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Recognizing complex instrumental activities of daily living using scene information and fuzzy logic ☆

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ABSTRACT

We describe a novel technique to combine motion data with scene information to capture activity characteristics of older adults using a single Microsoft Kinect depth sensor. Specifically, we describe a method to learn activities of daily living (ADLs) and instrumental ADLs (IADLs) in order to study the behavior patterns of older adults to detect health changes. To learn the ADLs, we incorporate scene information to provide contextual information to build our activity model. The strength of our algorithm lies in its generalizability to model different ADLs while adding more information to the model as we instantiate ADLs from learned activity states. We validate our results in a controlled environment and compare it with another widely accepted classifier, the hidden Markov model (HMM) and its variations. We also test our system on depth data collected in a dynamic unstructured environment at TigerPlace, an independent living facility for older adults. An in-home activity monitoring system would benefit from our algorithm to alert healthcare providers of significant temporal changes in ADL behavior patterns of frail older adults for fall risk, cognitive impairment, and other health changes.

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1. Introduction

Activities of daily living (ADLs) are a set of activities that are required for self-care such as walking, eating, dressing, and bathing. They are used to assess the functional capacity of older adults [11]. Instrumental ADLs (IADLs) are a subset of the functional tasks that older adults perform to support their independent lifestyles [9]. Examples of IADLs are housekeeping, cleaning, cooking. These activities, when measured over an extended period of time, can show deviations in health for older adults. Zisberg et al. [5] developed a new instrument called SOAR to evaluate routine patterns in the lives of older adults. Subjects from four retirement communities reported detailed information regarding ADLs like eating, meal preparation, watching television, bathing, etc. The study indicated that any deviation in the routine of frail older adults could correlate with a change in health and provides the motivation behind the work described in this paper. We describe the premise behind our study using the following case study revolving around the IADL *cleaning the table*. Suppose a healthy older adult living independently performs the IADL *cleaning the table* once every day at a certain time. However, due to some health related reason, she is unable to do so several days in a row. Once detected, this deviation from her normal routine could be a strong indicator of a health change which could help enable early interventions. The goal of this study is to build a model to learn these ADL or IADL patterns which can then be used for detection, and the changes in daily (or weekly or monthly) behavior patterns can then be used to detect early health changes.

The contributions of this paper are the following. We present a unique, vision-based method for recognizing components of ADLs and IADLs by combining their interaction with object surfaces with a set of linguistic fuzzy rules with heuristic parameters to model their activities. Specifically, in this paper we use the activities *walk*, *sit*, *clean object*, *clutter object*, *move near object*, *rearrange object*, and *move object* to describe our approach. We use the IADLs *make bed* and *eat* to describe the importance of combining scene information with moving object features to detect complex activities that are difficult to detect using only the foreground information or only the scene features. These activities further reinforce the importance of ontologies to provide context for each ADL or IADL that can provide the baseline for activity detection and help eliminate false alarms using contextual information. The results using our proposed algorithm are discussed and compared with another popular activity modeling algorithm, the

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hidden Markov model (HMM) and its variation, the details of which are provided in Section 8. We further test our method on data collected in an apartment at TigerPlace, an independent living facility for older adults. The data comprise depth information from an older resident (age 88, without any ambulatory needs such as a walker) as he goes through his daily routine in the apartment. We conclude with the discussion of the future steps for the ADL activity modeling framework. The next section reviews some of the related work in this field using vision and non-vision based sensors.

2. Background

Studies described in [4,5] indicate the importance of longitudinal analysis of the daily routine of older adults to study anomalies or deviations in their regular patterns in an automated, non-intrusive manner. In order to detect these deviations, the activities need to be recognized and ordered in a methodical way for day-to-day behavior comparison. One approach is based on ontological activity modeling. This is described in more detail in the next section.

In related activity modeling work using sensor information and probabilistic approaches, the researchers in [22,23] utilized motion sensor data to learn context-aware rules using a Bayesian network (BN). The ADLs tested were personal hygiene, bathing, toilet transition, housekeeping, eating, leaving home, sleeping, and taking medication on two residents; the resulting activity label accuracy was approximately 70%. In [34], the researchers also used BNs to learn a specific ADL, brushing teeth, using a combination of camera and motion sensors.

In work using vison-based sensors, Pirsiavash and Ramanan [35] used a wearable camera to detect objects of interest to identify 18 different ADLs using a combination of bag of words approach with an object detection model. However, this technique relied strongly on the ability of the algorithm to recognize different objects such as water faucet, oven, etc. Also, it is not realistic to expect older adults to wear cameras while they go through their normal routine. In work using fuzzy logic, Brulin et al. [32] detected the simple activity states of lying, squatting, sitting, and standing using a set of fuzzy rules. They also had a state called "undetermined" to identify unknown activity states. Simple bounding box parameters from the silhouettes obtained from a single camera were used as input to the single layered, eight ruled, fuzzy rule based system. Accuracy results range between 64% and 72% depending on the dataset. Their work, similar to the study in [10] focused on detecting falls in an in-home environment and not on the ADLs performed by older adults in their normal routines. In other works related to depth data, there are several studies to detect different ADLs [31,33,36–38]. However, all of these studies utilize both color and depth information to detect the ADLs. To our knowledge, there has been no work on ADL detection using only depth information from the Kinect sensors. We have chosen to restrict the data to depth images only due to privacy concerns. Prior research has shown that seniors are willing to accept the use of silhouette imagery even though they consider continuous RGB video monitoring to be a privacy invasion [39]. The techniques proposed here rely on segmented 3D silhouettes for ADL recognition.

In a review paper, Lavee et al. [24] described the different methods of activity event detection with vision-based sensors using pixel-based, object-based, and logic-based approaches. For pixel-based approaches, they described techniques using color, texture, as well as gradient information. For object-based approaches, they described features such as bounding box and speed of moving objects. For logic-based approaches, they described techniques that use rule-based activity models. Our approach incorporates features from the moving person as well as from the scene using depth data to build a robust activity model framework that can handle uncertainties of activities being performed in different ways. We illustrate this variance with the following scenario. Consider two residents, A and B. The normal routine for resident A having lunch is as follows: he goes to the refrigerator, gets some deli meat and cheese, makes a sandwich, and then sits at a dining table to eat his sandwich. The normal routine for resident B having lunch is as follows: she opens a can of soup from the cabinet, heats it on the stove and then eats in the living room. As can be seen, there are variations in the same activity *eating lunch* between different individuals. A robust activity model needs to be able to handle these variations within the same activity and still be able to identify both instances.

Another common approach to activity modeling is the use of HMMs as an event modeling formalism. An HMM is a doubly stochastic process, i.e. there is an underlying stochastic process that is not observable (hidden) but can only be observed through another set of stochastic processes that produce the sequence of observed symbols [20]. Several studies, including [18,25,26], use HMMs to detect activities such as meal preparation, eating snacks, and washing dishes. We will use this method for comparison with our activity framework.

3. Ontological framework

The idea for representing ADLs using an ontology is not new. In [6], Chen et al. proposed an ontological method to recognize ADLs such as housework, managing money, taking medicine, and using the phone. Theoretical foundations were set up to fuse information from different sensors (contact sensors, motion sensors, tilt sensors and pressure sensors), and then build an ontology of ADLs. Data from all the sensors were aggregated to describe the ADL occurring at a certain time point. Experiments were conducted under laboratory settings and tested on a subset of the ADL activities including brushing teeth, bathing, and watching television. An accuracy of 94% was achieved on a small subset of three subjects. In another study, Latfi et al. [7] described an ontological approach to describe the medical history of older adults in an assisted living facility using a system called Telehealth Smart Home system (TSH). In this framework, they created an ontology which comprised the person and his/her medical history. The person component contained the profile of the person, interactions with the staff, and other interactions on a social level. The medical history comprised the individual's deficiencies (physical, sensory), diseases, and risk factors. In ontologies related to eldercare technologies, Rodríguez et al. [8] proposed a framework called CARe to describe ADLs in a nursing home scenario. Similarly, the researchers in [42] proposed a framework called ELDeR to support independent lifestyles of older adults. In other ADL work, the study in [40] described ADLs using specific examples such as nocturnal activities, and the study in [41] gave an overview of ADL ontologies in the context of smart home applications. However, none of these studies were implemented or tested in a real smart home environment, and only theoretical foundations were mentioned.

We now describe our ontological framework for learning ADLs in general. One unique aspect of our approach is that it looks at the overall big picture of the ADL framework *while still being able to handle incomplete information*. Fig. 1 shows the ontological structure for the activities. There are five categories: activities, location, objects, sensors and time of day. The activities component can be atomic or complex. The atomic activities such as upright, walking, sitting, bending, and rising are the building blocks of complex activities. The complex activities comprise the ADLs and IADLs. The location parameter describes the locations inside the apartment which can provide context to the activity taking place. For example, making the bed is most likely to take place in the bedroom. The objects component refers to the objects with which seniors interact to perform the ADLs and IADLs. The sensors component describes the sensors in our smart home system used to detect the behavior patterns of older adults in their home setting. The final component, time of day, refers to the time when the activities take place. This is useful to learn the patterns of the behavior trends of older adults on a daily basis. For our study,

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