2010 IEEE International Conference on Multisensor Fusion and
Integration for Intelligent Systems
University of Utah, Salt Lake City, UT, USA, Sept. 5-7, 2010

Multi-sensor based segmentation of human manipulation tasks

Norman Hendrich, Denis Klimentjew, and Jianwei Zhang
Technical Aspects of Multimodal Systems
Dept. of Informatics, University of Hamburg
Hamburg, Germany
Email: {hendrich, klimentj, zhang}@informatik.uni-hamburg.de

***Abstract*—In this paper we present an overview of a multi-sensor setup designed to record and analyse human in-hand manipulation — tasks consisting of several phases of finger motions following the initial grasp. During the experiments all of the hand, finger, and object positions are recorded, as are the contact forces applied to the manipulated objects. The use of instrumented sensing objects complements the data.**

The goal is to understand and extract a basic set of finger and hand movement patterns, which can then be combined to perform a complete manipulation task, and which can be transferred to control robotic hands. The segmentation of whole manipulation traces into several phases corresponding to individual basic patterns is the first step towards this goal. Initial analysis and segmentation of two typical manipulation tasks are presented, showing the advantages of the multi-modal analysis.

***Index Terms*—grasping, in-hand manipulation, tactile sensing**

I. Introduction and Related Work

The capacity of the human hand to grasp and manipulate objects, known or unknown and of widely different sizes, shapes and materials is unmatched. Despite recent progress in the design and control of multi-finger robot hands, their use in service-robotics is still limited by the complexity of finding and applying grasp movements for any given task.

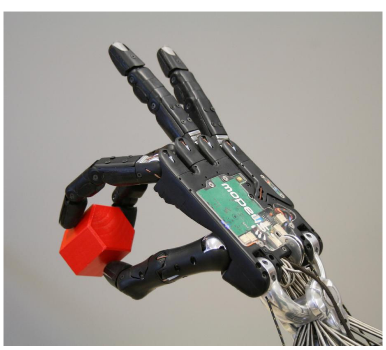


Fig. 1. The 24-DOF Shadow hand

The study of manipulation tasks can be categorised into two main groups. In analytical approaches, a *grasp* is formally defined as a set of contact points on the surface of the target object together with friction cone conditions [1]. The traditional solution to this problem is divided into two stages: first, suitable grasping points on the object are determined, and in the second step a robot hand posture is computed via inverse kinematics to reach those points with the fingertips. See [2] and [3] for extensive reviews.

To realise a better flexibility and robustness, the second approach is motivated by the way humans grasp and rely on empirical studies and classification of human manipulation tasks [4]. Typically, the manipulation task is divided into different phases, e.g. pre-shape, grasp, and stabilization of an object [5]. Analyzed strategies can then be mapped to a robot hand, and complex behaviour is created by sequencing and combining basic motion primitives [6].

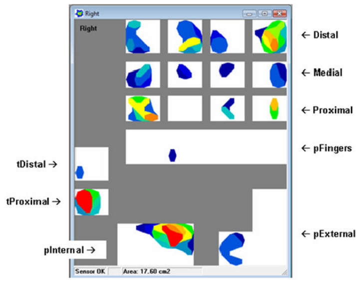
Vision systems and data-gloves are the most common sensors used to track the human hand and fingers in the experiments, and there is some overlap with research motivated by virtual reality and gesture recognition.

In vision based systems, both marker-based and markerless tracking of hand motions has been tried, and multi-camera setups are often required to reduce the inherent problem of occlusion and self-occlusion. Markerless approaches typically include a segmentation step based on skin color and shape-based tools like active contours. Different machine-learning techniques are then used to train the classifiers [7] [8].

However, humans can grasp and manipulate objects mostly without looking, guided only by haptics. Grasp recognition from hand postures recorded with a data-glove has been demonstrated in [9]. Unfortunately, so far there is no technical equivalent to human skin, and the recording of tactile data with high spatial resolution and high dynamic force range is a topic of active research; see [10] for a recent exhaustive review. Only a few of the different technologies are already available commercially [11]. For our experiments, the Tekscan grip system [29] was chosen. An analysis of human manipulation tasks based on force measurements similar to our approach was reported recently [12].

The most advanced robot hands available today approach the mechanical structure and size of the human hand. For example, the Shadow robot hand [13] is designed to closely match the human hand, with 24-DOF overall and human-like thumb movements. Successful grasping of a set of everyday objects with the Shadow hand has been demonstrated [14], but in-hand re-grasping and dexterous manipulation or the use of tools is still beyond the state of the art.

(a)



(b)

Fig. 2. The Tekscan grip system mounted on a right-handed Cyberglove. (a) Inside view. For each finger, three matrix sensors are provided for the distal (4x4 cells) medial (4x3), and proximal (4x3) phalanges. The thumb carries the distal and proximal sensor pads. Separate sensor areas (4x19, 5x9, and 5x4 plus 4x8 cells) are placed on the palm of the hand. (b) Layout and names of the Tekscan sensors for a right-handed glove. The 2D visualization corresponds to a behind-view of the hand.

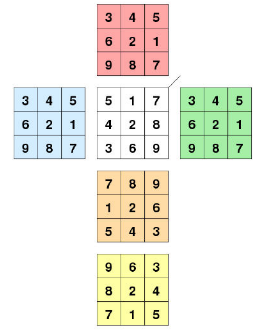
Given the kinematics structure of the hand, any finger posture is fully specified by the joint angles, and can be thought of as a point in a high-dimensional joint space. As the number of degrees of freedom to model the human hand ranges between 20..27 DOF, plus 6 DOF for the hand position and orientation, the resulting search space is enormous. However, previous research of human grasps [15] indicates that most human grasp postures are derived from a small set of common pregrasp shapes. Based on this insight, the concept of Eigengrasps was introduced in [16], where the finger postures are represented as a linear combination of basis vectors calculated by principal component analysis. The approach was refined in [17] and makes it possible to reduce the effective dimension of the parameter space for grasp generation dramatically.

Running the GraspIt! simulator [18] with this search technique, grasps could be generated quickly for thousands of 3D models, using a model of the human hand as well as different robotic hands. This collection of pre-calculated form closure grasps has been published recently as the Columbia Grasp Database [19]. The authors suggest to use an object's 3D geometry as an index into the database, so that finding suitable grasps for a new object turns into a database lookup.

An important area of current research is the modelling of object affordances, and the integration of the affordances and relevant object properties into the grasp generation and grasp quality evaluation [20]. For example, object shape is used in [21], while the handover of objects between robot and operator is considered in [22]. A flexible grasp quality estimation based on a weighted sum of different criteria is described in [23] and has been implemented in our in-house grasp simulator [24].

The rest of the paper is organized as follows. First, the multi-sensor setup used for the manipulation experiments is described in section II. Initial experimental results for two selected scenarios are then described in section III. We conclude with an outlook on future work in section IV and a short summary.

(a)



(b)

Fig. 3. Picture of an original and the instrumented Rubik cube (a) and numbering of the force sensors (b).

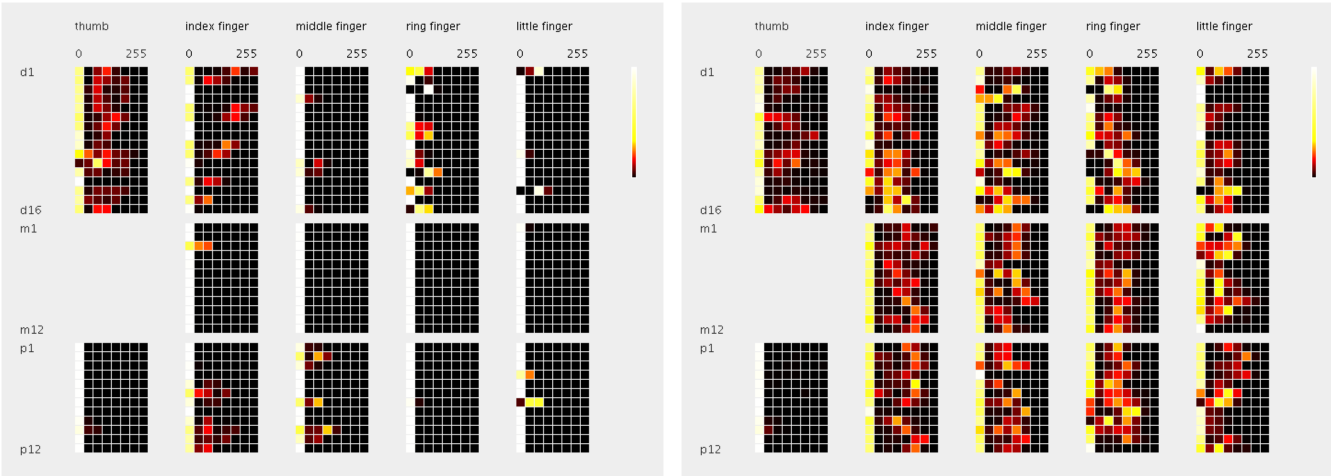
II. Multi-sensor Experiment Setup

Precise recording of the human hand during grasp and manipulation tasks is particularly challenging, because external sensors suffer from occlusion problems, while sensors mounted onto the hand must be very small and flexible to avoid restraining the finger movements.

Targeting the manipulation of everyday objects, a small table-scene environment observed by several sensors provides the basic setup for our experiments. As no single device can record all the data we want to collect, a complex multi-sensor setup is used which includes stereo cameras and magnetic or optical trackers as the external sensors. To record the finger positions, as well as contact forces, a special data-glove equipped with tactile sensing is used. At the moment, any of the following sensors are supported and used:

- stereo camera(s), used both for an overall view of the scene and also to gather depth-maps for hand tracking and object recognition (Videre systems STDC [25]).
- magnetic tracker (Polhemus Liberty with up to six sensors, each providing absolute 6D position and orientation data [26]).
- optical tracking of finger positions with active markers (PhaseSpace Impulse system [27]).
- data-glove for the recording of hand orientation and finger positions (Cyberglove [28]).
- high-resolution tactile sensing of finger forces (Tekscan Grip system [29]).
- instrumented objects with force, acceleration, and orientation sensors (Rubik-cube [30], Wiimote [31]).

Additionally, we record and analyse grasps from the teleoperated Shadow hand, controlled by the data-glove. While this approach is more difficult for the experimenter, due to the lack of tactile feedback and a sub-optimal mapping from the data-glove sensors to the actuators of the Shadow hand, it provides us with high-resolution hand and finger positions from the built-in resolvers of the robot arm and the Shadow hand. Of course, not all sensors are used at the same time or for all experiments. For the data presented in this paper, the stereo-camera, magnetic tracker, data-glove with tactile-sensing and the instrumented objects were used.



(a) (b)

Fig. 4. Example histograms of Tekscan force-sensor activations for the finger sensors. The five columns show the data for (from left to right) the thumb, and then index, middle, ring, and little finger. The upper, middle, and bottom group of histograms corresponds to the distal, medial, and proximal sensors. For each sensor cell, the color-encoded histogram visualizes the occupation numbers of the force values encountered during an experiment (log-scale, from left to right). The palm-sensors are not shown. (a) in-hand manipulation of the Rubik cube with a precision grasp. Only the proximal phalanges of the thumb and index finger are active, with some additional stabilization from the ring-finger. (b) using the ball-pen for writing. All fingers and most sensors except the proximal sensors on the thumb are activated during the experiment.

A. *Tactile sensing*

To record the contact forces applied during the experiments, a Tekscan grip system [29] has been stitched onto a standard Cyberglove [28]. A photo is shown in figure 2 together with the 2D visualization provided by Tekscan and re-implemented in our own software. The Tekscan grip system consists of a set of matrix sensor elements using force-sensitive resistive material and connected by a flexible circuit board. The layout of the sensors is shaped to match the human hand, with three groups of sensors (distal, medial, proximal) on each finger, two groups on the thumb, and three groups on the palm of the hand. Despite the extra weight and some restrictions on finger positions caused by the stiffness of the glove and sensors, many manipulation tasks can be performed well.

B. *Instrumented objects*

The use of special instrumented sensing objects is a third keystone of our experiment setup. The sensors in the object measure orientation, accelerations, and grasp forces to complement the data gathered from the glove and hand itself.

The first instrumented sensing object is a custom-built cube equipped with tactile sensors [30], see figure 3 for a photo of the prototype next to an original Rubik cube. Every face of the cube consists of a small circuit board carrying an array of 3x3 resistive force sensors and one 3-axis accelerometer. Six boards are interconnected, with a single CAN-bus interface to the host computer. For convenience, the faces are colored identically to the original cube, and the resulting numbering of the sensor cells is shown in figure 3b.

C. *Software environment*

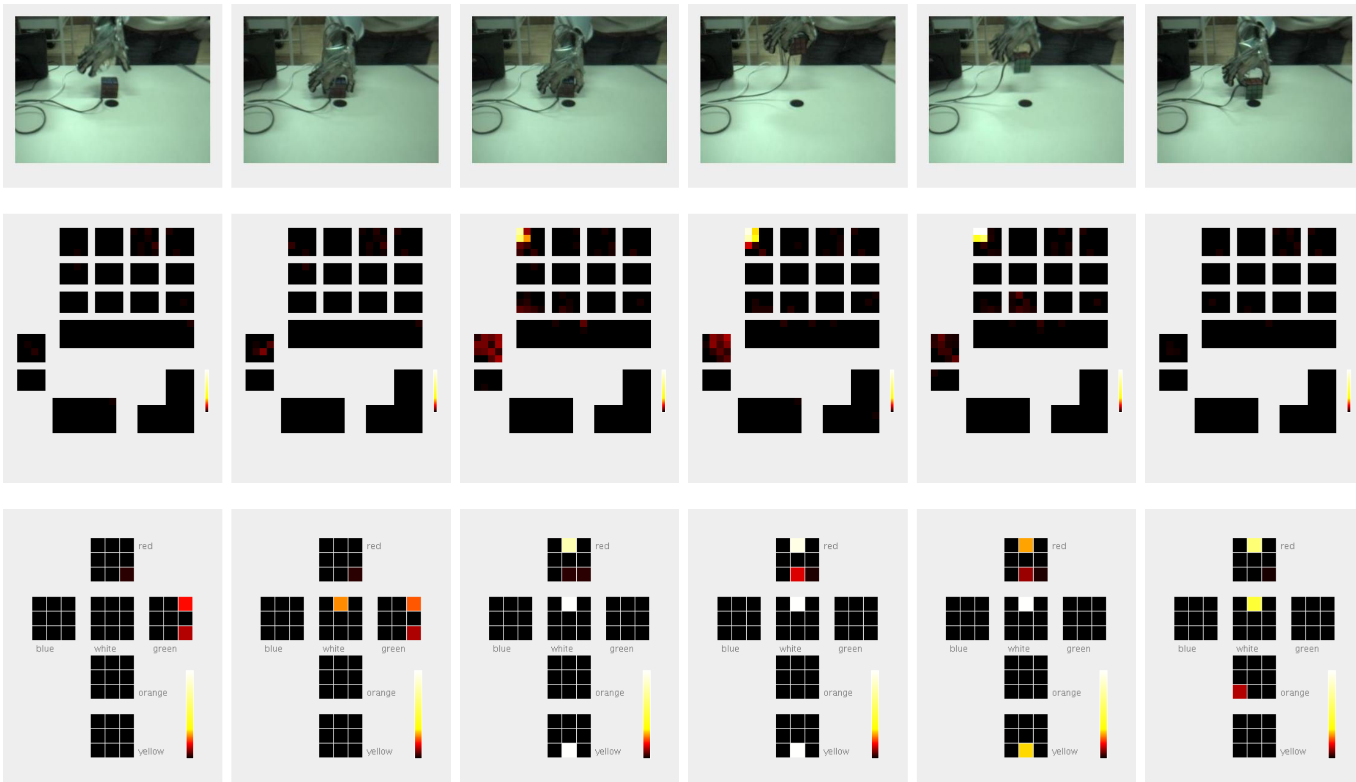
While real-time analysis and direct teleoperation of robots is planned for a later stage, the grasping and manipulation experiments reported here are just recorded for later offline analysis. Sacrificing file size for portability, all recorded sensor data is timestamped and encoded as XML, with a common basic structure including calibration information followed by the raw sensor samples. Video data from the cameras is stored as individual image files, which are in turn referenced from the XML. A single additional 'root.xml' file describes the overall experiment setup, the sensors employed, and also includes comments and annotations [32]. Both a Matlab toolbox and several Java tools are available for parsing and visualization of experiment traces.

D. *Multi-sensor calibration*

Given the variety and complexity of the sensors employed, the calibration of the multi-sensor setup is quite challenging, and so far only the stereo-camera calibration is performed automatically. The Polhemus tracker uses its own absolute coordinate system, which can be mapped into the coordinate system of the cameras.

The initial calibration of the Tekscan sensor cells has been performed with objects of known weight, but this is very time-consuming and suffers from problems with the Tekscan system mounted onto the data-glove. As a result, the experimental data presented below just uses the uncalibrated raw sensor data.

A similar approach with objects of known weights is used to calibrate all 6x3x3 force sensors of the instrumented Rubik cube. The accelerometers are factory-calibrated, but additional calibration in the range of ± 1 g is easily performed by putting the cube on all of its six faces in turn, and then on a simple rig with 30 and 45 degrees of tilt, providing a set of seven known levels and accurate offset for each accelerometer.



(a) (b) (c) (d) (e) (f)

Fig. 5. Picking up the instrumented Rubik cube. The photos in the upper row show the left-image of the recorded stereo-image pairs during the experiment, with the corresponding force-signatures from the Tekscan glove in the middle and the forces from the Rubik cube in the bottom row: (a) approach (b) first contact (intentionally off-center of the object) (c) lift-off, precision grasp with thumb and index finger only (d) lowering the finger forces to let the cube slide down (e) finger forces remain low, because the cube is now stabilized by gravity, (f) setting the cube on the table. Compare figure 9 for a plot of the recorded finger forces vs. time.

III. Experiments

We are currently recording a number of typical tasks involving everyday objects and tools, in order to compile a database of human manipulation strategies. While existing taxonomies and databases mostly concentrate on the finger positions for static grasps, our database includes the measured finger forces and the context information during the complete manipulation task, consisting of a sequence of several typical phases (e.g. reach, hand preshape, grasp, lift-off, stabilize, in-hand rotate, controlled lowering, release). The segmentation of the recorded data enables us to mark those phases and is therefore the first step towards data analysis and understanding.

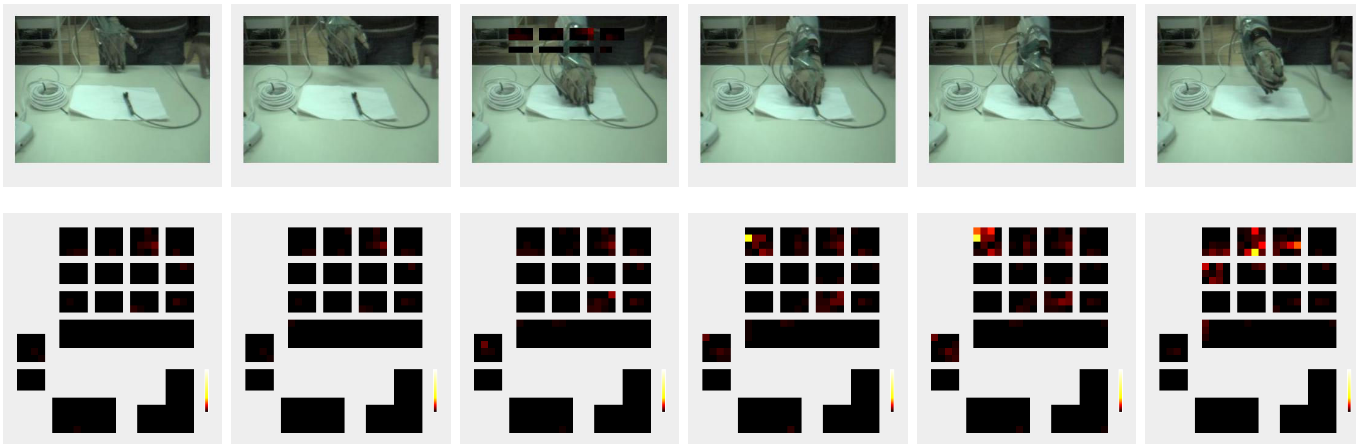
In this section, we present initial experimental results. Two simple experiments are picked to showcase two typical tasks and the resulting sensor data. The first task involves a precision grasp with the thumb and index finger, while the second task illustrates a complex manipulation task with in-hand re-grasping.

A. Force histograms

As shown in figure 4, even a first cursory glance at the data recorded with the Tekscan grip system provides a useful classification of the grasping. In the diagram, the forces recorded during an experiment are visualized using color-encoded histograms. The five columns correspond to the thumb, and the index, middle, ring and little fingers (from left to right). Inside a column, each row plots the force histogram recorded at a single sensor element, with the distal sensors as the upper group, followed by the sensors on the medial and proximal finger phalanges. For every sensor, the histogram shows the occupation number of the corresponding bin, with low forces on the left and the highest forces on the right.

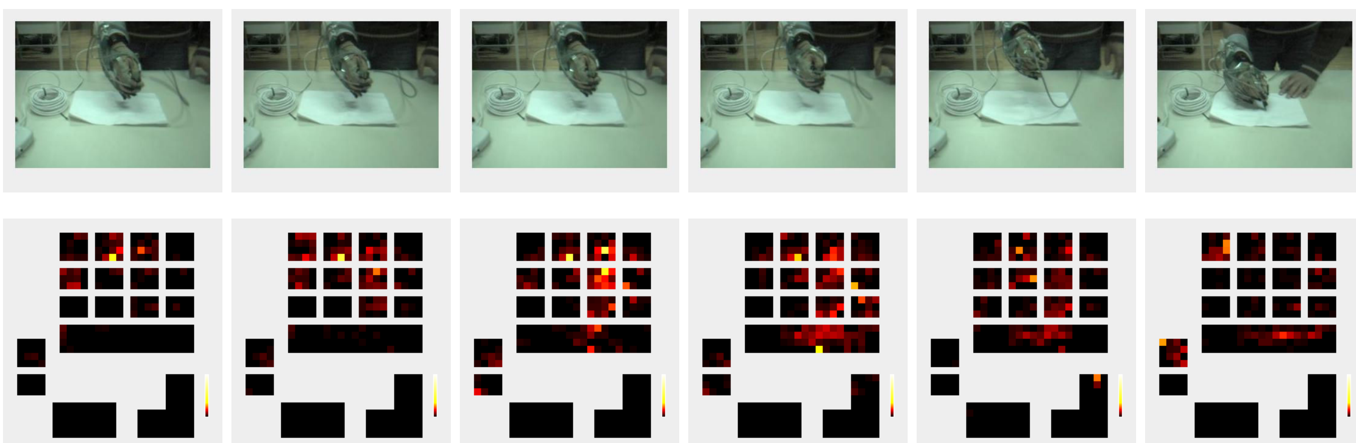
For the experiment shown in figure 4a, only the leftmost bin (zero force) of most histograms is populated, indicating that the corresponding sensor cells were never activated during the whole experiment. It is immediately evident that a precision grasp involving only the proximal phalanges of the thumb and index finger was performed, with some additional stabilization by some cells on the ring finger.

On the other hand, the data shown in figure 4b indicates that all sensors on the fingers were activated during the experiment, with the single exception of the proximal sensors on the thumb. The data correspond to the complex manipulation reported in more detail in section III-C, grasping a ball-point pen to pick it up, in-hand re-grasp to reach the button, clicking the pen, re-grasping again to the writing position, and writing a few characters.



(a) (b) (c) (d) (e) (f)

Fig. 6. Pickung u a ball-point pen for writing. The photos in the upper row show the left-image of the recorded stereo-image pairs during the experiment, with the corresponding force-signatures in the lower row: (a) initial position, (b) approach and hand-preshape, (c) first contact (d) grasping for pickup with thumb and index finger (precision grasp) (e) lift-off, (f) starting the in-hand re-grasping into a power-grasp configuration



(g) (h) (i) (j) (k) (l)

Fig. 7. In-hand manipulation to reach the "'click"' button of the ball-point pen. Starting from the initial position (g), the pen is put between the proximal phalanges (h) and then moved laterally until the thumb can reach the button of the pen (i-j-k). It can be seen clearly how the peak of the forces travels with the object. The last image (l) shows the forces while writing. Note that the palm sensors are activated by the little finger.

B. Grasping the Rubik-Cube

While in-hand manipulation tasks typically start and end with controlled stable grasps, the intermediate phases during re-grasping often involve short periods of time where finger forces are reduced until the resulting grasp is statically unstable.

The simple experiment shown in figure 5 was designed to track the finger forces in such situations. The first phase of the experiment consists of grasping and lifting the Rubik cube, but intentionally off-center.

Figure 8 shows the accumulated forces of the distal phalanges of the thumb and index finger as recorded with the Tekscan glove. The data is shown as uncalibrated raw sensor readings, and due to some sensor non-linearity the forces on the index finger are larger than the forces on the thumb.

The traces show that the thumb is first to make contact with the object, closely followed by the index finger at t =5.0 seconds. The forces increase rapidly and force closure makes it possible to lift the cube. Once in mid-air, the forces are slightly reduced and remain roughly constant. At $t = 8.6$ seconds, the test subject releases the grip force for a moment, and the cube rotates under the influence of gravity. At $t = 11$ seconds, the cube is put on the table again.

For comparison, the corresponding traces recorded by the force sensors on the instrumented cube are shown in figure 9. Initially, the cube rests on the green face, resulting in sensor response on that face. Then, the cube is grasped with the index finger at cell W1 and the thumb on cell Y1. Again, the reduced forces that initiate the sliding near $t = 8.6$ seconds are clearly recorded. Finally, the cube is set down on the orange face. Unfortunately, the mechanical design results in some crosstalk between neighboring faces. For example, note the erroneous activation of sensor cell R4 in figure 5 due to the strong force applied at cell W1.

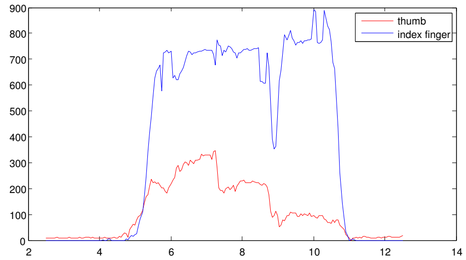


Fig. 8. Grasping the Rubik cube off-center, and letting it slip so that it swings downwards. The plot shows the accumulated forces on the tips of the thumb and index finger vs. time (in seconds) during the experiment shown in figure 5 as recorded by the Tekscan sensor. The different phases of the manipulation task are clearly visible: initial approach, lift-off at 5 sec, stabilization, swing at 8.6 sec, stabilization, drop-off at 11 sec. Forces are not scaled and correspond to the raw data values. Note that the experimenter intuitively keeps the thumb forces low once the Rubik cube is pointed downwards and kept stable by gravity.

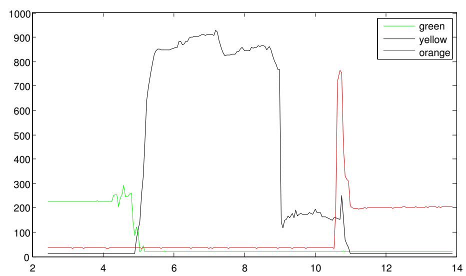


Fig. 9. Accumulated forces for the green, yellow, and orange faces as recorded by the instrumented object for the same experiment traced in figure 8. Initially, the cube rests on the green face, and is picked up by a strong grasp at cells W1 and Y1. After the slipping phase, the orange face is at the bottom. Note the short peak as the cube is set on the table.

C. Using a ball-point pen

Our second experiment consists of a typical everyday task: picking up a ball-point pen for writing. Camera images corresponding to a few key moments are shown in figures 6 and 7 together with the recorded force signatures. Starting from the resting position (6a), the human first pre-shapes the fingers (b) and reaches for the pen (c). The thumb and index fingers are closed into a pinch-grasp (d), and finger forces are increased for lift-off (e). Not shown here are the interesting different hand postures and finger pre-shapes for different initial positions of the pen on the table.

Immediately after lift-off, the experimenter starts the in-hand re-grasp required to reach the button on the back end of the pen in order to activate it by clicking the button. The first stage of this is shown in figure (6e) and (f), where the load shifts from the index finger to the middle and ring fingers. With the fingers closed around the pen, the pen is then moved inside the hand until the thumb can reach and click the button of the pen, see figure 7 (g) to (k). A second stage of re-grasping follows to shift the pen until thumb and index finger have reached the position for writing (l).

An example of human grasp force control is presented in figure 11 which shows six phases of clicking the ball-point pen on and off. The pen is held lightly in a power-grasp finger configuration (11a) so that all finger sensors and the palm sensors are activated. Note that the finger forces increase significantly during the clicking (b-c-d) to compensate the force applied by the thumb. After the clicking (e-f), the finger forces are reduced again.

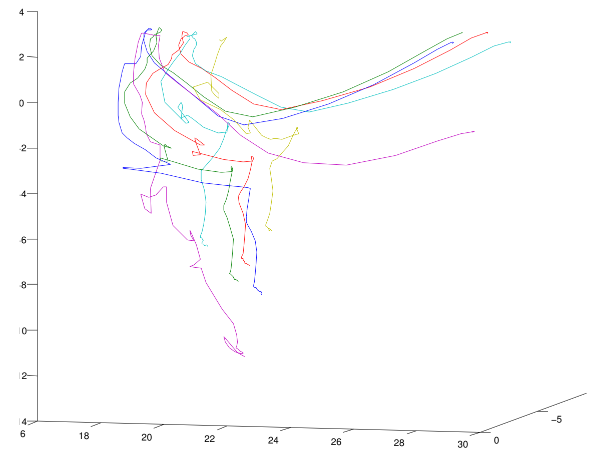


Fig. 10. Grasping a pen and writing. Trajectories of the fingertips during the first part of the experiment as recorded by the Polhemus sensors (purple: thumb, blue/green/red/cyan: index/middle/ring/little finger). The trajectory of the ball-point pen is tracked by a sixth Polhemus sensor (yellow). Note that the trajectories are very clean during the approach phase, but individual phases of the manipulation task cannot be recognized from the trajectories alone.

Compare figure 10 for the finger trajectories recorded by the Polhemus magnetic tracker during the first phase of the experiment. While the data itself is pretty clean, the trajectories are continuous and smooth, and the different phases of the overall manipulation task cannot be distinguished from the data.

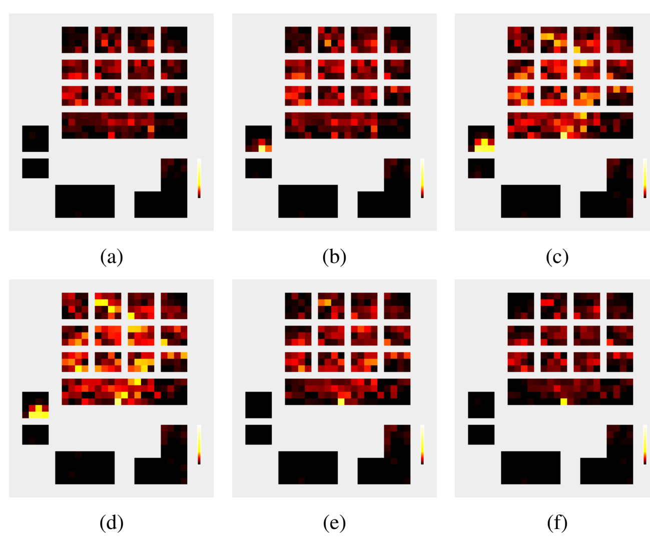


Fig. 11. Clicking a ball-point pen on and off. The pen is held in a power grasp with the thumb operating the button. In the initial phase (a-b), the grasp forces are quite low and distributed evenly across all fingers and the palm. The forces increase significantly while clicking the button (c-d) in order to stabilize the pen, but are reduced again afterwards (e-f). The outer palm sensors and the proximal part of the thumb do not touch the pen and are not activated.

IV. Future Work

While the experimental setup allows us to collect absolute position data for the fingers and objects during the manipulation tasks, this has not yet been exploited in our analysis. Therefore, we are now working on a integrated 3D physics simulation and visualization, which enables us to track and reconstruct the hand and finger movements during the grasp and manipulation experiments.

In the tool, the user can play back the recorded experiments, showing either or all of the reconstructed 3D positions of the fingertips and objects from the Polhemus sensors and stereo images, the reconstructed human hand model, and the force-values recorded from the Tekscan and instrumented objects mapped onto the hand. Contact points between fingers and objects will be visualized similar to GraspIt! and our in-house simulator zgrasp [24].

The next major step will be to model object affordances and to evaluate machine-learning approaches to automatically detect, segment, and analyse the several phases of human object manipulation. We are working on a mapping, allowing to transfer the reconstructed finger movements to a physical simulation of the Shadow hand, and then to validate the results with the real Shadow hand.

V. Conclusion and Discussion

The initial results of our multi-modal analysis of human manipulation tasks look promising. The different sensors complement each other nicely for our goal of segmentation of multi-stage operations into their different phases. For example, initial hand positions and finger pre-shapes are available from the camera images and Polhemus traces, while the force sensors give accurate information about the time of initial contact which would be hard to extract from the camera images. The spatial resolution of the force sensors in the Tekscan glove is enough to provide detailed information about in-hand manipulation tasks.

Acknowledgements

This work is partially supported by the European project HANDLE ICT-236410, www.handleproject.eu/. We wish to thank Jorge Lobo and Ricardo Martins from the Institute of Systems and Robotics, University of Coimbra, Polo II, Portugal, for providing us with experimental data. The authors acknowledge discussions and feedback from all partners of the HANDLE project.

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