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Rehabilitation-oriented human hand model reductions

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Abstract

Ischemic or hemorrhagic stroke, a common cause of loss of hand function, often results in spasticity and makes it impossible to perform activities of daily living (ADL). Recovering hand functions is therefore of vital importance. Neurorehabilitation, based on using robotic devices in the therapeutic process, is a promising way to exercise the hands, improve patient initiative, and increase neural connections with minimal intervention of the therapists. On the other hand, complex human hand anatomy complicates the development of specialised robotic rehabilitation devices. As a result, obtaining simplified but representative mathematical models of the human hand kinematics based on common grasps is crucial. The aim of this research is to identify the intra-finger dependencies for grasping types that are of utmost importance for the execution of ADL, such as opening a bottle, using a knife and holding a pen. The study is based on the largest known database of human hand movements, encompassing 77 test subjects. The first part of the research deals with data cleaning in terms of relabelling, pre-processing and filtering. The correlation analysis is performed next, enabling identification of highly correlated dependency-movement associations. The study in this work represents the foundation for further development of simplified but accurate rehabilitation-oriented human hand models.

rehabilitation robotics, rehabilitation-oriented hand modelling, dependency-movement associations, activities of daily living

1. Introduction

Stroke, increasing both in incidence and prevalence, is an ever rising society problem. Distributing timely therapy with proper intensity and frequency, critical for proper recovery, is becoming increasingly difficult. Robotic-assisted rehabilitation can be utilised as a possible solution to the problem. A fundamental problem in hand rehabilitation is selecting proper movement subsets, or grasps, which would benefit recovering ADL the most, as well as modelling them accurately and simply. Models should comprise as little as possible degrees of freedom (DOFs) while fully satisfying intended functionality. To obtain such models, it is necessary to research and understand hand kinematics using recorded hand movements. In [1, 2], kinematic models were presented, but only a few subjects were used, and grasps were divided into prismatic and circular types only. In [3], five sparse hand synergies were identified across 26 grasp types, but data from 22 subjects was used. A largest known database [4], recorded using a data acquisition glove fitted with sensors, including 77 test subjects is analysed in this paper. First, data is prepared using summary statistics and joint anatomical ranges of motion (ROMs), then correlation matrices were obtained for valid identification of highly correlated grasp-oriented intra-finger dependencies as a basis for generalisation of previously performed modelling [2] to 23 functional movements using everyday objects.

2. Data preparation and analysis

The dataset used in this paper, which contains synchronously collected values of joint angles in degrees, was prepared using Apache Spark and tidyverse [5], a collection of R packages for data science. Only the functional movements (grasps) were selected for further processing, while resting positions and different hand configurations (gestures) were omitted. All missing and duplicate values were removed from the database, as well as adduction/abduction (AA) movements since a lot of values were missing due to noise problems. Further processing was focused on identifying relationships between flexions/extensions (FE), but only reducing to intra-finger dependencies. After all subjects, movements and repetitions were concatenated, the resulting dataset contained over 50 million time recordings for 16 different finger joint angles, posing an admirable number for further analyses. Fingers were labelled using numbers (1 - thumb, 2 - index, 3 - middle, 4 - ring, 5 - little), and joints using abbreviations, list of whom can be found in [2]. The description of the database is summarised in Table 1.

Table 1. Description of the prepared database records.

Subject	Laterality	Gender	Movement	Repetition
1 - 77	right handed, left handed	male, female	1 - 23	1 - 6

2.1. Summary statistics and preprocessing

For preliminary analysis of the dataset, descriptive statistics was used since this was the most straightforward way to gain a quick insight into such a large database. The dataset was first grouped by subject, movement and joint angle, while computing boxplots (mean, min, max, median, 1st quartile Q1, 3rd quartile Q3, interquartile range IQR) considering all repetitions. It led to a conclusion that a lot of measurements fall outside joint anatomical ROM limits (adopted from [1, 6]), most likely due to sensor noise, and imperfect glove fit to different hand sizes. This necessitated the removal of errors in recorded joint angles to obtain valid data for further analysis. After data removal, some motion repetitions were left with too small sample size or diversity for proper inferences. Samples with less than 100 data points, and those with recorded insufficient portions of the entire movement range (IQR of the sample less than 50% of mean IQR for the same movement across all subjects) were also removed from the prepared dataset. Validation boxplots for small digit MCP joint angle medians (per subject), before and after anatomical ROM filtering, are shown in Fig 1. For each of 16 investigated joints, similar validation graphs were plotted. Also, by investigating boxplots in Fig 1 (top), many outliers still remained in the data, so an additional 1.5 IQR outlier detection and removal procedure was performed. It is applied on a subject-level summary statistics, where all measurements, whose median fell outside range (Q1 - IQR, Q3 + IQR) was deemed outlier and removed from further processing. In Fig 1 (bottom) the example of summary statistics for MCP5, after preprocessing and outlier removal steps, is presented.

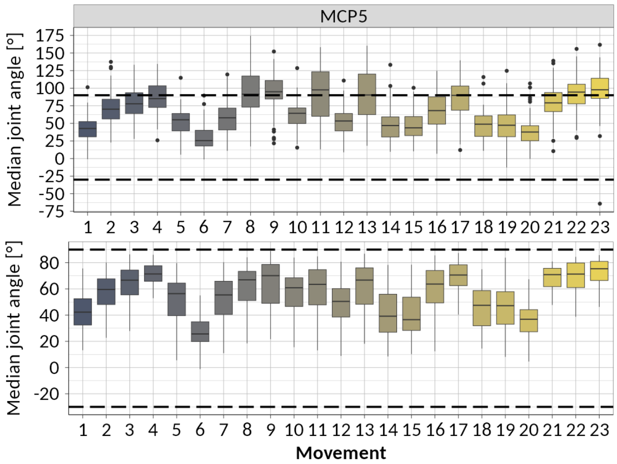

Figure 1. Validation for removing data points outside anatomical ROM.

3. Results and correlation analysis

After data preprocessing at a joint level, the subsequent steps involved forming 18 intra-finger dependencies, such that every combination of joint trajectories belonging to the same finger can be correlated using Pearson's *r*. Owing to data acquisition parameters, some repetitions comprised numerous measurements, while some only 100, resulting in disbalance in the dataset. Dependencies were observed on a repetition level as a unit for data analysis, thus balancing each subject share during further inferences since each subject performed 4 repetitions on average after data preparation. Correlation analysis was then performed, and more than 70 000 correlation coefficients obtained (matrices with combinations for each finger, movement, subject and repetition) for identifying further relationships. The same 1.5 IQR rule was then applied to correlation coefficients for each movement dependency to eliminate outliers. Only highly correlated intra-finger dependencies with absolute median correlation coefficient larger or equal to 0.7 (breakpoint according to [7]) were isolated. Outlier removal procedure example (for Movement 10, MCP5 - PIP5 dependency) is shown in Fig 2.

The correlation analysis resulted in dependency - movement matrix in Fig 3, where only the median coefficients are visualised. From a total of 18 investigated dependencies (y-axis in Fig 3), 16 were highly correlated during at least one movement, indicating a relationship, while ring and little finger DIP and PIP joints were the only ones not correlated. On the other hand, in each of the 23 investigated movements, there is at least one correlated dependency, while in movements 2 (power grip) and 3 (fixed hook grasp) a large number of joint dependencies (10 and 11 respectively) can be identified. Also, it can be concluded that the thumb is the most independent digit, with identified only 5 dependency-movement associations, agreeing with [3].

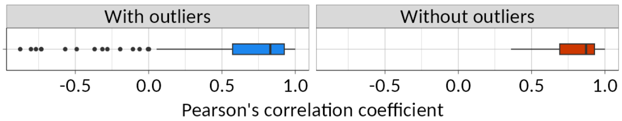

Figure 2. 1.5 IQR rule outlier removal on Movement 10, MCP5 - PIP5.

4. Conclusions and outlook

We presented a novel method for extracting useful data for grasp-oriented hand modelling using noisy sensor measurements. The validity of data was investigated, as well as 116 highly correlated dependency-movement associations identified (median absolute correlation $\geq$ 0.7). The provided identification will serve as a basis for future comprehensive modelling of hand grasps oriented at rehabilitation robotics. In future work, regression modelling is planned with the aim of estimating the corresponding coefficients for all the identified dependency-movement associations. Then, synthesis of all coefficients, using dependency matrix and clustering methods, will be necessary for presenting valid and comprehensive rehabilitation-oriented grasp models, as well as a grasp taxonomy based on similar intra-finger dependencies.

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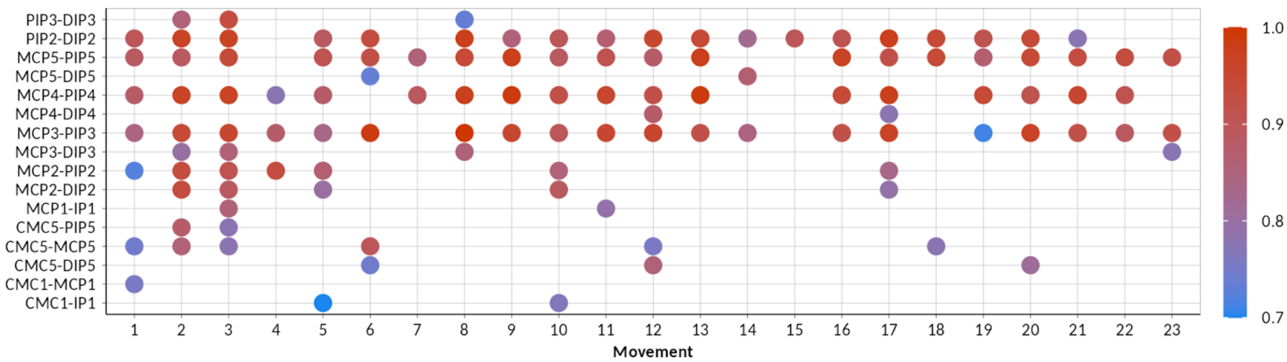

Figure 3. Correlation analysis of intra-finger joint dependency-movement association