Load identification during object handling

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Abstract— In this paper a new concept to identify environmental loads during the interaction with the human body by sensing interface forces and movement is proposed. Mass and spring loads were moved by hand over a fixed height difference. Kinematic and kinetic quantities were measured between the hand and the load using an instrumented handle. Force was measured using a force transducer module, movement was measured using an accelerometer and rate gyroscope. Under the condition that the human body was actively generating force at the load, while the load was passive, the dynamic characteristics of the load could be estimated. The estimated parameter values were compared to their specified values and appeared to be accurate within 4% for both mass and spring loads.

I. INTRODUCTION

Persons who suffered a stroke are trained to recover adequate control over their movements with the objective to optimize their daily-life functional performance. Critical is how good they are able to physically interact with their daily-life environment, in handling objects, controlling body balance during functional ambulation and while interacting with the environment. Monitoring such interactions during daily-life goes far beyond identifying activities using bodyworn movement sensors, commonly called activity monitoring, which is the current state-of-the-art in ambulatory monitoring. Besides identifying activities, the quality of performance of these activities needs to be assessed. This critically requires combined sensing of body movement and interaction forces, which provide information about the dynamics of the interaction with the environment, thus allowing for continuously evaluating the dynamic load imposed by the environment and power exchange with and work done on the environment. It should be noted that load dynamics is defined as the dependency of force on movement. In the linear case this yields the mechanical impedance. In addition, power exchange equals interface force times velocity of the interface.

Power exchange between the hand and the environment can be estimated from interaction force and velocity at the interface during handling objects, specifically masses and springs. This has been reported in our previous paper [1]. The estimated performed work was accurate within 4% for varying movements with net displacements and varying loads (mass and spring). In this paper, we additionally demonstrate that load can be identified under the same conditions. It should be noted that the relation between interaction force and velocity at the interface between two bodies is, in general, determined by the dynamic characteristics of both bodies, because both bodies form a closed-loop chain [2] (see figure 1).

However, if the following conditions are met, force divided by velocity approximately yields the impedance of the second body.

- 1) The first body is an active generator of force on the second body.
 - a) This force is minimally influenced by the joint movement of both bodies.
 - b) This force has a sufficiently high bandwidth.
- 2) The other body is a passive load with relatively low bandwidth.

These conditions are satisfied in part of our daily-life interactions with our environment. We will demonstrate that identification of the load characteristics is indeed possible under the above conditions.



Fig. 1. Dynamic interaction between human body and environment: Closed loop situation with the load (L) as an admittance. The human body is illustrated as a passive system (H) with an independent force source Fh.

II. METHODS

A. Measurement of kinematics and kinetics

Forces and torques were measured using a 6D force/torque sensor and angular velocities using a 3D rate gyroscope. Linear velocities were estimated by integration of linear accelerations obtained by a 3D accelerometer. Subsequent integration of linear velocities resulted in change of positions.

Accelerometers measure the contribution of both inertial and gravitational accelerations. Hence before integration, the gravitational acceleration had to be subtracted from the accelerometer signal. Since the gravitational acceleration is known in the inertial frame, accelerometer signals were transformed from sensor body frame to the inertial frame by a coordinate transformation. This transformation requires knowledge of the inclination which has been calculated

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using the known orientation at the beginning of movement and integration of the angular velocity over time during movement.

B. Estimation of physical parameters

The translational dynamics of a body is given by the relation between forces and velocities:

$$H = \boldsymbol{F}/\boldsymbol{v} \tag{1}$$

A linear regression model is used to describe the translational dynamics of the load:

$$\hat{y}(t) = \boldsymbol{\varphi}^T(t)\boldsymbol{\theta} \tag{2}$$

Here $\hat{y}(t)$ is the estimated model output , $\varphi(t)$ are the regressors and θ are the model parameters.

With $(y(t) - \varphi(t)^T \theta)$ defined as the predicted output error at time t, one can apply the following criterion function:

$$V_N(\boldsymbol{\theta}) = \frac{1}{N} \sum_{t=1}^{N} \left[y(t) - \boldsymbol{\varphi}^T(t) \boldsymbol{\theta} \right]^2$$
(3)

The optimal estimate $\hat{\theta}_N$ for this parameter set is the one that minimizes this criterion function.

$$\hat{\boldsymbol{\theta}}_N = \arg \min_{\boldsymbol{\theta}} V_N(\boldsymbol{\theta})$$
 (4)

Since our criterion is quadratic in the parameters, the analytic solution of this equation is given by the *Least Squares Estimate* (LSE) [3]:

$$\hat{\boldsymbol{\theta}}_{N} = \frac{1}{N} \left[\sum_{t=1}^{N} \boldsymbol{\varphi}(t) \boldsymbol{\varphi}^{T}(t) \right]^{-1} \frac{1}{N} \sum_{t=1}^{N} \boldsymbol{\varphi}(t) y(t) \qquad (5)$$

Because we assume a second-order physical load an ordinary second order model has been selected to characterize the system dynamics:

$$\boldsymbol{F}_{tot} = M(\boldsymbol{a} + \boldsymbol{g}) + D\boldsymbol{v} + K(\boldsymbol{x} - \boldsymbol{x}_0)$$
(6)

Here M, D and K are the mass, viscous damping and stiffness parameter, a and g are the inertial and gravitational accelerations and v, x and x_0 are the velocity, position and position at the start of the movement respectively. Since the estimated parameters (5) are of a time-discrete model, a transformation (e.g. Tustin) to the continuous time model (6) is required.

C. Experimental method

The proposed method was tested experimentally for mass (figure 2(a)) and spring loads (figure 2(b)).

Both loads were manipulated using a handle, instrumented with a 3D inertial and magnetic sensor unit (MTx, Xsens Motion Technologies [4]), rigidly and closely connected to a 6 DOF force/moment sensor unit (ATI-Mini45- SI-580-20, Schunk GmbH & Co. KG [5]).

The mass load was 9.37 kg. It was repeatedly lifted from ground onto a 0.75 meters heigh table. The spring load was an extension spring (Tevema T39210) with a spring constant of 87.9 N/m and a zero force length of 1.0 m. The lower end of the spring was attached to a vertical iron construction



Fig. 2. Experimental setup with a mass (a) and spring (b) load. Visible is the inertial/magnetic sensor unit (orange) and force transducer embedded by load and handle.

beam 0.15 m from the ground, the other side was attached to the instrumented handle. The handle could be secured to either of two hooks fastened to the construction beam at different heights with respect to the ground: 1.85 and 2.34 m. The handle was repeatedly moved from the lower hook, extended, and secured to the upper hook.

Both movement conditions were repeated 19 times.

Mean force was subtracted from the force recording before identification. Therefore, weight and/or offset spring force was not used for identification.

III. RESULTS

An example result of the mass movement trial is shown in figure 3. The sensor signals (acceleration, angular velocity, force, and moment), reconstructed linear and rotational movements are presented. A summary of the estimated load parameters is given in table I. The error was calculated by taking the difference of estimated parameter with the known measured (mass load) or specified (spring load) values. *Variance Accounting For* (VAF) scores were given for both movement conditions.

IV. CONCLUSIONS AND DISCUSSION

A. Discussion

We have proposed a method for identification of load parameters for relatively short free movements using kinetic and kinematic sensors on the interface between human body and environment. The evaluated human load interactions belong to the class of functional movements satisfying specific conditions for passive loads, as mentioned in the introduction.

It should be noted that it will not be possible to identify the dynamics of both human body and load in their complete

MEAN AND STANDARD DEVIATIONS OF ESTIMATED LOAD PARAMETERS PLUS VAF SCORES OF 19 TRIAL REPETITIONS

Load	Movement Duration	Estimated Parameters						VAF Scores
		Mass		Damping		Stiffness		(%)
	(s)	(kg)	Err.(%)	(Ns/m)	Err.(%)	(N/m)	Err.(%)	
Mass Spring	$3.3 \pm 0.3 \\ 4.2 \pm 0.9$	$8.9{\pm}0.2 \\ 0.9{\pm}0.6$	-4.2±2.2	$0.7 {\pm} 0.6$ $1.8 {\pm} 2.1$	-	3.2 ± 1.1 85.7 ± 5.1	-2.5 ± 5.9	99.98±0.01 99.80±0.10



Fig. 3. Example measurement results for a mass movement trial. Shown are the measured signals $a \ \omega F$ and M, the derived kinematic signals v and x = (x, y, z) and the trajectory of the mass position. The trajectory plots depict the mass every 200 ms by a circle and the applied force by a directed line element, of which the direction represents force direction and length the force magnitude. The x-components of the signals are depicted by dashed, y-components by dashed-dotted, and z-component by solid lines.

working range, since they are physically coupled during the interaction and, therefore have joint dynamics.

If the conditions are not satisfied, a closed loop identification approach with independent perturbations is required to distinguish the dynamic contribution of both human body and load correctly [2]. However, this is not practical in daily life conditions.

The class of daily life interactions, as considered in this paper, are performed mainly using feedforward and open loop control mechanisms of the CNS. When the body perturbs the load sufficiently by applying forces, information visible on the contact interface is merely a characterization of the load. This allows us to use the open-loop identification algorithms. In addition it is not necessary to identify loads in their complete working range as they will never express themselves, during interaction, outside the range where the human body is operating.

In order to decide when open-loop identification may be used, we need to evaluate the conditions specified in the introduction. This may be done using the sensed information and additional knowledge of the characteristics of the human body: the requirement that force has a higher bandwidth than movement can be checked easily. Whether the human body or the environment is causal may be checked by additionally measuring EMG of relevant muscles. Whether the human body generates force in open-loop (not dependent on actual movement may be assessed using information about the characteristic times of reflexes.

Only time invariant loads were considered, a recursive identification algorithm can be used for proper parameter estimation of time-varying loads.

In addition to estimation of power exchanged and load dynamics we propose that interface sensing of movement and force between the human body and environment may be useful for the evaluation of task performances, e.g. in reaching or displacement tasks.

B. Conclusions

Identification of mass loads were successful with an estimated mass error of 4%, while stiffness of the spring load condition was accurately estimated with an error of 3%. Mean VAF percentages where between 99% and 100% indicating that estimated models show a good fit.

Future Research: The proposed concepts will be applied in the ongoing PowerSensor research program, which aims to assess the dynamic interactions between the human body and environment quantitatively in a glove.

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