MASTER THESIS

ESTIMATION OF THE CENTRE OF MASS POSITION, LINEAR MOMENTUM, AND ANGULAR MOMENTUM OF A HUMAN WEARING AN EXOSKELETON

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1 General Introduction

Damage to the spinal cord, is called a Spinal Cord Injury (SCI) [1]. In severe cases this leads to loss of motor and/or sensory function below the site of the damage. The limited functionality as a result of SCI has a highly negative influence on the quality of life [2].

To date, no cure has been found to repair the damage. Instead, most people make use of supportive equipment such as crutches or a wheelchair. A more advanced solution involves the use of a motorised exoskeleton which is capable of guiding the human body through movements such as walking [3]. The use of an exoskeleton for people who suffer from an SCI could give them their mobility back.

A problem that currently exists with exoskeleton solutions is the lack of a balance controller and the need of pre-determined joint angles and/or torque trajectories to move around [4][5][6]. As a result, supportive equipment is necessary to keep the balance and the system is not capable of reacting to perturbations. In order to control the movement of the exoskeleton and the human in it with a more intuitive controller, a balance controller is necessary.

A measure used to quantify balance is the location of the Zero Moment Point (ZMP) with respect to the Base of Support (BoS). In order to relate the ZMP to the BoS, the Centre of Mass (CoM) position, linear and angular momentum must be known. Unfortunately, the CoM position and momenta cannot be measured directly, and therefore have to be estimated. Previous work [7] has shown that the Statically Equivalent Serial Chain (SESC) method can be used to successfully estimate the CoM position of a human body. In this work we introduce a novel method to estimate the CoM position and momenta based on the SESC method of a human wearing an exoskeleton.

The rest of this thesis is structured as follows. In section 2, the conducted research for finding the method to predict the CoM position, and linear, and angular momentum of a human wearing an exoskeleton is explained in a research paper. Section 3 gives a general conclusion. And last, extra tables and figures are presented in the appendices.

2 Research Paper

Estimation of the Centre of Mass Position, Linear Momentum, and Angular Momentum of a Human Wearing an Exoskeleton

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Abstract— **For people with a Spinal Cord Injury, performing daily tasks such as walking and standing upright are very difficult or even impossible. The use of a motorised exoskeleton can make it possible to perform the daily tasks again. However, a common problem for the current exoskeleton designs is the lack of a balance controller. The use of a balance controller to stear the movements of the exoskeleton and therefore of the human, makes balancing without extra support and react to perturbations possible. The quantification of the balance used for the balance controller could be the Zero Moment Point (ZMP). To determine the ZMP, the Centre of Mass (CoM) position and momenta need to be estimated.**

For this research the Statically Equivalent Serial Chain (SESC) method is used to predict the CoM position. To predict the CoM linear and angular momentum a novel method, inspired by the SESC method, is developed. The identification of the model parameters are performed by Recursive Linear Least Squares, and the uncertainty in the parameters are given by the 95% confidence inteval. The uncertainty in the predicted CoM position and momenta is given by the 95% prediction interval. The methods are tested with a virtual experiment for ideal (i.e. quantization-free and noise-free) data and more realistic measured data.

From the results it is concluded that for the ideal data the methods were able to predict the CoM position and momenta. For the measured data, the methods were still able to predict the CoM position and momenta. However, only the CoM position was predicted with the sufficient prediction interval.

To conclude, the method shows promising results for the estimation of the CoM position and momenta of a human wearing an exoskeleton. However, improvements can be made for the uncertainty measure and the learning time. Besides that, it is important to test the methods for real data.

Keywords - Spinal Cord Injury, Exoskeleton, CoM position and momenta estimation, Statically Equivalent Serial Chain Method, Recursive Linear Least Squares

I. INTRODUCTION

Damage to the spinal cord, often caused by a trauma, is called a Spinal Cord Injury (SCI). According to the World Health Organisation, every year about 250.000 to 500.000 people around the world suffer an SCI [1]. If the damage to the spinal cord is severe, it can lead to loss of part of or complete motor and/or sensory function below the site of the damage. The loss of these functionalities makes moving around, performing upright standing tasks and other daily activities a lot harder or even impossible [2]. Not being able to perform such activities has a highly negative influence on the person's physical and mental health and on the quality of life [3].

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To date, no cure has been found to repair the damaged spinal cord which in turn would restore the motor and sensory function. In the mean time people often use supportive equipment such as crutches or a wheelchair to increase their mobility. A rise in popularity is noticed for the use of exoskeletons as a replacement for the wheelchair. This type of supportive equipment is motorised and, in parallel, attached to the person's body. The motors of the exoskeleton can generate torques around the joints of the person in order to guide the body through, for example, a walking movement [4]. The advantage of this device over a wheelchair is that it supports natural movement of the human body enabling the person to walk around, stand up right and perform the daily activities again.

A critical problem with the current exoskeletons such as Rewalk [5], Ekso [6] and Indego [7] is the lack of a balance controller. Balance plays a key role in walking, standing upright without falling and reacting to perturbations; all important factors in ensuring the patient's safety [8]. In the current systems, actions like walking are performed by following a predefined joint angle or torque trajectory. Balance and safety is achieved by the use of crutches or a walker. However, being dependent on this extra support is not an option when the exoskeleton is going to be used in daily life. On top of that, it does not solve the inability to react to perturbations. As a result, the need for a balance controller in exoskeletons is very high.

In order to develop a proper controller, some sort of feedback from the system is needed. For the balance controller this means that a quantification of the balance of the exoskeleton including the person wearing the device is required. A measure that is widely used for quantifying balance is the location of the Zero Moment Point (ZMP) with respect to the Base of Support (BoS). The ZMP is defined as the point on the ground shifted in such a way that the vertical reaction force acting at that point is able to compensate for not only the system's vertical forces but also the horizontal moments. In other words, as the name already suggests, the horizontal components of the ground reaction moment at the ZMP are zero [9]. As long as the ZMP is located within the base of support, the system is dynamically stable. Dynamic stability becomes more important when the velocities of the system increase. An important element for relating the ZMP to the BoS in order to find the dynamic stability, is the Centre of Mass (CoM) position but also its linear and angular momentum [10]. Besides the role of the CoM momenta in finding the ZMP, they can also be used to build a direct momentum controller for the exoskeleton.

Unfortunately, knowing where the CoM is located and what its momenta are can be difficult as they cannot be measured directly.

For humanoid robots, similar to the exoskeleton, the CoM position and its momenta are generally estimated from link parameters and joint angle information gathered from the encoders. However, this information is much harder to get from the human body. In clinical use the CoM kinematics of a person are often estimated using motion capture systems in combination with standard body segment inertial parameters and using force plate data [11]. However, these methods for estimating the CoM kinematics are bound to the clinical setup and because the standard body segment inertial parameters are gathered from a selective population it is not applicable for everyone.

A method which is person specific and is used succesfully in [12] for the estimation of the CoM of a human is the Statically Equivalent Serial Chain (SESC) method. This method makes use of the fact that the position of the CoM of a system can be defined by the end-effector position of a statically equivalent serial chain (further explained in section II-A)[13]. A beneficial property of the SESC is that the segment inertial parameters can be identified by using linear regression. After identifying these parameters, only joint angles are needed in order to estimate the CoM position. Because portable sensors such as the Inertial Measurement Units (IMUs) have already been used succesfully for measuring the joint angles of a human [14] [15], these sensors together with the SESC method could form a suitable solution to estimate the CoM position at home or in the field. However, this solution does not yet include the estimation of the linear and angular momentum.

In this work we build upon the SESC method for estimating the CoM position of a human and apply this method to the human wearing an exoskeleton problem. Because it is also desired to estimate the CoM linear and angular momentum, new methods inspired by the SESC are introduced to estimate these. The methods designed are intended to be used in daily life. Therefore, it is required that the methods are able to estimate the CoM position and momenta without the use of a clinical setup. On top of that, the learning time of the method must be as short as possible such that it fits into people's morning ritual next to for example brushing their teeth or making coffee. at the same time, after identifying the model parameters, the method must be able to predict the CoM position and its momenta with a sufficient accuracy. For this reason, we want to use a method that can terminate as soon as we have achieved sufficient accuracy in the parameters or model prediction. The uncertainty in the parameters is indicated with a confidence interval (CI) and the accuracy in the predicted CoM position and momenta with a prediction interval (PI). These requirements of the methods for finding the CoM position and momenta are tested with a virtual experiment.

This work is structured as follows. In section II background information is given about the general SESC method followed by the explanation of the ordinary linear least squares and the recursive linear least squares and ending with the derivation of the confidence and prediction intervals of the parameters and the predicted value. Section III discusses how the estimation problem of the CoM position and momenta of a human wearing an exoskeleton is handled and how the measured data is filtered. In section IV a protocol for a real life experiment and the protocol for the virtual experiment are given. Section V presents the results and discussion of de virtual experiment. Lastly, section VI presents the conclusion and recommendations.

II. BACKGROUND

This section gives some more background information. In subsection II-A the general form of the SESC method is explained. After that the ordinary linear least squares and the recursive form are discussed. Lastly it is explained how for linear models with more than one explanatory variable the parameter confidence interval and the estimated output confidence and prediction intervals can be calculated.

A. SESC Method for CoM Estimation

To estimate the CoM of a multibody system, the SESC method can be used. This method states that the CoM position of every serial or tree structured multibody system can be presented by the end-effector of a statically equivalent serial chain [13]. The kinematics of this SESC are determined as follows starting of with the definition of the CoM position, p_c, of an i-linked multibody system:

$$p_c = \frac{\sum_{i=1}^{n} \left(m_i p^*_{c,i} \right)}{m_t}, \tag{1}$$

where m_i is the mass of segment i, m_t is the total mass of the system and $p^*_{c,i}$ is the position vector of the CoM of segment i. The superscript, *, indicates that the position vector is expressed in the global frame. Next, equation 1 is reformulated such that $p_{c,i}$ is expressed in the local frame attached to link i and homogeneous transformation matrices, T^*_i, are used to define the orientation and the location of these local frames.

$$\begin{Bmatrix} p_c \\ 1 \end{Bmatrix} = \frac{\sum_{i=1}^{n} \left(m_i T^*_i \begin{Bmatrix} p_{c_i} \\ 1 \end{Bmatrix} \right)}{m_t}, \quad T^*_i = \begin{bmatrix} R^*_i & d^*_i \\ 0 & 1 \end{bmatrix}$$

Here R^*_i and d^*_i are the rotation matrix and the position vector, respectively, of the local frame expressed in the global frame. Substituting the definition of T^*_i into the equation gives:

$$\begin{Bmatrix} p_c \\ 1 \end{Bmatrix} = \frac{\sum_{i=1}^{n} \left(m_i \begin{bmatrix} R^*_i & d^*_i \\ 0 & 1 \end{bmatrix} \begin{Bmatrix} p_{c_i} \\ 1 \end{Bmatrix} \right)}{m_t}$$
$$= \begin{Bmatrix} \frac{m_1(R^*_1 p_{c,1} + d^*_1) + \cdots + m_n(R^*_n p_{c,n} + d^*_n)}{m_t} \\ 1 \end{Bmatrix}$$

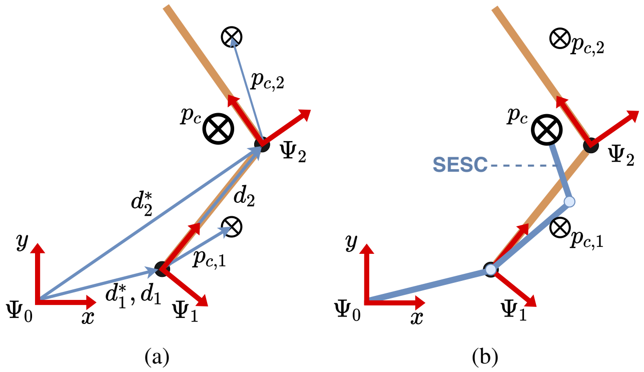


Fig. 1: Schematic representation of a planar two link system. Subfigure (a) show the positioning of the segment CoMs and the total system CoM together with the reference frames and the position vectors d_i^*, d_i and $p_{c,i}$. Subfigure (b) illustrates the corresponding SESC of which the end-effector defines the total system CoM position.

Which gives the equation for p_c as:

$$p_c = \frac{m_1(R_1^* p_{c,1} + d_1^*) + \cdots + m_n(R_n^* p_{c,n} + d_n^*)}{m_t} \tag{2}$$

To illustrate the next steps, a simple planar example of a two link system (see figure 1) is introduced. For this example, equation 2 becomes:

$$p_c = \frac{m_1(R_1^* p_{c,1} + d_1^*) + m_2(R_2^* p_{c,2} + d_2^*)}{m_t} \tag{3}$$

Because d_1^* and d_2^* are expressed in the global frame, they will differ for different configurations of the system. However, as will become clear later in this section, it is more convenient to define them as follows:

$$d_1^* = d_1\ , \quad d_2^* = d_1 + R_1^* d_2, \tag{4}$$

where d_1 and d_2 are the position vectors of local frame 1 and local frame 2, respectively, expressed in the local frame attached to the previous link $i-1$. Substituting 4 into equation 3:

$$p_c = \frac{m_1(R_1^* p_{c,1} + d_1) + m_2(R_2^* p_{c,2} + d_1 + R_1^* d_2)}{m_t}$$

Rearranging the equation and writing it into a matrix-vector multiplication form gives:

$$\begin{aligned} p_c &= \frac{(m_1+m_2)d_1}{m_t} + R_1^* \frac{m_1 p_{c,1} + m_2 d_2}{m_t} + R_2^* \frac{m_2 p_{c,2}}{m_t} \\ &= \begin{bmatrix} I_{2\times 2} & R_1^* & R_2^* \end{bmatrix} \begin{Bmatrix} d_1 \\ \frac{m_1 p_{c,1} + m_2 d_2}{m_t} \\ \frac{m_2 p_{c,2}}{m_t} \end{Bmatrix} = BS, \end{aligned} \tag{5}$$

where B is a 2×6 matrix containing the rotation matrices and S is a 6×1 vector containing the system parameters. Because $p_{c,i}$ and d_i are defined in the local frames, and the system only contains rotational joints, $p_{c,i}$ and d_i will remain constant for every configuration resulting in a constant vector S as well. Using this together with the linear characteristics of equation 5 (see section II-B), linear regression techniques can be used to identify the system parameter vector.

B. *Linear Regression Techniques*

A model is called linear when it is of the following linear form:

$$y = X\beta, \tag{6}$$

where y is an $n \times 1$ vector containing the n observations of the dependent variable, X is the $n \times k$ matrix of k independent variables for every observation, β is the $k \times 1$ unknown parameter vector and ϵ is the $n \times 1$ vector of the disturbances or error. Or in matrix-vector form:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1k} \\ X_{21} & X_{22} & \cdots & X_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & X_{nk} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix} \tag{7}$$

For such models linear regression techniques can be used to identify the model parameters β which gives the "best" model fit for the observed data. In order to find this best fit, a certain cost function needs to be minimised. A commonly used cost function is the sum of squared error used in the linear least squares regression method. How this method works is explained in the next section.

1) *Linear Least Squares*

The cost function used for linear least squares is the sum of squared errors. The errors, e, are defined as the difference between the real data and the predicted output of the model:

$$e = y - X\hat{\beta} \tag{8}$$

Next the sum of squared errors can be calculated and rewritten into:

$$\begin{aligned} e^T e &= (y - X\hat{\beta})^T (y - X\hat{\beta}) \\ &= y^T y - y^T X\hat{\beta} - \hat{\beta}^T X^T y + \hat{\beta}^T X^T X\hat{\beta} \\ &= y^T y - 2\hat{\beta}^T X^T y + \hat{\beta}^T X^T X\hat{\beta} \end{aligned} \tag{9}$$

In order to find the values for $\hat{\beta}$ that minimise the sum of squared errors, the partial derivative of equation 9 with respect to $\hat{\beta}$ is calculated and set to zero:

$$\frac{\partial e^T e}{\partial \hat{\beta}} = -2X^T y + 2X^T X\hat{\beta} = 0 \tag{10}$$

Rewriting this equation gives what is called the normal equations:

$$X^T X\hat{\beta} = X^T y \tag{11}$$

Solving this equation will give the values for $\hat{\beta}$ that minimises the cost function:

$$\begin{aligned} X^T X\hat{\beta} &= X^T y \\ (X^T X)^{-1}(X^T X)\hat{\beta} &= (X^T X)^{-1} X^T y \\ I\hat{\beta} &= (X^T X)^{-1} X^T y \\ \hat{\beta} &= (X^T X)^{-1} X^T y, \end{aligned} \tag{12}$$

where $(X^T X)^{-1} X^T$ is known as the pseudo inverse of X.

2) Recursive Linear Least Squares

For the linear least squares method described in the previous subsection the unknown parameter vector $\hat{\beta}$ can only be estimated after all observations are collected. However, as explained in the introduction it is beneficial to estimate the parameters for every new observation such that it can be stopped as soon as the parameters are accurate enough. This can be done with the recursive linear least squares method [16]. Instead of identifying the parameters over the whole data set this method updates the estimated values for every new incoming data point. How the update function is build up will be explained next. The first step is to realise that the following equalities hold:

$$X^T X = \sum_{i=1}^{t} X_i X_i^T \tag{13}$$

$$X^T y = \sum_{i=1}^{t} X_i y_i \tag{14}$$

where X_i and y_i represent the data measured at timestep i. Next, in equation 12 let $(X^T X)^{-1} = P(t)$ and use equation 14 such that the equation for $\hat{\beta}$ at timestep t becomes:

$$\hat{\beta}(t) = P(t) \sum_{i=1}^{t} X_i y_i = P(t) \left(\sum_{i=1}^{t-1} X_i y_i + X_t y_t \right) \tag{15}$$

The equation for the previous timestep, $t-1$, is given by:

$$\hat{\beta}(t-1) = P(t-1) \sum_{i=1}^{t-1} X_i y_i \tag{16}$$

Taking the inverse of $P(t)$ and using equation 13 gives:

$$P^{-1}(t) = X^T X = \sum_{i=1}^{t} X_i X_i^T = P^{-1}(t-1) + X_t X_t^T$$

$$P^{-1}(t-1) = P^{-1}(t) - X_t X_t^T \tag{17}$$

Combining equation 16 and 17 gives:

$$\begin{aligned} \sum_{i=1}^{t-1} X_i y_i &= P^{-1}(t-1)\hat{\beta}(t-1) \\ &= \left(P^{-1}(t) - X_t X_t^T\right) \hat{\beta}(t-1) \end{aligned} \tag{18}$$

Finally, substituting this into equation 15 and rewriting gives:

$$\begin{aligned} \hat{\beta}(t) &= P(t) \left(\left(P^{-1}(t) - X_t X_t^T\right) \hat{\beta}(t-1) + X_t y_t \right) \\ &= P(t)P^{-1}(t)\hat{\beta}(t-1) - P(t) X_t X_t^T \hat{\beta}(t-1) + P(t) X_t y_t \\ &= \hat{\beta}(t-1) + P(t) X_t \left(y_t - X_t^T \hat{\beta}(t-1) \right) \end{aligned} \tag{19}$$

To use this equation for updating $\hat{\beta}$ first $P(t)$ is updated with the following function:

$$P(t) = (P^{-1}(t-1) + X_t X_t^T)^{-1}$$

Next, the new $P(t)$ is used in equation 19 to calculate the new $\hat{\beta}$. However, this requires the matrix inversion of P, which is not always possible. To avoid this, the Kalman gain is used:

$$K(t) = \frac{P(t-1) X_t}{1 + X_t^T P(t-1) X_t} \tag{20}$$

$$\hat{\beta}(t) = \hat{\beta}(t-1) + K(t) \left(y_t - X_t^T \hat{\beta}(t-1) \right) \tag{21}$$

$$P(t) = P(t-1) - \frac{P(t-1) X_t X_t^T P(t-1)}{1 + X_t^T P(t-1) X_t}, \tag{22}$$

where $K(t)$ is known as the Kalman gain.

C. Parameter Confidence Interval

When model parameters are estimated from noisy measurement data, they are determined with limited accuracy. This can be regarded as a confidence bound on the parameter values [17]. To find the e.g. 95% confidence interval of the estimated model parameters first the covariance matrix needs to be determined. The parameter covariance matrix is defined as follows:

$$\begin{aligned} V_{\hat{\beta}} &= \left[\frac{\partial \hat{\beta}}{\partial y}\right] V_y \left[\frac{\partial \hat{\beta}}{\partial y}\right]^T \\ &= [X^T V_y^{-1} X]^{-1} X^T V_y^{-1} V_y V_y^{-1} X [X^T V_y^{-1} X]^{-1} \\ &= [X^T V_y^{-1} X]^{-1} [X^T V_y^{-1} X] [X^T V_y^{-1} X]^{-1} \\ &= [X^T V_y^{-1} X]^{-1}, \end{aligned} \tag{23}$$

where V_y is the covariance matrix of the measurement error. The parameter covariance matrix, $V_{\hat{\beta}}$, is also called the error propagation matrix because it describes how the random measurement errors in the data propagate to the estimated model parameters. Because, it is often not known what the values of random measurement errors are, V_y must be estimated. For now, it is assumed that the measurement error has the same distribution over time and that the measurement errors are uncorrelated such that V_y becomes:

$$V_y = \sigma_y^2 I \tag{24}$$

next, σ_y^2 is estimated using:

$$\begin{aligned} \hat{\sigma}_y^2 &= \frac{1}{n-p} (y - \hat{y})^T (y - \hat{y}) \\ &= \frac{1}{n-p} (y - X\hat{\beta})^T (y - X\hat{\beta}), \end{aligned} \tag{25}$$

Where n is the number of observations and p is the number of model parameters. The covariance matrix of the estimated model parameters is obtained by:

$$V_{\hat{\beta}} = \hat{\sigma}_y^2 (X^T X)^{-1} \tag{26}$$

In order to find the standard error of the parameters, the square root of the diagonal of $V_{\hat{\beta}}$ is taken:

$$\sigma_{\hat{\beta},i} = \sqrt{V_{\hat{\beta},ii}} \tag{27}$$

after calculating the standard parameter errors, these values are used in the following equation to obtain the confidence intervals:

$$\hat{\beta} - t_{1-\frac{\alpha}{2}} \sigma_{\hat{\beta}} \leq \beta \leq \hat{\beta} + t_{1-\frac{\alpha}{2}} \sigma_{\hat{\beta}} \tag{28}$$

Here $1-\alpha$ defines the desired confidence level. For a large data set ($n-p>100$) the critical t-value for a 95% confidence interval is given by $t=1.96$. Substituting the value for t into equation 28:

$$\hat{\beta}-1.96\sigma_{\hat{\beta}}\leq\beta\leq\hat{\beta}+1.96\sigma_{\hat{\beta}} \tag{29}$$

D. Confidence and Prediction Interval CoM kinematics

Because the certainty of the output of the found model is of even more interest, the confidence and prediction intervals of the output are determined as well [17]. First the covariance matrix of the estimated output must be calculated:

$$V_{\hat{y}}=XV_{\hat{\beta}}X^T=\hat{\sigma}_y^2X(X^TX)^{-1}X^T \tag{30}$$

again, the square root of the diagonal of the covariance matrix is used to find the standard error. The confidence interval of the estimated model output is:

$$\hat{y}(x;\hat{\beta})-1.96\sigma_{\hat{y}}\leq y\leq\hat{y}(x;\hat{\beta})+1.96\sigma_{\hat{y}} \tag{31}$$

However, for unobserved data used for future predictions, both the variance of the fitted model and the variability of the measurement data must be taken into account. Therefore, the predictive covariance matrix is calculated using:

$$V_{\hat{y}p}=V_{\hat{y}}+V_y=\hat{\sigma}_y^2X(X^TX)^{-1}X^T+\hat{\sigma}_y^2 \tag{32}$$

And the prediction interval becomes:

$$\hat{y}(x;\hat{\beta})-1.96\sigma_{\hat{y}p}\leq y\leq\hat{y}(x;\hat{\beta})+1.96\sigma_{\hat{y}p} \tag{33}$$

III. Setting-Up Estimation Problem

This section will discuss how the estimation problem of the CoM position, linear momentum and angular momentum of a human wearing an exoskeleton is tackled. First, section III-A presents how the SESC method introduced in section II-A is used for estimating the CoM position of a human wearing an exoskeleton. Sections III-B and III-C introduce the new methods developed for estimating the linear and angular momentum, respectively. Last, section III-D presents how the measurement data is filtered and how joint velocity and acceleration are estimated from the measured joint angles.

A. SESC Method for CoM of the Human and Exoskeleton

To find the SESC for the human and exoskeleton, first the structure of the human and exoskeleton needs to be determined. Because the exoskeleton is attached in parallel to the limbs of the human, and therefore makes the same movement, it is assumed here that the addition of the exoskeleton to the human body only changes the inertial parameters and mass distributions and not the orientation of the segments. Due to that assumption, the structure of the human body is representative of both the human and the exoskeleton. How the structure is defined is depicted in figure 2a. The human wearing the exoskeleton is viewed from the right and analysed in the sagittal plane. The structure consists of five links representing the shank, thigh, torso, upper arm and lower arm. The origins of the local reference frames are located in the joints and the y-axis is aligned with the link. The joints are assumed to be purely revolute joints rotating around the z-axis and consist of; ankle, knee, hip, shoulder and elbow. Figure 2b shows how the joint angles are defined. The corresponding SESC, shown in figure 2c, is described by:

$$p_c=\begin{bmatrix}I_{2\times2} & R_1^* & R_2^* & \cdots & R_5^*\end{bmatrix}\begin{bmatrix}d_1\\ s_1\\ \vdots\\ s_5\end{bmatrix}=BS \tag{34}$$

Where B is the matrix containing the rotation matrices and S is the vector of unknown system parameters. Now to identify the vector with unknowns the CoM and the joint angles need to be measured. For the CoM position, the ZMP is measured during static poses, because the non-vertical coordinate(s) coincide. The joint angles of the ankle, knee and hip are measured with the encoders of the exoskeleton. The shoulder and elbow joint angles are obtained from IMUs attached to the upper body.

B. Rewriting Linear Momentum Equation

To calculate the linear momentum, l, of the CoM the following equation is used:

$$\begin{aligned}l&=\sum_{i=1}^{n}m_i\dot{p}_{c,i}\\ &=m_1\dot{p}_{c,1}+\cdots+m_5\dot{p}_{c,5}\\ &=m_t\left(\frac{m_1\dot{p}_{c,1}+\cdots+m_5\dot{p}_{c,5}}{m_t}\right)\\ &=m_t\dot{p}_c\end{aligned} \tag{35}$$

The velocity of the CoM is calculated taking the time derivative of equation 34 using the property that the time derivative of a rotation matrix is given by the product of a skew-symmetric matrix and the rotation matrix itself:

$$\begin{aligned}\dot{p}_c&=(\dot{BS})=\dot{B}S\\ &=\begin{bmatrix}0_{2\times2} & \tilde{\omega}_1^*R_1^* & \tilde{\omega}_2^*R_2^* & \cdots & \tilde{\omega}_2^*R_5^*\end{bmatrix}\begin{bmatrix}d_1\\ s_1\\ \vdots\\ s_5\end{bmatrix}\end{aligned} \tag{36}$$

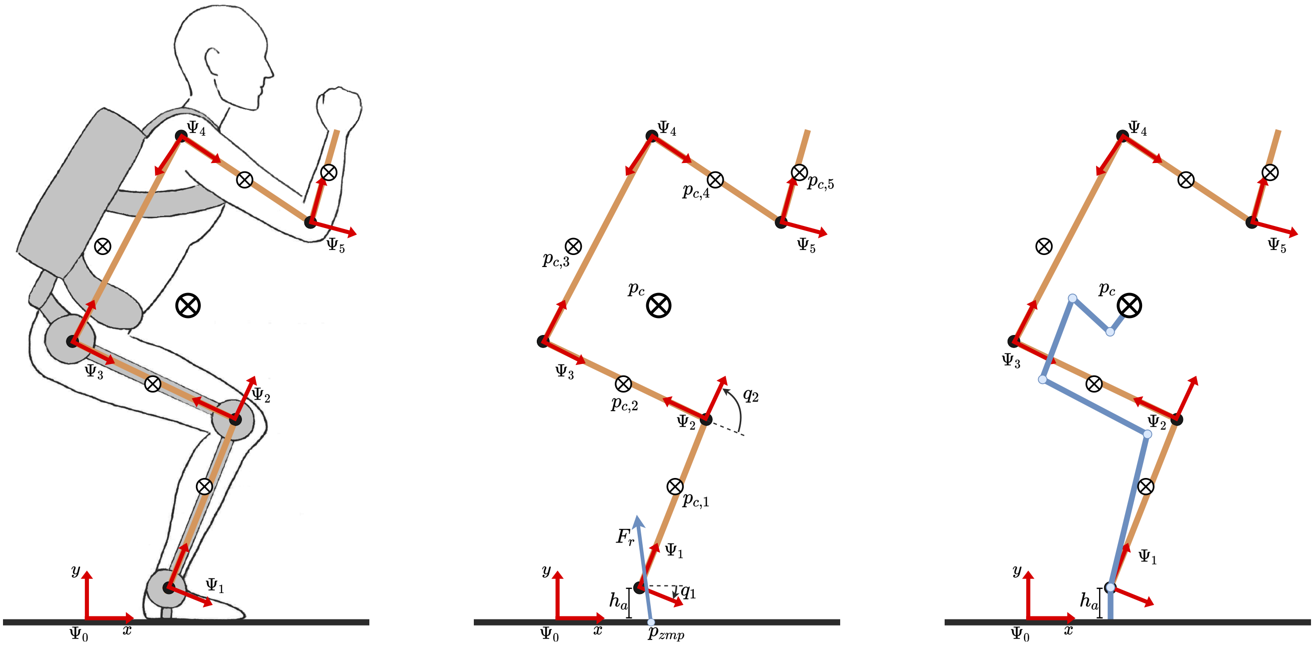
where $\tilde{\omega}_i^*$ is the skew-symmetric matrix built up as:

$$\tilde{\omega}_i^*=\begin{bmatrix}0 & -\omega_{z,i}^* & \omega_{y,i}^*\\ \omega_{z,i}^* & 0 & -\omega_{x,i}^*\\ -\omega_{y,i}^* & \omega_{x,i}^* & 0\end{bmatrix} \tag{37}$$

Substituting equation 36 into equation 35 gives:

$$l=m_t\dot{p}_c=m_t\dot{B}S \tag{38}$$

In order to identify S using this equation, both the regressor, $m_t\dot{B}$, and the output, l, must be measurable. Unfortunately,



(a) (b) (c)

Fig. 2: (a) Abstract illustration of a human wearing an exoskeleton. The five link structure used to model the human and exoskeleton is presented by the orange lines. (b) Representation of the locations of the segment CoMs, $p_{c,i}$, and the total CoM, p_c. The heel height of the person is indicated with h_a and the joint angles, q_i, are defined as illustrated. The force plate depicted as the horizontal line measures the location of the ZMP, p_{zmp}, and the reaction forces, F_r. (c) The SESC corresponding to a human wearing an exoskeleton standing in this pose is given in blue.

the linear momentum, l, cannot be measured directly. However, it is possible to measure the linear momentum rate with a force plate and the following relation:

$$\dot{l} = F_r + \begin{bmatrix} 0 \\ -m_t g \end{bmatrix} \tag{39}$$

Where F_r is the 'ground' reaction force measured by the force plate. If the linear momentum rate is used as the output, it is also necessary to take the time derivative of the regressor. The total function becomes:

$$\dot{l} = F_r + \begin{bmatrix} 0 \\ -m_t g \end{bmatrix} = m_t \ddot{B} S \tag{40}$$

with $\dot{l}$ as the output, $m_t \ddot{B}$ as the regressor matrix and S the model parameter vector.

C. Rewriting Angular Momentum Equation

The equation for calculating the angular momentum, k, around the CoM of a multibody system is:

$$k = \sum_{i=1}^{n} ((p_{c,i} - p_c) \times m_i(\dot{p}_{c,i} - \dot{p}_c) + I^i \omega_i) \tag{41}$$

Which can also be written as:

$$\begin{aligned} k &= \sum_{i=1}^{n} (m_i p_{c,i} \times \dot{p}_{c,i} + I^i \omega_i) - m_t p_c \times \dot{p}_c \\ &= \sum_{i=1}^{n} m_i p_{c,i} \times \dot{p}_{c,i} + \sum_{i=1}^{n} I^i \omega_i - m_t p_c \times \dot{p}_c \end{aligned} \tag{42}$$

Now, p_c and $\dot{p}_c$ can be replaced with respectively BS and $\dot{B}S$, where B, $\dot{B}$ and S are the same matrices and vector mentioned in sections III-A and III-B. A similar replacement can be done for the CoM position and velocity of the individual segments; $p_{c,i} = BS_i$ and $\dot{p}_{c,i} = \dot{B}S_i$. Here, B and $\dot{B}$ are again the same as in sections III-A and III-B and S_i is the segment specific version of S. Substituting this into equation 42 gives:

$$k = \sum_{i=1}^{n} m_i BS_i \times \dot{B}S_i + \sum_{i=1}^{n} I^i \omega_i - m_t BS \times \dot{B}S \tag{43}$$

Because S is already identified using the methods described in sections III-A and III-B, there is no need to identify it again and therefore it can be included in the output:

$$k + m_t BS \times \dot{B}S = \sum_{i=1}^{n} m_i BS_i \times \dot{B}S_i + \sum_{i=1}^{n} I^i \omega_i \tag{44}$$

The next step is to take the right hand side of the equation and seperate the knowns from the unknowns to find the regressor matrix and the model parameter vector. For clarity reasons, the right hand side of the equation is divided into two parts, $\sum_{i=1}^{n} m_i BS_i \times \dot{B}S_i$ and $\sum_{i=1}^{n} I^i\omega_i$, which are handled seperatly. First, the former of the two is rewritten starting with expanding $BS_i \times \dot{B}S_i$ and rearanging it such that:

$$\begin{aligned} &BS_i \times \dot{B}S_i \\ &\quad= \sum_{j=1}^{n}\sum_{k=1}^{n}\left(B_{1,j}S_{i,j}\dot{B}_{2,k}S_{i,k} - B_{2,j}S_{i,j}\dot{B}_{1,k}S_{i,k}\right) \\ &\quad= \sum_{j=1}^{n}\sum_{k=1}^{n}\left(B_{1,j}\dot{B}_{2,k} - B_{2,j}\dot{B}_{1,k}\right)S_{i,j}S_{i,k} \\ &\quad= \sum_{j=1}^{n}\sum_{k=1}^{n}\beta_{j,k}S_{i,j}S_{i,k} \end{aligned} \tag{45}$$

With:

$$\beta_{j,k} = (B_{1,j}\dot{B}_{2,k} - B_{2,j}\dot{B}_{1,k})$$

Writing equation 45 into vector multiplication form gives:

$$\sum_{j=1}^{n}\sum_{k=1}^{n}\beta_{j,k}S_{i,j}S_{i,k} = \begin{bmatrix}\beta_{1,1} & \beta_{1,2} & \cdots & \beta_{n,n}\end{bmatrix}\begin{bmatrix}S_{i,1}S_{i,1}\\ S_{i,1}S_{i,2}\\ \vdots \\ S_{i,n}S_{i,n}\end{bmatrix} \tag{46}$$

Substituting equation 46 into $\sum_{i=1}^{n} m_i BS_i \times \dot{B}S_i$ gives:

$$\begin{aligned} &\sum_{i=1}^{n} m_i BS_i \times \dot{B}S_i \\ &\quad= \sum_{i=1}^{n} m_i \begin{bmatrix}\beta_{1,1} & \beta_{1,2} & \cdots & \beta_{n,n}\end{bmatrix}\begin{bmatrix}S_{i,1}S_{i,1}\\ S_{i,1}S_{i,2}\\ \vdots \\ S_{i,n}S_{i,n}\end{bmatrix} \\ &\quad= \begin{bmatrix}\beta_{1,1} & \beta_{1,2} & \cdots & \beta_{n,n}\end{bmatrix}\sum_{i=1}^{n} m_i \begin{bmatrix}S_{i,1}S_{i,1}\\ S_{i,1}S_{i,2}\\ \vdots \\ S_{i,n}S_{i,n}\end{bmatrix} \end{aligned} \tag{47}$$

Next, $\sum_{i=1}^{n} I^i\omega_i$ is handled. For the human-exoskeleton model this part of the equation becomes:

$$\begin{aligned} \sum_{i=1}^{n} I^i\omega_i &= \omega_1(I_1 + \cdots + I_5) + \cdots + \omega_4(I_4 + I_5) + \omega_5 I_5 \\ &= \begin{bmatrix}\omega_1 & \cdots & \omega_5\end{bmatrix}\begin{bmatrix}I_1 + \cdots + I_5 \\ \vdots \\ I_5\end{bmatrix} \end{aligned} \tag{48}$$

Now combining equation 48 and equation 47 and substituting this into equation 44 gives:

$$\begin{aligned} k + k_{pc} &= B_k S_k, \\ k_{pc} &= m_t BS \times \dot{B}S, \\ B_k &= \begin{bmatrix}\begin{bmatrix}\omega_1 & \cdots & \omega_5\end{bmatrix} & \begin{bmatrix}\beta_{1,1} & \beta_{1,2} & \cdots & \beta_{n,n}\end{bmatrix}\end{bmatrix}, \\ S_k &= \begin{bmatrix}\begin{bmatrix}I_1 + I_2 + \cdots + I_5 \\ I_2 + \cdots + I_5 \\ \vdots \\ I_5\end{bmatrix} \\ \begin{bmatrix}m_1 S_{1,1}S_{1,1} + \cdots + m_5 S_{5,1}S_{5,1} \\ m_1 S_{1,1}S_{1,2} + \cdots + m_5 S_{5,1}S_{5,2} \\ \vdots \\ m_1 S_{1,n}S_{1,n} + \cdots + m_5 S_{5,n}S_{5,n}\end{bmatrix}\end{bmatrix} \end{aligned} \tag{49}$$

However, as for the linear momentum, angular momentum cannot be measured directly either. Therefore, the angular momentum rate is used which can be measured with:

$$\dot{k} = (p_{zmp} - p_{c,x})F_{r,y} + p_{c,y}F_{r,x} \tag{50}$$

with p_{zmp} is the location of the ZMP, $p_{c,x}$ and $p_{c,y}$ are the location of the total CoM in x and y direction and $F_{r,x}$ and $F_{r,y}$ are respectively the x and y component of the reaction force. Together with the time derivative of equation 49:

$$\dot{k} + \dot{k}_{pc} = \dot{B}_k S_k \tag{51}$$

Where $\dot{k} + \dot{k}_{pc}$ is the output, $\dot{B}_k$ is the regressor and Σ the model parameter vector.

D. Data Filtering and Joint Velocity and Acceleration Estimation

With the joint encoders and the force plate the following data are measured; joint angles (q), the zero moment point (p_{zmp}) and the ground reaction force (F_r). To reduce noise, the measured data needs to be filtered first. The filtering is performed with a Hann-window based FIR filter which is defined as:

$$W(z) = \sum_{n=0}^{501} sin^2\left(\frac{\pi n}{n+1}\right)z^{-n} \tag{52}$$

The linear phase property of this type of filter results in a group delay (251 samples for a filter with length 501), which means that all frequency components of the input signal are shifted in time by the same constant amount [18].

To estimate the joint velocity and acceleration, the filtered joint angles are filtered again with central derivative stencils [18]. For finding the first derivative the stencil is built up as follows:

$$W(z) = \frac{-1z^{-1} + z}{2T_s} \tag{53}$$

and for the second derivative:

$$W(z) = \frac{-1z^{-1} + 2 - z}{T_s^2} \tag{54}$$

where T_s gives the size of one timestep. Both stencils require a unit-delay. This delay together with the group delay from the Hann-window results in a total delay of 252 samples (or 252ms). In order to align all data for a correct regression it is necessary to delay the other data with the same amount.

IV. Experimental Method

This section presents the experimental method. Section IV-A explains how the estimation of the CoM position, linear momentum and angular momentum method can be tested with a real life experiment. However, for this research, to make sure that the methods introduced are functioning correctly a proof of concept on the basis of a virtual experiment is conducted. How the virtual experiment is build up and how it is performed will be discussed in section IV-B. To make a clear distinction between the S identified using the CoM position, p_c, and the S identified using the CoM linear momentum, l, from now on the former will be denoted as S_{pc} and the latter as S_l.

A. Test Protocol

To perform this experiment the following equipment is needed:

- exoskeleton
- force plate
- IMUs
- Safety equipment to prevent the subject from falling

Before the experiment is started, some preparations need to be done. First the subject is informed about the experiment. After that the subject is installed in the exoskeleton. To make sure the person is safe during the experiment it is important to use for example a safety harness, to prevent the person from falling. After being installed IMUs are placed onto the upper body segments. The last step of the preparation is to calibrate the force plate and the IMUs. After these devices are calibrated the experiment can be started.

Two main experiments are conducted; a parameter identification experiment and a CoM position and momenta prediction and validation experiment.

1) Parameter Identification Experiment

The parameter identification experiment is performed to find the values of the parameter vectors S_{pc}, S_l and S_k. First the parameter vectors S_{pc} and S_l are identified in the same experiment. For this experiment the subject has to perform different poses. Which poses the subject has to perform is instructed by means of example pictures. In sync, the exoskeleton will move towards the same poses following a predefined reference trajectory. Arrived at the correct pose the subject is instructed to wait for a few seconds and stand as still as possible until the subject receives the signal to move to the next pose. During the experiment, data is logged and the parameter vector, S is updated using recursive linear least squares. At the same time the 95% confidence and prediction intervals are determined by the software. When the software detects a confidence and prediction interval that lies within the acceptable range, the experiment is stopped.

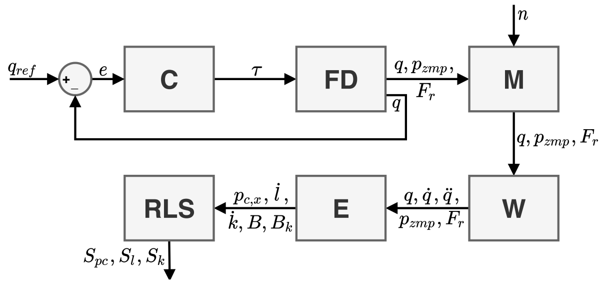


Fig. 3: Schematic block diagram of the virtual setup built in Simulink and MATBLAB containing a PD controller, C, a forward dynamics model of the human wearing an exoskeleton, FD, the measurement with the encoders and force plate, M, data filtering and joint velocity and acceleration estimation which introduce a pure delay in the estimates, which requires also a pure delay of the outputs, W, the block that builds the regressor matrices and output, E, and the recursive linear least squares, RLS.

After that, the second experiment is started. The only differences for this experiment compared to the previous experiment is that the subject has to perform a movement instead of poses and that S_k is identified instead of the vectors S_{pc} and S_l.

2) Prediction and Validation Experiment

For this experiment, the identified parameter vectors S_{pc}, S_l and S_k are used to predict the CoM position, linear momentum and angular momentum respectively. This prediction will be carried out for newly gathered data. This means that the subject is asked to perform a few poses and movements again. The poses and movements will be instructed the same way as for the identification experiments. Normally, the force plate is no longer needed for predicting the CoM position, linear momentum and angular momentum. However, to validate whether the predictions are accurate, the ZMP and the reaction forces are measured as well. For the static poses, the x component of the predicted CoM position can be compared to the ZMP. And predicted linear and angular momentum rate of change can be compared to the ones found from the relations given by the equations 39 and 50.

B. Virtual Experiment

For this research a virtual experiment is used to test the proposed methods for estimating the CoM position and momenta of a human wearing an exoskeleton. The advantage of a virtual experiment is that everything is known and can therefore be used to validate the results.

1) Virtual Setup

The virtual experiment is built in MATLAB and Simulink version R2018b. Figure 3 gives a schematic representation of the main components of the virtual setup. First the subject wearing the exoskeleton has to be modelled. For this human-exoskeleton model, the same structure is used as illustrated in figure 2a. The subject's segment lengths, weigths and inertias are estimated using data from Winter [11] based on a person with a height of 1.78m and a total mass of 75kg. To include the exoskeleton, extra weight is added to the shank, thigh and torso in the proper location, possibly shifting the segment CoM w.r.t. the human's segment CoM. The inertias of the shank, thigh and torso are adjusted as well.

After that, the movement of the model is simulated with the use of a forward dynamics model (FD). With the Equations of Motion (EoM) derived for the FD model joint accelerations are calculated from the joint torques. The torques applied to the FD model are controlled with a PD controller (C) which uses the error, e, between the reference signal, q_{ref}, and the actual joint angles, q. Which reference signals are used will be explained in the sections IV-B.2 and IV-B.3. The joint accelerations calculated with the FD model are then twice integrated to get the joint velocities and joint angles. Next to that, the CoM, ZMP, reaction forces, linear and angular momentum and momentum rate are calculated.

From these calculations only the joint angles, ZMP and the reaction forces are measured. For this virtual experiment, all joint angles are simulated as if they were measured by encoders (also the ones which are measured by IMUs for the real life experiment). The effect of this choice will be discussed in section V. The measurement of the joint angles by the encoders is simulated with the quantization of the data. The measurement of the ZMP and the reaction forces by the force plate is simulated by addition of zero-mean Gaussian white noise.

Next, the joint angles, ZMP and the reaction forces are filtered and the joint velocities and acceleration are estimated as explained in section III-D. This introduces a delay of 252 ms (see Sec III-D) After that, the regression matrices and output are derived according to sections III-A, III-B and III-C. The recursive linear least squares block is then used to identify the parameter vectors and the parameter confidence intervals. The data is also stored in order to perform the ordinary linear least squares over the whole data set.

2) Virtual Identification Experiment

For the identification of the parameter vectors S_{pc}, S_l and S_k, two consecutive virtual experiments are conducted. Both Experiments have a run time of 420 seconds (seven minutes) and use a joint reference signal of several different poses to simulate the movement of the virtual subject. Every ten seconds a new pose is generated, resulting in a total of 42 poses per experiment. The poses are chosen such that the virtual subject is dynamically stable at all time and that the joint angles have realistic values. During the first experiment, Both S_{pc} and S_l are identified with the recursive linear least squares. At the same time all data is stored such that at the end of the simulation the whole data set can be used to identify the parameters with ordinary linear least squares. Next, the results of the first experiment are used in the second experiment to identify the parameter vector S_k. Again, all data is stored in order to identify S_k for the whole data set. These two experiments are performed in sequence to avoid that the error in S, which is still large at the beginning of the identification, negatively influences the identification of S_k.

During the experiments the parameter vectors are identified twice; once using ideal (i.e. noise-free and quantization-free) data obtained directly from the forward dynamics model and once using the filtered measurement data. The first data source is used to test whether the methods are working properly. The second data source is used to get a better understanding of how the methods will perform in real life.

3) Virtual Prediction and Validation Experiment

Next, to validate how well the different methods work, a third experiment is conducted. For this experiment, the parameters identified in the virtual identification experiments are used, i.e. we now exploit the learned model, to predict the CoM position and the linear and angular momentum for new test data. The reference used for this experiment is a smooth movement without stopping (see Appendix A.2). The run time of this experiment is set to 240 seconds (four minutes). After the 240s the prediction the Root Mean Squared error and the mean Prediction interval are evaluated. For the CoM position a RMS of $0.01m$ and a PI of $\pm 0.03m$ is stated as sufficient. For the CoM linear and angular momentum a RMS of $2kgm/s$ and a PI of $\pm 4kgm/s$ is stated as sufficient.

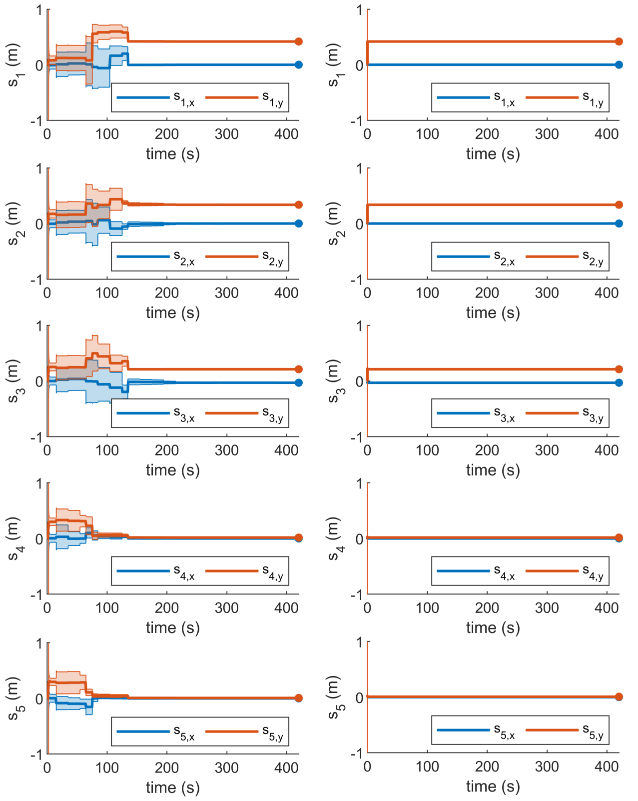
V. Virtual Results and Discussion

This section presents the results from the virtual experiments and discusses the findings. To evaluate if the methods proposed in section III are working correctly the results of the ideal data are discussed first. After that, it is evaluated how well the methods would perform for the more realistic filtered measurement data.

A. Results and Discussion Ideal Data

For ideal data both the S_{pc} and the S_l converge to the target values (see Figure 4). This means that the relations found for the CoM position and linear momentum in section III-A and III-B, respectively, are also found by the recursive linear regression. However, it takes S_{pc} about 140s before it levels out while S_l is almost instantly at its final value, even though both vectors contain the same amount of unknowns. The reason for this is that S_{pc} can only use static data to update the parameters while S_l can also use the dynamic data. Therefore, it takes ten different poses (ten unknowns) to find the correct S_{pc} and only ten different data points to find the correct S_l. The estimation of the parameters of S_{pc} and S_l with the ordinary linear least squares over the whole data set gives a similar results as the recursive linear least squares (see Appendix B.1).

The method for estimating the parameters of S_k is not able to estimate the expected target values for all 45 parameters(see Figure 5). This is also reflected in the confidence intervals, which are broader for the unexpected parameter values. This can be explained by the fact that not all 45 parameters are necessary to describe the behaviour of the



(a) $\boldsymbol{S_{pc}}$ **for Ideal Data** (b) $\boldsymbol{S_l}$ **for Ideal Data**

Fig. 4: Graph of the identified parameter vectors S_{pc} and S_l from ideal data using recursive linear least squares. The 95% confidence interval is presented as a shaded area. Every subgraph shows two parameters of the total vector. The target values of the parameters are presented with a dot at t=420s.

CoM angular momentum. Using the singular value decomposition on the regression matrix it was found that the angular momentum behaviour can also be described with just 35 parameters (i.e. 10 fewer) resulting in a non-unique solution. What is interesting to point out, exactly 10 of the parameters of S_k identified with the ordinary linear least squares (see Appendix B.2) are set to zero. This results in a more confident prediction of the other parameters.

Using the parameter vectors S_{pc}, S_l and S_k estimated from the real data, the identified models are able to predict the CoM position and its momenta accurately (see Figure 6). This means that, even though the parameters of S_k are not the expected values, the prediction of the angular momentum is still possible. This supports the explanation in the previous paragraph for the incorrectly estimated parameters of S_k.

B. Results and Discussion Realistic Data

For the filtered measurement data, S_{pc} and S_l approach the target values (see Figure 7a). However, both parameter vectors require a longer learning time to level out compared to real data. On top of that, both vectors show a larger error and confidence interval at t=420s for measured data compared to ideal data (see table 7a). Especially for S_l, this could be a result of errors introduced in the joint velocities and accelerations because these are both estimated from the joint angles and not measured directly.

	Ideal		Measured	
	RMS	PI	RMS	PI
pos. x (m)	0.000	0.008	0.007	0.023
pos. y (m)	0.000	0.008	0.006	0.021
lin. mom. x (kgm/s)	0.000	0.015	0.714	7.592
lin. mom. y (kgm/s)	0.000	0.015	1.271	7.609
ang. mom. (kgm/s)	0.000	0.097	1.195	4.924

TABLE I: Table of the results from the prediction experiment for ideal and measured data. The Root Mean Squared (RMS) error and the $\pm$ PI are presented.

Another point of discussion is the confidence interval in relation to the correctness of the estimation of the parameters. Even though the values of the parameters are not accurate, the confidence interval is very small. This can be seen in figure 7b. This could be a result of the sequential presentation of new data to the model, as the variance between two individual datapoints is relatively small.

The parameters of S_k are estimated less accurately compared to S_k when estimated using ideal data. This can be explained by the non-unique solutions for the parameter estimation, but amplified because of the possible errors introduced in the estimated joint velocities and accelerations.

Figure 9 shows the predicted CoM position, linear and angular momentum rate of change, and linear and angular momentum. The associated confidence intervals are also plotted. For the linear and angular momentum and their rate of change, the mean prediction is quite accurate but the prediction interval is relatively broad (see table I). An explanation for the angular momentum is that the parameters are estimated correctly, but it appears that the uncertainty in the model parameters for the angular momentum (S_k) due to the non-unique parameter solution is reflected in the CoM angular momentum prediction interval. The explanation for the relatively high uncertainty in the predicted linear momentum could be that for the prediction interval also the variance in the measurement errors is taken into account.

VI. Conclusion and Recommendations

A. Conclusion

The goal of this research was to design a method to estimate the CoM position and linear and angular momentum of a human wearing an exoskeleton. Requirements for the method were that it is able to give the uncertainty in the parameters and model and eventually is able to estimate the CoM kinematics outside of a lab environment. Furthermore, it was hypothesised that the SESC method for estimating the CoM position together with the extended methods for the linear and angular momentum would be able to estimate the CoM position and its momenta of a human wearing an exoskeleton.

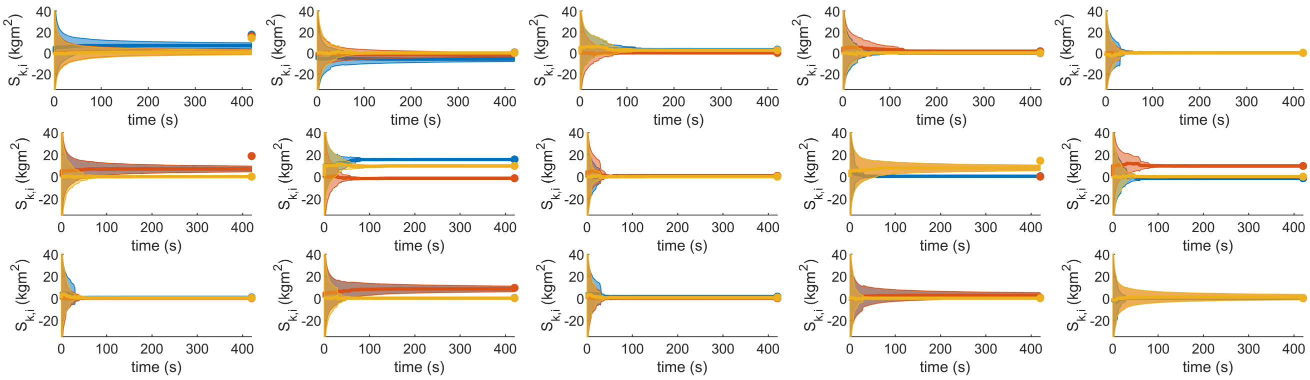


Fig. 5: Graph of the identified parameter vector S_k using recursive linear least squares for ideal data. The 95% confidence interval is presented as a shaded area. Every subgraph shows three parameters of the total vector. The target values of the parameters are presented with a dot at t=420s.

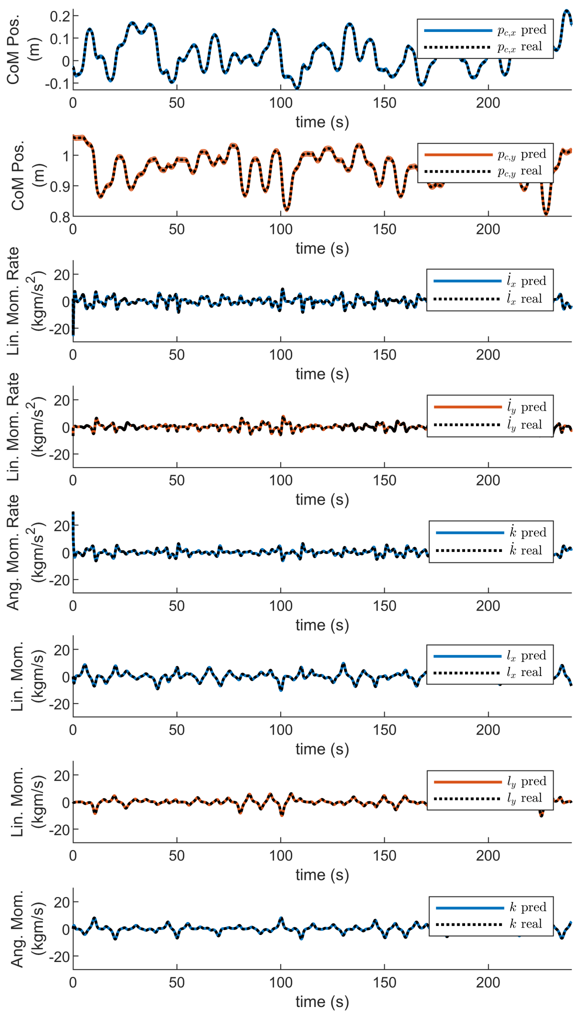
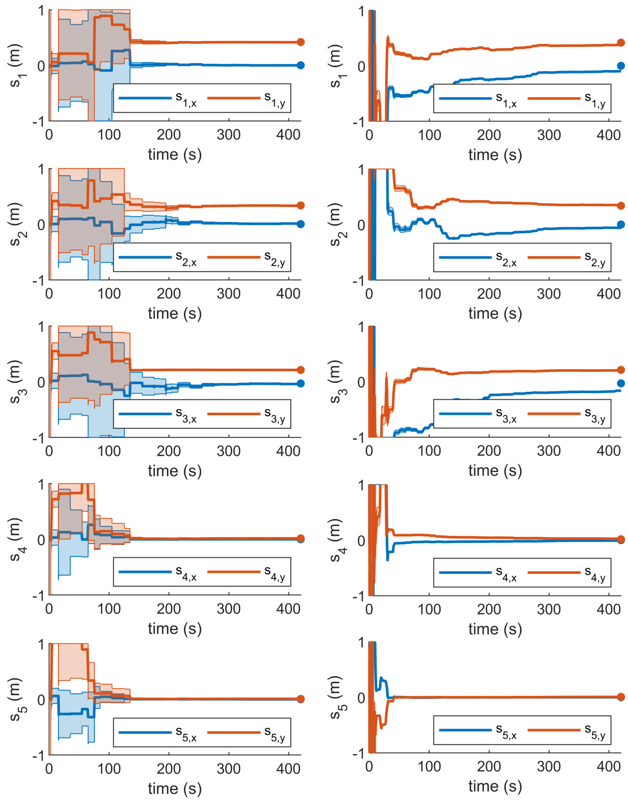


Fig. 6: The prediction of the CoM position, linear and angular momentum rate of change, and the linear and angular momentum from ideal data. The prediction interval is presented as a shaded area. The dotted black line shows the actual values.



(a) S_{pc} **for Measured Data** (b) S_l **for Measured Data**

Fig. 7: Graph of the identified parameter vectors S_{pc} and S_l from filtered measurement data using recursive linear least squares. The 95% confidence interval is presented as a shaded area. Every subgraph shows two parameters of the total vector. And the target values of the parameters are presented with a dot at t=420s.

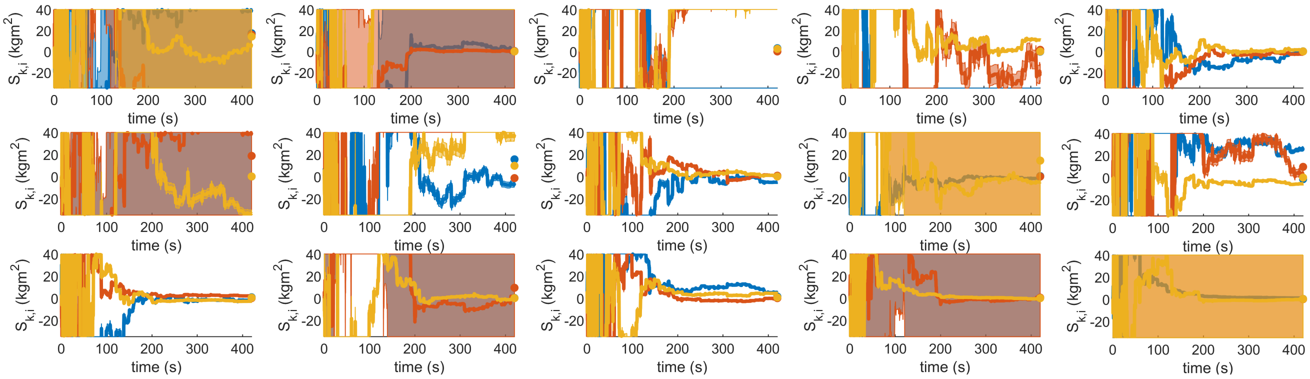


Fig. 8: Graph of the identified parameter vector S_k using recursive linear least squares for filtered measurement data. The 95% confidence interval is presented as a shaded area. Every subgraph shows three parameters of the total vector. The target values of the parameters are presented with a dot at t=420s.

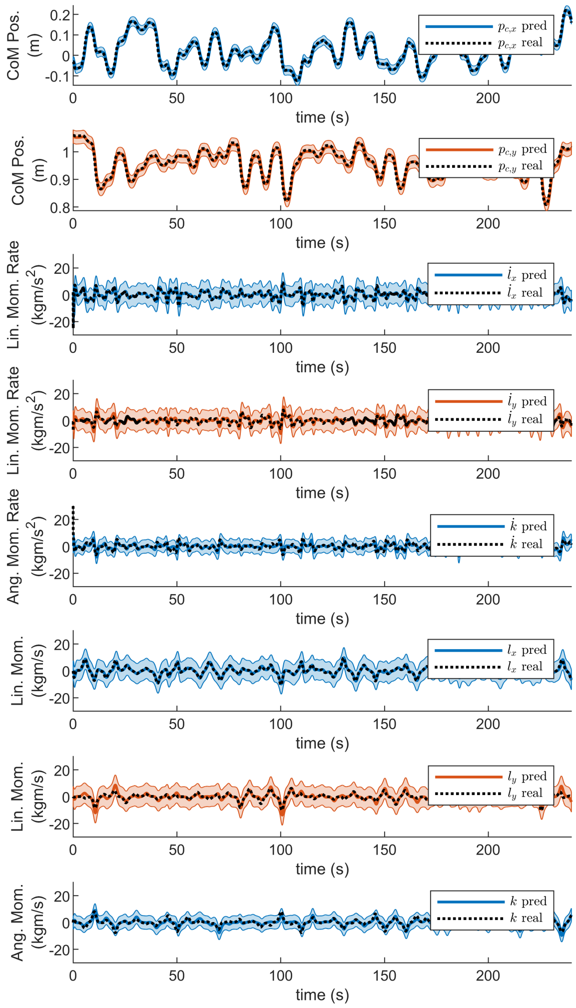


Fig. 9: The prediction of the CoM position, linear and angular momentum rate of change, and the linear and angular momentum from filtered measurement data. The prediction interval is presented as a shaded area. The dotted black line shows the actual values.

First of all, from the ideal (i.e. noise-free and quantization-free) data results, it can be concluded that the methods described in sections III-A and III-B are able to estimate the parameter vectors S_{pc} and S_l. The method described in section III-C for identifying S_k was found to have a non-unique solution. As a result, the method is able to identify a set of parameters using ideal data different from the expected parameter set. Nevertheless, from figure 6 it can be concluded that with the use of S_{pc}, S_l and S_k from ideal data, it is possible to estimate the correct CoM position and linear an angular momentum. Table I shows that the sufficient RMS and PI mentioned in Section IV-B.3 are met for ideal data.

For the filtered measurement data, the results are also promising. Even though S_l and S_k were predicted less accurate, Figure 9 shows that the methods are still able to predict the CoM position and linear an angular momentum. Table I shows that the sufficient RMS mentioned in Section IV-B.3 are met. However, the sufficient PI was only achieved for the CoM position.

The uncertainty measure eventually will be used to determine whether the parameters are sufficiently learned to predict the CoM position and momenta. However, the used uncertainty measure can give a distorted picture when used for the recursive linear least squares method. Therefore, it is recommended to use a different uncertainty measure to indicate whether the parameters are learned sufficiently.

The run time for the identification experiments were set to seven minutes each, resulting in a total of 14 minutes to identify all three parameter vectors. Within this time the method is able to identify the parameters sufficiently and some of the parameters leveled out even earlier. A learning time of 14 minutes is acceptable, but leaves room for improvements.

To conclude, the method described in this paper shows promising results for the identification of the CoM position and linear and angular momentum of a human wearing an exoskeleton.

B. Recommendations

This research gives a proof of concept for the proposed methods for the identification of the CoM position and momenta for a human wearing an exoskeleton. However, there are some improvements that have to be made before it can be used in practise.

First of all, the method is tested for a virtual situation which has the advantage that everything is known and therefore can be validated more easily. However, using a model to simulate reality also requires some simplifications. For the model used in this research the joints of the person and exoskeleton were assumed to be purely rotational. Besides that, the lengths of the segments and the location of the segment's CoM w.r.t. the segment were assumed to be constant. However, this is not entirely correct for a real human. This will probably have a negative influence on the performance of the methods. To get a better understanding of how the methods will work for real data, the model can be made more realistic, or the method can be tested for example on a healty person without an exoskeleton first.

Second, for this research the measurement of all joints were simulated as if they were measured with joint encoders. However, in the final design the upper body is not measured with encoders but with IMUs. The IMU measurements have to be included in the simulation as well to test how this influences the results. Because IMU data is filtered with a Kalman filter this might give a problem with the alignment of the data for the regression.

Third, it was concluded that the confidence interval of the parameters gave a distorted view on the correctness of the parameters of S_l for the recursive linear least squares method. It should be further investigated whether this is due to how the parameters are updated by the recursive linear least squares. If this is the case, a more suitable uncertainty measure for the recursive linear least squares method should be used.

Fourth, for this experiment the updating of the parameters was stopped after seven minutes. Eventually, the method is intended to stop after the parameters are learned sufficiently in order to predict the CoM position and angular momentum accurate enough. Therefore, it must be examined what value of accuracy for the parameters is enough for an accurate enough prediction.

Fifth, the learning and updating time can possibly be improved, by using a 'warm' start for the model parameters instead of starting from zero. For example, the parameter values can be based on the dataset from Winter [11]. On top of that, it can be investigated what the best poses are for the identification of the parameters. It is likely that when more diverse poses are used the learning time and the accuracy are improved. Last, to make sure that this method is suitable for all kinds of people and that it is a reliable method for estimating the CoM position and momenta of a human wearing an exoskeleton, more tests should be performed for a diverse group of people. Especially, experiments with real data are needed.

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3 General Conclusion

The goal of this work, was to find a method that could predict the Centre of Mass (CoM) position and linear and angular momentum for a human in an exoskeleton. The method should be able to predict the CoM position and momenta outside of a lab environment, and therefore capable of using data from portable sensors. The model should also be able to limit the learning time to only the required amount. As a result, we proposed a novel method based on the Statically Equivalent Serial Chain method, and extended this to include a method to identify the linear and angular momentum. The method makes use of a recursive update function, this allows the model to stop the learning process as soon as the confidence for the parameter vectors are sufficient. The method was evaluated with a virtual experiment for ideal data, in order to verify the correctness of the method, but also evaluated for measured data (simulated data with noise) to mimic a more realistic setting.

For ideal data, the CoM position and linear momentum parameter vectors converged to the correct values, but for angular momentum this was not the case. This is a result of a non-unique solution for the parameter vector. For the realistic data, there was an increase in uncertainty and final error in the parameter estimation compared to ideal data. The final model was able to predict the CoM position and momenta quite accurately, although the uncertainty could be improved. The overall learning time for the method was 14 minutes, which fits in a everyday morning routine.

In order to improve the method, several suggestions are given. The current method uses simplifications for the simulated model, and therefore should be tested in a real world setting. Secondly, to make the experiment more realistic, IMUs have to be used for the upper body instead of joint encoders, which is expected to have a negative influence on the performance. This impact has to be investigated. The current uncertainty measure can give a distored view of the correctness for the linear momentum parameters. Therefore a different uncertainty measure should be used which better fits the recursive linear least squares method. A warm start could be used to improve the learning time of the method. Finally the method should be tested on a diverse group of people to ensure that the method is a reliable way to estimate the CoM position and momenta for all kinds of people.

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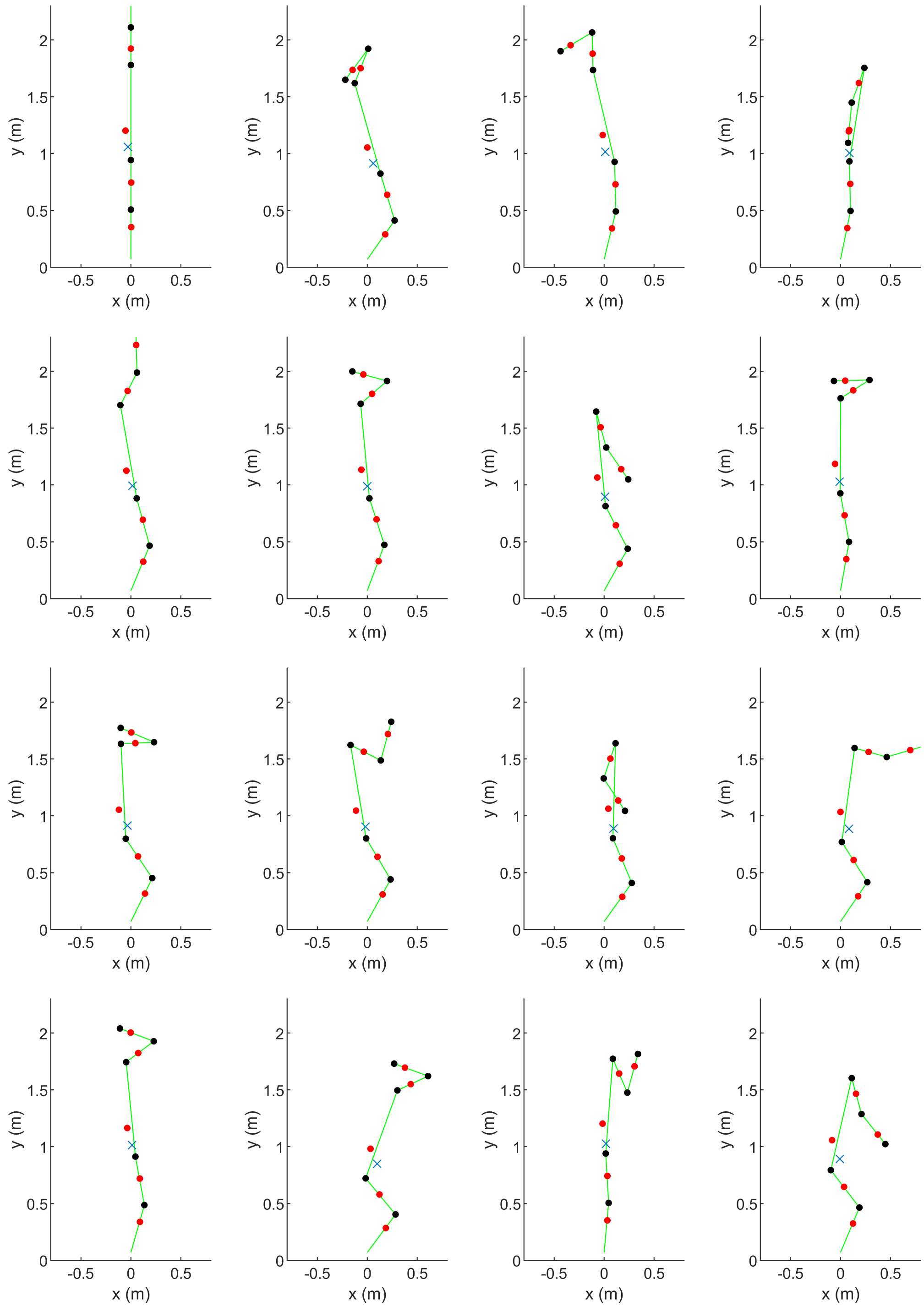
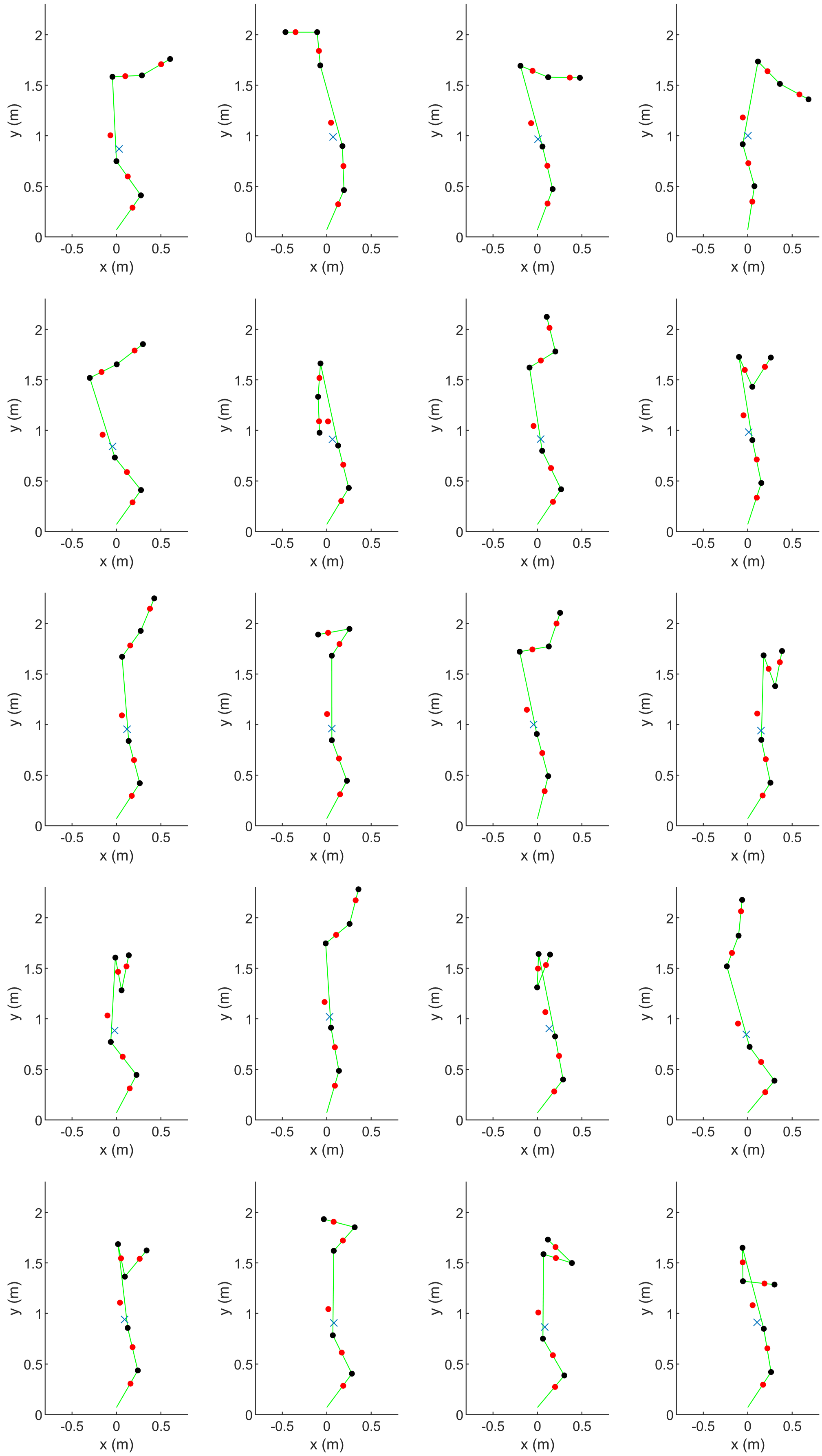
Appendices

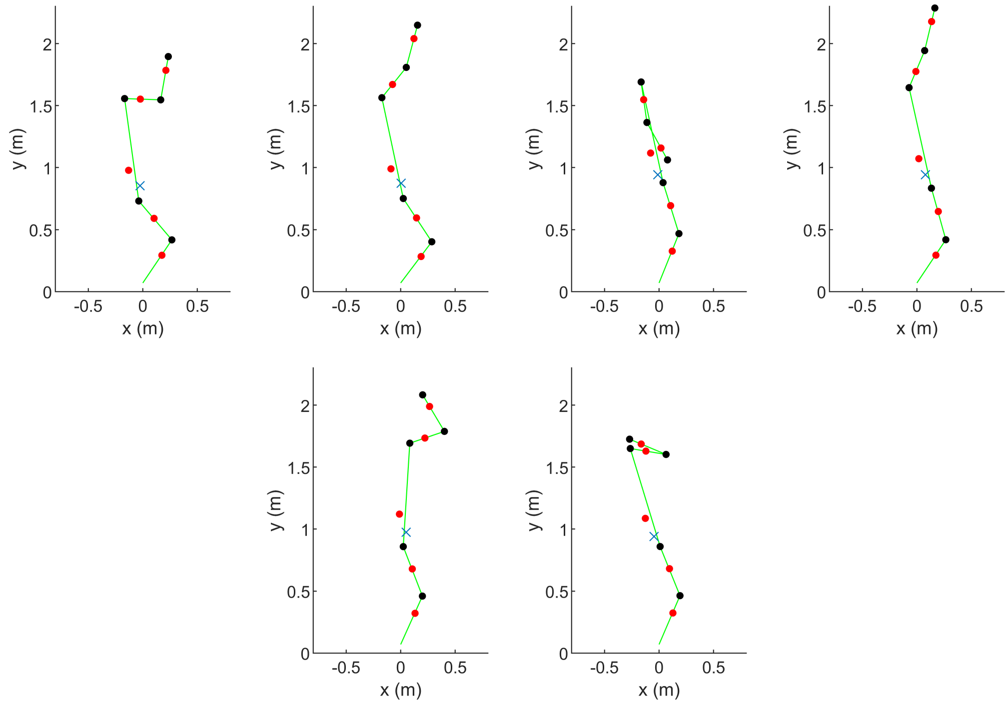
Appendix A References for Identification Experiment and Validation Experiment

A.1 Poses used for identification of the parameters

In this appendix the 42 poses used for the identification of the parameters S_{pc}, S_l and S_k are presented. In figure **??** the poses are presented with the use of stick figures.

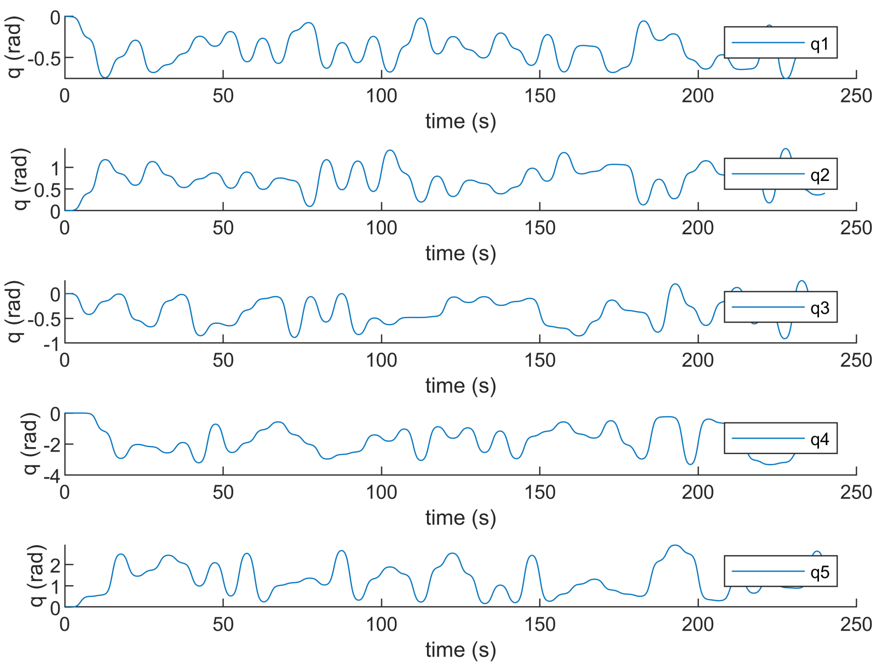



y (m)
x (m)
0
0.5
1
1.5
2
-0.5
0
0.5



A.2 Reference Movement used for Validation

The joint angle reference used for the validation experiment is shown in the figure below.



Appendix B Tables Results

B.1 Identification of S_{pc} and S_l

	$S_{pc}(m)$								$S_l(m)$							
	Ideal				Measured				Ideal				Measured			
	OLS		RLS		OLS		RLS		OLS		RLS		OLS		RLS	
	err	CI	err	CI	err	CI	err	CI	err	CI	err	CI	err	CI	err	CI
$S_{1,x}$	0.002	0.000	0.000	0.002	0.000	0.000	0.002	0.005	0.000	0.000	0.000	0.000	0.117	0.016	0.098	0.004
$S_{1,y}$	0.001	0.000	0.000	0.001	0.003	0.000	0.003	0.003	0.000	0.000	0.000	0.000	0.056	0.016	0.041	0.004
$S_{2,x}$	0.004	0.000	0.000	0.002	0.004	0.000	0.007	0.006	0.000	0.000	0.000	0.000	0.076	0.010	0.060	0.003
$S_{2,y}$	0.003	0.000	0.000	0.001	0.001	0.000	0.003	0.004	0.000	0.000	0.000	0.000	0.015	0.010	0.012	0.003
$S_{3,x}$	0.004	0.000	0.000	0.002	0.002	0.000	0.005	0.007	0.000	0.000	0.000	0.000	0.331	0.011	0.131	0.003
$S_{3,y}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.013	0.011	0.009	0.003
$S_{4,x}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.013	0.002	0.008	0.001
$S_{4,y}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.020	0.002	0.010	0.001
$S_{5,x}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.000
$S_{5,y}$	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.003	0.001	0.002	0.000

Table 1: Results of the identification of the parameter vectors S_{pc} and S_l from ideal and measured data and for the ordinary least squares and the recursive least squares methods. The absolute error (err) and the $\pm$ confidence interval (CI) are given.

B.2 Identification of S_k

	$S_k(kgm^2)$											
	Ideal						Measured					
	OLS			RLS			OLS			RLS		
	value	err	CI	value	err	CI	value	err	CI	value	err	CI
$S_{k,1}$	0	17.305	0.000	6.963	10.341	2.636	0	17.305	3.429	39.589	22.285	135.369
$S_{k,2}$	-19.976	35.974	0.000	0.937	15.060	2.363	-164.812	180.810	2.703	-44.440	60.438	121.358
$S_{k,3}$	-36.200	50.375	0.000	0.522	13.651	2.341	-105.687	119.861	2.286	5.162	9.012	120.262
$S_{k,4}$	-59.503	59.924	0.000	-5.923	6.344	2.334	-111.647	112.068	1.555	0.097	0.323	119.885
$S_{k,5}$	0.481	0.195	0.000	-1.507	1.792	2.254	-0.422	0.708	0.391	-0.411	0.697	115.786
$S_{k,6}$	0.003	0.000	0.000	-0.011	0.014	0.119	77.974	77.971	6.391	77.745	77.742	6.369
$S_{k,7}$	3.053	0.000	0.000	3.082	0.028	0.235	-134.623	137.676	12.836	-133.668	136.721	12.783
$S_{k,8}$	0.005	0.000	0.000	0.013	0.007	0.088	81.281	81.275	4.783	81.620	81.615	4.781
$S_{k,9}$	2.463	0.000	0.000	2.480	0.016	0.149	102.802	100.339	7.819	103.401	100.938	7.811
$S_{k,10}$	-0.229	0.000	0.000	-0.226	0.003	0.064	-50.075	49.846	3.399	-50.363	50.134	3.402
$S_{k,11}$	1.540	0.000	0.000	1.555	0.014	0.166	-20.417	21.958	8.641	-20.564	22.105	8.632
$S_{k,12}$	0.000	0.000	0.000	0.001	0.001	0.022	10.722	10.722	1.168	10.873	10.873	1.169
$S_{k,13}$	0.118	0.000	0.000	0.118	0.000	0.015	-1.554	1.672	0.804	-1.457	1.575	0.805
$S_{k,14}$	0.000	0.000	0.000	-0.000	0.000	0.010	-2.515	2.515	0.574	-2.542	2.542	0.574
$S_{k,15}$	0.056	0.000	0.000	0.056	0.000	0.010	1.580	1.524	0.547	1.613	1.557	0.547
$S_{k,16}$	0	0.000	0.000	6.963	6.963	2.636	0	0.000	3.4299	39.589	39.589	135.369
$S_{k,17}$	0	18.669	0.000	6.963	11.705	2.636	0	18.669	3.429	39.589	20.920	135.369
$S_{k,18}$	0.033	0.000	0.000	0.027	0.005	0.057	-33.311	33.344	3.275	-33.425	33.458	3.272
$S_{k,19}$	15.536	0.000	0.000	15.531	0.005	0.049	-6.250	21.786	2.643	-6.347	21.884	2.641
$S_{k,20}$	-1.445	0.000	0.000	-1.445	0.001	0.052	57.517	58.962	2.961	58.168	59.612	2.979
$S_{k,21}$	9.717	0.000	0.000	9.716	0.001	0.079	37.158	27.441	4.524	37.659	27.942	4.532
$S_{k,22}$	0.000	0.000	0.000	-0.000	0.000	0.012	-5.086	5.086	0.670	-5.154	5.154	0.671
$S_{k,23}$	0.744	0.000	0.000	0.744	0.000	0.008	0.767	0.023	0.455	0.757	0.014	0.455
$S_{k,24}$	0.000	0.000	0.000	0.000	0.000	0.006	1.071	1.071	0.340	1.063	1.063	0.340
$S_{k,25}$	0.351	0.000	0.000	0.351	0.000	0.006	-1.796	2.146	0.338	-1.821	2.172	0.338
$S_{k,26}$	0	0.000	0.000	7.900	7.900	2.601	0	0.000	2.009	-4.850	4.851	133.549
$S_{k,27}$	0	14.401	0.000	7.900	6.500	2.601	0	14.401	2.009	-4.850	19.251	133.549
$S_{k,28}$	-1.439	0.000	0.000	-1.438	0.000	0.032	26.393	27.832	1.754	26.525	27.964	1.756
$S_{k,29}$	9.677	0.000	0.000	9.675	0.002	0.063	4.484	5.193	3.394	4.126	5.550	3.397
$S_{k,30}$	0.000	0.000	0.000	-0.000	0.000	0.007	-5.590	5.590	0.422	-5.606	5.606	0.422
$S_{k,31}$	0.741	0.000	0.000	0.741	0.000	0.007	-2.096	2.837	0.408	-2.098	2.839	0.408
$S_{k,32}$	0.000	0.000	0.000	0.000	0.000	0.004	2.106	2.106	0.221	2.104	2.104	0.220
$S_{k,33}$	0.349	0.000	0.000	0.349	0.000	0.004	-2.805	3.154	0.238	-2.804	3.153	0.238
$S_{k,34}$	0	0.177	0.000	8.423	8.245	2.597	0	0.177	2.137	0.311	0.134	133.386
$S_{k,35}$	0	9.372	0.000	8.423	0.948	2.597	0	9.372	2.136	0.311	9.060	133.386
$S_{k,36}$	0.000	0.000	0.000	-0.000	0.000	0.009	-1.218	1.218	0.498	-1.296	1.296	0.499
$S_{k,37}$	1.421	0.000	0.000	1.421	0.000	0.007	5.391	3.970	0.395	5.311	3.889	0.397
$S_{k,38}$	0.000	0.000	0.000	0.000	0.000	0.005	-0.519	0.519	0.276	-0.489	0.489	0.276
$S_{k,39}$	0.670	0.000	0.000	0.670	0.000	0.005	4.254	3.583	0.311	4.245	3.575	0.311
$S_{k,40}$	60.568	60.568	0.000	2.500	2.500	2.587	112.570	112.570	0.583	0.409	0.409	132.877
$S_{k,41}$	0	0.449	0.000	2.500	2.051	2.587	0	0.450	0.583	0.409	0.039	132.877
$S_{k,42}$	0.000	0.000	0.000	0.000	0.000	0.001	-0.633	0.633	0.087	-0.631	0.631	0.087
$S_{k,43}$	0.265	0.000	0.000	0.265	0.000	0.001	1.049	0.784	0.061	1.051	0.786	0.061
$S_{k,44}$	0	0	0.000	0.994	0.993	2.452	0	0	0.196	-0.002	0.002	125.935
$S_{k,45}$	0	0.195	0.000	0.994	0.799	2.452	0	0.195	0.196	-0.002	0.196	125.935

Table 2: Results of the identification of the parameter vector S_k from ideal and measured data and for the ordinary least squares and the recursive least squares methods. The absolute error (err) and the $\pm$ confidence interval (CI) are given.