GRIP RECOGNITION AND CONTROL OF A THREE FINGER GRIPPER WITH A SENSOR GLOVE

Igor Zubrycki, Grzegorz Granosik
Lodz University of Technology
tel +48 42 6312554
Email: igor.zubrycki@dokt.p.lodz.pl, granosik@p.lodz.pl

Abstract—We propose the structure of the control system to intuitively operate the multi-finger gripper SDH from Schunk. The sensor glove can be used as an input device. However, the transformation from 5 fingers of human hand down to 3 fingers of the gripper is not trivial. Our approach includes a grip recognition phase followed by a grip execution phase. This paper shows some preliminary tests of the performance of this controller.

I. Introduction

This paper details the design of 3-finger gripper controller using a sensor glove as an input device. Proposed system has the ability to recognise different grip types and, as a result enables to control all 7 degrees of freedom of the 3-finger gripper with our simple in house made sensor glove. Paper describes sensor glove functionality and provides a comparison between two learning methods used to enable grip recognition.

As a continuation of our previous work [1], where we designed a system to control a virtual model of the 3-finger gripper, this paper describes some control aspects related to using real gripper and presents results of several tests performed on the 3-finger gripper SDH from Schunk.

II. Motivation

Dexterous grippers provide a method to manipulate objects in constrained environments in ways that would be otherwise impossible with only 6-dof manipulator and parallel-jaw grippers [2]. However, coordinated motion of such gripper in not trivial and, in fact, the whole system can be considered as a robot with three manipulators working in the common space. Therefore, controller not only has to produce grip that is optimal for a certain task, but also has to deal with transitions stages and avoiding self-collisions. In the proposed system, we have decided to use a sensor glove as a main input device. Intentions of the operator moving his or her hand (with a sensor glove) are translated to movements of 3-finger gripper having 7 DOF. This transformation has to be accurate and intuitive for the user.

Resulting solution provides a way to teleoperate a dexterous gripper without significant expertise [3] as well as gives us a platform for learning grasp methods from human demonstrations [4].

III. Proposed control structure

The proposed system to control 3-finger gripper consists of 7 parts (shown in Fig. 1):

1. Sensor glove which is a two-layer textile glove with flexion and force sensors attached to it. We have used resistive sensors and added appropriate voltage dividers to safely connect output voltages directly to A/D ports of Arduino board.

2. Data filtering program. This program reduces effects of the sensor noise and its temperature sensitivity.

3. Gesture recognition. Filtered sensor data are used to recognize the grip type. Program is based on the machine-learning algorithm and is explained in detail in further sections.

4. Planner of pose change. This program is used in case of the grip change. As different types of the grasp can require rapid changes of the poses of three fingers, this process may sometimes be danger (risk of the self-collision of SDH hand). To reduce the risk we propose the planner that would generate safe trajectories to change the pose in case of different grip recognition.

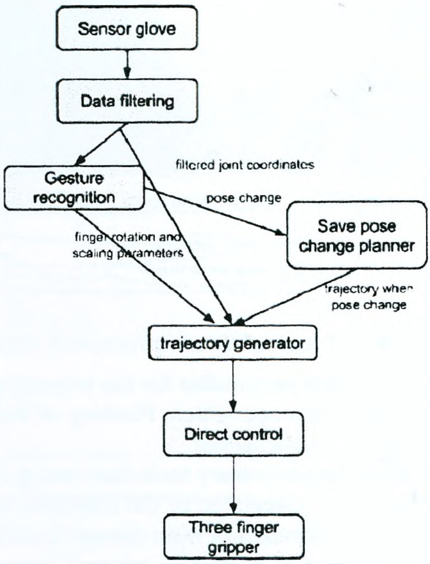

Figure 1 - Proposed control structure

5. Trajectory generator. This program consists of a state machine that manages the gripper behavior in different scenarios. For each recognized grip, the relation between readings from flex and force sensors and the pose of the gripper is different. Therefore, movements of the operator's fingers are transformed to the movements of 7 DOF in the specific way. In case of grip change the trajectory generator gives priority to the trajectory generated by the planner of pose change.

6. Direct control node. This node realizes the trajectory by sending velocity commands to the gripper, with position feedback from SDH hand. It also transfers to the system information about the current state of the gripper.

IV. Physical control layout

To realise the proposed control structure, we have implemented a ROS based network of nodes, each with some part of the aforementioned functionality, as shown in Fig. 2. To simplify development, nodes are implemented on two PC computers, interconnected by the TCP protocol, with master-slave configuration. Master computer has also the ability to control the slave's functionality (e.g, switching-on devices connected to it) using secure ssh connection.

Master computer has two key functionalities - direct control of the SDH gripper and managing communication between different ROS nodes using built-in DNS-like functionality.

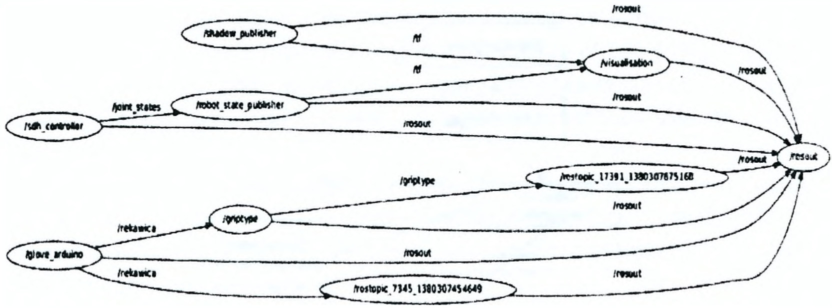

Figure 2 - Graph of control structure in ROS

Slave computer provides nodes responsible for the trajectory generation, gesture recognition, data filtering and data acquisition. Planning of the safe movement between different grips is not yet implemented.

We have observed during the preliminary tests that having visual presentation of the target position of the gripper calculated by the trajectory generator is very useful for the operator, who can calibrate it or even change it while gripper is still moving. Such visualization is provided as a "shadow gripper", shown in Fig. 3. Solid texture is used to present actual pose of the SDH hand while transparent picture represents output from the trajectory generator. When the system is in operation the solid picture follows the shadow. As the SDH hand is not very fast, that can be read from bode plots presented in Fig. 4 the operator has some time to make corrections in the grip before the fingers reach the object.

Visualisation in done in the tool available in the Robot Operating System named Rviz. It allows for easy presentation of 3D models, described by Unified Robot Description Format (URDF). Special node (robot_state_publisher, Fig. 2) computes forward kinematics for each coordinate frame attached to robot's joints, that further allows moving any object on the 3D scene (in our case 3D meshes described by COLLADA files).

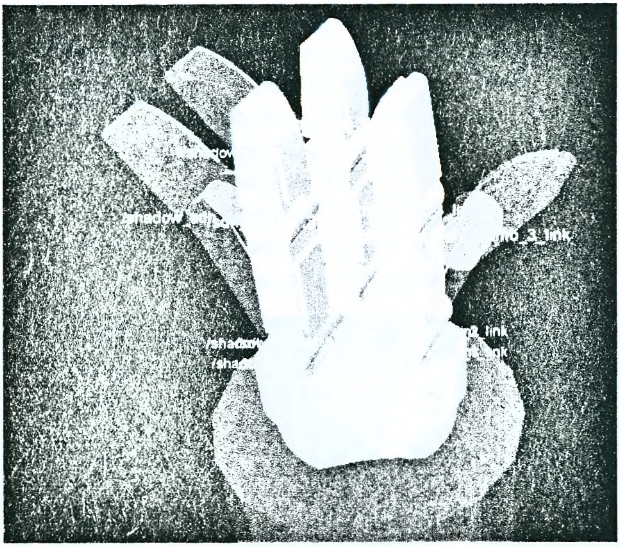

Figure 3 - Visualisation of gripper pose and shadow hand in Rviz

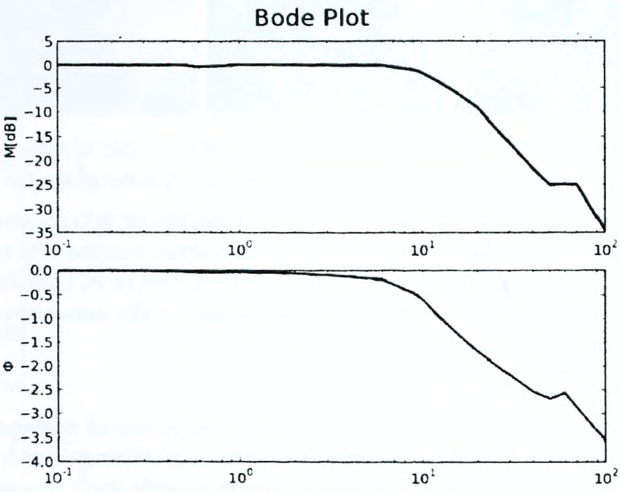

Figure 4 - Bode plot of gripper's joint

V. Sensor glove

Sensor glove designed for hand movement and grip estimation consists of 10 flex sensors: five positioned on the upper side of the hand, as shown in Fig. 5a, another set of five is positioned on the bottom side of hand as shown in Fig. 5b, the force sensors are mounted on fingertips and in the middle of palm, as shown in Fig. 5c. The two-directional FS Flex sensors have 25 kOhm flat resistance and maximally 125 kOhms of bend resistance. They are combined with 10 kOhm resistors to compose voltage dividers. Finger joints have limited range of movement of about 90 degrees. At this range all sensors had a nearly linear characteristic, as shown in Fig. 6. One can see that these characteristics vary in both inclination coefficient and offset from sensor to sensor between 18.7 kOhm and 28.8 kOhm. This called for the need of individual calibration for each sensor. Force sensors have much less linear characteristic in the range of 0-15 N, as shown in Fig. 7, but they are more homogenous in the set of 6 sensors we have tested.

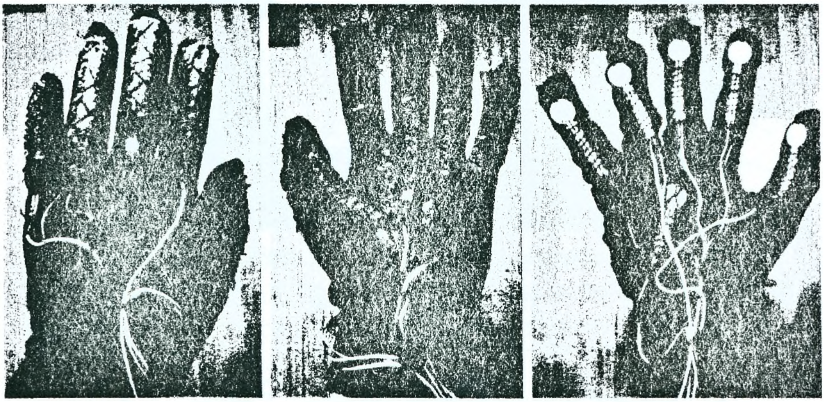

Figure 5 - Sensor placement on our sensor glove (for left hand) [5]: a) inner glove, upper side flex sensors, b) inner glove, bottom side flex sensors c) outer glove, force sensors

Sensor glove is connected to the 16 channels of the 10- bit A/D converter built in Arduino Mega 2560 board. The acquired data is formatted into the ROS Message directly on the Arduino Board. Then data is serialized and sent to PC computer by USB port. Special *rosserial*_node controls communication, checks data correctness and publishes topics created by Arduino on the ROS System.

VI. Learning grips

Robust and fast grip recognition is essential for the proposed trajectory generation scheme. There are several procedures for learning grip recognition from sensor data. We assumed that successful algorithm would provide good overall precision and recall, and would not require re-learning for each new user.

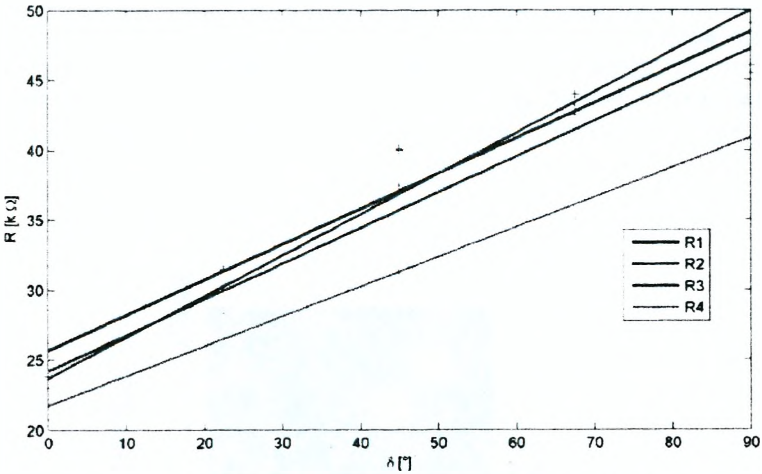

Figure 6 - Static characteristics of the flex sensors [?]
(delta - bending angle, R - sensor's resistance)

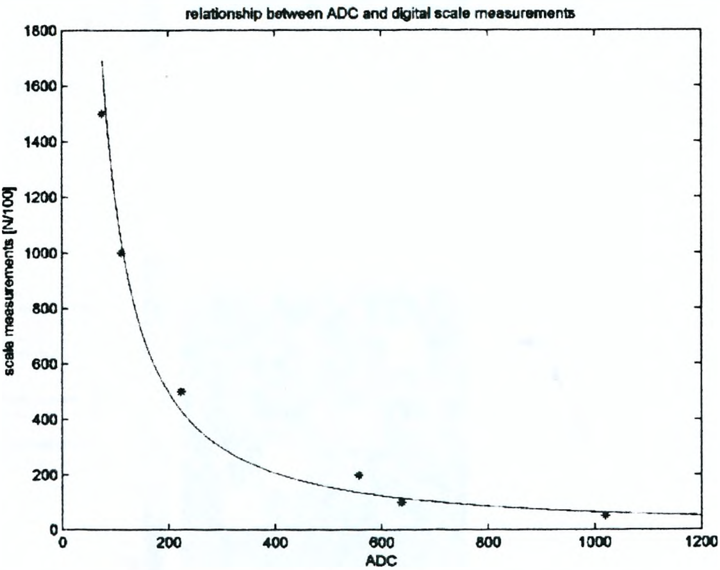

Figure 7 - Relationship between ADC and measured force

In our research we have tested two algorithms - Forest of Randomized Trees (FoRT) and Support Vector Classification (SVC) as they provide good performance and generalisability.

To teach our algorithms we have used 230 training vectors, that were acquired by asking six users to perform grips on different objects and with different intentions. Performance was tested on additional 70 vectors.

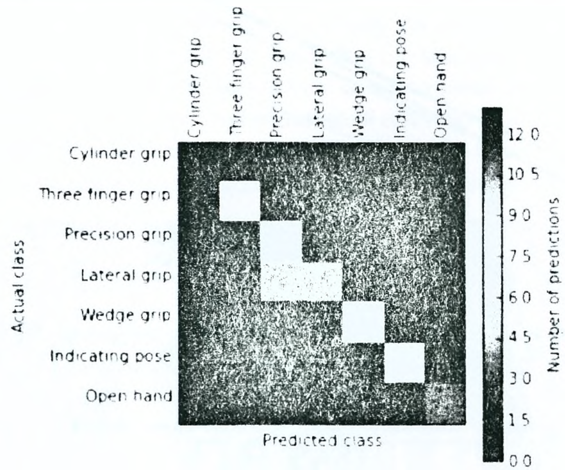

Figure 8 - Confusion matrix for Forest of Randomized Treees method

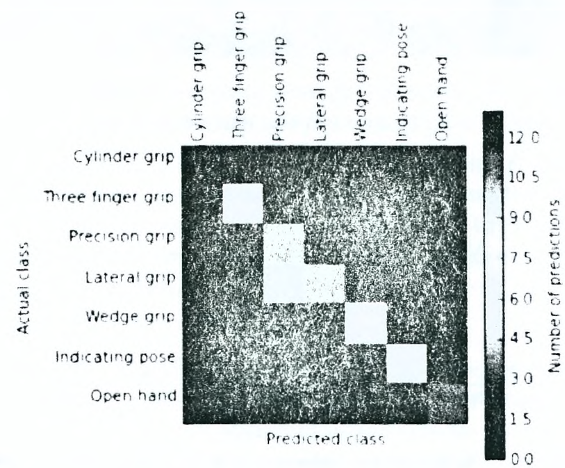

Figure 9 - Confusion matrix for Forest of Randomized Treees method

To find the best parameters for learning algorithms, we have used 10 fold cross validation. In case of Forests of Randomized Trees, we have used grid search for number of estimators (trees) ranging from 1 to 40 and minimum sample split ranging from 1 to 30, and maximum number of features ranging from 1 to 16. Best results were found for number of estimators 19, maximum number of features 9, and minimum sample split of 6. In that case, for test data algorithm had f-1 score of 0.77, precision 0.8 and recall 0.78. Confusion matrix is shown in Fig. 8.

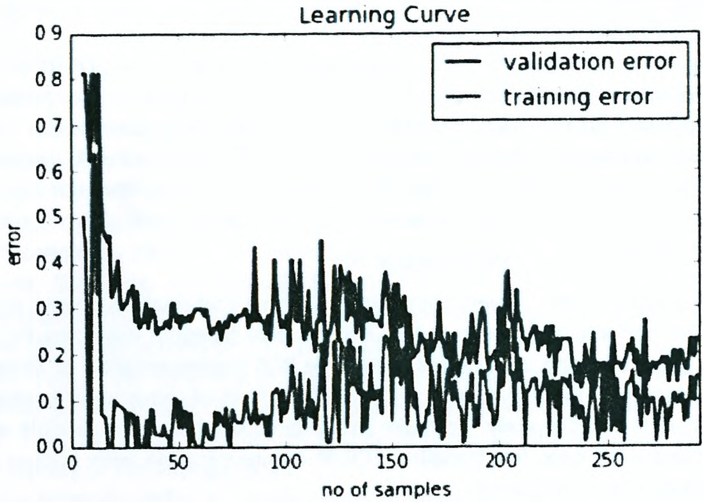

Figure 10 - Learning curves for SVM algorithm used for grip recognition

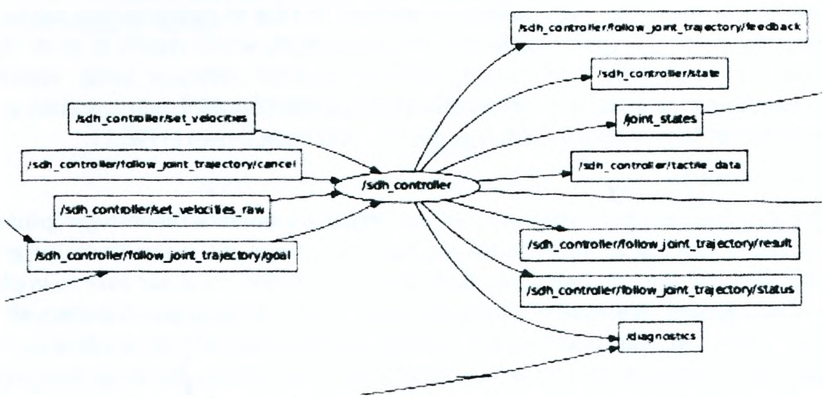

Figure 11 - Schunk SDH controller input/output flow diagram

Similar prediction results were obtained for the second of the algorithms we have tested with mean precision score of 0.78 and mean recall score of 0.77 (obtained f1 value 0.76). Confusion matrix (Fig. 9) shows that precision and lateral grips were the most difficult to tell apart.

In order to decide when we should finish the teaching process, we have conducted tests on in-sample (training) and out-of sample errors to assert the state of learning as a function of number of training vectors [6]. For both algorithms learning curves, shown in Fig. 10 indicate that errors are diverging, so we can assume that additional training would only marginally improve performance for the learning models chosen.

The biggest difference between tested algorithms was in the prediction performance. We have measured the prediction time for both algorithms on the randomly chosen data and for the 10000 repetitions. The results show that for the SVC algorithm single prediction takes on average 79 μs while for the FoRT algorithm the mean value is 2.65 ms, being over 30 times slower. Considering that our algorithm is going to be used for online grip recognition, we have chosen SVC.

VII. Schunk SDH 3 finger gripper properties

Schunk's SDH gripper is a very sophisticated device that enables precise control of a grip angle and a grip shape as it has 7 degrees of freedom driven by DC motors with low gear ratio and precise encoders. The ROS implementation of Gripper API (initially developed by [7]) allowed us to control most of the gripper's parameters directly from the ROS system. To make the original solution more flexible we have implemented additional functionality: TCP/IP communication with gripper (RS232 and CAN was already available).

To use the sensor glove to control the gripper we also had to change the behaviour of the gripper when receiving new position - which is normal in situation when operator's hand (wearing sensor glove) moves. The default hardware position controller has to stop after each position is reached. In case of receiving new position during the motion, fingers rapidly stop the movement, which results in jerks. We solved this problem by implementing software position controller using velocity commands and the position feedback from the gripper. Control, communication and diagnostics of Schunk SDH Gripper was put to a ROS node shown in Fig. 11.

VIII. Conclusion

We have proposed the control system to intuitively operate the 3-finger gripper using sensor glove as an input device and two main stages of the algorithm: the grip recognition and the grip execution. Both tasks are neither trivial nor easy to implement in real time. We have shown quite good results of the grip recognition after the SVC algorithm was taught by 230 training vectors obtained from 6 subjects. We have also tested some performance of the SDH hand, namely: dynamics and position control in the continuous teleoperation mode. We have shown effective control of the SDH hand using sensor glove and the shadow hand philosophy. The visualisation of the results of the transformation from the sensors readings to the expected gripper's movement helps operator to correctly show his/her intentions and on-line control the 3-finger gripper.

IX. Acknowledgment

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REFERENCES

[1] Zubrycki, Igor; Granosik, Grzegorz, "Test setup for multi-finger gripper control based on robot operating system (ROS)," Robot Motion and Control (RoMoCo), 2013 9th Workshop on , vol., no., pp.135,140, 3-5 July 2013 doi: 10.1109/RoMoCo.2013.6614598

[2] Onda, H., and T. Suehiro. "Motion planning and design of a dexterous gripper-graspability, manipulability, and virtual gripper." Intelligent Robots and Systems, 1998. Proceedings., 1998 IEEE/RSJ International Conference on. IEEE, 1998. - Vol. 1.

[3] Kang, Sing Bing, and Katsushi Ikeuchi. "Toward automatic robot instruction from perception-mapping human grasps to manipulator grasps." Robotics and Automation, IEEE Transactions on 13.1 (1997): 81-95.

[4] Lin, Yun, et al. "Learning grasping force from demonstration." Robotics and Automation (ICRA), 2012 IEEE International Conference on. IEEE, 2012.

[5] M. Fraszczyski, Interface design to control the multi-finger gripper, BSc Thesis, Lodz University of Technology, 2013

[6] Abu-Mostafa, Yaser S., Malik Magdon-Ismail, and Hsuan-Tien Lin. Learning from data. AMLBook, 2012. p.66-68

[7] Schunk Modular Robotics ROS Repository. Fraunhofer-Institut Produktionstechnik und Automatisierung, 2013. Web. 7 Oct 2013. https://github.com/ipa320/-schunk modular robotics

EVALUATION OF THE OPTONCDT ILR SENSOR

Richard Balogh
Slovak University of Technology in Bratislava
Faculty of Electrical Engineering and Information Technology
Bratislava, Slovakia
richard.balogh@stuba.sk

Abstract—In this paper we evaluate metrological properties of the optoNCDT ILR sensor and compare it with the producer's datasheet. Then we describe its use for the purposes of map creation in mobile robotics. Results are promising so we can use this sensor for cheap map-making mobile robot applications.

Keywords—laser scanner, distance sensor, mapping, mobile robotics