IN-VIVO ESTIMATION OF UNKNOWN UPPER-LIMB KINEMATIC PARAMETERS

Chetan Jadhav and Venkat Krovi
Department of Mechanical and Aerospace Engineering
State University of New York at Buffalo, NY

ABSTRACT

The overall goal of our research is to create a low-cost, home-based computer-based tool to monitor and assist the functional recovery of people with Upper Limb (UL) dysfunction. Our framework, implemented in the form of a Networked Virtual Driving Environment, takes advantage of manipulation of an instrumented manipulandum along prescribed movement patterns to create a sensitive and quantitative assessment/diagnostic tool. In this paper, we present the adaptation of kinematic calibration techniques for the continuous and in-vivo estimation of the unknown upper-limb kinematic parameters and joint ranges-of-motion. Simulation studies were conducted on a simplified planar problem and the results demonstrate significant robustness to measurement errors.

INTRODUCTION

It is estimated that in the U.S. alone, each year, there are over 750,000 people who experience a new or recurrent stroke, leading to motor disability and upper limb (UL) dysfunction [1]. There is considerable evidence which directly links functional recovery to the duration, frequency, regularity and intensity of the rehabilitation therapy [2-3].

However, there are many issues pertaining to the successful implementation of such a rehabilitation therapy regimen. First, we have the issue of accurate, quantitative and ongoing monitoring of the disease coupled with careful characterization of the level of functional impairment. Current functional assessment methods involve clinician/therapist based evaluation of physiological characteristics like speed, range of motion and strength using subjective/semi-quantitative tests such as the Rivermead motor assessment score [4]. There is a clear need for quantitative methods which can bring forth desirable characteristics such as specificity (to distinguish between different diagnoses), sensitivity/resolution (for finer gradation), and repeatability/stability (observer-, spatial- and temporal-invariance). Second, and perhaps most importantly, remains the issue of overall economic viability and logistics of deployment. Unfortunately, while the number of patients with such UL dysfunction has increased, the resources for rehabilitation therapy available for them have reduced. The problem is particularly acute for those people living in rural or remote locations, where regular visits by a therapist over a period of time become infeasible.

It is to address some of these issues associated with conventional stroke rehabilitation, we are developing a system for remotely-supervised telerehabilitation using a networked virtual driving simulator paradigm as shown in Fig. 1. In the proposed system, a patient at home would interact with a low cost programmable rehabilitation manipulandum (selected to be a gaming driving wheel) and perform a series of rehabilitation exercises (presented as "parameterized driving tasks") within an immersive 3D graphical environment on the patient's computer. Additional unobtrusively mounted sensors are also employed in capturing the patient's motion interactions. For example, touch sensors on the driving wheel could monitor the hand contact position while piezoelectric rate-gyros strapped to

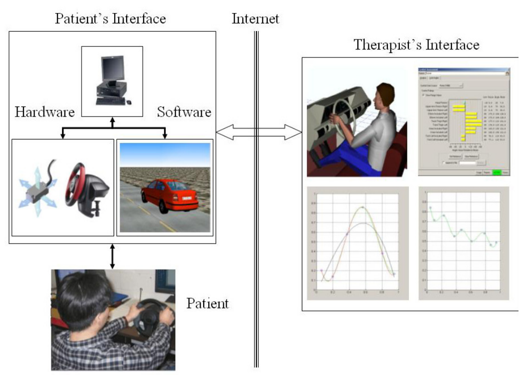


Fig. 1: Implementation Framework

the patient's arms could capture the instantaneous angular rates. The overall intent is to take advantage of the simplified interfaces of low cost commercial of the shelf (COTS) hobby electronic components to acquire data without explicit data acquisition cards.

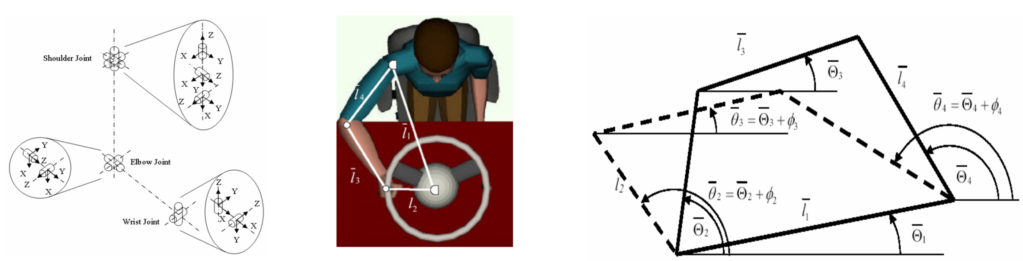
From the therapist's point of view, this telerehabilitation system should facilitate effective visualization and quantification of the patient's motions and associated pathologies as the patient follows a prescribed exercise regimen. We use JACK [5], a commercial software package for human body simulation, to develop the therapist interface. Synthetic models of the human user consist of parametric articulated rigid body models (69 scalable articulated parts, 138 degrees of freedom and 70 joints) that reflect the geometry and the kinematics of the user [6]. This JACK model forms the virtual prototype of the patient with whom the therapist interacts within this virtual environment. The remotely collected data can be used to replay the patients driving (exercise) session on the digital human model and reviewed from various viewpoints. Further, the interface can also provide the therapist with additional computed/postprocessed information (such as computed ranges of motion, comfort index, etc.) to aid the assessment process. The therapist can now appropriately modify the therapeutic regimen, examine the effects on the human model prior to transmitting/downloading a new therapeutic regimen to the patient's machine.

RESEARCH ISSUES

There is considerable variation within human population and in order to use the interface effectively the corresponding virtual/synthetic model of the patient needs to be *customized* to reflect the individual patient's characteristics [7]. One approach is to customize the JACK model with statistical averaged numerical values (like link lengths, initial posture) obtained from an anthropometric database [6]. However, the drawback of this approach is that it is unable to capture the full extent of the variations between individuals. The alternate approach of non-invasive estimation using image-based measurements of skeletal parts from X-Ray, MRI or CT images has other drawbacks, including the need for multiple 3-D scans and extensive computations to determine kinematic quantities such as the center of rotation and the direction of its axis [8]. Hence in our approach, we similarly propose to use the ongoing and continuous streaming measurements to facilitate the automated and in-vivo estimation of various kinematic parameters of the upper-limb, building on the rich background of kinematic calibration in robotics [8, 9]. The accurate estimation of such parameters is especially important subsequent estimation of other quantities such as joint ranges of motion (and in the longer terms also the actuation forces at the joints). The end goal is a system that is capable of adaptively estimating these parameters based solely on the streaming measurements obtained with inexpensive COTS devices, without requiring expensive calibration tools.

UPPER LIMB KINEMATIC CALIBRATION

Modeling of the kinematics of the human arm offers considerable challenges since the considerable play in the mating joint surfaces combines with the surrounding tissue deformation to result in complex motions. For example, the gleno-humeral joint (shoulder) acts like a cam and slides on glenoid surface resulting translation of joint axis [10]. However, as an initial approximation, that is consistent with biomechanics literature, we model the human arm as an articulated kinematic linkage with 7 revolute joints as shown in Fig. 2(a).



(a) (b) (c)

Fig. 2: (a) Human Upper Limb Kinematic Model; (b) Formation of a closed kinematic Loop in the transversal plane; and (c) parameters of the 4-bar mechanism.

A closed kinematic loop is formed when the patient then holds onto the driving wheel. For the purposes of our initial kinematic calibration efforts, we restrict the motion of the arm to the transverse plane, parallel to the ground, passing through the shoulder. By assuming that that the torso of the patient is restrained by a seat-belt, the kinematics are reduce to that of a four bar mechanism, as shown in Fig. 2(b). A ground link, with unknown link-length ($\overline{l}_1$) and unknown initial configuration $\overline{\Theta}_1$ is assumed to stretch between the center of rotation of the wheel and the shoulder joint. The steering wheel forms the input-crank of known link-length (l_2), the fore-arm is the coupler link of unknown length ($\overline{l}_3$) and the upper-arm is the follower link of unknown length ($\overline{l}_4$). During the calibration process, we assume that the steering wheel encoder measures the relative joint rotations (ϕ_2) with respect to an (unknown) initial configuration ($\overline{\Theta}_2$). Similarly, the relative angular orientations (ϕ_3, ϕ_4) with respect to (unknown) initial configurations ($\overline{\Theta}_3, \overline{\Theta}_4$) are generated by resetting the integration constant of the gyro-rate integration at the first calibration position. Thus the true joint angles may be written as $\overline{\theta}_i = \overline{\Theta}_i + \phi_i,\ \forall i = 2,3,4$. Using the coordinates of the hand grip on the steering wheel as the point of interest, the difference between the measured and nominal approximated position may be written as:

$$\Delta X = X_{measured} - X_{nominal} = \begin{bmatrix} l_2 \cos\overline{\theta}_2 \\ l_2 \sin\overline{\theta}_2 \end{bmatrix} - \begin{bmatrix} \overline{l}_1 \cos\overline{\theta}_1 - \overline{l}_3 \cos\overline{\theta}_3 + \overline{l}_4 \cos\overline{\theta}_4 \\ \overline{l}_1 \sin\overline{\theta}_1 - \overline{l}_3 \sin\overline{\theta}_3 + \overline{l}_4 \sin\overline{\theta}_4 \end{bmatrix} \tag{1}$$

In particular, we note $\overline{\theta}_2, \overline{\theta}_3, \overline{\theta}_4$ are considered to be the estimates solely due to the presence of the unknown initial configurations $\overline{\Theta}_i, \forall i = 2,3,4$. A Taylor series expansion of Eq. (1) in terms of variations of these unknown parameters can be written as Eq. (2), where Φ is calibration matrix and $\Delta\zeta$ the vector of parameter variations.

$$\Delta X = \Phi\Delta\zeta = \begin{bmatrix} \cos\overline{\theta}_3 & -\cos\overline{\theta}_4 & -l_2\sin\overline{\theta}_2 & -\overline{l}_3\sin\overline{\theta}_3 & \overline{l}_4\sin\overline{\theta}_4 \\ \sin\overline{\theta}_3 & -\sin\overline{\theta}_4 & l_2\cos\overline{\theta}_2 & \overline{l}_3\cos\overline{\theta}_3 & -\overline{l}_4\cos\overline{\theta}_4 \end{bmatrix} \begin{bmatrix} \Delta l_3 \\ \Delta l_4 \\ \Delta\Theta_2 \\ \Delta\Theta_3 \\ \Delta\Theta_4 \end{bmatrix} \tag{2}$$

The calibration equations developed in Eq. (2) for a single position typically are undetermined. However, by making k such measurements for successive increments of ϕ_2, an overdetermined system of equations may be obtained as:

$$\Delta\overline{X} = \begin{bmatrix} \Delta X_1 \\ \vdots \\ \Delta X_k \end{bmatrix} = \begin{bmatrix} \Phi_1 \\ \vdots \\ \Phi_k \end{bmatrix} \Delta\zeta = \overline{\Phi}\Delta\zeta \tag{3}$$

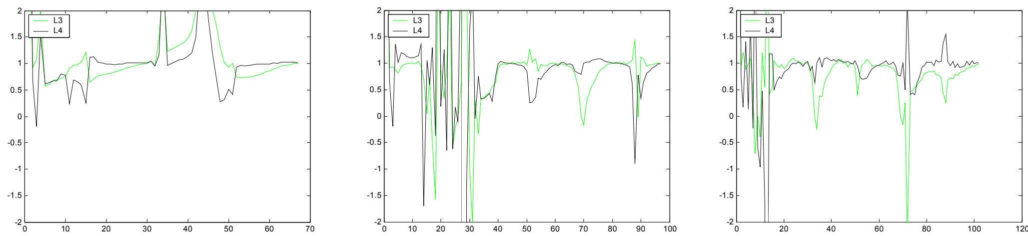
and a least-squares solution for the unknown parameter variations ($\Delta\zeta$) can be obtained by taking the pseudoinverse of this overdetermined system of equations.

$$\Delta\zeta = \left(\overline{\Phi}^T\overline{\Phi}\right)^{-1}\overline{\Phi}^T\Delta\overline{X} \tag{4}$$

The estimated parameters $\overline{l}_3, \overline{l}_4, \overline{\Theta}_2, \overline{\Theta}_3, \overline{\Theta}_4$ are updated using $\Delta\zeta$ and the process is iterated for next set of k measurements until ΔX falls below a threshold ε.

RESULTS

For the purposes of algorithm testing, a simulated 4-bar mechanism served as the source of measurements for ϕ_2, ϕ_3 and ϕ_4. However, noting that the use of hobby electronic components in the final deployment is likely to give noisy measurements, we also study the effect of the measurement noise on our online parameter estimation. Fig. 3 depicts the results of the parameter estimation, while including the effects of addition of random measurement noise, ranging from 5% to 25% of the true value. Each subplot depicts the ratio of the estimated link-length to the true-value vs. the number of iterations. In general, the parameter estimation process converges rapidly for all cases but requires increasing number of iterations as the percentage of added noise increases. The results of these trials are also tabulated in Table 1.



(a) (b) (c)

Fig. 3: Ratio of estimated link-lengths to true values with increasing measurement noise (a) 5%; (b) 10%; and (c) 25%.

Table 1: Percentage error in estimation of link parameters.

Lengths	% Length Error (5 % Noise)	% Length Error (10 % Noise)	% Length Error (25 % Noise)
l_3	4	-2	4
l_4	0.3	-1	6
Iterations	43	99	103

DISCUSSION

In this paper, we motivated and developed an online parameter estimation scheme for in-vivo measurement of upper-limb parameters in conjunction with development of a low-cost tool for assessment of upper-limb dysfunction. Simulation studies were used to demonstrate the robustness of the procedure for estimation of link parameters, even in the presence of noisy measurements. Subsequent to successful kinematic calibration, we note that measurement of the steering wheel angles alone (in conjunction with the loop-closure equations) would be adequate to completely infer all motions of the system. This reduction in measurement and transmission requirements would greatly aid the interactive monitoring of the patient's progress even over low-bandwidth connections.

Preliminary clinical testing with patients with UL disabilities and a remote therapist are currently underway to determine the usefulness of this telerehabilitation approach.

REFERENCES

1. National Stroke Association, [Online] http://www.stroke.org.
2. Krebs, H., Hogan, N., Aisen, M., Volpe, B., Robot-Aided Neurorehabilitation, IEEE Transactions on Rehabilitation Engineering, vol. 6, no. 1, March 1998.
3. Volpe, B., Krebs, H., Hogan, N., Edelsteinn, L., Diels, C., Aisen., M., Robot training enhanced motor outcome in patients with stroke maintained over 3 years, Neurology, vol. 53, pp. 1874–1876, 1999.
4. Collen, F., et al., Mobility after stroke: Reliability of measures of impairment and disability, Int. Disability Studies, vol. 12, pp. 6–9, 1990.
5. JACK, http://www.eds.com/products/plm/efactory/jack/
6. Badler, N.I., Phillips, C.B., and Webber, B.L., Simulating Humans. Oxford University Press, 1993.
7. Krovi, V., Kumar, V., Ananthasuresh, G.K., Vezien., J.M., Design and Virtual Prototyping of Rehabilitation Aids, ASME Journal of Mechanical Design, Vol. 121, No. 3, pp. 456-458, September 1999.
8. Rohling, R.N., and Hollerbach, J.M., Modeling and Parameter Estimation of Human Index Finger, Proc. IEEE Intl. Conf. Robotics and Automation, San Diego, pp. 223-230, May 8-13, 1994.
9. Hollerbach, J.M., and Wampler, C.W., The Kinematic Calibration Index and Taxonomy for Robot Kinematic Calibration Methods, International Journal of Robotics Research, Vol. 14, pp. 573-591, 1996.
10. Palastanga, N., Field, D., and Soames, R., Anatomy and Human Movement: Structure and Function, Heinemann Medical Books, Oxford, 1989.