Make me a Sandwich!
Intrinsic Human Identification from their Course of Action

Peter Lightbody[1] Christian Dondrup[1] Marc Hanheide[1]

***Abstract*— In order to allow humans and robots to work closely together and as a team, we need to equip robots not only with a general understanding of joint action, but also with an understanding of the idiosyncratic differences in the ways humans perform certain tasks. This will allow robots to be better colleagues, by anticipating an individual's actions, and acting accordingly. In this paper, we present a way of encoding a human's course of action as a probabilistic sequence of qualitative states, and show that such a model can be employed to identify individual humans from their respective course of action, even when accomplishing the very same goal state. We conclude from our findings that there are significant variations in the ways humans accomplish the very same task, and that our representation could in future work inform robot (task) planning in collaborative settings.**

I. INTRODUCTION

Facilitating close human-robot collaboration to bring about productivity gains and to relieve human workers from mundane and straining tasks while still benefiting from the imminent dexterity of humans is one of the most cited prospects of advances in robot design and automation. While a lot of research is dedicated to the development of frameworks of general joint action and to mutually understand the actions taken by a human and a robot in a collaborative setting, very little research has been looking at the *idiosyncratic differences* in which humans engage with a robot. We put forward the hypothesis that indeed humans accomplish tasks very differently, even when asked to accomplish the very same goal state. We believe that a robot collaborating with a human should not only have a reactive planning model to account for specific deviations from a pre-learned routine, but instead have an explicit model of an individual's way of accomplishing a certain task, to be able to adapt in a better and more anticipating way to the humans actions. While still at the beginning of our work to facilitate individualised adaptation in human-robot collaborative assembly, in this paper we present a first analysis of the different ways in which humans accomplish given tasks, and present a representation based on Hidden Markov Model (HMM) and Qualitative Spacial Relations (QSR) that are suitable to later feed into the task planning framework of our Baxter robot. Hence, the aim of this research is to identify and analyse any underlying patterns in the way humans perform these tasks, and to show that indeed idiosyncratic patters can be identified, even strong enough to be able to distinguish different subjects solely based on their course of action taken very reliably. These results confirm our hypothesis that indeed there are significant difference in the course of action between individuals.

*The research leading to these results has received funding from the European Community's Seventh Framework Programme under grant agreement No. 600623, STRANDS

[1]Peter Lightbody, Christian Dondrup, and Marc Hanheide are with the School of Computer Science, University of Lincoln, LN6 7TS, Lincoln, UK {plightbody, cdondrup, mhanheide}@lincoln.ac.uk

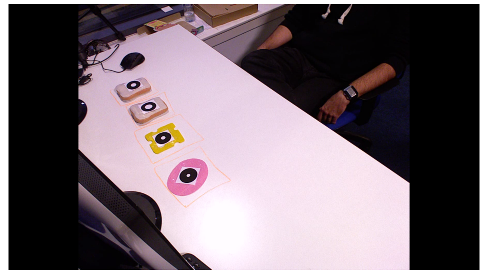


Fig. 1. Experiment set-up through the left camera. A tabletop workplace to make a ham and cheese sandwich showing the objects in the starting positions.

Summarised, the main contributions of this paper are i) a probabilistic model of individuals' course of action in defined assembly tasks utilising qualitative state descriptors joint into a Markov Model of individual action traits, and ii) an analysis as to how specific these models are and their suitability to recognise an specific worker based on their course of action. We have analysed three different simple tasks involving four objects being manipulated and show compelling recognition rates based on those idiosyncratic differences.

A. RELATED WORK

Much of the work currently being done in the field of Human-Robot Interaction (HRI) views a collaboration as a human acting upon a system, giving the impression that an autonomous robotic collaborator is "merely an intelligent tool that a human operator commands, at times relinquishing some level of control" [1]. In order for this to change, the level of individualisation must increase from the collaborating robot without performing irrational behaviours which would otherwise decrease the relations between the collaborating pair. However, many manufacturing based implementations are motivated towards performing a specific task in a set way such as [2] in which the near optimal task is worked out and performed, resulting in the human worker still having to make allowances for the robots inability to comprehend the scene around it. However, a slightly different approach was taken in [3] in which the system tried to learn the humans preference and adapt to them, rather than attempting to find the optimal behaviour. The focus of this was on applying properties to objects and using explicit

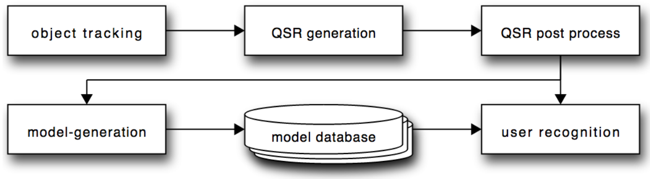


Fig. 2. The overall process flow of our system.

feedback to allow the user to convey how proficient the robots trajectories were. This reinforcement based learning meant that over a period of time the robot is able to learn what the specific individual thought was a good trajectory and what was not, whilst also generalising well to tasks which it had not seen before. This is particularly relevant to work presented in this paper, as it suggests that an individuals preferences can not only be identified but also learnt, by the way in which the human uses the items around them to complete a joint task.

II. MODELLING INDIVIDUAL TASK ACTIVITY

The cornerstone of our approach is to represent the current situation and how it changes due to the course of action taken by a human accomplishing a task. Here, we model activity as a sequence S of states s_i of the objects in the environment $S = s_1, s_2, \ldots s_n$. Each of these states is represented as a set of qualitative spatial relations $R^t(o_i, o_j)$ between the objects o_k that hold true. The idea here is that the set of relations changes due to the manipulation actions carried out by the human. So, rather than having an explicit model of actions, we observe a sequence of changing environment states represented by the relation between all involved objects at a given time t. A state s_t is therefore described by the set of all possible relations between any two of the m objects:

$$s_t = \left\{ R^t(o_i, o_j) | i, j \in \{0, 1, \ldots, m\}, j > i \right\}. \qquad (1)$$

An action trace is hence composed of a sequence of such states s_t, where t is an index of time given by the rate of the tracker (10Hz).

Given this approach, our computational models consists of components to i) *track* manipulated objects, to ii) generate respective QSR relations from those tracked and augment the states for invisible (occluded) objects, and to iii) either build Markov models from the observed sequences or test any test sequence against those trained models to identify different users based on their model. The process flow is indicated in Fig. 2.

A. Tracking

The ability to effectively track the movement of the objects during their manipulation is essential for the system to work. To track the detected objects, we use a *Bayesian tracking* framework from [4], [5] which integrates results from object detection utilising multiple sensors and can estimate the 3D position of tracked objects at a fixed rate independent of the frame rate of the sensors. Tracking here employs an unscented Kalman Filter configured with a constant velocity motion model for prediction and fixed noise models for observations made by the individual detectors. These compensate for the temporary loss of detection; an aspect which is presented in [6]. In order to reduce the chance of assigning false positives and wrong observations, a gating procedure is applied which uses a validation region relative to the target for each new predicted observation [7]. New detections are then associated to the correct target using a Nearest Neighbour (NN) association algorithm where as only detections of the same object type are associated with corresponding tracks. If no suitable target track could be found, the detections were stored and eventually used to create a new track, providing they were stable over a predefined time frame. While this tracking-by-detection approach is generic and can work with any object detection and recognition approach, in our study we employed a marker detection algorithm, which allows to reliably discriminate a fixed number of predefined markers, as detailed in Sec. III-A.

B. QSR generation

In order to represent the constellation of objects in the world as the undergo changes due to them being manipulated, we employ QSR. QSRs are a well-established approach in activity recognition [8], with many different QSR calculi having been developed over the last decades in computing. They have in common that a specific situation can be represented as a set of finite states rather than using a continuum. In this work we look at QSRs to represent the relation of two objects on a 2D plane, obtained from projecting the 3D tracks onto the table surface (our camera setup is calibrated).

Our implementation supports a variety of different Qualitative Spatial Representation, facilitated by a third-party multi-purpose QSR library[1]. In this work, we analysed data mainly using two representation, namely the RCC3 calculus, a simplified version of the RCC8 calculus, and a qualitative representation of distances between two objects termed DIST. These two representation are simple enough to avoid having too many potential states to keep the problems we are looking at tractable. The basic relations for RCC3 and DIST for two objects o_i and o_j at a time t, are

$$\begin{aligned} \hat{R}^t_{RCC3}(o_i, o_j) &\in \{dc, po, eq\} \\ \hat{R}^t_{DIST}(o_i, o_j) &\in \{cl, ne, fa\} \end{aligned}$$

In RCC3, the basic relations are *disconnected* (dc, objects do not touch each other), *partial overlapping* (po, object boundaries overlap), and equal (eq, one fully covers another). In DIST, these are *close* (cl, less than $20cm$ between the centre points of the object), *near* (ne, less than $50cm$), and *far* (fa, centres more than $50cm$ apart). It shall be noted that due to the nature of occlusion when tracking the objects, the basic relation eq is not occurring, and is subsumed by na in our actual data recordings.

In order to account for the absence of specific objects or their temporary occlusion, either by the manipulating hand or when actually occluded by an object placed on top of another, we extended the sets of basic relations by

[1] https://github.com/strands-project/strands_qsr_lib/

an additional basic relation na (*not available*), given the following final sets: $R^t_{RCC3}(o_i, o_j) \in \{dc, po, eq, na\}$ and $R^t_{DIST}(o_i, o_j) \in \{cl, ne, fa, na\}$.

C. Probabilistic Activity Model

In order to encode and facilitate automatic recognition of different activities – or in our case different subjects – and reasoning about the observed interactions, the sequence of qualitative states needs to be represented in a coherent model accounting for individual variations. We employ a HMM [9] based representation that models the automatically recognised QSR relation as emissions of the underlying activity, allowing for uncertainty in the actual recognition process. This allows us to deal with state classification errors that arise from the discretisation of human movement and unobservable objects due to occlusion into the respective qualitative states. We initialised our HMMs with actually observed state sequences, and created such models for each individual human performing a task. Hence we have created individualised models of activity, that can be employed to recognise individuals based on an observed QSR state sequence. To improve the initial models and obtain optimised transition probabilities between states and corresponding emission probability tables for these states, we trained the individual HMMs using Baum-Welch training [9] (Expectation Maximisation) for each activity behaviour and person, respectively. In order to overcome the problem of a lack of sufficient amounts of training data and unobserved transitions therein, we allow for pseudo transitions with a very low probability, by following the idea of the *add one* [9] approach for unobserved state transition.

III. EXPERIMENT

In order to test the representational power of our models and to gain evidence towards our hypothesis that the actual accomplishment of a task varies between individuals, we performed a user study based on a number of quite simple tasks. The aim of this study was therefore to identify if trained models are indeed specific for individuals. In a way this is negating the goal generally pursued in pattern recognition: While generally models are sought that are generally applicable, here we aim to develop models that allow discrimination between indivudals by their idiosyncratic differences in the course of their actions.

A. Study Design

The study was designed as a tabletop workplace, using two extrinsically calibrated RGB cameras on either side focusing the centre of the table to ensure optimal coverage for the object tracking (see Fig. 1). As objects, we used two slices of bread, one slice of cheese, and one slice of ham from a toy felt food set with attached circular markers to bypass costly object detection. The markers were detected using the WhyCon algorithm [10] to not only detect their position but also distinguish them based on the shape of the marker. The results were fed into the tracker described earlier to achieve data association between the two cameras. The experiment was sitting on the table next to the participants to ensure the correct recording of the sequences.

TABLE I

CONFUSION MATRIX OF VERTICALLY ALIGNING THE OBJECTS IN RCC3

	P1	P2	P3	P4	P5	P6	Total
P1	8	2					10
P2		10					10
P3			10				10
P4				10			10
P5	1	2	1	1	5		10
P6	1					9	10
Total	10	14	11	11	5	9	60

We had a total of 6 participants (4 male and 2 female) of which 5 are working in computer science. The participants were equally distributed over the three age ranges 18-24, 25-34, and 35-44; each of the participants was right-handed. During the study, the QSRs were recorded online using the system described above.

B. Tasks

The tasks required each participant to complete repetitions of three pre-set activities. The participants were asked to move the four objects from a set locations to another, final position. The starting positions of each of the objects, to which they were reset after each trial, can be seen in Fig 1 and were clearly marked on the table.

Participants were instructed to

1) Move the objects into a vertical line on the table with one slice of bread on either end
2) Move the objects into a horizontal line on the table with one slice of bread at either end
3) Stack the items to build a ham and cheese sandwich with one slice of bread at both the top and bottom of the sandwich

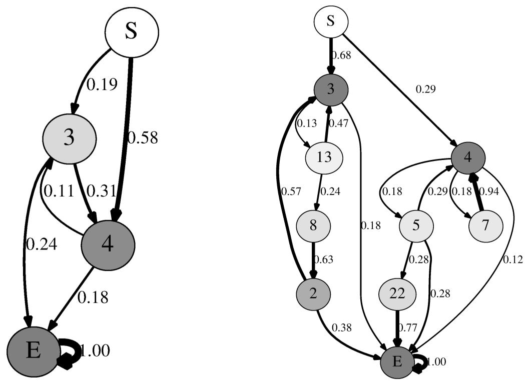
All the tasks were always performed in this order. For the stacking task, participants were instructed to only use one hand where in the other two tasks, no specific instructions were given. Each of the six participants was asked to repeat every tasks ten times resulting in 60 recorded actions for each task.

C. Evaluation

To evaluate the recorded actions, we employed standard Leave-one-out cross-validation using the described HMM and training method. Therefore, we had a test-set of one action and trained an HMM on the remaining 9. Using this test-set we generated the log-likelihood of it being produced by the HMM created from the training-set and the HMMs created for each of the remaining participants. If the test-set of the person produced the maximum log-likelihood on the training-set of the same person, compared to any of the HMMs for the other participants, it was counted as correctly classified.

D. Results

In Fig. 3 we can see two different examples of participants accomplishing the same task. Whereas in Fig. 3(a) we can



(a) Action 1 for participant 6.

(b) Action 1 for participant 2.

Fig. 3. These graphs show the transition probabilities of the HMM (disregarding self-transitions) on the arcs and the grey level denotes the a-priori probability of being in that state form white ("S") to dark grey ("E"). The graph has been pruned of transition probabilities $p < 0.1$ for visibility. Both show the same action encoded in RCC3 using an artificial (S)tart and (E)nd state, showing the difference in complexity between participants.

see that the whole interaction consists of 2 states where everything is disconnected in state 3 and the same for state 4 with the exception of the ham being occluded. For Fig. 3(b) we can see a more complicated structure with 3 and 4 still being the states with the highest a-priori probability but with the second most likely state chain of 3 all disconnected, 13 and 2 where either the top bread slice or the bottom one was partially overlapping with the cheese, and 8 where cheese and ham partially overlapped; all remaining objects where disconnected.

From Tab. I showing the vertical alignment task classified using RCC3, we can see that the majority of people used working patterns that are distinguishable from the other participants. With the exception of Participant P5 the majority was classified correctly with P2 accumulating additional matches. Tab. I also represents the most interesting example compared to DIST scoring 100% classification rate in all three tasks and RCC3 with 88.33%, 91.67%, and 96.67% for the three tasks respectively.

E. Discussion

Our results show that we can reliably classify the person executing an action using simple QSRs like DIST and RCC3. We have shown that for our experiment, using DIST we can distinguish participants with 100% reliability whereas using RCC3 only resulted in 88.33% to 96.67% reliability. This loss of precision can be explained with RCC3 being unable to reason about disconnected (DC) objects which especially in the first two tasks of putting the objects into a vertical or horizontal line plays an important role. In these tasks, the DIST QSR clearly outperforms RCC3 compared to the stacking task where we achieve correct classification in 96.67% of the cases even when using RCC3. One of the main influencing factors for this high classification rate is time. Since we did not exclude self transitions, a person doing the task slower will have a higher self transition probability compared to a fast working participant and, therefore, is less likely to achieve a high log-likelihood value when comparing the two.

One of the main limiting factors of this work is the number of participants. However, this pilot-study mainly served the purposed of investigating if we can capture the differences between the execution of the given tasks using basic QSRs which we could demonstrate, despite the low amount of training data.

IV. CONCLUSION

In this paper we used the identification of individuals from their course of action to make a case for the representation of idiosyncrasies of humans accomplishing the same task. We showed that our probabilistic sequential model of qualitative states, despite it being relatively simple, can capture the essence of those differences and allows to very reliably identify the humans acting. Despite all participants being predominantly right handed and being given very simple tasks to complete with the same start and end states, there was a large number of variations in the way in which they performed. The future work for this project includes extending this study not only to further study the suitability of different QSRs, but also to use such models to inform the collaborative task planning, allowing the robot to anticipate the human's next step from the most probable next states in our model.

REFERENCES

[1] G. Hoffman and C. Breazeal, "Collaboration in Human-Robot Teams," pp. 1–18.

[2] J. Shah, J. Wiken, B. Williams, and C. Breazeal, "Improved human-robot team performance using chaski, a human-inspired plan execution system," *Proceedings of the 6th international conference on Human-robot interaction*, pp. 29–36, 2011. [Online]. Available: http://portal.acm.org/citation.cfm?id=1957668

[3] A. Jain, B. Wojcik, T. Joachims, and A. Saxena, "Learning Trajectory Preferences for Manipulators via Iterative Improvement," *Advances in Neural Information Processing Systems*, pp. 575–583, 2013.

[4] N. Bellotto and H. Hu, "Computationally efficient solutions for tracking people with a mobile robot: an experimental evaluation of bayesian filters," *Autonomous Robots*, vol. 28, no. 4, pp. 425–438, 2010.

[5] N. Bellotto, C. Dondrup, and M. Hanheide, "bayestracking: The bayes tracking library v1.0.5," Mar. 2015. [Online]. Available: http://dx.doi.org/10.5281/zenodo.15825

[6] X. R. Li and V. P. Jilkov, "A survey of maneuvering target tracking: Dynamic models," in *Proc. of SPIE Conf. on Signal and Data Processing of Small Targets*, FL, USA, 2000, pp. 212–235.

[7] Y. Bar-Shalom and X.-R. Li, "Multitarget-multisensor tracking: principles and techniques," *Storrs, CT: University of Connecticut, 1995.*, 1995.

[8] J. Chen, A. G. Cohn, D. Liu, S. Wang, J. Ouyang, and Q. Yu, "A survey of qualitative spatial representations," *The Knowledge Engineering Review*, vol. 30, pp. 106–136, 1 2015. [Online]. Available: http://journals.cambridge.org/article_S0269888913000350

[9] G. A. Fink, *Markov Models for Pattern Recognition*. Springer-Verlag Berlin Heidelberg, 2008.

[10] T. Krajník, M. Nitsche, J. Faigl, P. Vaněk, M. Saska, L. Přeučil, T. Duckett, and M. Mejail, "A practical multirobot localization system," *Journal of Intelligent & Robotic Systems*, 2014. [Online]. Available: http://dx.doi.org/10.1007/s10846-014-0041-x