A Simulation-based Feasibility Study of a Proprioception-inspired Sensing Framework for a Multi-DoF Shoulder Exosuit

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***Abstract*—The compliant nature of exosuits makes them ideal for providing assistance to complex joints like the shoulder. Exosuits require soft, compact and accurate sensing units for reliable feedback control. In this work, we introduce an OpenSim simulation-based prototype of a proprioception-inspired sensing framework for a multi-DoF shoulder exosuit. The prototype is used to study the feasibility of the sensing system concept to accurately track multiple degrees of freedom (DoFs) of the shoulder simultaneously.**

The sensing system fuses data from 4 custom string potentiometers (SPs), that work together to sense the joint angles at the shoulder. The tendon-routing of the SP modules in the exosuit is proprioception-inspired and based on the organization of the muscles influencing shoulder movement. The sensor fusion/mapping of the simulation data from multi-sensor space to joint space is a multivariate multiple regression problem and was solved using Multi-Layer Perceptron (MLP) & Long Short-Term Memory (LSTM) neural networks. A simulation of the framework in OpenSim on 200,000 random shoulder movements achieved a root mean square error (RMSE) of $\approx 0.2^\circ$ when trained on 70,000 random movements and tested on 130,000 random movements in both DoFs simultaneously.

I. INTRODUCTION

A new generation of soft, wearable robots taking advantage of natural anatomical structures is now making use of soft materials like fabrics, elastomers, *etc.* and soft actuation technologies to provide rehabilitation and assistance [1]. The compliant nature of exosuits makes the concept ideal for providing assistance to complex multi-DoF joints like the shoulder that can inherently induce misalignments [1, 2]. Rigid-bodied alternatives end up becoming bulky, restrictive and are not portable [1]. Currently, a few soft wearable robotic systems focus on 1-DoF [2] and multi-DoF [3–5] assistance for the shoulder joint. Though the systems [4, 5] are compliant, they are extensive and would be more suited to rehabilitation rather than portable assistance-based applications.

In exosuits, sensing networks are crucial to get a clear understanding of the state of the human-suit system, understand the pathology, design user-specific assistance strategies, and acquire physiological, non-physiological and intention-based data. A number of research works have explored different soft-sensing modalities for measuring the kinematics of different joints including liquid metal alloys [6], micro-fluidics [7], and dielectric elastomers [8] along with more traditional sensing technologies like flex/bend sensors [2] and Inertial Measurement Units (IMUs) [2]. A number of these systems have limitations like hysteresis and/or drift that makes it challenging to achieve the high accuracy needed for robust control. IMUs, though extremely good for robot-control, were not considered as the system is also being designed to actively counter the effects of muscle atrophy experienced during prolonged space travel, and traditional IMUs would not work in space [9].

In this work, we introduce a virtual prototype of the sensing framework of our exosuit. The suit is being developed for the aging population and astronauts to provide multi-DoF assistance at the shoulder. The novelty of our system is in bio-inspired tendon-routing architecture which tries to replicate the mechanism behind our sense of proprioception to sense multiple joint angles of the shoulder simultaneously. Section II presents the design concept of the sensing framework followed by the framework evaluation methods and experiments in Section III. The results of the virtual prototyping and the learning of the sensor mapping on the simulation data is presented in Section IV, followed by a discussion of the limitations and future work in Section V.

II. SENSING FRAMEWORK DESIGN

The glenohumeral (shoulder) joint, is an extremely complex joint, and its kinematics cannot be approximated completely as a 3-DoF ball-and-socket joint [10]. The change and rate-change in length of the nerve endings in muscle spindles scattered within skeletal muscle around the shoulder (and not direct sensing at the joint) is responsible for the sense of the joint's position and movement, known as the sense of 'proprioception' [11]. In our exosuit, we sense the 2 DoFs that manifest in the shoulder conjointly while the third DoF (internal/external rotation) manifests at the elbow and can be measured separately.

In the proposed tendon-driven exosuit concept, we take inspiration from the organization of the muscles around the shoulder joint to design the tendon-routing of our sensing and eventually actuation framework. Analogous to the human body, we employ a configuration where both the actuation (from the motors) and sensing (from the SPs) tendons are routed parallel to each other and along the same path. **The actuation tendon layout is only presented briefly for context, and its framework is not discussed in this paper**. The suit is made up of 4 sets of tendon-based sensing+actuation units- **F, SF, SR, R**, and each tendon runs parallel (‖) along a pair of muscles that work together for a particular movement (mvmt(s)): (see Fig.1):

- Tendon-**F** ‖ (Pectoralis major and Anterior deltoid) - F/E and horizontal A/A mvmts.
- Tendon-**SF** ‖ (Anterior and Lateral deltoid) - A/A mvmts.

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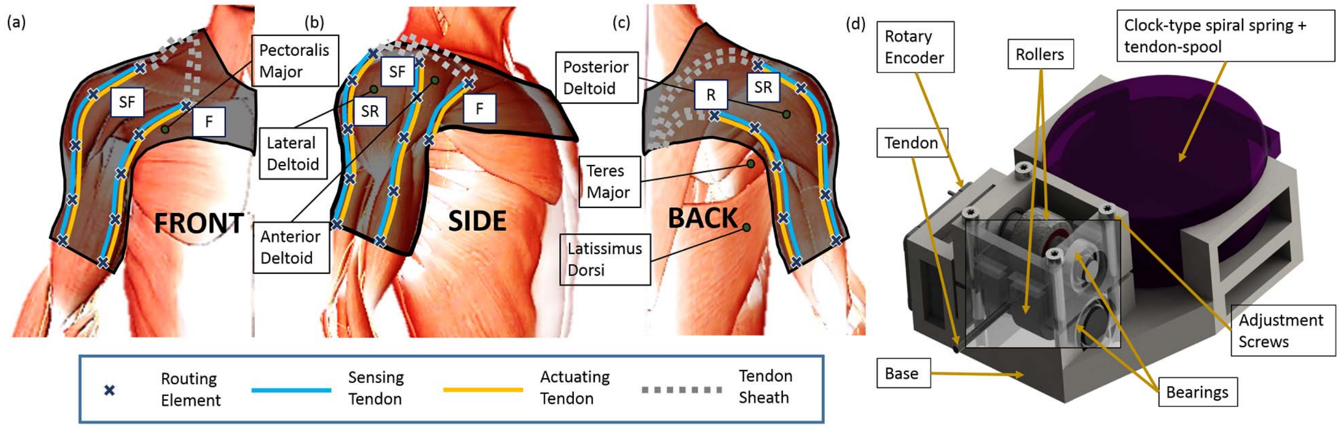

Fig. 1. Schematic of system design concept: The tendons are labeled based on their position in the suit: Front(**F**), Side-Front(**SF**), Side-Rear(**SR**), and Rear(**R**). The organization of muscles that inspired the tendon-routing have also been labeled for comparison. The tendons are routed through 3-D printed pulley-like routing elements that are fixed to the shoulder sleeve. A CAD rendering of the custom-built SP prototype is shown in Fig.1(d), and it measures the change in path lengths along the different paths as the arm moves.

- Tendon-**SR** || (Lateral and Posterior deltoid) - A/A mvmts.
- Tendon-**R** || (Posterior deltoid, Teres major and Latissimus dorsi) - F/E and horizontal A/A mvmts.

The tendons on the prototype will be routed through multiple 3-D printed pulley-like routing elements that are fixed to the exosuit. When a movement is made, the tendon, just like the muscle spindles in the corresponding muscle, shorten/elongate and this displacement/stretch is tracked by the SPs (shown in Fig.1(d)). Multiple SPs track different regions of the shoulder's surface and all the data is fused together to derive the joint angles.

III. SENSING FRAMEWORK EVALUATION METHODS & EXPERIMENTS

A. Virtual Prototyping of the Sensing Framework

To test the concept, we first created a virtual prototype of the sensing framework in OpenSim [12]. OpenSim is an open-source software system for creating musculoskeletal (MS) models and performing multi-body dynamics simulations [12]. We used the upper-limb MS model developed by Saul *et al.* in [13] for our forward kinematics simulations. The simulations were performed in MATLAB (Mathworks, MA, USA).

To generate a virtual model of the sensing framework, a prototype of the exosuit (see Fig.2(b)) was used. Reflective markers were fixed on the routing elements to mimic the routing elements and record their position in space. Markers were also fixed at different anatomical features to scale the generic model accurately. Virtual anatomical and movement markers matching the real markers were introduced into the generic MS model. The movement of each virtual marker was assigned to a parent rigid body (bone). A multi-camera motion capture system (Smart DX, BTS Bioengineering, Italy) was used for capturing static pose data for a subject, and this data was used to scale the original model. The data was transformed into the OpenSim coordinate system, and the model scaled using the native OpenSim scaling tool which resulted in an RMSE $< 1cm$ for all markers. This error is only for the scaling and does not impact the virtual prototyping results.

A combination of splines and straight lines connecting the markers (see Fig.2(a)) were used to model the path traversed by the different tendons. As the upper-arm is moved in the simulation, the markers also move and this results in the lengthening/shortening of the virtual tendons. Change in arc lengths of the virtual tendons are computed at each instant in a movement and this is the same measure sensed by the SP sensing module. The methods to do the virtual forward kinematics and record virtual sensor data is discussed next.

B. Forward Kinematics Simulation-based Data Generation & Conditioning

Forward kinematics simulations were performed to generate 200,000 random movements in 2 DoFs of the shoulder and the corresponding sensor values were recorded. To generate a movement, random velocities within physiological limits were randomly chosen for both DoFs, and a random destination joint angle for one DoF (picked randomly) was set as the termination point. Forward kinematics simulations to follow this joint angle/velocity profile (while keeping joint angle constraints) was performed and the data from the virtual sensors recorded. To condition the data, a number of data conditioning techniques including global scaling, and rounding to 1 decimal place was incorporated. Shuffled data was used to train the MLP network, but left unshuffled for the LSTM network. The network was trained on the first 70,000 movements and tested on the following 130,000 movements. Over 200,000 movements, a single movement had on average $\approx (75-78)$ data points. The training was done using the Keras-TensorFlow API in Python 3.5.

C. Learning Sensor Map using Neural Networks

Decoding joint angles from 4 sensors is a multivariate multiple regression problem. From Fig. 2(c-f), it can be seen that the

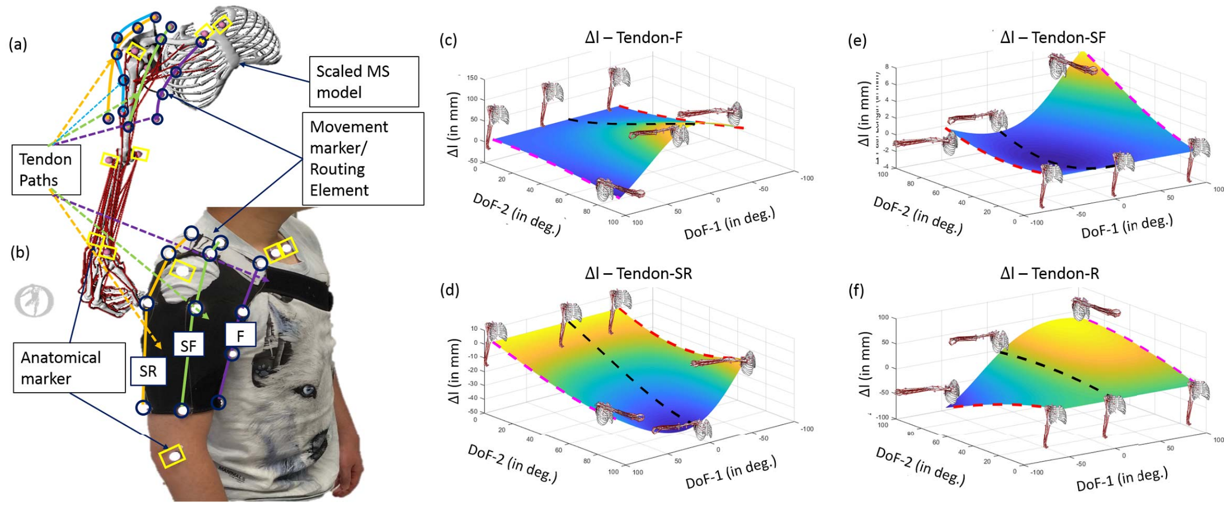

Fig. 2. Virtual Prototyping setup & results: a)-b). Comparison of virtual and real sensor framework used to generate virtual sensor data. c)-f). Results of the virtual sensor framework emulating the custom-built SP sensors to compute shoulder DoF values: c). tendon-**F**, e). tendon-**SF**, d). tendon-**SR**, and f). tendon-**R**. The magenta/red and black dashed lines denote the change in tendon lengths measured by the 4 sensors during F/E and A/A movements respectively. This is shown by the overlaid OpenSim MS model graphics.

sensor data do not have a typical one-to-one correspondence with the DoFs. 1-layer deep neural networks can solve such regression problems successfully. We used MLP and LSTM networks to learn the sensor-to-joint space mapping for our sensing framework. Both networks were trained using different combinations of sensors as inputs (see Fig.3) to understand the impact of each sensor on the mapping.

An MLP with 1 hidden layer was initially used. The input layer had 2-4 dimensions -one for each sensor, and the output had 2 dimensions -one for each DoF. The MLP network performed really well when trained with a shuffled dataset but the RMSE more than doubled when the trained on the original continuous time-series dataset. This is primarily because MLPs do not have any memory and hence cannot take advantage of the temporal information in the input data, which is crucial in our case (see Fig.2).

The data was, therefore, also used to train an LSTM network. The LSTM is qualified to encode both spatial and temporal aspects of the mapping. The original data (unshuffled) was used to train this network. The data was reframed as a series of overlapping windows of size 10 (timesteps) with a stride of 1 (timestep), making each input of size (2-4)x10 (one for each sensor), and 2 output (DoF) dimensions.

IV. RESULTS & DISCUSSION

A. Virtual Prototyping of the Sensing Framework

It can be seen from Fig.2(c-f) that the tendons behave as expected during movements made along DoF-2 while holding DoF-1 constant. For *e.g.*, it can be seen that during flexion tendon **F** monotonously contracts and tendon **R** monotonously extends, and vice-versa during extension (see dashed magenta/red lines in Fig.2(c),(f)). Similarly, during abduction tendons **SF** and **SR** monotonously contract and tendons **F** and **R** monotonously extend, and vice-versa during adduction (see dashed black line in Fig.2). These tendons behave just like the muscles parallel to which they are routed and validates the proposed concept for these movements.

However, contradicting results are observed when DoF-1 is changed while holding DoF-2 constant, *e.g.* during horizontal A/A movements. During horizontal abduction, tendon-**F** sensor value should increase, and this can be seen until DoF-1 = 0, but then it drops again. This non-monotonous behavior does not comply with musculoskeletal biomechanics. Similar behavior can be seen in the other tendons as well. The primary reason for this is that in OpenSim markers are associated with a parent bone, as opposed to being fixed onto the skin. This limitation becomes glaring during movements when the bones might move internally, but that movement is not actually reflected at the skin, *e.g.* during internal/external rotation and the movement of the scapula. A second reason is that the tendon-routing is eyeballed to route along the muscles but this has not been optimized. We intend to address this shortcoming in the future.

B. Sensor-to-Joint Space Mapping

An 8-unit LSTM network was able to achieve the same performance as a 75-neuron MLP, as they were both able to track 2 DoFs of the shoulder with an RMSE of $\sim 0.2°$ when tested on 130,000 movements (see Fig.3). The LSTM's capability to encode historical velocity-based information made it more robust to shoulder movements not encountered before. During training, the LSTM networks took $\sim 26-28 secs$ per epoch as compared to $\sim 5-8$secs in the case of the MLP, but this wouldn't affect real-time feed-forward evaluation.

Fig.3 also compares the performance of the different sensing configurations in predicting the joint angles. The graphs have

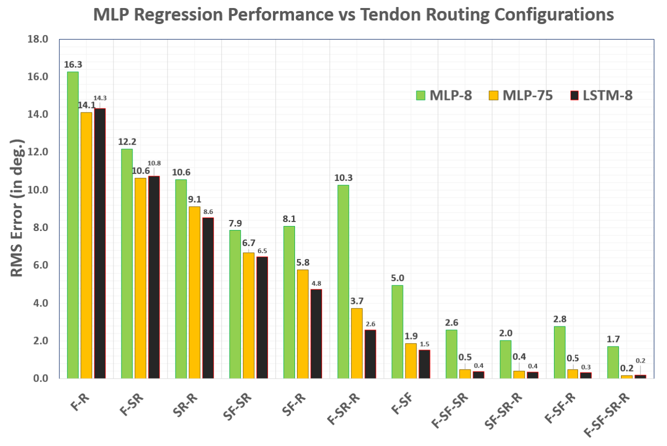

Fig. 3. Sensor Mapping Results: RMSE performance of 2 MLP & 1 LSTM networks over different sensing configurations tested on 130,000 movements.

been organized going from worst to best performing configuration. Unsurprisingly, the best performance is observed when the sensor data from all 4 tendons are fused together to obtain the joint angles followed by the 3-tendon configurations that also provide good joint tracking. From Fig.3, we can see that most 3-tendon configurations have very similar performances except the combination **F-SR-R**, which does not have the tendon-**SF**. Even from the 2-tendon configuration results, we can observe that configurations having tendon-**SF** performed the best as compared to the configurations with the other three tendons. The reason for this could be because tendon-**SF** is the only tendon that has a relatively less non-monotonous nature against both DoF-1 and DoF-2 movements (see change in colour gradient in Fig.2(c-f). The next best tendons look to be **F** followed by **R** and **SR**. The performance of the mapping in Fig.2 & 3 clearly show that the sensing concept could be translated to a physical prototype, but the non-monotonous nature needs to be verified with human subject experiments.

V. CONCLUSION

In this paper, a feasibility study of a proprioception-inspired sensing framework for measuring 2 DoFs of the shoulder simultaneously is presented. The concept was prototyped in OpenSim, and the data from the simulations was then used to train MLP & LSTM neural networks to learn the sensor-joint space mapping and achieved an RMS error of $\approx 0.2°$, proving the feasibility of the sensing framework.

One of the limitations of the virtual prototyping is that the markers are attached to bone rather than skin, and the mapping changes on changing the associated bones. This could have resulted in the non-monotonous sensor measurements, and the actual mapping needs to be verified with human subjects. Another limitation is that the compliant nature of the skin and exosuit has not been modeled, and the virtual sensors are assumed to be ideal. We intend to address these limitations in our future work.

An exosuit prototype using this tendon-routing configuration with both the sensing and actuation will be able to provide assistance/physical therapy to not just the shoulder joint but could be extended to other simple/complex joints like the elbow, knee torso, hip, ankle, wrist, neck *etc*. The configuration of this suit also has other advantages like being able to compensate for misalignments presented due to the compliant nature of the suit and backlash compensation, thereby allowing for more robust and intuitive control of the suit.

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