WCBUDDY: USING THE TOILET MORE AUTONOMOUSLY VIA ICT

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ABSTRACT: The number of people with dementia is rising and projected to almost double every 20 years. The worldwide amount of people diagnosed with dementia in 2015 is 46.8 million and is estimated at 131.5 million in 2050. Beginning in the second to fifth year of dementia, people need help with personal care like toileting, washing and dressing. The dependency on others increases with the stage of dementia. People with mild to moderate dementia experience diminished autonomy and sense of personal dignity. A great benefit and high acceptance is expected if it is possible to support by ICT people with cognitive challenges in the autonomous use of the toilet. Based on recent experiments and results, a new project *WC-Buddy* investigates the feasibility of a computer-vision approach for analyzing people's activities on the toilet and comparing them with "normal" behavior using a depth sensor. Multiple ways of giving individualized instructions are examined, using and extending the dialog options developed in the former *iToilet* project. Additional functionalities like detecting falls and giving reminders for the regular visit of the toilet are considered. In this paper we present the technique and methodology applied to support people with cognitive challenges to use the toilet. Users and care givers are involved to raise the requirements for and acceptance of an intelligent toilet system. Simulations are carried out in a laboratory environment to enable the utility evaluation by experts.

1   INTRODUCTION

Dementia globally affects between 5.6% and 7.6% of people aged 60 and older by 2015 [1]. Rising in its prevalence with age, the number of people diagnosed with dementia is driven by the ageing population [2]. The amount of people with the illness is projected to almost double every 20 years [3]. The worldwide amount of people with dementia in 2015 is 46.8 million and is estimated at 131.5 million in 2050 [1].

Beginning in the second to fifth year of dementia, people need help with personal care like toileting, washing and dressing [3]. The dependency on others increases with the stage of the disease [3]. People with mild to moderate dementia experience diminished autonomy and sense of personal dignity [4]. A major part of maintaining a person's dignity is the ability to continue living in the community rather than having to move into a care facility [5]. Disorientation is one of the disease patterns of dementia, which can lead to the inability to locate, recognize and use toilets [6]. Thus, methods to guide affected persons through the process of toileting are expected to meet a high acceptance.

2   METHODS

A computer vision approach is used to detect key activities on the toilet and compare them with "normal" behavior, meaning a set of activities carried out in a specific order (sequence

example: enter the room, go to toilet, turn around, undress, sit down, stand up, dress, leave the room). When the activity deviates from the typical one, an input is given, either via voice instructions, light or the use of an avatar. In order to give appropriate guidance, knowledge on the difficulties people with dementia have on the toilet is required. Therefore, experts on dementia are part of the project team for providing information on the illness itself, to demonstrate typical use cases and to evaluate the usefulness of the outputs.

2.1   DEFINING CRITICAL EVENTS ON THE TOILET

Typical situations of caregivers assisting people suffering from dementia on the way to the toilet are the basis for extracting the most critical events. These situations, also indicated as key activities, are events where guidance is needed because the person has a blackout and is unable to remember the next task.

2.2   PRIVACY

In order to discover whether a person has difficulties carrying out the key activities, the computer vision system has to automatically detect humans and analyze their behavior. To achieve this goal, a machine learning approach with real-life training data is used. In a private place like the toilet, privacy protection is a central issue and must be ensured for acceptance in this area. The use of a depth sensor enables privacy protection, since it delivers information based on the distances between objects and in contrast to an RGB camera does not reveal a person's identity [7] (see Figure 1). Furthermore, no data like depth data is stored or transmitted. All data is processed in real time during the acquisition phase.

Figure 1: Depth (left) and RGB (right) image. (Image from [8])

2.3   DATA ANALYSIS

For detecting the key activities, two main steps are essential. At first, persons have to be detected and distinguished from objects. Secondly, the activity itself has to be recognized. For the recognition of people in depth images the detection of objects moving or recently moving is used. This is done by background subtraction, which is the formation of a model of the static objects in the scene and the subsequent comparison of new images with this model [9]. In a next step, areas that show people and those which show other objects are distinguished. This can be considered as a classification problem and is solved by a combination of feature extraction and an automatic learning procedure. Human activity in 3D data is then detected by the temporal analysis of skeleton points of the head, shoulder, spine, hip and knees. The

position of objects and persons, speed and posture serve as characteristics to identify individual relevant activities [10]. On this basis, sequential models such as graphical models [11] or neural networks [12] are trained. These are then able to determine the absence of activities.

2.4   OUTCOME EVALUATION

In the course of the *WCBuddy* project, different dialogue components like voice, video or light are experimentally tested. A basic system is demonstrated which analyzes pre-defined key activities that can be detected in a robust way (e.g. sitting, standing). If these activities are not carried out in the typical order or if a certain time threshold is exceeded, voice or avatar instructions are given, or relevant objects are illuminated. The demonstrator is reviewed by the dementia experts regarding perceived usefulness, ease of use and integration possibilities.

Apart from giving instructions on the toilet to guide demented people through the toileting process, the proposed system can be used to detect falls in the bathroom and send notifications to the nursing staff. Furthermore, on the basis of the time differences between the toilet visits, reminders for the regular visit are considered.

3   DATA

Since the suspicion of image-based technologies intruding people's privacy is particularly high [13], the analysis on the depth data is done locally on a Raspberry computer. Only numeric output representing the motion state of a person is transmitted in order to call the corresponding guidance input. Figure 2 demonstrates exemplary depth images in a bathroom scenario, revealing the shape of a person, but not its identity.
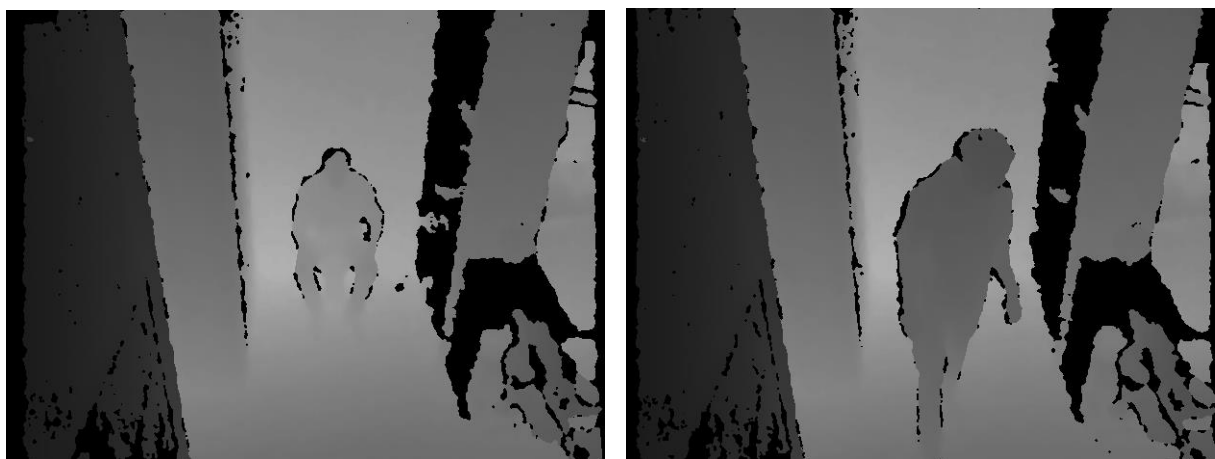
Figure 2: Depth images of a person in a bathroom situation: on the toilet (left) and close to the sensor (right).

3.1 SENSOR

In the *WCBuddy* project, the depth sensor from the previous project *fearless* is taken (see Figure 3), which originally is used for detecting falls. The core of *fearless* is the Orbec Astra, which delivers at least 15 depth images per second. The advantage of using a depth sensor in this application is its insensitivity to illumination change [14]. Furthermore, the person detection with 3D images is more robust than with video cameras [15].

Figure 3: fearless - the intelligent fall sensor[1]

3.2 REAL-LIFE DATA

The computer-vision based system requires a training dataset in order to distinguish between normal and atypical behavior on the toilet. Therefore, real-life data is collected in a care home for a pre-defined time period. The depth data sequences are then labelled in order to build a basis for the machine-learning algorithm.

4   ACKNOWLEDGEMENTS

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