitive	Insensitive
1 cm	2/5	0/5	0/5
5-15 cm	5/5	4/5	2/5
Fire	5/5	5/5	5/5

Table 2. Success rate of the object tracking

As you can see on the table 2, whenever the fire is starting to grow, the module practically always detects it. When it is set to very sensitive, it can even detect flames as small as 1 cm. However, keeping in mind that a fire detection system needs to avoid, as much as possible, false positives, the actual default setting is insensitive. Indeed, false positives could lead the user in disabling the system, which then would lead to a much riskier use of the appliance [16]. The stove is also able to perform, by itself, an emergency call to fire department. Nevertheless, this function has not yet been deployed on the prototype.

AI Module Monitoring Recipes and Guidance

The new prototype is built to assist the user in carrying out simple recipes. To do so, the user can choose between an assisted mode and a free mode. In assisted mode, the user has to select a specific recipe listed on the interface shown on Figure 3. In both modes, the system will provide assistance, but it can be fairly more precise when the recipe is specified. For instance, let us suppose that the user has forgotten to remove the chicken from the oven. In free mode, the AI will estimate the normal cooking time based only on the weight of the object placed in the oven and will warn the user after a certain delay. However, if the user selected a recipe, the AI will know that it is a chicken in the oven and will infer with precision the normal cooking time according to the weight. It will then be able to intervene before the chicken is burnt.

The recipes are recorded in a knowledge base accessible by the AI. Each recipe is modeled by a stochastic state-transition model [7]. In these models, probabilities are used to infer which transition is taken from a state when all the conditions are met. This enables the AI to choose accurately between two or more transitions if all conditions seem to be properly filled. The probabilities were engineered for this work, but a learning method could be designed in the future. The general idea, illustrated on Algorithm 1, is to be able to determine the state of the user (normal/abnormal). A simple priority is also associated automatically to the current step corresponding to how dangerous the situation is. Whenever the AI determines that the user is in an abnormal state, an assisting solution is constructed using the model described in [1].

```
Input: Stove state (Ω), activity (α)
Output: State of the user (S), Priority (ρ)
----------------------------------------------------
Fetch each transitions of the current step α → κ[]
For all κ[i]
| If conditionsMet (κ[i], Ω) Then
| | Mark κ[i] as a possible transition
| End
| Evaluate possible transitions
| Select and set next step of α
| Infer current user's state S
| Calculate priority of the state ρ
End
Return S, ρ
```

Algorithm 1. Detection of abnormal situations

The Figure 4 shows, as an example, a simplified version of a state-transition model for the *preparation of a pizza* with some of the errors that could be observed.

Experiments and Results

To validate the potential of our new prototype, we conducted a first phase of experiments with normal human subjects. We recruited six persons that came directly to our laboratory to perform four recipes each. The goal of this first experimental protocol was to simulate real-case errors that could be performed by cognitively-impaired people. To design the protocol, we referred to the *Naturalistic Action Test* [6], a well-known cognitive test that implements kitchen activities. For the first recipe, each subject had to cook a chicken to familiarize themselves

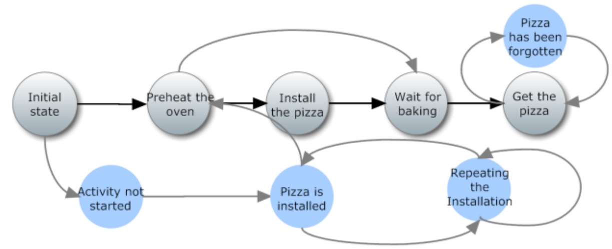

Figure 4. A simplified state-transition model: make pizza.

with the interface. In that case, we explained the general steps to perform the recipe and did not ask them to perform any mistake. Even so, in two cases, the system detected minor errors (correctly) where the user realized the step putting the chicken in the oven before waiting for the preheat to be completely completed. For the second recipe, we asked the subjects to perform the same recipe again, but this time by proposing them a number of possible errors and asking them to choose at least two of their choice. A total of 8 errors were proposed such as inversing steps, add an action or omit one of the steps. For the third recipe, we asked the subjects to prepare pasta. Again, we described the usual steps to perform the activity and asked them to creatively make at least two mistakes. Finally, for the fourth recipe, we asked them to bake a pizza by doing exactly scripted scenario (including errors). At the end of this preliminary testing phase, we analyzed the results with our experts in neuropsychology. We checked if the system was able to correctly identify the errors and compiled the result for each type described in the NAT (Figure 5).

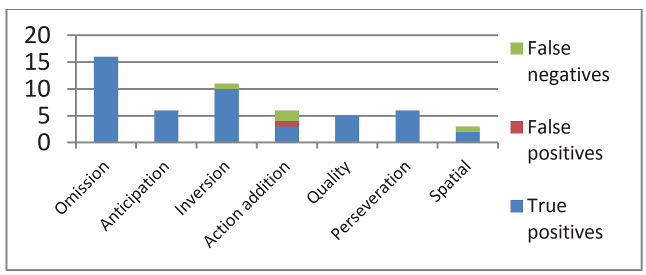

Figure 5. Results: cognitive errors recognition

The omissions refer to isolated step omissions that come at the end of a sequence or when a longer sequence is omitted. The anticipations appear in the middle of a strong sequence, where an upcoming step is performed in advance of an intervening one. The inversions include sequence of steps or subtasks performed in reverse order. The action additions are errors where an action not readily interpretable as a step in the task is performed. Quality regroups errors of inexact and inadequate performance in the realization of the task. The perseverations occur when an act is performed for an extended period of time (e.g. a step is repeated). Finally, spatial errors regroup bad estimation of the proportion of the ingredients or the material needed to cover things, etc.

As we can see, anticipation, omission, perseveration and inversion errors are easily detected by our system. The score was also perfect for quality errors. However, only a small subset of quality errors can be detected and the same goes for the spatial estimation. Quality errors can be complex to identify because they are related to subjective elements such as the type of ingredients. Spatial estimation can obviously become very complex to detect, even for a human, when the recipe is composed of many steps. Action addition can also cause problems. Sometime, the added action is simply meaningless and the system does not detect it. For instance, a subject can change the temperature in the middle of cooking a chicken. This step addition can be meaningless (if it is a small change) or problematic (is the temperature is too low). Overall, the system successfully detected 92% of the errors simulated by the six subjects. It is also noteworthy to mention that all subject found the use of the interface intuitive. In the future, that aspect will be the subject of users' study.

Conclusion

In this paper, we presented a new assistive system, taking the form of a patented smart range prototype. This original invention allows monitoring the preparation of a meal by a cognitively-impaired user and to give adapted assistance [1] in the completion of a recipe. The prototype is also able to prevent accidents by anticipating risky situations (e.g. potential fire). The device is equipped with an artificial intelligence module that interprets the inputs coming from multiple sensors (load cells, heat sensors, electromagnetic contacts, etc.) and infers the actual state of an on-going activity. This module is also able to identify specific errors related to cognitive impairment using the well-known NAT model [6]. The artificial intelligence relies on a stochastic representation of each activity with stochastic state-transition model [7]. A first experimental phase is now completed implying six users. This phase showed promising results in monitoring, anticipation of risky situations and detection of cognitive errors.

This work represents a concrete and useful application of artificial intelligence addressing an important issue of our society. It is the first step toward the valorization of this new technology. Our objective is to make a partnership with a company toward the commercialization of our invention. Indeed, a lot of work remains to be done before. Much more tests in real-life context, implying targeted end-users and therapists are required to ensure the robustness of the system. However, considering the encouraging results we obtained and the actual state of the prototype, we are confident for the future of this invention.

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