Kitchen Task Assessment Dataset for Measuring Errors due to Cognitive Impairments

Kristina Yordanova[1,2], Albert Hein[1], Thomas Kirste[1]
[1]*Department of Visual and Analytic Computing*
[2]*Department of Computer Science*
University of Rostock
Rostock, Germany
{kristina.yordanova, albert.hein, thomas.kirste}@uni-rostock.de

***Abstract*—With the demographic change towards ageing population, the number of people suffering from neurodegenerative diseases such as dementia increases. As the ratio between young and elderly population changes towards the seniors, it becomes important to develop intelligent technologies for supporting the elderly in their everyday activities. Such intelligent technologies usually rely on training data in order to learn models for recognising problematic behaviour. One problem these systems face is that there are not many datasets containing training data for people with dementia. What is more, many of the existing datasets are not publicly available due to privacy concerns. To address the above problems, in this paper we present a sensor dataset for the kitchen task assessment containing normal and erroneous behaviour due to dementia. The dataset is recorded by actors, who follow instructions describing normal and erroneous behaviour caused by the progression of dementia. Furthermore, we present a semantic annotation scheme which allows reasoning not only about the observed behaviour but also about the causes of the errors.**

***Index Terms*—activity recognition, annotation, data collection**

I. Introduction and Motivation

People with dementia wish to remain independent and continue their social life as long as possible. To achieve this, they usually need assistance, as they have difficulties in performing everyday activities [2]. Assistive technology devices (ATD) have the potential to help people with dementia to maintain their independent social life by supporting their everyday activities [25]. To build a model of human behaviour during the execution of everyday activities, however, one needs a suitable dataset, with which to identify relevant model elements and to train the model to recognise normal and problematic behaviour.

One aspect of computational behaviour analysis research for people with dementia is to recognise activities of daily living (ADL) [9], some of them characterised by the usage of specific objects or tools (this is also known as instrumented ADL, or iADL). Traditionally the latter lies in the field of computer vision, where cameras and specific algorithms are used to locate and recognise certain objects and how they are handled. However, cameras are often unsuitable for certain environments and usually require a certain amount of computing power. Over the last years more and more approaches investigated the use of wearable motion sensors for detecting even high-level abstract and complex activities [7], [30] based on computational behavioural models. A sensing modality and a dataset for recognising object usage based on motion sensors would provide valuable information and be a logical extension of those techniques. Currently a new generation of cheap and low-energy miniature motion sensors becomes available, which, in combination with wrist worn devices like smart watches and low-energy wireless communication finally allow us to look in that direction.

At the time of the data collection and annotation Kristina Yordanova was funded by the German Research Foundation, grant number YO 226/1-1. Albert Hein was funded by the German Federal Ministry of Education and Research, grant number 03ZZ0519D.

In this paper we analyse the feasibility of such an approach using a flock of wireless motion sensors and a simple algorithm with low computational complexity for detecting similarities in motion patterns between handled objects in kitchen applications. We use this sensing approach to record a sensor dataset describing the kitchen task assessment (KTA) setting, which consists of both normal and simulated erroneous behaviour due to dementia. Additionally, we provide a semantic annotation schema for the dataset, which allows reasoning about the action class, objects being manipulated as well as causes of observed behaviour. The paper is structured as follows: In section II we discuss the related work with respect to existing datasets about people with dementia and the corresponding annotation schema. Section III discusses the methods and materials used in the paper, while Section IV presents the collected dataset, the corresponding annotation and the object recognition accuracy. Finally Section V concludes with a discussion and planned future work.

II. Related Work

A. Object detection for activity recognition tasks

The idea of detecting object usage for recognising activities of daily living itself is not new at all and there can be found some initially promising approaches in the past. Different works propose various sensor modalities and techniques for identifying the objects being manipulated. One very popular type of data for activity recognition is sensor data. Sensor-based approaches for object detection for activity recognition rely on accelerometer data [8], [13], [14], sound data [8], wrist-worn sensors [10]. For example, Stick et al. propose the combination of accelerometer and RFID data for object detection [18]. In other work, Stein et al. use the combination of sensor and accelerometer data to recognise complex human activities [17]. To address the problem of labelled data, some works propose the combination of video-based object detection and clustering of video descriptions to identify action classes and their relations to objects [12]. Other works propose methods for automatic generation of semantic behaviour models based on textual instructions [21]. These models are then used to recognise the action classes and the objects on which the classes are executed. In our approach we use accelerometer and gyroscope data from sensors attached to objects and wearables. This data is first used to recognise the object being manipulated and based on that activity recognition can be performed.

B. Datasets for behaviour of people with dementia

Above we saw different works addressing the problem of object detection for activity recognition. These works, however, usually address the behaviour of healthy persons, who do not exhibit challenging behaviour due to cognitive impairments. This indicates that models trained on normal behaviour will not be able to detect problems caused by the progression of dementia. To address this problems there are several datasets that contain data from people with dementia. For example, the InsideDem project recorded one month of data with the behaviour of people with medium to severe dementia in two senior homes [3]. The data was recorded with wearable bracelet and consist of motion, rotation, as well as surrounding loudness level, light level, and air pressure. In another project, Dem@Care, various types of data were recorded in different experiments in laboratory settings [4]. These included video and audio data, motion sensors on objects, and sleep sensors. Another project, SinDem, addresses the outdoor mobility of people with dementia and contains the accelerometer and GPS data of people in the early phases of dementia [15]. The problem with all these datasets is that they are either not publicly available as they contain data from real patients, or they are conducted in laboratory settings and do not address the types of behaviour errors in a systematic manner.

C. Datasets for cooking behaviour

Kitchen activities are central to our everyday life and the ability of independently preparing and intaking food to a great degree defines our ability to lead independent life. While there are not many datasets addressing the kitchen activities of people with dementia[1], there is a variety of datasets for kitchen activities executed by healthy participants. For example, Krüger et al. record a dataset describing the preparation and consumption of carrots soup [5]–[7]. The experiment is recorded with accelerometer sensors from a motion tracking body suite. Another dataset recorded at the SPHERE house in Bristol contains the unscripted cooking activities of different people in real home settings [11], [30]. The used sensors are environmental sensors such as temperature, light, water and electricity consumption, and movement, as well as cupboard sensors detecting opening and closing of cupboards. Another popular dataset with kitchen activities is the CMU kitchen dataset consisting of preparation of pizza, brownies, salad, and eggs [19]. The dataset consists of cameras from different angles, as well as body-worn accelerometer sensors.

[1]Such activities are partially covered in the InsideDem and Dem@Care datasets but they are not annotated for the observed behaviour problems.

D. Types of annotation

One of the main challenges in using existing datasets is the lack of high quality annotation [29]. Producing annotation is a time consuming and error-prone process that is even more complicated when one needs to additionally annotate relations between actions and objects. According to Yordanova and Krüger, there are three types of annotation based on the label structure [27], [28]. The first type of annotation is the one that uses strings that have no semantic meaning. This is the easiest and most common annotation type as it requires less time to be produced. The second type of annotation is plan annotation. It is divided into goal labelling (what is the goal the person is pursuing) and plan annotation (what are the steps for reaching the goal). The third type of annotation is semantic annotation and the produced labels have semantic structure. This kind of annotation contains relations between the annotated actions and objects as well as additional contextual information, which is not present in the first two types of annotation. In the case of dementia, we usually need semantic annotation as we want to recognise normal and challenging behaviour and to reason about its causes.

III. Methods and Materials

A. Kitchen task assessment

The aim of the kitchen task assessment (KTA) problem [1] is to detect whether the person is able to perform kitchen tasks independently by measuring the way the task is executed and the types of errors that appear during its execution. Generally, with the progression of the disease, also the frequency of errors increases until at some point the person is no longer able to perform kitchen activities independently [16]. In our experiment, however, we do not simulate the progression of the disease but we rather concentrate on simulating one type of error per run.

B. Errors due to dementia

There are different kinds of behaviour errors caused by disorientation in persons with dementia. According to Serna et al. the exhibited errors can be classified into six categories according to the type of physically observed problem in the execution of the task [16]. These are initiation error, organisation error, performance error, sequencing error, judgment and safety error, and completion error. Table I lists the types of errors and the corresponding explanations. In our work we simulate these errors during the execution of kitchen tasks.

TABLE I
ERRORS DUE TO DEMENTIA

Type of error	Description
initiation error	Can the person begin the task?
organisation error	Can the person gather the items necessary to perform the task?
performance of all steps	Can the person perform all the steps necessary to complete the task?
sequencing	Can the person sequence the activities that make it possible to complete the task?
judgement and safety	Is the person safe in performing the task?
completion	Does the person know when he or she is finished with the task?

TABLE II
DESCRIPTION OF THE SUB-TASKS IN THE KTA EXPERIMENT DURING NORMAL RUN.

1) Initiate the task
   1) Go to the refrigerator
   2) Open the refrigerator

2) Measure
   - Take the milk out of the refrigerator
   - Close the refrigerator
   - Pick up the measuring cup
   - Measure the right quantity of milk

3) Stir
   - Pour the measured milk into the saucepan
   - Pour the pudding mix into the saucepan
   - Pick the wooden spoon
   - Stir the ingredients

4) Cook
   - Turn on the stove
   - Place the saucepan on the stove
   - Stir until the mixture is hot
   - Turn off the stove

5) Pour
   - Pick up the saucepan
   - Pour the mixture into the four dishes
   - Pick up the spatula
   - Scrape out the saucepan

6) Clean up (end of task)
   - Put all the tools into the sink

C. Semantic annotation

As already mentioned in Section II, in order to be able to reason about the causes of observed behaviour, we need to produce semantic annotation. In this work we follow the approach proposed in [26]. We use semantic representation of the objects and actions combined with state representation of the progression of the world to track changes in the observed behaviour and how it influences the environment. Figure 1 shows an example of the progression of the state space in the case of taking a knife to cut some product. In the initial state the knife is in the drawer, it is not on the cutting board and no object has been taken. With the execution of the action "take", the new state changes and the knife is no longer in the drawer and one object has been taken. In that manner, we represent not only the semantic structure between actions and objects but how their state changes with the execution of each action.

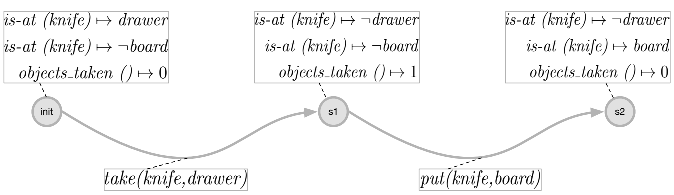

Fig. 1. Example of the state space progression with the execution of new action. Figure adapted from [26].

As the manual model definition for semantic annotation is time consuming process (e.g. see [27], [28]), we utilise an approach for automatic model generation based on the label strings produced through the ELAN annotation tool. This approach is based on works proposing learning behaviour models from textual instructions [20], [21] and is described in [22].

D. Experimental setup

1) Scenario: The goal of the experiment was to repeat the kitchen task assessment and in the same time to simulate the different types of errors due to dementia listed in Table I. Table II shows the execution sequence for the KTA when normal behaviour is ehxibited. Apart from the normal runs, also runs with different variations of errors were recorded. Each participant received instructions with the execution steps similar to the execution sequence listed in Table II. The participants were provided with instructions both for the normal behaviour execution and the erroneous behaviour.

2) Setting: Seven tools were involved in the experimental setup. These were stove plate, saucepan, wooden spoon, rubber scraper, measuring cup, tool jar (containing spoons), coaster, clip board with instructions. Apart from the tools, five ingredients were used: box of milk, paper cups (at least 4), pudding mix chocolate, pudding mix vanilla, pudding mix farina. 12 test subjects took part in the experiment where each subject performed one KTA normal run and one KTA erroneous run.

3) Sensor setup: The following sensors were used during the experiment. For acquiring sensor data we used object motion sensor from Bosch Sensortec (DIANA-boards). Each sensor node is 27x17x6.5 mm in size and powered by a CR1225 button cell. Thus, it provides a very unobtrusive sensing hardware and makes it possible to instrument even small tools like for example a knife without influencing its usability. The sensors were mounted on 37 objects by using tape (see Figure 2). Each sensor contained accelerometer, gyroscope, and magnetometer with a sampling rate of 25Hz. Each participant was equipped with full body motion capture suite (XSens MVN-Biomch) with 17 sensors with a sampling rate of 120Hz (see Figure 2). Apart from that the electrocardiogram and electrodermal activity was recorded (ECG 1024Hz, EDA 64Hz, Acc 64Hz, Temp 1Hz, Barometric Pressure 8Hz). Finally, the experiment was recorded with two cameras: first person video hand interactions were recorded with a chest mounted GoPro ultrawideangle camera with resolution 1280x720 and sampling rate of 25Hz. Additional hand-held camcorder was used to record third person video full body with resolution 704x576 and sampling rate of 25Hz. All videos have been annotated frame by frame using ELAN whenever an object was handled using the instrumented wrist and also synchronised to the sensor recording.

E. Data preprocessing for object recognition

As the clocks of the wireless sensor nodes may drift, the effective output data rate of each node is slightly different, which needed to be compensated by resampling To synchronise and resample the data, the spline method was used. The method is based on an adjusted similarity measure for vectors and is related to the Pearson correlation coefficient and cosine similarity (Equation 1).

$$\frac{(x-\overline{x})\cdot(y-\overline{y})}{Var(|x-y|)} \quad (1)$$

The sliding window we used considered 128 samples with 75% overlap between samples. For both accelerometer and gyroscope we calculated the mean, variance, skewness, kurtosis, FFT (dominant frequency and its magnitude).

IV. Dataset and Results

The data collection consisted of 4 days of recording and one additional day for pretesting. It took ca. 2h of recording per participant and additional time needed for setup preparation and post processing of the data.

This resulted in 408GB of raw data and 155GB preprocessed data. 24 runs were recorded, 12 runs with normal behaviour and 12 with erroneous. Each type of error was observed in two of the erroneous runs. Apart from the sensor data, for each run video data from the two different camera angles was recorded. The video logs were used to produce semantic annotation for the 24 runs. The sensor data together with the semantic annotation can be downloaded from [23][2].

A. Annotation

The annotation was produced according to the procedure proposed in [22]. 22 types of objects were annotated, together with three additional object types describing the hand occupancy (left, right, and both). The list with object types can be seen in Table III. Apart from the objects, 17 action classes

TABLE III
Objects used in the annotation and their types.

Type	Objects
placable object	sauce pan, hot plate, measuring cup, paper cups, tool jar, cutting board
other object	saucepan lid, manual, hotplate dial, wooden spoon, rubber scraper, milk lid, milk seal, pudding seal, plastic spoon
location	fridge, sink, table, floor
container	paper cup, milk, pudding mix
hand	left, right, both

were annotated. These can be seen in Figure 3. The actions are open, close, walk, wait, turn on, turn off, put, take, stir, swap, turn, shake, pour, tear, unscrew, screw, scrape, and drop. On average an annotation sequence consists of 180 steps. Each step is annotated based on the scheme *action_object1_object2*. This scheme is then automatically converted in PDDL plans that can be used to test the causal correctness of behaviour models (for example, see [24]) An example plan can be seen in Table IV. The plan describes an execution sequence, which was not completed due to initialisation error. The first column is the action's start time in milliseconds, the second column indicates whether the action is a new one or the same action as the previous one, and the last column shows the action being executed together with the involved objects.

[2]https://doi.org/10.18453/rosdok_id00002605

TABLE IV
A plan for a run with initiation error.

Time	New?	Action
0	*	(INITIALIZE)
1	*	(take manual both)
1961	*	(wait)
7161	*	(swap manual left)
7361	*	(put manual table left)
8921	*	(walk table fridge)
16681	*	(open fridge right)
18801	*	(wait)
23601	*	(close fridge right)
25681	*	(walk fridge table)
32921	*	(wait)
51601	*	(FINISHED)

Based on these plans and the underlying model structure one can infer information such as the most probable object being currently manipulated, the current location of the object, or the causal structure of the plan. For example Figure 3 shows the causal structure for all action classes in the KTA experiment. There the nodes are the actions while the transitions show how probable it is to observe a transition from one action to another. The thicker the line between two actions, the more probable it is that we will observe a transition.

B. Object recognition

To test the approach's ability to correctly recognise the object being manipulated, we used the accelerometer and gyroscope data. As already explained, the sensor data was synchronised and resampled using the spline method mentioned before to avoid temporal drift. After data synchronisation, the cross-correlation between corresponding windows, as well as mean and variance were calculated for the accelerometers and the gyroscopes. Based on these the classifier estimated the most probable object interaction (see Table V) for accelerometers only (*acc*), gyroscopes only (*gyr*), or a combination of both (*acc+gyr*). Comparing the estimate to the annotation, the accuracy was calculated as seen in Table V. As no training or machine learning was utilised, no cross validation is required.

The ROC curve for object usage detection when using accelerometer or gyroscope can be seen in Figure 4. The area under the curve for accelerometer data is 0.96, while for gyroscope it is 0.92. In both cases the results show that using the sensors attached to objects together with wrist sensors is a reliable means of object detection.

V. Discussion and Conclusion

In this work we introduced a sensor dataset for the kitchen task assessment based on accelerometer and gyroscope data from objects and wearables attached to the hands. The dataset consists of normal executions of the KTA as well as executions that contain one of six types of erroneous behaviour exhibited by people suffering from dementia. The dataset is a valuable addition to the state of the art in datasets describing the behaviour of people with dementia as there are not many publicly available datasets for this domain. What is more, the accompanying semantic annotation allows the research community to measure activities being executed, objects being

Fig. 2. During recording of the Kitchen Task setting. Test subject is equipped with Motion Capturing Suit, ECG, EDA, and chest mounted camera (left). Objects were instrumented with custom BLE wireless motion sensor platform (right).

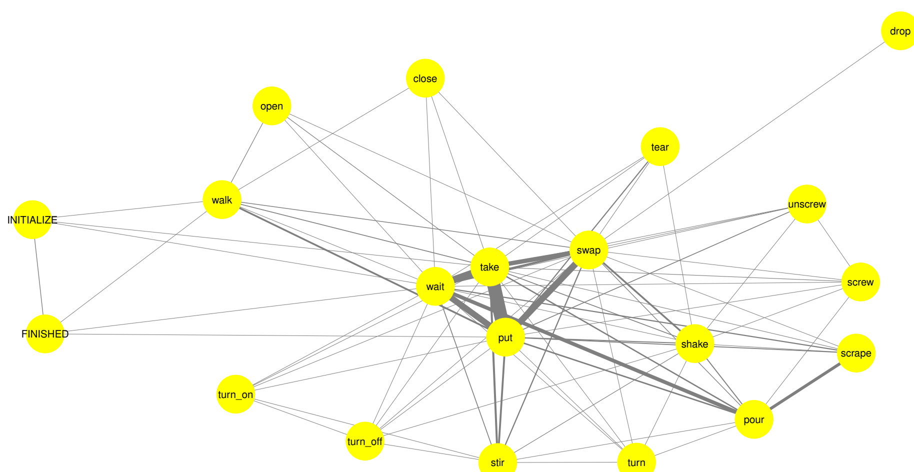

Fig. 3. Causal graph of actions. Apart from the annotated actions, there are two additional actions, one describing the initial condition and one describing the end condition of the plan. The thicker the line the more probable it is to observe the transition between the two actions.

TABLE V
OBJECT USAGE DETECTION RESULTS

tn	fn	fp	tp	sensor	object	accuracy	precision	recall	specificity
1466097	5937	99938	53870	left acc	all	0.9348799	0.3502418600	0.9007307	0.9361841
1453808	5199	112227	54608	left gyr	all	0.9277753	0.3273174094	0.9130704	0.9283369
1525781	8233	40254	51574	left acc+gyr	all	0.9701773	0.5616369735	0.8623405	0.9742956
1373216	10060	89546	153020	right acc	all	0.9387357	0.6308386171	0.9383125	0.9387829
1395116	20224	67646	142856	right gyr	all	0.9459542	0.6786443834	0.8759872	0.9537546
1433526	27601	29236	135479	right acc+gyr	all	0.9650415	0.8225055399	0.8307518	0.9800132
1305407	12864	99779	207792	both acc	all	0.9307171	0.6755903515	0.9417011	0.9289923
1347312	15851	57874	204805	both gyr	all	0.9546543	0.7796778578	0.9281642	0.9588140
1374776	24601	30410	196055	both acc+gyr	all	0.9661646	0.8657187645	0.8885097	0.9783587

manipulated as well as the semantic relations and underlying causal relations between activities.

Furthermore, we showed that is is possible to use the accelerometer and gyroscope data to track the object being manipulated. Based on these results, in the future we plan to combine the output from the object recognition with com-

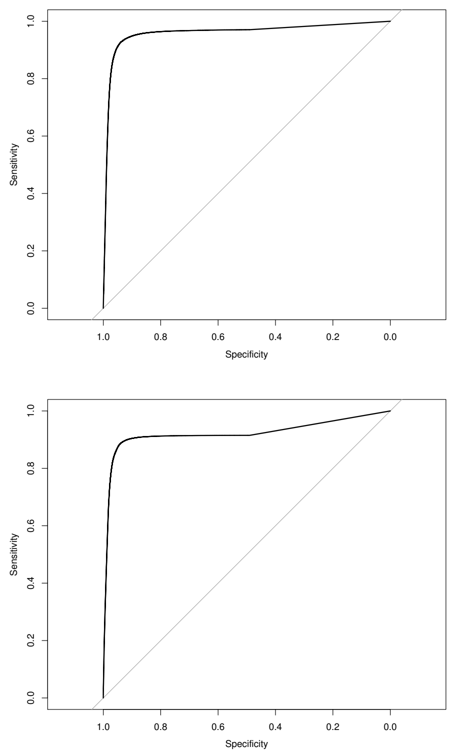

Fig. 4. ROC plots for Object usage detection accelerometers top ($AUC = 0.9593934$), gyroscopes bottom ($AUC = 0.9210555$).

putational state space models [7] to build a model able to reason in a causal manner about the person's behaviour and the underlying causes of the observed errors.

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