An Assistive Robot to Support Dressing – Strategies for Planning and Error Handling

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***Abstract*— Assistive robots are emerging to address a social need due to changing demographic trends such as an ageing population. The main emphasis is to offer independence to those in need and to fill a potential labour gap in response to the increasing demand for caregiving. This paper presents work undertaken as part of a dressing task using a compliant robotic arm on a mannequin. Several strategies are explored on how to undertake this task with minimal complexity and a mix of sensors. A Vicon tracking system is used to determine the arm position of the mannequin for trajectory planning by means of waypoints. Methods of failure detection were explored through torque feedback and sensor tag data. A fixed vocabulary of recognised speech commands was implemented allowing the user to successfully correct detected dressing errors. This work indicates that low cost sensors and simple HRI strategies, without complex learning algorithms, could be used successfully in a robot assisted dressing task.**

I. Introduction

Between 2000 and 2050, the proportion of the world's population of over 60 years olds, is expected to double from about 11% to 22% and the absolute number of people aged 60 years and over is expected to increase from 605 million to 2 billion over the same period [1]. The incidence and prevalence of diseases and disabilities in the ageing population will have a profound socioeconomic impact on all aspects of our economy and society. To address growing health and social care needs, government agendas are promoting wellbeing and independence for older people and carers within communities to help people maintain their independence at home.

Assistive technologies, such as smart home environments, integrated sensors and service robotics, are recognized as important tools in helping older people improve their quality of life and live independently for longer [2]. Current research is looking into a range of different ways in which robots might be used such as assisting older adults and their carers with age-related disabilities and long-term conditions in daily tasks, to enable independent living and active ageing [3].

The focus of this research is to investigate assistance that can be provided by a robot to support dressing, where an interactive robot could be guided through voice commands or used in a semi-autonomous mode. In a typical scenario, an able carer might be physically supporting a frail person where they might need “an extra pair of hands” that can hold clothing in a specific position and complete the dressing task.

Additionally, support for dressing or removal of garments can be particularly helpful in environments where there is a high-risk of contamination – such as removal of protective clothing for health-care workers in areas of infectious disease or radiation exposure, or assisting surgical staff don protective gowns without risk of contamination.

Support with dressing, which is the focus of this research, has the potential to increase independent living. Support for dressing is an extremely challenging task, however working as an extra pair of hands for an able carer can have a considerable impact in a situation where this task would be performed by two carers. The key challenges are being able to learn a specific series of actions and then make appropriate adjustments as part of the dynamic process to ensure safety and effectiveness.

This paper presents the initial experiments using a Baxter Robot from Rethink Robotics. Baxter was used to dress one arm of a jacket onto a wooden mannequin by tracking the joint locations of the arm and calculating the trajectory. All other parts of the mannequin are ignored and dressing further than the shoulder is not considered in this current work.

To mitigate safety issues a wooden mannequin was used for the majority of testing work. Another key safety issue is the detection and handling of *dressing errors*, these faults occur due to snagging of the garment at some point on the arm and otherwise result in a force excessive for dressing which ultimately may be uncomfortable for the user. Dressing error detection was explored through; 1) force sensing at the robotic joints and 2) a wireless IMU used at the end effector.

Additionally, a simple fixed vocabulary for speech interaction was implemented to enable the user to work collaboratively with the robot. This was primarily used here for correcting the trajectory of the end effector when trajectory planning was incorrect.

The aim of this work was to automatically plan and execute 10 dressing trajectories using random mannequin poses and detect and handle a dressing error either automatically or through implementation of speech-based HRI including trajectory re-planning. The test is deemed successful if the jacket is completely on the mannequin’s arm up to the shoulder. The dressing time was recorded as a performance metric.

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II. Related Work

The shifting of robotics technology from industrial applications to more unconstrained, dynamic environments and incorporating human-robot interaction, triggers the use of force regulation strategies as a fundamental aspect to successfully performing tasks requiring physical interaction between a robot and person in close proximity. In considering safe close-proximity, it is important to monitor: the speed of the manipulator in real-time as it approaches the user, define areas in the robot's workspace where it can move safely, monitor the motion and forces on the end effector, and be able to carry out an emergency stop effectively.

In [4] a method for close safe-proximity is proposed. The authors suggest a simplified single-input single-output (SISO) fuzzy controller with a compliant manipulator which dynamically adapts to the surfaces it approaches or touches. Distance between the sensor and object is classified into three categories: *close*, *safe* and *far*, from which the output variables are *backward*, *constant* and *forward*.

Another method presented in [5] is a real-time safety method capable of allowing safe human-robot interaction in very close proximity. Given the case that the position of the human and that of the end effector are both known, then very accurate separation distance measurements can be extrapolated in real-time.

Some research studies have shown implementation of reinforcement learning for adapting to posture variation such as in [6] relating directly to a dressing task. However there was less evidence found for handling deformable objects (such as clothing) [7], path planning [8] and safety [5] with actual assistive dressing tasks, with the key studies being conducted by [6] and [9].

The solution presented by Tamei et al. [6] was based on reinforcement learning dressing a t-shirt on a mannequin with a dual-arm robot. The two objectives of their study were to handle non-rigid materials and to adapt movements of the manipulators to the assisted person's posture. The initial state of the mannequin has both arms inside the sleeves of the T-shirt and the dual-arm robot holds the hem. The experiment also included a motion capturing system. The state of relationship between the assisted person and the T-shirt needed to be observed as much as possible. This was implemented by using topological coordinates [10] for implementing motor learning skills by the robot and through a reward function. The algorithm then analyzed these topology coordinates and modified the joint angles of the robot by optimizing the path of the joint trajectories.

During a dressing task, failure detection is needed in two principal instances; during changes to the user's pose which would require an adaptation of the planned trajectory, and secondly if the clothing should become caught or not able to move easily over the arm. Yamazaki et al. [9] present a leg dressing method with a failure detection and recovery function. This is implemented through a technique which recognizes the state of the dressing clothes based on dynamic state matching presented in [11]. The emphasis of this research was on the determining the state of the manipulated garment by supplying a mix of visual and force sensory information. If a dressing failure is detected a recovery function is planned automatically. The estimation of the clothing state is checked through an online process which uses a set of preregistered and labelled regions to determine whether the present clothing state is appropriate to the required state of dressing.

In addition, as stated by Kulić et al. [12] each planned trajectory path needs to be classified as interactive or non-interactive. In their research, the entire space of the human was treated as an obstacle through a representation of a set of spheres. In the implementation of the research presented here, as a safety precaution only the area around arm is classified as interactive for trajectory planning. If at any point the manipulator is recorded to be anywhere outside this region the system was interrupted.

Failure detection could be achieved through interpretation of the Cartesian force at the end effector. This then provides reference trajectory modification relative to the force exerted on the end effector. Typically, robot force control is classified into direct and indirect force motion control. Unlike direct motion, indirect motion, also known as impedance control, implicitly considers the three stages of interaction with the environment without a switching strategy from free motion to constrained motion. Portillo-Velez et al. [13] proposed a solution for an optimization-based impedance approach for robot force regulation with force limits provided. Alternatively, Braun et al. [14] proposed a framework for simultaneous optimization of torque and impedance profiles in order to optimize task performance. The latter provides a linear quadratic regulator (LQR) while the former a dynamic optimization problem (DOP) considering a dynamic robot impedance model.

There is also a growing area of research in the recognition of garment states through computer vision. This research area fits very well with the assistive dressing as the recognition of garments and classification of them is crucial when it comes to correctly handling the garments or handing clothes in the correct order to people who suffer from dementia.

III. Methodology

This methodology is reported in sections, each looking at a different part of the safety or implementation of the system. In all cases the robot platform was Baxter from Rethink Robotics (software v1.1) running via ROS (Indigo) on a Linux platform (Ubuntu 14.04), a full scale wooden mannequin, a Vicon Tracker System (VTS) and 2 jackets (1x lightweight cotton/ polyester rain coat and 1x heavier, stiffer neoprene jacket). The jacket was always manually attached to the gripper at the end effector in the same location.

Initially we consider the trajectory planning and how this can be achieved using a Vicon camera system. We tested this aspect of the system with two jacket types on 10 random mannequin poses (arm at different angles and hence different trajectories and waypoints). The aim was to get one arm of the jacket to the shoulder of the mannequin and report the time taken if the task was successful.

We then look at failure detection and handling, either through the robot force sensors or using a wireless IMU. Here we look to establish which method is sensitive and reliable enough to detect dressing errors and most suitable for implementation into the system. Errors were artificially introduced into the system by either moving the mannequin's arm or restraining the dressing causing it to snag. Here we observe if the system can correct errors automatically.

Trajectory re-planning will follow a detected dressing failure and we discuss how this is achieved for two types of error; garment snagging or incorrect arm posture.

Finally, we discuss using speech based HRI as a method of correcting an incorrect trajectory. We tested this using the same 10 mannequin poses and report the success rate and the time taken compared to the case where HRI was not implemented. The variables here were the words that the system was programmed to respond to.

A. Trajectory planning

The Vicon Tracker System (VTS) was used to get an estimate of the joint position of a mannequin's arm by attaching reflective markers to the joints (wrist, elbow and shoulder) of the mannequin. The initial state of the mannequin was set with an arm position elevated from a vertical position (to an angle of approximately 30 degrees). The position of the hand was not considered due to variability and occlusion.

This data and the techniques in [15] were used to identify the arm and its pose. These points are on the surface of the arm and therefore are useful for calculating the trajectory. To determine waypoints for the end effector the projection angles that the wrist, elbow and shoulder made with the axis were found. Initially the distances between joints were established, elbow-to-wrist ($L_{elbow\text{-}wrist}$) and shoulder-to-elbow ($L_{sh\text{-}elbow}$) lengths were calculated from the following:

$$L_{elbow-wrist} = [X_{wrist} - X_{elbow}]^2 + [Y_{wrist} - Y_{elbow}]^2 + [Z_{wrist} - Z_{elbow}]^2 \quad (1)$$

$$L_{elbow-wrist} = [X_{wrist} - X_{elbow}]^2 + [Y_{wrist} - Y_{elbow}]^2 + [Z_{wrist} - Z_{elbow}]^2 \,. \quad (2)$$

The difference along the three axes between the elbow and wrist were calculated from:

$$X_{diff} = X_{elbow} - X_{wrist} \quad (3)$$

$$Y_{diff} = Y_{elbow} - Y_{wrist} \quad (4)$$

$$Z_{diff} = Z_{elbow} - Z_{wrist}. \quad (5)$$

The projection angles considered were: α, β and θ. α represents the angle between the y-axis and the projection of the length $L_{wrist\text{-}elbow}$ on the x-y plane. β represents the angle between the x-axis and the projection of the length $L_{wrist\text{-}elbow}$ on the x-y plane. θ represents the angle between the wrist-to-elbow phase and the x-y plane. θ is calculated as such:

$$\theta = arcsin\left[\frac{Z_{diff}}{L_{elbow-wrist}}\right]. \quad (6)$$

The projection of the first phase of the trajectory on the x-y plane is calculated as follows:

$$XY_{elbow-wrist} = L_{elbow-wrist} cos(\theta) \quad (7)$$

where α and β are calculated as follows:

$$\beta = arccos\left(\frac{X_{diff}}{XY_{elbow-wrist}}\right) - \pi. \quad (8)$$

$$\alpha = \arccos\left(\frac{Y_{diff}}{XY_{elbow-wrist}}\right). \quad (9)$$

The coordinates for the end of the hand can be estimated from the following

$$X_{hand} = X_{wrist} + \{L_{fingers-wrist} \times cos(\beta) \times cos(\theta)\} \quad (10)$$

$$Y_{hand} = Y_{wrist} - \{L_{fingers-wrist} \times cos(\alpha) \times cos(\theta)\} \quad (11)$$

$$Z_{hand} = Z_{wrist} - \{L_{fingers-wrist} \times sin(\theta)\} \quad (12)$$

where $L_{fingers\text{-}wrist}$ is an estimated distance of 0.13m which represents the distance from wrist to end of fingers. Another parameter was used to represent a reference distance between the arm and the end effector, L_{ref}. This distance was empirically chosen as less than half the sleeve hole diameter. This is used to calculate the position for trajectory planning obtained by the following three equations:

$$X_{init} = X_{wrist} + \{(L_{ref} + L_{fingers-wrist}) \times cos(\beta) \times cos(\theta)\}. \quad (13)$$

$$Y_{init} = Y_{wrist} - \{(L_{ref} + L_{fingers-wrist}) \times cos(\alpha) \times cos(\theta)\}. \quad (14)$$

$$Z_{init} = Z_{wrist} - \{(L_{ref} + L_{fingers-wrist}) \times sin(\theta)\}. \quad (15)$$

The equations above were used in order to plan all the waypoints. Several fixed arm positions were used in order to find the angles for all viable configurations that the arm may take, see Fig. 1. This was done to explore the limits of the system and the general trajectory directions expected.

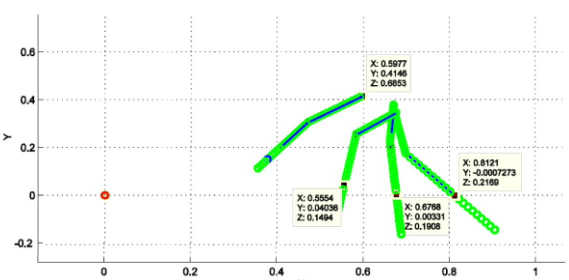

Figure 1. Using several fixed arm positions, all the possible arm angles could be determined to find the extents of the dressing trajectory. The reference frame origin for Baxter is at X,Y=(0,0), several arm poses of the mannequin are shown projected onto the XY plane (plan view).

Each waypoint calculated had to be communicated to Baxter through its interface in the form of quaternions. This involved calculating each of the robot joint angles at each coordinate. The orientation of the end effector was also calculated so that it was perpendicular to the trajectory path that it was following.

B. Safety and close-proximity manipulation

The requirement of having humans and robots interact within a decreasing distance of separation demands more effective safety considerations. As such, safety measures would require robots to pre-plan with respect to the user's position in relation to the robot. The robot also needs to be able to re-plan and adapt tasks in real-time based on any changes that the user makes. Applications where human-robot interactions take place in close proximity need to meet international standards (ISO 13482:2014).

As proposed by Lasota et al. [5] the end effector speed can be adjusted based on distance from the user:

$$\alpha(\mathrm{d}) = \begin{Bmatrix} 1-\beta(\mathrm{d}-\mathrm{d_{stop}})^{\gamma} & \mathrm{d}|\mathrm{d_{stop}} \leq \mathrm{d} \leq \mathrm{d_{slow}} \\ 0 & \mathrm{d}|\mathrm{d} > \mathrm{d_{slow}} \\ 1 & \mathrm{d}|\mathrm{d} < \mathrm{d_{stop}} \end{Bmatrix} \quad (16)$$

where α represent the percentage reduction in the robot's speed, β and γ are tuning parameters. β was chosen to be 0.9 while γ was chosen to be 0.4 based on empirical tests. The robot joint velocities can be set between 0 and 1. The joint velocities were written into the control system to give the response as shown above.

Further to velocity control for close proximity, the robot should be limited in movement to mitigate collision potential. As stated in [12] there should be an interaction area defined where the end effector may move. Fig. 2 shows the defined interactive workspace volume (circles) that is dynamically allocated around the planned trajectory route (line). The system was set to interrupt if the end effector moved outside the workspace volume.

This velocity information with the trajectory coordinates was sufficient information to complete the trajectory planning.

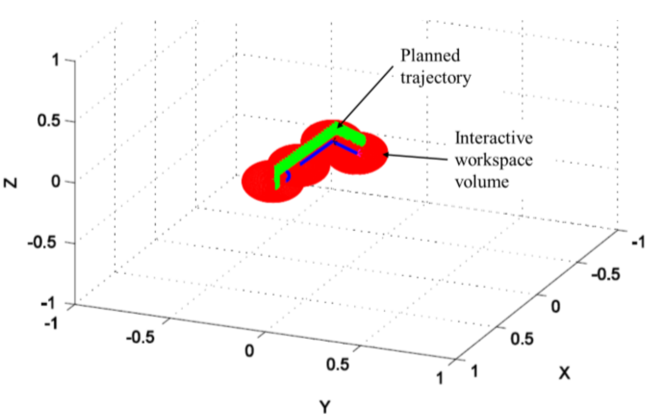

Figure 2. Defining the interactive workspace volume around the planned trajectory route.

C. Failure detection using force dynamics

The first approach for failure detection was optimization of the Cartesian force at the end effector. This provided a reference trajectory modification. In this case, a dynamic optimization problem was implemented as described in [13]. This required the minimization of a performance index I:

$$\min_{\chi_r \in R^m} I = \frac{1}{2}[E(t) + \alpha\dot{E}(t)]^T[E(t) + \alpha\dot{E}(t)] + \frac{1}{2}X_r^T\Theta X_r. \quad (17)$$

where X_r is the online computed reference trajectory, E(t) is the weighted sum of the interaction force error and $\dot{E}(t)$is its time derivative. This minimization function is subject to, $F \leq F_{max}$, $F \geq F_{min}$, and

$$\boldsymbol{D}\ddot{E} + \boldsymbol{B}\dot{E} + (K + K_0)E = \boldsymbol{K}\boldsymbol{F}_r - \boldsymbol{K}K_0(X_r - X_0). \quad (18)$$

where **D**, **B** and **K** are (m x m) positive definite diagonal mass, damping and stiffness matrices respectively and F_r represents an external force. The above inequalities are transformed into two equations which represent an upper interaction force threshold and a lower interaction force threshold. This leads to a gradient–based solution X_r. This method was implemented and tested for a set of specific force limits.

D. Failure detection using a wireless sensor

The most common dressing failures identified were the garment snagging on the hand, elbow or other part of the arm. It was hypothesized that an effective way of detecting this could be achieved through an inertial measurement unit (IMU). The Texas Instruments SensorTag (CC2541) was chosen as it was found to provide reliable data wirelessly. The sensor provides 3-axis acceleration and gyroscope data. Being small in size, (approx. 20x25x60mm) the sensor could be easily attached close to the end effector, Fig. 3.

A repeatability study was undertaken to determine if the sensor could be used to detect garment snagging. Baseline data comprised moving the robot arm through a pre-recorded trajectory without a jacket, recording the accelerometer data and repeating this cycle 20 times. This data was analyzed to

Figure 3. Sensor being tested during a dressing task. The sensor can be seen attached to the right arm near the end effector.

determine the confidence intervals and outliers of the accelerometer sensor for all three sensor axes.

Sudden changes in acceleration could be due to garment snagging and this data was monitored as a potential indicator to dressing errors.

E. Trajectory re-planning

When a dressing task failure was detected trajectory correction would be initiated based on the error type: the arm being in an unanticipated position or the garment snagging. If the arm was in a position different to that of the initial trajectory planning, the displacement of the arm from the original position was determined and recorded. The waypoints could then be calculated based on a new set of projection angles.

If the error was due to garment snagging, a response similar to that in [9] could be implemented. From observing repeated experiments, failure detection at the start of the wrist-to-elbow phase was usually due to the garment being stuck at either the finger or thumb. To determine in which direction the end effector should move, the robot was programmed to try a sequence of different directions until no failure is detected. The sequence was set to be primarily in the z-direction and secondly in the direction of the thumb.

Detection of garment snagging at any other position along the trajectory was considered. This could include the garment catching on the elbow or on another garment worn underneath the jacket. The magnitude and direction of correction vectors were based on repeated empirical tests.

This correction technique is limited to this particular scenario due to the predefined assumptions. A more suitable and flexible approach to this task would be to incorporate feedback from the user (HRI) at the cost of added complexity.

F. Human-Robot Interaction (HRI)

In order to provide corrective feedback, changes to the end effector position were allowed along the 3 orthogonal Cartesian axes: up (+z), down (-z), forward (-y), back (+y), left (-x) or right (+x). These corrections were made to the end effector but the absolute direction relates to the user and not to the global coordinate system for the robot. This enables the user to give directions without having to think about the relative position of the robot.

A fixed vocabulary was used to issue commands to Baxter. A simple limited word vocabulary was formulated which included: 'Yes' and 'No' to confirm correct end effector position or to confirm start and ending of a manoeuvre. The other words used to correct end effector's position are: 'up', 'down', 'right', 'left', 'forward' and 'backward'. The correction requested would generate new set of projection angles (θ, β and α). It was assumed that the position of the shoulder would not change during the dressing task. Upon receiving a correction request the distance to move the end effector was chosen based on empirical testing. A correction of 0.03m was found to be suitable.

For speech to text recognition, a Python based Google speech API was used to recognize text and convert speech to text. This was necessary for the HRI node implementation on ROS. This was implemented by generating computer speech from text using the *pyttsx* Python library. This is to make the vocal communication between the user and the robot as natural as possible. Vocal feedback from the robot was used to inform the user of the start and finish of the task, to ask if the position of the garment is correct, and to ask for the adjustment direction upon receiving an error.

IV. Results And Discussion

The majority of the dressing task tests were successful, in as much as both the planning was carried out correctly and the task of getting the arm into the sleeve of the jacket, was completed. The merits or failures of each of the strategies explored are reviewed here.

A. Trajectory planning

Trajectory planning using the techniques outlined here was successful in this dressing task research. By using a few key locations on the body a succession of waypoints can be calculated for garment dressing. This was implemented by determining projection angles in 3D space based on the location body joints. This can be achieved with some simple geometric equations. We have proven this to be successful in our experiments. This technique is adaptable to other similar scenarios.

The mannequin was adjusted into 10 different poses, a graphical representation of the poses are shown in Fig.4. For these poses two jackets were dressed onto the mannequin. For each the successful dressing time is reported and whether or not the jacket finished at the shoulder, see Table I. The heavier jacket caused snagging at the hand more often than a lighter jacket.

Using a coordinate system it was easy to implement close proximity limits, areas of the workspace designated for safer, slower operation and areas away from the user could be allocated for quicker and less accurate movement.

Determining the orientation of the end effector is also

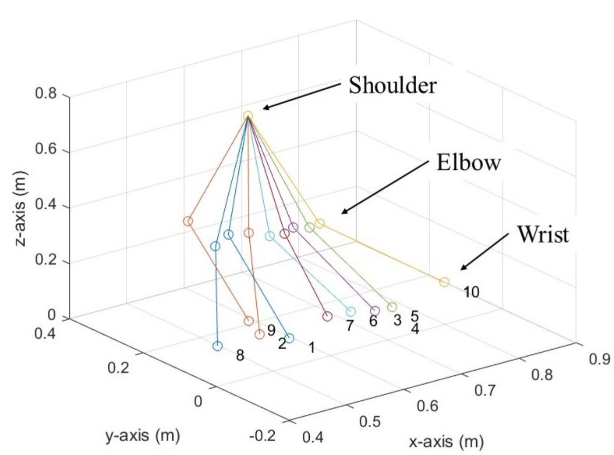

Figure 4. Mannequin arm poses (1-10) used for trajectory planning.

TABLE I. MANNEQUIN DRESSING RESULTS

Pose no.	Dressing time (minutes, seconds, 1/100 seconds)		
	Jacket 1	***Jacket 2***	***Jacket 1 with HRI***
1	1.30.37	Fail	2.23.32
2	2.33.93	1.43.52	3.45.11
3	1.37.87	1.42.11	3.13.42
4	1.55.40	Fail	2.53.42
5	1.49.21	1.15.12	2.43.32
6	1.23.65	1.33.21	2.51.52
7	1.56.22	Fail	3.08.12
8	Fail	1.49.43	3.21.42
9	2.01.43	1.46.11	2.39.51
10	Fail	1.49.31	3.04.33

important for the correct holding of the garment in the best possible orientation.

An error in the arm position estimation could occur as a result of poor quality or noisy data returned from the VTS. This may result in a dressing failure as the system does not know the position of the arm accurately enough. Using a different technique for pose detection of the arm may rectify this issue.

Dressing failures also occurred if the robot arm was working at the edge of its workspace and therefore inverse kinematics could not always be solved for the requested position. With a static base, the position of user becomes important to avoid a dressing trajectory that encounters singularities. Solutions to this could include a mobile robot or implementing HRI to prompt the user to move if possible.

B. Cartesian force for failure detection

Cartesian force readings are internally processed by Baxter from the joint torque sensors and propagated through forward dynamics to the end effector. In practice it was found that the forces measured at the robot arm joints were not consistent enough to detect the small changes in force experience during garment snagging. Gravity affected the force value reported at the joints and this would vary for the position and orientation of the arm. However, more work is required to fully explore the capabilities of the robot.

C. Wireless sensor for failure detection

The accelerometer was tested for repeatability in a pre-recorded arm movement test. This test highlighted the variability in the robot arm and/or the variability of the sensor. The maximum 3σ confidence interval was $0.067ms^{-2}$ at any point in a typical dressing trajectory. However, the outliers to the data would make using this practically difficult, with some values often exceeding $0.3ms^{-2}$ relative to the mean.

For the gyroscope, it was much easier to differentiate errors from a signal baseline, Fig. 5. It was seen that the gyroscopic

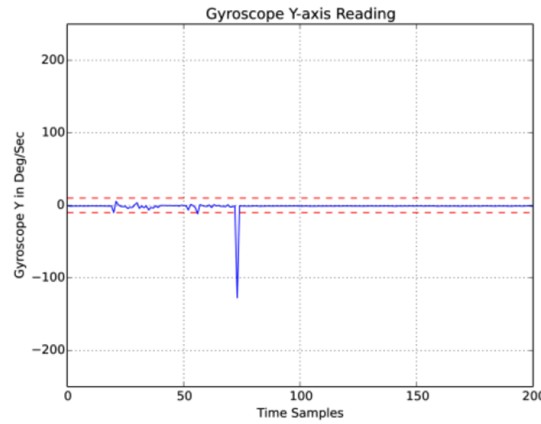

Figure 5. Gyroscope data (degrees/second) as a function of time measured during a dressing task showing when the sensor experiences motion outside of expected bounds (dashed lines).

readings could be used reliably for detection of obstructed or unplanned movement. Garment obstruction could be detected when there was no discernible change in the accelerometer data.

In 10 successful dressing tasks the accelerometer resulted in 3 false errors and during the same test the gyroscope reported no false positives. It may be possible to use data fusion to provide a robust real-time analysis of this data, to reduce false positives and increase total confidence.

D. Trajectory re-planning

The VTS constantly monitors the joint positions of the mannequin and compares the position of the joints to the initial state. If a difference in states is detected, then a correction to the initial trajectory was required.

Correcting an error due to garment snagging or catching on the mannequin took a slightly different approach. The robot was programmed to search for a trajectory offset that would free the garment. This would involve moving the end effector backwards along the planned trajectory 0.05m then trying a sequence of small corrections; for example, add 0.05m to all z-axis coordinate elements of the remaining trajectory. This was based on empirical tests and proved successful.

E. Human-Robot Interaction

When the HRI intervention was added it was immediately noticed that the requested correction at a specific instance solved the trajectory planning dynamically and in a clear and simple manner. By using HRI, errors from the VTS could be adjusted online and the trajectory re-planned. Furthermore, any potential problems arising from using different types of garments could be solved, allowing the user or carer more control over the robot control prior to starting the dressing task. Using the same 10 mannequin poses the mannequin was dressed using HRI for error correction.

However, adding the pauses in the task and waiting for voice commands to process caused the execution time to increase. Dressing time increased on average from 1 minutes 55 seconds without HRI to 3 minutes 55 seconds with HRI a

60% increase, see Table I.

In order to further evaluate the HRI approach, the dressing task was tested using erroneous starting positions. Despite this, the dressing task could be completed with instruction from the user. Using a starting position with a very large error took longer to complete due to the fixed distance used in the correction factor.

V. Conclusions

This preliminary research has shown that for a constrained dressing task, a combination of simple accelerometers and gyroscope at the end effector, together with human-robot interaction using a restricted word vocabulary can be an effective strategy.

There is still more research remaining to realize the system as a complete assistive dressing solution, but this initial work looks promising, particularly the use of HRI which helped to achieve improved results.

The approach taken to solve this task was to implement trajectory planning along all different possible arm positions in the workspace. This was implemented by deriving equations that would work for all postural configurations.

The approach to safety and close-proximity was considered, which included maneuverability in the workspace through controlled speed and a definition of what parts of the workspace Baxter could work in, avoiding singularities.

The task also required a failure detection strategy to know when a dressing error occurs. The simplest and most robust failure detection approach was a gyroscope sensor. Trajectory re-planning was implemented in response to the failure detection, as well as for adjustments in response to user commands.

HRI was implemented by a two-way communication between the robot and user. A failure detection from the IMU triggered a correction request. The user could then give verbal commands to adjust the end effector. This solved the problem that occurred when an incorrect starting position for the hand or elbow was introduced. The only drawback of implementing this style of HRI is that there is an expected increase in task completion time. However, it does offer an additional element of control over the robot that may benefit the user or caregiver.

These strategies have the benefit of being simple to implement and do not require any computer learning algorithms. Further, the method investigated has the advantage of using a small number of low cost sensors which can be used to sense unplanned movement in smooth trajectories. Combining the interactive HRI methods and the sensors provides a simple control strategy that could be implemented in a more dynamic environment.

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