KINEMATIC MEASUREMENT AND ANALYSIS OF HUMAN ARM MOVEMENTS

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Theses of the Ph.D. Dissertation

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1 Introduction

Quantitative measurement and analysis of human motion is a key concept in understanding processes of our movement system. Evolved, high precision measurement devices have advanced research activity in movement rehabilitation [1], performance analysis of athletes [2] and general understanding of the motor system [3] during the last decades by making objective movement pattern comparison possible. This advancement was further accelerated by model-based analysis approaches that enabled explicit characterization of the studied movement patterns [4].

From behavioral aspects, manual and visual target tracking represents an important part of human movements and shows strong predictive behavior. This becomes most obvious when comparing tracking onset delay with phase delays during pursuit of periodic movements [5] or when the movement continues after disappearance of the target [6]. Oculomotor and manual tracking responses affect each other and seem to share predictive mechanisms [7]. Studies investigating predictive manual tracking so far focused on the explanation of finger acceleration as a function of the 2D-tracking error [8] and on the relation between the 3D-tracking error and path curvature and spatial depth [9] but did not consider the control of shoulder, elbow and wrist joints.

By utilizing quantitative measurements, the analysis of joint angle variability, especially its structural decomposition into task-relevant and task-irrelevant components with respect to hypothesized task variables, is used to address redundancy in movement control mechanisms and is known as the *Uncontrolled Manifold Method* (*UCM*) [10]. In this context the term *task variable* does not imply that it was explicitly addressed in the instructions to the subject, but that the covariation in the effector space is optimized to stabilize this variable. The main concept of the *UCM* is to divide the total variance of the joint angles into two orthogonal sub-components that do and do not affect the proposed task variable. The variance in the component which does not influence the task variable is called the "uncontrolled variance" (V_{UCM}) and can be used as an indicator of flexibility of the control system, while variance in its orthogonal component is called the "controlled" or "orthogonal variance" (V_{ORT}). The relative size of V_{UCM} with respect to V_{ORT}, quantified by the so-called synergy index, can be used to characterize the stability of the task variable [11]. A large synergy index of the joint angle variance with respect to the task variable indicates that the *bad* variance (affecting the task variable) is relatively small compared to *good* variance (not affecting the task variable). It is important to note that this synergy index is specific for the chosen task variable and is not a general measure of covariation. The *UCM* method has been used to show the synergistic properties of the motor control system involving reaching, finger coordination and bimanual pointing tasks.

In quantitative movement analysis, the most widely used measurement systems apply line-of-sight (LoS) methods (optical or ultrasound-based) that require a fixed *marker-sensor* structure and a controlled laboratory environment. This means that even the spatial positions of the markers can be determined with good accuracy - especially with optical systems - the possible range of motion is constrained by the actual measurement volume covered by the sensors of the system. Although this property is not an issue for many movement analysis scenarios, there are cases when a measurement method allowing unconstrained free space movement is more beneficial (e.g. various outdoor activities or ergonomic assessment of work environments).

Advancements in the field of inertial sensor technology have given rise to new development directions in laboratory-free movement analysis methods. The main difference between LoS and inertial systems is the recorded modality: while LoS methods determine the *spatial locations* of markers based on planar position (optical) or timing (ultrasound) information, inertial sensors give their *orientation* in space by measuring physical quantities (linear acceleration, angular velocity and magnetic fields) acting on them directly. To obtain orientation from raw inertial measurements, various sensor fusion algorithms have been developed utilizing Kalman-filters [12], gradient descent methods [13] and complementary filters [14] among other techniques, most of them being capable for real-time operation in embedded systems. In addition, recent evolution of chip-scale inertial sensors based on MEMS (Micro-Electro-Mechanical-System) technology further widened the possibilities of wearable measurement device development by making the core sensing elements available for better integration.

In addition to accurate measurement, proper evaluation of the recorded motion is an other key building block of human movement analysis. Although various geometric approaches have been developed to describe movement kinematics, the need for standardization of kinematic (and kinetic) analysis of human movements have led to the development of model based tools like SIMM [15] and OpenSim [16]. These software packages provide biomechanical models and analysis pipelines to perform various processing steps like model editing, scaling, kinematic and dynamic calculations. For anatomical joint angle reconstruction they use the "standard" offline *measurement-scaling-inverse kinematics* pipeline where the actual biomechanical model (single limb to full body) is fitted to measurement data. During this process, positions of virtual markers placed on specific model segments are fitted to experimentally recorded marker positions of the subject with the same arrangement. Scaling is important to generate subject-specific model instances while inverse kinematics (IK) is performed to extract model-defined anatomical joint angles that produced the movement. Using these tools obtaining useful movement properties have became a standard process that produces outputs directly comparable across movement tasks and studies.

Complex measurement and analysis of upper limb movements including kinematics and muscle activities is an exciting and growing subfield of human movement analysis that promises better understanding of control patterns during specific movements, and as an example benefit may - on the longer term - advance control techniques currently applied to arm and hand prostheses. This process however needs tighter integration of kinematic measurement and reconstruction (from raw data to anatomical joint angles) as the time and computational overhead of the offline *measurement-scaling-inverse kinematics* scheme gives a bottleneck in applications where real-time analysis of the control patterns with respect to the actual kinematics would be beneficial.

The aim of this thesis work is to make contributions to the following fields of human movement science:

Evaluation of prediction effects on the synergistic control of arm movements during manual target tracking. An experimental setup and procedure was designed to investigate how motor synergies differ between predictive and non-predictive movements. Motor synergies were evaluated by applying the UCM method to the joint angle variance during 2D tracking of a target on a graphics tablet, where the 2D pen position was used as the hypothetical task variable. It was investigated whether the synergy index drops during predictive, internally driven tracking movements compared to visually, externally driven tracking movements. To address this question, tracking movements between periodic (and pre-trained) and non-periodic presentation modes were compared, which are known to challenge predictive and visually driven tracking modes respectively.

Measurement and kinematic reconstruction of arm movements. Based on my experiences with the Zebris ultrasound based movement analyzer system, I started to develop the engineering prototype of a custom wearable measurement device. The prototype incorporates inertial sensors for movement recording to overcome issues accompanying measurements with the Zebris system (i.e. bulky setup, highly constrained measurement volume or low sampling rate) and enables evaluation and analysis of various sensor calibration, filtering and sensor fusion algorithms in a fully customizable manner. An additional goal was to extend the measurement and analysis workflow of human arm movements with a method that allows accurate and real-time calculation of anatomical joint angles for a widely used SIMM/OpenSim upper limb model when measurements are performed with the developed prototype. For this purpose a custom kinematic algorithm was proposed that utilizes orientation information of arm segments (directly measurable with inertial sensors) to perform joint angle reconstruction in real-time.

2 Applied tools and methods

2.1 Experimental setup and procedure to analyze predictive tracking arm movements

Subjects Seven healthy subjects participated in the study (6 males, 1 female, age: 33.4 ± 12.4 years, M ± SD). All subjects had normal or corrected-to-normal vision. Five subjects had right hand dominance and 2 subjects had left hand dominance according to their preferential hand use during writing. All subjects performed the movements with their dominant hand.

Experimental setup The subjects sat in front of a table which was mounted with a graphic tablet that featured an integrated display (WACOM Cintiq 21UX, 43.2 × 32.4 cm, frame rate: 60 Hz) used for presentation of the target (Figure 1). The target was a white colored disk (diameter 1 cm) and moved in front of a gray background. The sitting position of each subject was adjusted to minimize trunk and head movements during the experiment. The viewing distance of the display was 40 cm.

Subjects were asked to track the target as accurately as possible with the pen of the graphic tablet using their dominant hand. Tracking performance was analyzed based on the pen data, recorded as 2D coordinates in the tablet's reference frame. Arm movements were recorded by an

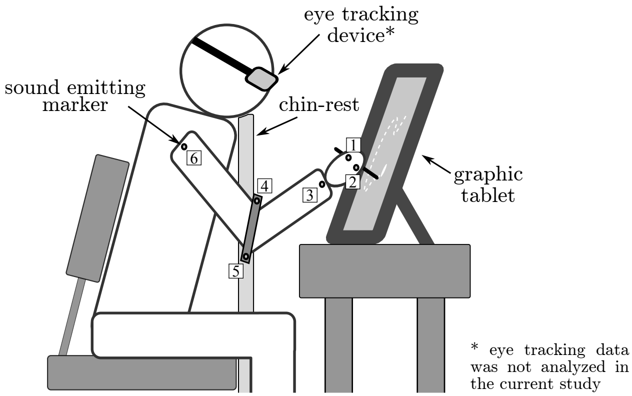

Figure 1: Experimental setup. Numbers 1-6 indicate ultrasound markers of the motion analysis system. Subjects sat on a chair with its back adjusted to fixate the trunk. The target is depicted on the screen as a white disk. The dashed line was never presented on the screen; it is only used in the figure to imply target movement.

ultrasound-based movement analyzer system (Zebris Medical, Isny, Germany) running at 33 Hz using markers attached to anatomically relevant locations on the arm. From these marker positions a geometrical model of the arm with 7 degrees of freedom (DoF) was reconstructed in the tablet's reference frame using a method described in [J3]. The origin of this reference frame was the center of the tablet's screen, its x and y axes coincided with the screen's horizontal and vertical axes, while the z-axis was perpendicular to the screen pointing towards the subject (forming a right-hand system).

Trajectories Various 2D target trajectories with a pseudo-random shape were generated. One of these trajectories (TR1) was only presented in periodic repetitions, whereas the other trajectories (TR2, TR3, TR4) were presented in a random order without repetitions. The trajectories were generated by integrating independent x and y velocities that were constructed as sums of 5 harmonics with random phase and a base frequency corresponding to a period of 4 s. Movements along the trajectories that obeyed the two-thirds power law were derived by nonlinear re-sampling of the whole trajectories to adjust the sampling distance (sd) according to the relation showed in Eq. (1), where V denotes the tangential velocity, r is the radius of curvature, and K and α are the two free parameters of the two-thirds power law [17].

$$\frac{sd}{\Delta t} = V = K\left(\frac{r}{1+\alpha\cdot r}\right)^{\frac{1}{3}} \tag{1}$$

In this way 14 different random trajectories were generated independently from each other. Figure 2 shows the 4 trajectories (TR1 to TR4) used for repeated presentation while the remaining 10 trajectories (not shown) were used to introduce "unpredictable" sections, as described below.

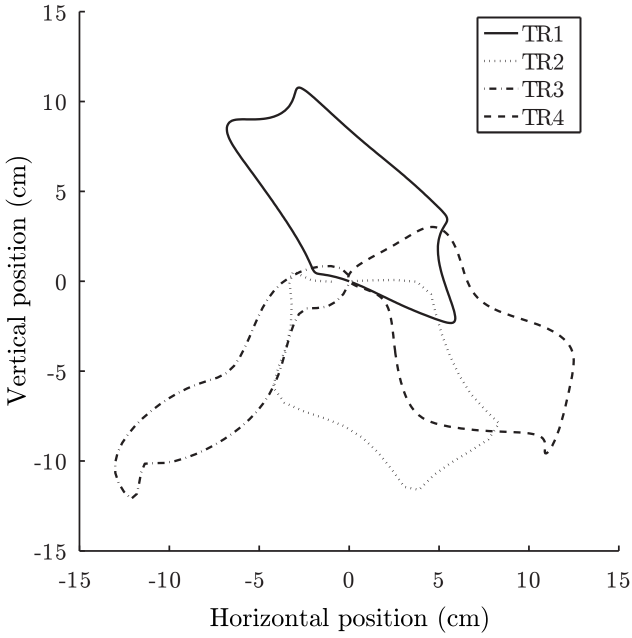

Figure 2: Presented target trajectories. Closed traces were generated by integrating sums of 5 harmonics with a random phase and a base frequency corresponding to a period of 4 s. Labels (TR1-TR4) were assigned randomly to the generated trajectories.

Measurement blocks The smallest unit of the design was one presentation of a generated trajectory, which is referred to as a "trial". Trials were grouped into so-called "sub-blocks", followed by a pause of 4 s. The initial trials of these sub-blocks were not included in the analysis because they differed from the other continuation trials in the movement initiation required after the 4 s pause. The main experiment was composed of 6 blocks, each consisting of several sub-blocks. Blocks were separated by a break of about 5 minutes:

(1) In the first block, only the trajectory TR1 was presented in the so-called *periodic training* presentation mode with the purpose to make the subject familiar with the selected trajectory without introducing unwanted fatigue effects.

(2) The *periodic training* block was followed by 5 test blocks, each presenting 12 sub-blocks. Six of these sub-blocks showed the *non-periodic test* presentation mode and contained the three trajectories TR2, TR3 and TR4 in a pseudo-random order led by one of the unpredictable sections. Alternating with the *non-periodic test* sub-blocks, 6 sub-blocks were inserted with TR1 in the so-called *periodic test* presentation mode. This presentation mode was - apart from the vicinity to the *non-periodic test* sub-blocks - identical to the *periodic training* mode. The specific structure of the non-periodic sub-blocks kept the subjects under the illusion of path randomness despite repetitive presentations of TR2-TR4. These repetitions were necessary to calculate joint angle variance-covariance which is the basis for the Uncontrolled Manifold Method.

To test whether effects of periodic or non-periodic presentations were related to differences between the trajectories rather than to the presentation modes a control experiment was performed on a different day, at least five weeks after the main experiment. This control consisted of a single "non-periodic" block with 10 sub-blocks, each starting with one of the "unpredictable" sections followed by TR1, TR2, TR3 and TR4 in a random order.

Analysis of tracking delay Tracking delay was assessed by the time lag (ms) of pen position, evaluated by an algorithm described in [9]. In this algorithm, the hand-target distance is computed between the current hand position and the target position at any sampling point between 500 ms before and 100 ms after the current time. The lag is defined as the time point at which the hand-target distance is minimal. The average tracking delay was computed separately for each *subject*, *block*, *presentation mode*, and was averaged across all respective sampling points.

The uncontrolled manifold method (UCM) The total variance of the joint angles across trials was calculated followed by a structural decomposition using the uncontrolled manifold method [10, 11] with respect to the task variable formed by the two components of the pen position on the screen. In the framework of the uncontrolled manifold, the total variance is divided into two components, one affecting and one irrelevant for the proposed task variable. For small deviations of the joint angles from the average across trials, the task-irrelevant variance can be approximated by the variance of the projection of joint angles on the null-space of the Jacobian of the task variable with respect to joint angles. Accordingly, the relevant variance is approximated by the variance of the joint angle projection on the orthogonal subspace. The synergy index is defined as the ratio between the irrelevant and the relevant variance, each being normalized to the dimension of the respective subspace. Larger values of the synergy index indicate higher flexibility and adaptability of the system against external perturbations [11].

Like the average tracking delay, the uncontrolled manifold method was evaluated separately for each combination of the factors *subject*, *block*, and *presentation mode*, averaged across all respective sampling points.

Statistical analysis To test whether tracking performance differed between the trajectories (TR1 - TR4), each of the dependent variables *tracking delay*, the *total variance* and the *synergy index* of the control experiment was submitted to a repeated measures ANOVA with the factor trajectory (4 levels). For the main experiment each of these dependent variables was submitted to two repeated measures ANOVAs, one for the periodic training block and one for the test blocks. To analyze potential learning effects during the training consecutive pairs of the 10 sub-blocks were pooled to form a repeated factor *block number* with 5 levels. To analyze the differences between periodic and non-periodic presentation modes and potential training effects in the test blocks, the two repeated measures factors *presentation mode* (2 levels) and *block number* (5 levels) were used. Post-hoc tests were performed using Tukey's HSD test. Effects were considered significant for α-errors $p < 0.05$. Normality of the analyzed variables was checked with the Lilliefors test. Data sphericity was tested using Mauchly's sphericity test. Wilks' lambda multivariate test was applied if sphericity was not fulfilled. Descriptives of normally distributed variables were given as mean ± standard deviation and as median [interquartile range] otherwise.

2.2 Wearable measurement device prototype

Development platform and device firmware The prototype of the wearable measurement device is designed around an STM32F407VG microcontroller unit (MCU) that is a high performance ARM Cortex-M4F core running at up to 168 MHz. To ease development, an STM32F4 Discovery board was used as the central hardware element of the system which provides access to all pins of the MCU and a debugger unit in the same package.

Device firmware was implemented in C using the *Eclipse* IDE and the *GNU Tools for ARM Embedded Processors* package on an Ubuntu 12.04 LTS system. Device programming and debugging was performed with *OpenOCD*. The prototype's firmware was designed and implemented using the *FreeRTOS*^{TM} [1] real-time operating system for straightforward execution scheduling. For low-level device driver implementation, ST's *Standard Peripheral Library* for the STM32F4 Discovery kit (version 1.1.0) was used. The MCU's DMA controller was utilized in each scenario where it was applicable to further improve execution parallelism.

Inertial Measurement Units (IMUs) To perform measurements of joint kinematics, single chip 9-axis MEMS inertial sensors were used (MPU-9250, 3×3×1 mm package). Each sensor integrates an individual 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer with properties that are able to provide enough flexibility to measure most common human movement tasks without saturation. Considering the target application of the device (measurement of low to moderate speed arm movements) sensor components were configured as follows:

Accelerometer: ± 2G, 16-bit, 200Hz
Gyroscope: ± 500°/sec, 16-bit, 200Hz
Magnetometer: ± 4800μT/sec, 16-bit, 100Hz

Sensor fusion for the IMUs A computationally efficient open source orientation filter [13] was used to provide sensor orientations in software using a gradient descent based 9-axis fusion algorithm. The applied method provides direct quaternion output (avoiding the phenomenon of

[1] http://www.freertos.org/

gimbal lock) and is easily capable to provide stable 200 Hz output rate on the selected development platform.

Device control and data visualization A PC-side software application was developed in MATLAB (Mathworks, Natick, MA, USA) for device control, real-time data visualization and storage, and to perform custom post-processing tasks. Based on experiences with this sample application, a new implementation of the control software has been started in Python using the Kivy framework[2] to make device usage independent from MATLAB and to include Android and iOS as possible target platforms in addition to the three major desktop operating systems, while keeping the same code base for all variants.

2.3 Real-time reconstruction of arm kinematics

Model based movement analysis In this thesis work OpenSim was chosen as the reference model-based movement analysis tool because it uses a mature multibody dynamics engine (Simbody), it can handle SIMM's model format, it provides various APIs (MATLAB, Java, Python) for integration with custom software and it is free and open source with a growing community behind. OpenSim uses a text based structured XML model format that contains all information needed for the biomechanical description of the human body (bodies, kinematic constraints and forces (i.e. muscles)) that are accessible through API calls, too.

To analyze arm kinematics with OpenSim the most complete model available was chosen known as the Stanford VA Upper Limb Model [18]. It is based on experimental data, includes 15 degrees of freedom and 50 muscle compartments and enables the evaluation of kinematics, muscle-tendon lengths, moment arms, muscle forces and joint moments in an anatomically reasonable setup.

Marker locations and compound matrices of consecutive rotations To enable the utilization of the upper limb model with inertial measurements, a prototype marker set was defined. For this purpose, orthonormal bases were formed for each anatomical joint of interest in the model (shoulder, elbow and wrist) and markers were placed at specific locations in these bases to reflect the actual compound rotations among the respective degrees of freedom.

[2]http://kivy.org/

Because all prototype markers follow their parent bodies' orientation during analyzed movements, the compound rotation matrix in each anatomical joint can be determined from marker positions in the global reference frame at any time instant. To utilize this feature it is crucial that the structure of each joint's marker subset remains consistent during measurements. As a consequence, it is recommended to use arm segment *orientations* to calculate the actual positions of prototype markers instead of measuring them directly that makes the application of inertial sensors possible and beneficial for this task.

Spatial rotations about arbitrary axes To determine model defined anatomical joint angles from prototype marker positions, methods for spatial rotations about arbitrary axes were applied. For rotations about a specific axis Rodrigues' formula was used. Reconstruction of model defined joint angles in the wrist required the application of a decomposition algorithm [19] that makes the calculation of three Euler angles about arbitrary axes possible from a rotation matrix if the rotation axes are known.

3 New scientific results

Thesis I. *I have shown experimentally that during target tracking arm movements the human movement system optimizes different cost functions based on knowledge about the target trajectory in a way that for visually driven tracking of unfamiliar trajectories the task error to be minimized is defined in target coordinates, whereas for familiar trajectories it is defined in motor coordinates.*

Corresponding publication: [J1]

I have designed an experimental study and the corresponding measurement setup to investigate the differences in motor synergies between predictive and unpredictive tracking arm movements for cases when subjects tracked a target moving in 2D on a graphics tablet with a hand-held pen, while their arm movements were not restricted. The measurement setup assured time accurate presentation of the visual stimulus to trigger subject movement while synchronized recording of the pen's planar position and 3D kinematics of the subject's arm were also realized. By applying the Uncontrolled Manifold Method and techniques from optimal feedback control theory of human arm movements, I have shown that the movement goal differs between tracking of familiar and unfamiliar trajectories. The difference can be characterized by a modification of the task error being minimized for different movement execution modes.

Thesis II. *I have developed a wearable measurement device and a corresponding model-based kinematic reconstruction algorithm that is able to determine the arm's anatomical joint angles in real-time, based on the spatial orientations of arm segments. The overall performance gain of the method compared to the approach of a widely used biomechanics simulation software is 1) up to* x14982 *on CPU, 2) up to* x149 *on an ARM Cortex-M4 MCU and 3) up to* x324 *on an ARM Cortex-M7 MCU while it maintains numerical accuracy with the reference solution.*

Corresponding publications: [C1], [J2]

Model based analysis of human upper limb movements has key importance in understanding the motor control processes of our nervous system. Various simulation software packages have been developed over the years to perform model based analysis. These packages provide computationally intensive – and therefore off-line – solutions to calculate the anatomical joint angles from motion captured raw measurement data (also referred as inverse kinematics). In addition, recent developments in inertial motion sensing technology show that it may replace large, immobile and expensive optical systems with small, mobile and cheaper solutions in cases when a laboratory-free measurement setup is needed. The thesis contributes to the workflow of measurement and analysis of human arm movements with an engineering prototype of a wearable measurement system and an algorithm that allows accurate and real-time estimation of anatomical joint angles for a widely used OpenSim upper limb kinematic model when inertial sensors are used for movement recording.

By utilizing the inherent kinematic structure of the selected OpenSim upper limb model (Stanford VA Upper Limb Model [18]), I have created a numerical algorithm that is able to reconstruct model-defined custom rotation angles based on marker positions within a virtual marker set specifically defined for this task. The virtual markers are placed in specific locations within the local coordinate frames of selected model bodies in a way that they form separate orthonormal bases in each anatomical joint of interest (shoulder, elbow and wrist) and represent the corresponding compound rotation matrices of model-defined joint angles in the global reference frame. Having the markers bound to their parent bodies, their positions in the global reference frame are determined by the actual orientation of their corresponding arm segments during any movement within the valid joint limits defined by the model. As the orientation of inertial sensors can be reconstructed from their measured physical quantities with efficient algorithms, by proper placement and calibration they can be used to update virtual marker positions – and as a result, the compound rotation matrices of model-defined joint angles – during measured arm movements. The developed numerical algorithm utilizes this feature to reconstruct the anatomical joint angles of the model in real-time by extracting angle values from the corresponding compound rotation matrices.

4 Application of the results

Given that the thesis covers both theoretical and technical topics of human movement science, several fields of application are possible. In the first part, the behavioral aspects of specific target tracking arm movements were investigated. It was found that available knowledge about the target trajectory has an impact on the actual execution mode of the movement. Experimental data showed that subjects tried to minimize the pen position error when the trajectory of the target was unknown while this goal was shifted towards the minimization of joint angle variability in the case when target trajectory was known as a result of preliminary training. While these findings contribute to the understanding of the human movement system in general, they may be utilized in practical rehabilitation applications as well. Considering post-stroke assessment, the developed experimental setup and procedure may be used to give deeper insight into the actual state of the patient's movement system and reveal higher level effects of the injury (e.g. reduced effectiveness of motor learning and visuo-motor coordination).

In the second part of the thesis, by developing the prototype of a wireless and wearable measurement device based on inertial sensors, the evaluation of laboratory-free measurement of human arm movements was started. As the prototype enables evaluation and analysis of various sensor calibration, filtering and sensor fusion algorithms in a fully customizable setup, it may be used in various applications where measuring the actual kinematic state of the arm can be utilized (e.g. state assessment for rehabilitation, human-machine interfaces or better presence integration in virtual reality environments).

Another contribution to the field of human movement recording was the development of a real-time reconstruction algorithm that is ~~cap~~able to determine model based anatomical joint angles from inertial sensor data directly. As a result, tighter integration of kinematic measurement and reconstruction can be achieved to resolve the time and computational overhead of the offline *measurement-scaling-inverse kinematics* scheme applied in human movement science that has been giving a bottleneck in applications where real-time analysis of the control patterns with respect to the actual kinematics would have been beneficial. As an example, the algorithmic concept of a system for the classification of forearm muscle activity signals based on the arm's kinematic state is presented in [C2], while the design of a practical implementation using real-time data labeling with the developed prototype is shown in [C3].

The author's journal publications

[J1] **Bence J. Borbély**, Andreas Straube, and Thomas Eggert. "Motor synergies during manual tracking differ between familiar and unfamiliar trajectories". In: *Experimental Brain Research* 232.3 (2013), pp. 1–13. ISSN: 00144819. DOI: 10.1007/s00221-013-3801-0.

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[J3] Melanie Krüger, **Bence J. Borbély**, Thomas Eggert, and Andreas Straube. "Synergistic control of joint angle variability: Influence of target shape." In: *Human movement science* 31.5 (Oct. 2012), pp. 1071–89. ISSN: 1872-7646. DOI: 10.1016/j.humov.2011.12.002.

The author's conference publications

[C1] **Bence J. Borbély**, Attila Tihanyi, and Péter Szolgay. "A measurement system for wrist movements in biomedical applications". In: *European Conference on Circuit Theory and Design (ECCTD)* (Aug. 2015). DOI: 10.1109/ECCTD.2015.7300047.

[C2] **Bence J. Borbély** and Péter Szolgay. "Estimating the instantaneous wrist flexion angle from multi-channel surface EMG of forearm muscles". In: *2013 IEEE Biomedical Circuits and Systems Conference, BioCAS 2013* (2013), pp. 77–80. DOI: 10.1109/BioCAS.2013.6679643.

[C3] **Bence J. Borbély** and Péter Szolgay. "A system concept for EMG classification from measurement to deployment". In: *2016 15th International Workshop on Cellular Nanoscale Networks and their Applications (CNNA)*. 2016, pp. 121–122.

[C4] **Bence J. Borbély**, Zoltán Kincses, Zsolt Vörösházi, Zoltán Nagy, and Péter Szolgay. "Analysis of myoelectric signals using a Field Programmable SoC". In: *Circuit Theory and Design (ECCTD), 2013 European Conference on*. Sept. 2013, pp. 1–4. DOI: 10.1109/ECCTD.2013.6662255.

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