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Socially Assistive Robotics and Wearable Sensors for Intelligent User Dressing Assistance

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***Abstract*— Individuals living with cognitive impairments are faced with unique challenges in completing important activities of daily living such as dressing. In this paper, we present the first socially assistive robot-wearable sensors system to provide dressing assistance through social human-robot interactions. A novel robot-wearable architecture is development to classify, prompt and provide feedback on user dressing actions. Namely, strain sensor based smart clothing on the user are used for joint angle mapping, which are then classified into different dressing steps. The robot uses a MAXQ hierarchical learning method to learn assistive behaviors to aid a user with the sequence of dressing steps. Experiments were validated the performance of the joint angle mapping model, dressing action classifier, and behavior adaptation modules as well as the overall system for dressing assistance.**

I. Introduction

Activities of daily living (ADLs) such as eating, dressing, and grooming are essential everyday tasks for personal independence [1]. For individuals living with mild to moderate cognitive impairments [2] or stroke [3], these tasks can be difficult to complete on their own. ADL limitations can have a negative effect on the overall wellbeing and quality of life (QoL) of these individuals [1]. Dressing is essential not only in being able to select and put clothes on/off based on the activities engaged in and the weather, it is also critical to self-confidence and personal identity [4]. As a result, individuals who are physically assisted with dressing by caregivers or assistive technologies, when they are capable of completing the task themselves, have reduced confidence and lose their ability for self-expression [5].

A handful of assistive technologies for dressing assistance have been developed and can be categorized as: 1) dressing recommendation applications [6],[7], and 2) robots that provide physical assistance using their manipulators [8]–[11]. Dressing recommendation applications provide cognitive assistance by giving clothing suggestions to relieve the burden of decision making, however they fail to monitor the user state such as compliance or disengagement as they lack the necessary sensory inputs. Robotic systems directly undertake the dressing task for the user and are currently limited to helping put on one type of clothing such as hats [8] or sleeveless jackets [11].

In general, physical assistance solutions can pose potential safety risks in the event of system malfunction including collisions with the robot, user loss of balance, or an invalid motion performed by the robot that strains the user due to limited range of motion [12]. Given the psychological and cognitive consequences of dressing dependency, the demand placed on caregivers, and the limitations of current assistive technologies for dressing, there exists a need to develop socially assistive robots to help users dress themselves through human-robot interaction (HRI) using their own existing capabilities.

Our own previous work in this area has focused on the development of a clothing recommendation robot and corresponding app that is able to autonomously recommend clothing options from a user's wardrobe, personalized to an activity, weather, and clothing preferences [13], [14]. However, it only recommended outfits to wear and did not assist in the dressing task. Furthermore, we have developed cost-effective smart clothing consisting of integrated switches to identify user dressing states [15]. Although, the smart clothing could be used to give feedback on user dressing actions, it customized the garment with the required sensors, limiting its generalizability to multiple people and clothing types.

In this paper, we present a novel socially assistive robot (SAR) for autonomous dressing assistance that uses a strain sensor based smart clothing to classify dressing actions and adapt its assistive behaviors. To the authors' knowledge, this is the first SAR-wearable system for dressing assistance. Strain sensor arrays embedded in smart clothing are used to output joint angles, which are classified into different dressing steps. The robot uses a MAXQ hierarchical learning approach to learn assistive behavior strategies based on these dressing steps for various clothing items.

II. Related Work

Herein, we present the literature on: 1) robotic technologies for dressing, 2) smart clothing for user motion detection, and 3) wearable sensors for assistive robotic applications.

A. Robotic Technologies for Dressing

Robotic assistance for dressing has mainly focused on physical assistance of robot manipulators putting clothing on a stationary user [8]–[11]. For example, in [8], the Baxter

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robot was used in a dressing assistance system that would map manipulator motions for putting on clothes to angular velocities, and then generate user repositioning requests when the action was out of the robot's reach. A camera-based skeleton joint tracker was used to track the user position relative to the robot. Test trials consisting of Baxter placing a hat on a person showed it was adaptable to user constraints but faced challenges in maintaining an accurate user model when Baxter's arms obstructed the camera field of view. To address occlusion from robot arms and the clothing itself, in [9], an RGB-D camera facing the user was implemented with Baxter to assist with putting on a jacket. When elbows became occluded, positional information from other joints such as the shoulder and hip were used with a recurrent neural network (RNN) to predict the location of user elbow joints. Regression trees learned the most influential features in determining elbow locations which were used as inputs to the RNN for elbow location prediction in 3D space.

Force-torque sensors have also been used by robotic manipulators as the main sensory inputs [10],[11]. In [10], a PR2 robot with a haptic feedback controller was used for upper body dressing assistance with t-shirts and hospital gowns. The robot learned dressing techniques using deep reinforcement learning (DRL) based on haptic feedback from its arm joint sensors to infer joint locations first in simulation and then on the physical PR2 robot. Initial sim-to-real experiments showed success on other physical robots acting as users with limited mobility. In [11], the Baxter robot was used for putting on a sleeveless jacket using a probabilistic user tracking model developed from torque-force information with the goal of minimizing forces between the user and robot. After an RGB-D camera was used for initializing the user model, tracking was achieved with only the torque sensors on Baxter's arm joints. Manipulation goal locations were provided by a hierarchical multitask controller using probabilistic models. Initial results showed the robot was capable of dressing users with various ranges of motion.

In addition to physical assistance, socially assistive robots have also been developed to assist with dressing tasks by providing clothing selections [13], [14] and verification if clothes are put on correctly [15]. In [13], [14], the Leia robot provided clothing recommendations using a multinomial logistic regression (MLR) approach. User preferences for clothing items were updated using stochastic gradient descent. An app was developed in correspondence with robot emotional behaviors to guide the user through the selection. User studies showed the system was adaptable, provided appropriate recommendations, and was easy to use.

In [15], a smart collared shirt was developed with built-in sensors for detecting dressing states which were proposed as input to the Pepper robot for providing informed dressing task feedback to a user. The sensors included: 1) an IR LED at the front of the shirt used for detecting front/back orientation, 2) contact switches on the buttons to detect if they were fastened, and 3) capacitive switches on the arm sleeves and back to detect the presence of a torso or arms respectively. Initial results validated that using these sensory inputs, the smart system was able to classify different dressing states including correctly worn, partially worn, backwards, or inverted.

B. *Smart Clothing for User Motion Detection*

Smart clothing integrates flexible and conformable sensors and transducers into a garment [16]. They provide sensory information of user motions with respect to: 1) joint positions [17] or 2) joint angles [18], [19]. In addition, wearable sensors can address challenges faced by camera-based systems such as occlusion and varying lighting conditions [17]. Among the many modalities that have been studied for motion detection, three types of sensors are the most common: inertial measurement unit (IMU) [17], optical fiber sensors (OFS) [20], and strain sensors [18], [19], [21].

Strain sensor-based smart clothing use resistance or capacitance signals to determine joint angles. Smart clothing developed for one degree of freedom (DOF) joints such as smart gloves [21] place one strain sensor across the joint of interest to detect motion. Mapping between joint angles and sensor signals for 1-DOF joints is achieved through linear regression [21]. To detect motion of joints with multiple DOF, sensor arrays are embedded in smart clothing. Deep learning methods such as convolutional neural networks (CNN) [18] are commonly utilized as regression models to obtain joint angles. To train these networks via supervised learning, the sensor signal is used as the input and ground truth joint angles are found using camera-based systems.

For complex joint surfaces that are covered by large muscles, such as the shoulder or hip, sensor placement on the smart clothing is an active area of research. In [18], 50 reflective markers were distributed across smart pants around the right hip joint in a grid pattern, and 6 cameras were used to capture the motion of these markers during running. Distance between neighboring markers was obtained by subtracting the 3D positions of these markers and was used to predict the hip angles. A combination of genetic algorithm and sequential forward methods were used to find the optimal sets of markers and thus sensor locations that produced the highest prediction accuracy. However, using such methods to obtain sensor placement requires specialized equipment.

An alternative approach to using reflective markers and camera-based systems is to use theoretical lines of non-extension on the human body that neither stretch or contract during motion [22]. This concept was utilized in [19] to develop smart clothing for 3-DOF shoulder motion tracking using eight capacitive sensors. The sensors were placed perpendicular to the lines of non-extensions to maximize the deformation of sensors during motion. Despite the linearity and low hysteretic behavior of capacitive sensors, their sensitivity can be low. Contrary to capacitive sensors, resistive sensors can have much higher sensitivity with the tradeoff of low linearity and high hysteresis [23]. In addition, each capacitive sensor used in smart clothing requires a capacitance-to-voltage converter that has high power consumption, whereas the readout system (voltage divider) for resistive sensors consumes much less power.

C. *Wearable Sensors for Socially Assistive Robotics*

Wearable sensors for people have been used specifically by SARs for user state estimation including for the detection of engagement [24],[25] and emotions [26],[27].

For example, in [24] the social robot Brian was developed to provide cognitive interventions for card matching memory games. A heart rate sensor worn on their ear was used to determine user arousal as either low or high based on changes in heart rate relative to the user's resting heart rate. This was combined with activity performance to define user state, to which the robot adapted its emotional assistive behavior. User study results showed Brian's ability to maintain positive user states during the game. However, since heart rate alone cannot capture activity progress, sensors such as a webcam were required for full user state classification.

In [25], the Nao robot was used to assist users in memory cognitive training based on their task performance and task engagement. A Muse EEG headband was used to measure raw EEG signals of different frequency ranges to provide an engagement score. Using the engagement score and the current game score as a reward, the SAR adapted its behavior to encouraging or challenging. In [27], the Muse EEG headband was also used to develop a user affect detection model for the Pepper robot via eliciting user emotional responses. EEG signals were used by a fast Fourier transform to give power spectral density features which were input into a multilayer perceptron neural network to classify user valence and arousal levels. Initial user studies showed classification results were limited due to intra-user variability.

In [26], a negative emotion management system was developed using a smart shirt with embedded ECG sensors for a SAR to initiate interactive emotion improving conversations with users. Recurrence quantitative analysis was used on training data to extract EEG plot features such as the percentage of recurrence points and input them to various ML algorithms such as decision trees to classify between negative or non-negative emotional states. Results showed accurate emotional classification by the system and confirmed the robot's potential to improve moods.

In summary, wearable sensors have mainly been used to obtain psychological signals for HRI. To the authors' knowledge, user motion monitoring using wearable sensors, particularly strain sensors, has not been developed for ADL task assistance including dressing.

III. Social Robot-Wearable Sensors Dressing Assistant Architecture

The proposed socially assistive robot-wearable system architecture is presented in Fig. 1. Sensory inputs are provided by our novel *Strain Sensor Smart Clothing* on the user. Resistance signals from the smart clothing are used by the *Joint Angle Mapping Model* to output rotations in either the 1-DOF elbow or 3-DOF shoulder joints. These angles are then provided to the *Dressing Step Classifier* to classify the user's dressing actions. The *Robot Adaptive Behavior Deliberation* uses this action to determine the SAR's assistive behaviors displayed by the Leia robot using a combination of speech and gestures.

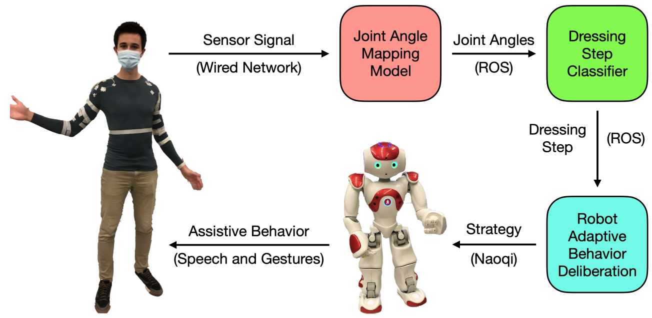


Figure 1. SAR-wearable proposed architecture.

A. *Strain Sensor Smart Clothing*

We designed and fabricated Piezoresistive (PZT) strain sensors to be used within our proposed smart clothing. These PZT sensors are composed of two layers – an elastomer layer and a conductive layer. The elastomer layer is made from a thermal polyurethane (TPU) fibrous mat, and the conductive layer is made from carbon nanotube (CNT) ink using a procedure similar to [28]. The sensor structure and fabrication process are shown in Fig. 2. The TPU fibrous mat is fabricated through electrospinning: a nanofabrication technique using high voltage to deposit nanofibrils solution on a substrate. Rectangular strips are then cut from the TPU fibrous mat to form the elastomer layer of the sensor and CNT ink is dispensed onto it. After airdrying at room temperature, copper foil electrodes are attached to both ends of the sensor using silver paste.

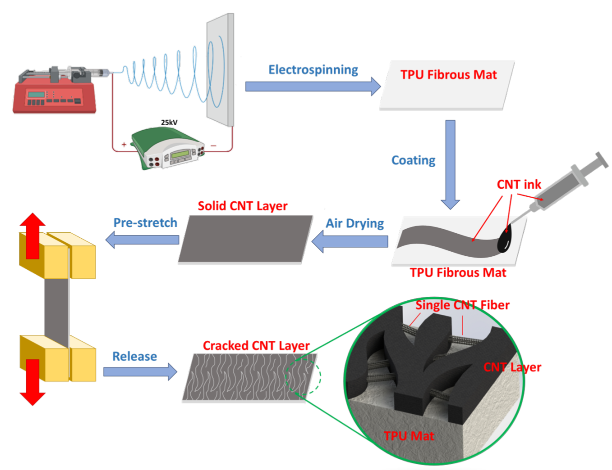


Figure 2. Nanofabrication of the thin film structure of sensor.

As shown in Fig. 3, one PZT sensor is placed across each elbow joint (location 1) on the capitellum perpendicular to the rotational axis to maximize elongation during elbow movement. Four PZT sensors (locations 2-5) are placed on various locations to maximize elongation during shoulder motions [19]. Sensors are detachable to ensure similar placement for users of different body shapes. In total, five PZT sensors are used on each side of the body to measure the 1-DOF motion of the elbows and 3-DOF motion of the shoulders. Resistance of the sensor is measured using a voltage divider:

$$R = R' (V_{in} - V_{out}) / V_{out} \quad (1)$$

where R' is the resistance of the fixed resistor, V_{in} is the supplied voltage of the voltage divider, and V_{out} is the measured voltage signal. An Arduino Nano is used to collect V_{out} signals and convert them to R $\{r_1, r_2 \dots r_{10}\}$ signals according to Eq. (1) for each side of the upper limb.

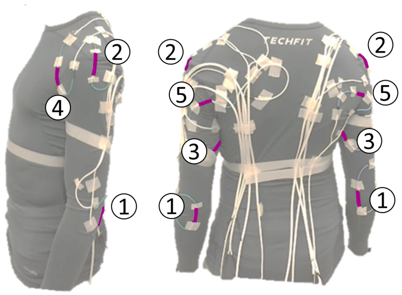


Figure 3. Sensor placecment (purple) on smart clothing design.

B. Joint Angle Mapping Model

Decoupled from the array of resistances R, two separate arrays R_{left} and R_{right} for each side of the user are considered to determine two sets of shoulder and elbow angles:

$$\Theta_{\text{left}} \{\theta_1 \dots \theta_4\} = f(R_{\text{left}} \{r_1 \dots r_5\}) \quad (2)$$

$$\Theta_{\text{right}} \{\theta_5 \dots \theta_8\} = g(R_{\text{right}} \{r_6 \dots r_{10}\}) \quad (3)$$

where functions f and g each take five sensor resistance signals and convert them into four joint angles. Elbow joint angles, θ_1 and θ_5, are single angles since the forearm and bicep are on the same plane, while the shoulder angles are represented as two sets of three Euler angles $\{\theta_2, \theta_3, \theta_4\}$ and $\{\theta_6, \theta_7, \theta_8\}$ in the order of ψ, θ, ϕ.

A 2D-CNN approach was developed for functions f and g in Eqs. (2) and (3). To consider inter-signal features between all sensors, a *signal image* was used equivalent to the activity image representation of wearable sensor data in [29]. The *signal image* concatenates three reordered duplicates of the resistance arrays (R_{left} or R_{right}) such that each resistance signal r_i neighbors each other signal in R_{left} or R_{right}. A window size of 25 timesteps was used to filter sudden fluctuations while ensuring fast processing time. The inclusion of past timesteps also allows the CNN to learn from past motion to address sensor hysteresis. This results in a final *signal image* of dimensions 15x25 input to the CNN with two convolutional layers using 2x3 kernels to identify features between the signals before two fully connected layers outputting four continuous joint angles per side in the Θ_{left} and Θ_{right} arrays.

The CNN model was trained by sampling the sensor array at 100 Hz to obtain R and was labelled by simultaneously calculating and recording the ground truth joint angles, Θ'. Ground truth angles were obtained from a RGB-D sensor and Nuitrack skeleton tracking software [30], matching the time stamp of Θ' and the last element in R. During data collection, users would mimic dressing steps such as arm through, head through, and button up. 35,000 R to Θ' mappings were obtained, which were randomly used for training, validation, and test sets based on a 70%, 20%, 10% split. The loss function was the root mean squared error (RMSE) between output and actual joint angles to capture the continuous nature of the signal. Hyperparameters such as learning rate, batch size, and model depth were tuned based on the RMSE of the validation set. The final joint angle mapping model outputs joint angles at 50 Hz.

C. Dressing Step Classifier

For the dressing task, joint angles need to be converted to task related data that the SAR can use to monitor user progress. Dressing steps were defined as distinct actions a user performs while dressing involving arm movements that can be captured by the smart clothing. They include: 1) right arm through, 2) left arm through, 3) head through, 4) button up, 5) zip up, or 6) random inaction/disengaged. A one-dimensional moving window CNN was used for classification. Eight joint angles, $\{\theta_1 \dots \theta_8\}$, with a window size of 50 timesteps, equally 1 sec, formed an 8x50 tensor as the input to the dressing step classifier. The input tensor is first decoupled into eight 1x50 tensors and used by the CNN which consists of three convolutional layers with 1x3 kernels to extract action features. Then the action features from the 8 joint angles are concatenated before entering three fully connected layers and being classified into one of the six dressing steps formatted in one-hot encoding.

The model was trained using a labelled dataset with 24 samples of each action performed with variation in motion path and speed. Each sample was collected by a user performing a single action once while wearing the smart clothing. Resistance signals R were then used to obtain joint angles Θ. To ensure a minimum of 4 samples for validation and testing for sufficient model tuning and accuracy assessment, the sets were split 66.6%, 16.7%, 16.7%. The loss function used was cross entropy to compare the output to the categorical target. Validation set accuracy was used to tune hyperparameters of learning rate and batch size.

D. Robot Adaptive Behavior Deliberation

We have developed an *Adaptive Behavior Deliberation* module for SAR assistance during dressing. A MAXQ reinforcement learning hierarchical method [31] is used to determine the robot's behaviors. We choose MAXQ due to its temporal abstraction as users take different amounts of time to complete dressing steps, state abstraction for considering only relevant variables for a given subtask level such as the current clothing items for identifying the clothing type, and subtask abstraction to group similar actions that emerge during dressing given its repetitive nature. The overall MAXQ hierarchical task graph is presented in Fig. 4. The task graph follows the MAXQ decomposition structure, where a given Markov decision process (MDP) task M is decomposed into a finite set of sub-tasks $\{M_0, M_1, \dots, M_n\}$.

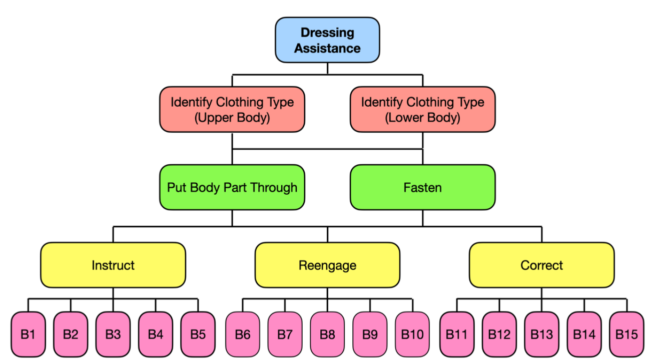


Figure 4. MAXQ robot dressing assistance task graph.

The *Root Task* is the overall dressing assistance task of helping a user put on clothing items. Subtasks M_i contain a set of actions A which are lower subtasks or primitive robot behavioral actions at the lowest level of the graph. The 1st level subtasks include *Identify Clothing Type (Upper Body)* and *Identify Clothing Type (Lower Body),* both of which determine the type of clothing the user should put on and if the clothing goes on the upper body or lower body of the user. The 2nd level subtasks of *Put Body Part Through* and *Fasten* identify the dressing step for the user to perform. The 3rd level subtasks define the robot's primitive behaviors to assist the user which include *Instruct*, *Reengage*, and *Correct*.

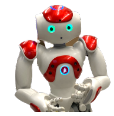
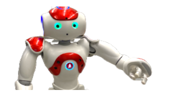
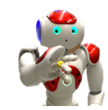
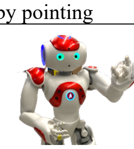
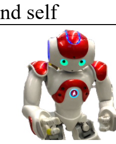
Within the MAXQ graph, a set of states, S, have been defined for each subtask. These state functions beginning with the root task are: 1) *Root Task, s(cd, cu)*, 2) *Identify Clothing Type, s(c, pd, pu)*, 3) *Put Body Part Through/Fasten, s(p, u)*, and 4) *Instruct/Reengage/Correct, s(c, p, u)*. All state variables are declared using one-hot encoding. *cd* is the set of desired clothing items to be worn by the user to complete the dressing task and *cu* is the set of clothing items currently on the user. *c* is the current clothing item of interest, *pd* is the set of required dressing steps for this clothing item, and *pu* is the set of dressing steps the user has already completed for the current item. *p* is the current dressing step of interest and *u* is the user state described as the most recently completed dressing step.

The *Instruct* primitive actions provide direct instructions to a user on how to complete a specific dressing step (right arm through, zip up, etc.) using different behavioral strategies. For users suffering from cognitive decline such as some older adults, distraction becomes more prevalent and can decrease task performance [32]. The *Reengage* primitive actions are used to re-engage a distracted user in completing the dressing task. The *Correct* primitive actions are used in the case when a user makes a dressing step mistake, providing varying behavior strategy prompts for correcting the error.

Compliance gaining behaviors (CGB) are strategies used by people [33] and robots [34] to persuade other people to change their behavior. The following strategies were chosen to provide robot assistance: 1) logic, 2) emotion, 3) direct request, 4) cooperate, and 5) motivate. Examples of each behavior strategy are presented in Table I. Logic and emotion strategies are based on HRI research that has shown these two CGBs to be the most effective in persuading users to use information provided by the SAR [34]. The remaining three strategies of direct request, cooperate, and motivate are based on clinical experience of caregivers assisting older adults to get dressed [35] and guidelines by the Alzheimer's Society for effective dressing assistance which focus on clear communication, creating sense of teamwork, and providing consistent positive verbal encouragement [36]. Leia displays these strategies using a combination of speech and illustrative gesture to emphasize spoken ideas [37].

Each subtask has a terminal condition. The *Root Task* terminal condition is $cu = cd$, signifying the user has put on all clothing in the desired outfit set. *Identify Clothing Type* has terminal condition $pu = pd$, signaling the current clothing item has been put on and a new item should be selected. *Put Body Part Through/Fasten* uses terminal condition $u = p$ to determine whether the user followed the instruction provided. Since *Instruct/Reengage/Correct* are primitive actions. they terminate immediately using the selected behavior strategy.

TABLE I. BEHAVIOR FRAMEWORK EXAMPLES

Action Type	Behavior Strategy	Utterance	Gestures
Instruct	Logic	"My sensors tell me it's time to put your right arm through your t-shirt"	 References self
Reengage	Emotion (Happy)	"It would make me happy if you refocused and put your head through your t-shirt"	 Expansive for positive emotion
Correct	Direct Request	"Incorrect step. Please undo when you buttoned up your dress shirt."	 References user by pointing
Instruct	Cooperate	"Let's work together to zip up your zip hoodie"	 References user and self
Reengage	Motivate	"Refocus on putting your left arm through your dress. You can do it!"	 Quick moving celebration

IV. EXPERIMENTS

We performed several experiments to verify the performance of our robot-wearable architecture including: 1) the root-mean-square error (RMSE) of the *Joint Angle Mapping Model*, 2) the performance accuracy of the *Dressing Step Classifier*, 3) MAXQ convergence and cumulative reward based on the total number of required steps for the *Robot Adaptive Behavior Deliberation* module, and 4) the success rate of Leia correctly identifying and responding to a variety of user states and dressing step actions.

A. Experiment #1: RMSE of Joint Angle Mapping Model

RMSE was used to evaluate the performance of the *Joint Angle Mapping Model*, it represents the average deviation between the output joint angles θ and ground truth θ' in the test set. The RMSE values for each joint angle in Θ_{left} and Θ_{right}, are {9.7°, 2.6°, 6.9°, 5.8°} and {15.6°, 3.0°, 8.8°, 13.0°}, respectively. To the best of the authors knowledge, this is the first smart clothing design that monitors both elbow and shoulder joint angles. Using the first iteration of sensors fabricated by our team, the RMSE values we obtained are relatively higher compared to existing constrained and higher power consumption smart clothing. For example, in [19], although elbow angles was not monitored, RMSE of shoulder Euler angles (ψ, θ, ϕ) were 2.80°, 1.64° and 4.13°, respectively. Future sensor improvements will focus on fabrication optimization and improved characterization which can be easily integrated into the system due to its modularity.

In general, joint angle mapping of the shoulders is more accurate than elbows, likely due to the larger strain produced by the bending of the elbows. As the strain sensors have low sensitivity at larger strain, the resistance signals saturate at strain around 50%, resulting in a greater error at large elbow bending angles. Even with this saturation, using a window of 25 timesteps at 100 Hz the model learned to output the entire range of elbow joint angles by using relative changes in the resistance signal as seen in Fig. 5 and 6.

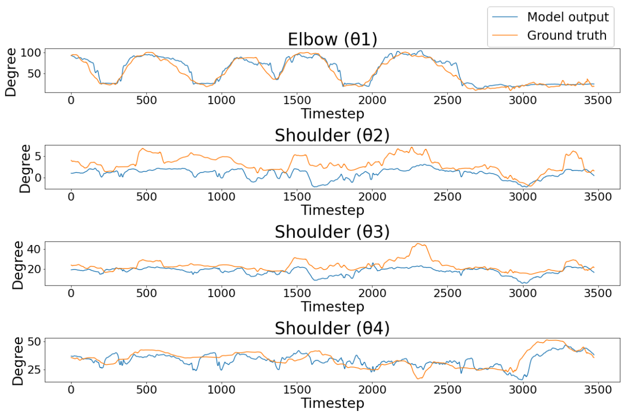


Figure 5. Left joint angle mapping model performance.

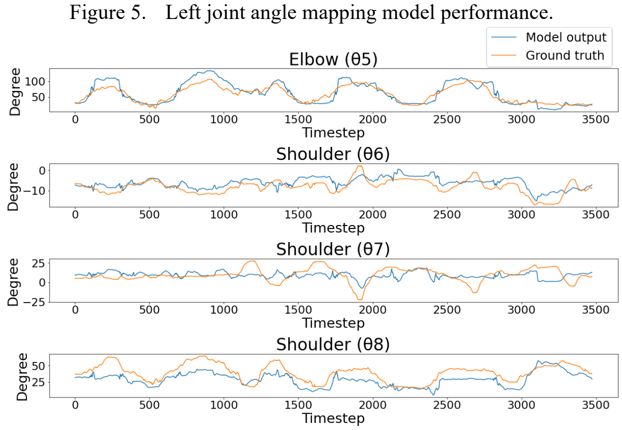


Figure 6. Right joint angle mapping model performance.

B. *Experiment #2: Dressing Step Classifier Performance*

A confusion matrix was used as the performance metric for the dressing step classifier to determine overall classification accuracy and identify the most challenging classes. An overall classification accuracy of 96% was obtained by the *Dressing Step Classifier* on 24 test samples of dressing actions. Fig. 7 presents the confusion matrix. There was a 25.0% rate of “head through” being misclassified as “button up”, hypothesized to be the result of the high elbow strain for both actions.

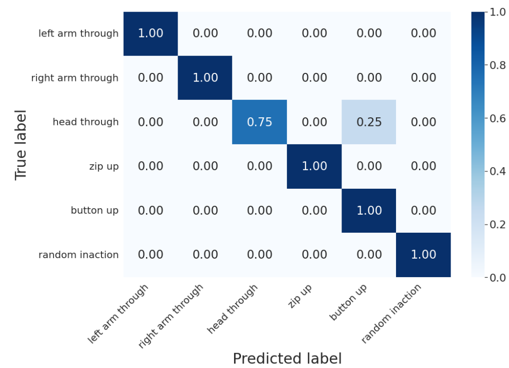


Figure 7. Confusion matrix for task classification.

C. *Experiment #3: Robot Adaptive Behavior Deliberation*

To test the adaptive behavior deliberation model, five different simulated users were created by defining user functions to return a dressing step based on the behavior strategy used and the requested dressing step. Each user had a different probability rate for complying, being disengaged, or making a mistake which were changed within the user if their preferred behavior strategy was used. Rewards given for the task levels in descending order were ± 5 for *Root Task*, ±3 for *Identify Clothing Type*, and ±1 for *Put Body Part Through/Fasten*. At the primitive level, a reward of 0 was given when the user performed the dressing step correctly as requested by the SAR. If the user performed an incorrect step or required reengagement, the reward was -1.

To verify model convergence, one of the five simulated users was implemented in offline training with the adaptation framework for 10,000 iterations. The learning rate was α = 0.01 as determined by testing to optimize reward stability and the epsilon was ε = 0.05 to maintain a chance of using unpreferred strategies and thus adjust to changes in user preferences over time. The MAXQ method converged as shown in Fig. 8.

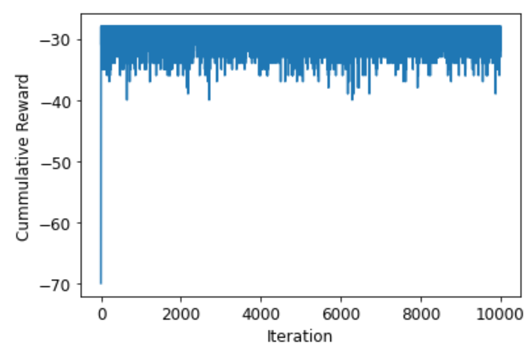


Figure 8. Offline behavior adaption model convergence.

To test framework adaptation capabilities, the remaining four users were implemented individually in online training for 20 full task completions using the same learning rate and epsilon values. As shown in Fig. 9, all users show significant improvements in task performance and an upward performance trend compared to the initial task completion. Fluctuations in cumulative reward are the result of simulated user randomness. The framework robustness can be observed in trials for users 1 and 2 where the model recovers from a poor result within one to two task completions.

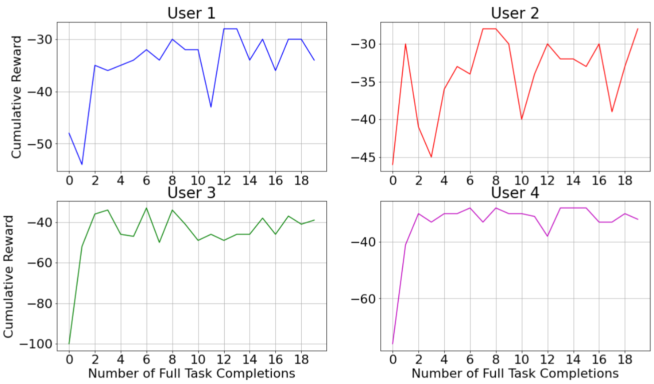


Figure 9. Online behavior adaption with different users.

D. Experiment #4: Overall System Performance

A physical SAR-wearable system experiment was performed with a human user to measure system reliability. A user with normal cognition put on the smart clothing with strain sensors at the marked locations. Subsystem modules were run concurrently, and Leia provided assistive behaviors based on the user's dressing step. Ten trials were conducted where the user would perform either: 1) the correct step, 2) no step, or 3) an incorrect step to trigger *Instruct*, *Reengage*, and *Correct* actions. The success of each trial was measured by whether Leia responded as expected to the user dress step, specifically if Leia: 1) correctly identified the executed dressing step and 2) responded to the identified dressing step with the correct behavior based on previously expressed user preferences. The user did not report any discomfort in wearing the sensors during the experiment.

Table II presents the success rates for Leia identifying and responding correctly with an assistive action. The overall classification success rate was 86.7% and overall correct response behavior rate was 100%. Errors in identification occurred when the user performed the "head through" action which was improperly classified as "button up" or "zip up". The success rate for dressing step classification is within 3% of the accuracy rate for other studies using strain sensors on elbow and shoulder joints for dynamic action classification such as police traffic signals [38]. However, our experiment considered more complex actions.

TABLE II. OVERALL SYSTEM PERFORMANCE

Robot Action Condition	No. of Trials	Success Rate for Step Classification	Success Rate for Assistive Behavior
Instruct user	10	80.0%	100%
Reengage user	10	100.0%	100%
Correct user	10	80.0%	100%
Total	30	86.7%	100%

V. CONCLUSION

In this paper, we present a novel social robot-wearable system to assist users with the ADL of dressing. A strain sensor smart clothing was designed and fabricated to detect upper body motion via joint angle mapping. A dressing step classifier converted these joint angles to task related user actions. The robot Leia then adapted its assistive behaviors based on user compliance using MAXQ learning. Experiments conducted validate the reliability and accuracy of the overall system as well as the individual modules. Identification error was attributed to sensor signal saturation and test set variation. Future work will include optimizing the sensory performance and conducting assistive HRI studies with our social robot-wearable system on users with diverse cognitive abilities.

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