Making Dressing Easier: Smart Clothes to Help With Putting Clothes on Correctly

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Abstract—Dressing is an Activity of Daily Living (ADL) that can be difficult to do for individuals living with cognitive disorders and can, therefore, negatively impact their quality of life. Our research focuses on the development of an assistive robot and smart clothing system to aid a user with this ADL. In this paper, we present our autonomous Clothing Perception System that uniquely incorporates smart sensors into clothing in order to perceive if a person has worn the clothes correctly. Four different dressing states can be identified: correctly worn; partially worn; backwards; or inverted (inside out). Our novel system uses a combination of capacitive sensors, contact switches, an infrared LED and an RGB-D sensor to determine the dressing state. The multi-modal sensing system was integrated into a collared shirt and tested to verify its performance. Results with different individuals putting on the shirt showed that the system was able to perceive the four distinct dressing states for all of them.

I. INTRODUCTION

Dressing is a complex Activity of Daily Living (ADL) that can be challenging for individuals with cognitive impairments or neurodevelopmental conditions, including older adults living with dementia or children living with Autism Spectrum Disorder (ASD). This important ADL consists of physical, cognitive and perceptual components [1]. In particular, dressing is one of the ADLs most affected by dementia [2]. Not being able to complete this activity can lead to reduced quality of life, decline of self-esteem and frustration for the person living with dementia [3]. In addition, young children with ASD can have lack of attention, poor imitation and performance skills, and underdeveloped motor skills, which are essential for the dressing ADL [1].

Some dressing assistance systems have been proposed to lessen the burden of the dressing ADL [4-7]. For example, in [4], a user could interact with a “smart wardrobe” through a tablet application that provided clothing choices. In [6], a user interacted with a 5-drawer dresser through audio and video prompts from a tablet application with dressing instructions. In [7], a tablet application provided instructional videos and photos to help children to put clothes on. Our own previous work used the social robot Leia to help older adults to select clothing items based on the type of activity they would perform, the weather and their own preferences [8].

Only a handful of existing systems can also monitor the user during the activity and detect dressing mistakes [5,6]. For example, in [5] the perception system used computer vision (i.e. color clustering) and RFID tags embedded in clothes to detect dressing failures, such as putting clothes on partially, backwards or in the wrong order. However, it was not able to detect clothing with complex color patterns, lower limb garments or clothes worn inside out. In [6], the intelligent wardrobe relied on visible fiducial markers detected by a camera to perceive dressing failures. Such visible markers were attached to the clothes, which resulted in two limitations. Firstly, the markers were subject to deformation, which decreased their recognition rate. Secondly, the markers degraded the clothes’ overall appearance, which could make users feel uncomfortable, since clothes also have high cultural value [3] and influence self-esteem and social identity [8].

Our research focuses on developing an autonomous assistive system which uniquely combines both socially assistive robotics and smart clothing to assist with the important ADL of dressing. Socially assistive robots are being developed to assist ADLs such as exercising [9], meal preparation and monitoring [10], as well as leisure activities [11-13]. Studies have shown that such robots can make tasks more enjoyable [14], increase motivation [9] and provide companionship and social stimulation [15]. For our dressing application, a socially assistive robot can be used to prompt a user through the steps of dressing and provide feedback when needed. Smart clothing can be used as part of the perception system to the robot to assess clothing states during the activity.

In this paper, we present the development of our novel clothing perception system, shown in Figure 1, which uniquely combines smart clothing and an RGB-D sensor to monitor the overall dressing activity and detect dressing mistakes such as partial dressing (e.g. not putting an arm through the correct sleeve, or not buttoning the shirt) or putting on clothes inside-out or backwards. The developed embedded smart sensors are not easily visible on the items of

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Figure 1. Architecture of the Clothing Perceotion System for Dressing.
clothing, therefore do not change the visual aspects of the clothes. The clothing states can be determined and eventually used by a socially assistive robot to provide feedback to a user.

II. RELATED WORK

A. Dressing Assistance Systems

In [7], the iPhone application “iDo Getting Dressed” was designed for children, teenagers and young adults living with ASD. The application was used to teach activities such as getting dressed, undressing and preparing clothes for the next day. The activities were demonstrated through a video or a sequence of images with narrated text. The application included a board game to make dressing tasks more enjoyable.

In [4], a tablet and wardrobe were used to help people with mild dementia with daily dressing. LEDs were placed around the wardrobe’s shelves forillumination. When the user selected a calendar entry on the tablet, the outside temperature, weather forecast, and duration of an appointment was obtained to suggest appropriate clothing. If the user rejected the suggestion, he or she could browse additional suggestions on the tablet. The system used a learning algorithm to learn the user’s preference and recommended those garments more frequently. Once the user selected a garment on the tablet, the corresponding shelf was illuminated.

In [5], a dressing status detection system used a dressing booth to automatically detect clothing errors of users with motor impairments. The system detected clothes dressed correctly, backwards or partially. The booth had 3 hidden RFID antennas. A camera was placed at the entrance of the booth to monitor the dressing activity. The clothes contained RFID tags on the shoulders and lower part of the back to detect if they were put on forwards or backwards. Images from the camera were also taken to complement the RFID tag detection. A k-Nearest Neighbor method was used to segment color clusters. Then, the system identified where the clusters were and whether they belonged to the top of the body, bottom or background. This allowed the system to recognize if the clothing was put on partially.

In [6], a smart dresser named DRESS (Development of a Responsive Emotive Sensing System) assisted people with memory loss to get dressed through audio and visual prompts. The dresser had a motion sensor on top of it to identify when the user was close by. Once the user’s presence was detected, an iPod Touch attached to each drawer would help the user pick the drawer with the clothing item using different colors on the screen. RFID tags were embedded in the clothing to trigger the clothing guidance process when the receiver located in the drawer detected movement of the tag. A Kinect sensor was used to identify a user dressing through skeletal tracking, and fiducial markers were used to identify if clothing was worn correctly or incorrectly. The fiducial markers were attached on the clothes and a camera was placed on the dresser facing the user. A skin conductivity sensor within a wrist or leg band worn by the user would measure his/her frustration.

Our proposed novel Clothing Perception System consisting of an RGB-D sensor and clothing embedded with smart sensors can address a number of the limitations of existing systems. It can directly monitor the dressing ADL and detect common dressing mistakes. It can also be integrated with different types of clothing including those with complex color patterns, as it does not depend on color segmentation as in [5]. The sensors embedded in clothing are not visible outside the clothing and the deformation of the garment does not affect the performance of the sensors during detection as in [6], which relies on fiducial markers.

B. Smart Textiles

The goal of smart textiles is to add sensing ability into flexible composite materials with the ability to respond to different environmental stimuli accordingly [16]. Smart textiles can be developed from a variety of methods. For example, resistive or piezoresistive based sensors are commonly used in motion or gesture monitoring [17], while capacitive based sensors can be used for heart rate or electrocardiogram (ECG) monitoring applications [18].

Smart textiles have been employed for ADLs such as walking, grooming, and household chores [19]. They have also been used for health monitoring, including fall detection for older adults [20]. To the best of the authors’ knowledge, this is the first application of smart textiles for monitoring and assisting the dressing ADL. The capacitive sensors and contact switches developed in this work, as well as the infrared (IR) LED, are non-visible since they are embedded into the clothing directly, which improves user comfort while minimizing the impact on the overall clothing appearance.

III. CLOTHING PERCEPTION SYSTEM FOR DRESSING

Identifying if a person has correctly worn a clothing item is not a trivial task, due to clothes being highly deformable and potentially having dense features. In this work, we propose the unique combination of smart sensors and an RGB-D sensor, which are robust to these deformations and varying patterns on clothes, in order to detect dressing states. Our proposed approach: (i) does not rely on the visual detection of the clothes using image processing; and (ii) unlike fiducial markers, does not change the overall appearance of the clothing. The objective of our clothing perception system is to determine the following clothing states:

1. **Correctly Worn**: the clothing is put on forwards with all buttons in the corresponding buttonholes.
2. **Partially Worn**: one or both arms are not in through the sleeves and/or one or more buttons are either not fastened or not in the corresponding buttonhole.
3. **Backwards**: the clothing is worn backwards, with its back at the front of the person.
4. **Inverted**: the clothing is worn inside out.

To determine these clothing states, we have designed a multi-modal sensing system consisting of capacitive sensors, contact switches, and an IR LED embedded in clothes. The sensors and the LED are managed by an ESP32 IoT board, which enables the smart clothes to communicate, via Wi-Fi, sensory information to the robot. The ESP32 consists of a microcontroller designed by Espressif Systems. This microcontroller is ideal for use in wearable electronics due to its multi-functional capabilities such as onboard wireless communication, low power usage, and compact size. The RGB-D sensor is also used to determine when a person has finished dressing based on their movements.

A. Capacitive Sensors

The capacitive sensor in our system (ESP32) detects touch by forming a capacitor when a connection is established.
between the corresponding pin and human skin. The chip is designed to supply a pre-set current from its “sourcing” pin and charging the “receiving” pin to a predetermined voltage. When the “receiving” pin reaches a pre-defined voltage (fully charged by the “sourcing” terminal), the sourcing current stops, and the internal capacitor discharges [21]. ESP32 defines this full “charge-discharge” sequence as one cycle. When human skin touches the electrode of the ESP32, a capacitance is formed between the ESP32 and the skin, and overall capacitance increases. Due to the increase in capacitance, a longer charging cycle is required to fully charge the “receiving” terminal. The number of charging cycles that occur can be counted to determine whether the ESP32 is in contact with skin or not (i.e. 22 charging cycles and above represent the ESP32 is not in contact with the skin). A drop in the number of cycles to 18 or below indicates that skin contact has occurred [21].

The ESP32 has built-in capacitive touch sensors that can be used to identify correct, partial and inverted dressing through the placements of electrodes on the clothing based on skin contact. When the clothing is correctly worn, higher charging cycles from the capacitive sensors infer that the skin is not in contact with the sensor. Therefore, if a limb is not present in a sleeve, then a partial dress can be inferred since there is no contact with the skin and the sensor would read more charging cycles. We aim to incorporate an electrode for the sensor to minimize discomfort and so the wearer does not notice that it is present. Therefore, we designed a conductive stainless-steel fiber that can be embedded or sewn within the clothing to function as the electrode for the capacitive sensor. The fiber’s length also increases the contact area with the skin, providing a more significant change in the measured capacitive signal.

B. Contact Switches

Buttons are commonly found on clothing articles to serve as a fastening mechanism. They require dexterity to attach. Although buttons can be treated as a binary system (either fastened in a buttonhole or not), it is possible that a mismatch can occur (a button is fastened in an incorrect buttonhole). In order to identify the state of the button, a mechanical contact switch was developed by wrapping a conductive copper wire around a buttonhole with a copper film placed at the back of the button. A 3.3V potential is applied to the button. Once a button is fastened into the buttonhole, the system will detect a short circuit which will produce an increase in signal intensity in the output voltage.

To identify the fastening state of each button and buttonhole, a sequential process is applied to check the output voltage at each buttonhole. In the case where a button is fastened correctly (i.e. button 1 is in buttonhole 1), a 3.3V potential would be read at buttonhole 1, since a 3.3V potential was applied to button 1 and a short circuit between the button and buttonhole exists. On the other hand, if buttonhole 1 does not produce a 3.3V signal, then a partial dressing state has occurred since no short circuit between button 1 and buttonhole 1 is present. If a pin connected to another buttonhole that is not buttonhole 1 yields 3.3V, then the dressing state can be further classified as a mismatch.

C. RGB-D sensor

An 850nm IR LED is embedded in the front of the clothing item. The IR camera of a Microsoft Kinect sensor is used for detecting the LED to determine if it is worn frontwards. A blob detector is used to identify white blobs from the images. If a blob is not detected, the clothing is considered to worn backwards or inverted.

Motion detection is also performed to determine when the dressing activity is completed in order to verify the clothing state based on the smart sensors. This is achieved by utilizing depth images provided by the Kinect sensor with the OpenNI and NITE software frameworks [22]. The 3D skeleton of the person is detected using the following 15 joints: head, neck, torso center, and left/right shoulder, elbow, hand, hip, knee and foot. The 3D coordinates (x, y, z) of each joint of the detected person is obtained. The displacement $d_i$ of each joint $i \in [1,15]$ in sequential frames (using 10 fps) is determined:

$$d_i = \|P_i^f - P_i^{f-1}\|,$$  \hspace{1cm} (1)

where $P_i^f$ denotes a 3D vector with the (x, y, z) coordinates for joint $i$ in the current frame $f$, and $P_i^{f-1}$ denotes the 3D vector for joint $i$ in the previous frame. If one or more joints have a displacement $d_i$ higher than a given threshold $\theta$ we consider that the person is moving. Herein we utilize $\theta = 0.05$ m, so that small movements or sensor noise would not affect the detection. This value was obtained empirically.

IV. IMPLEMENTATION

To demonstrate and evaluate the Clothing Perception System for dressing, we integrated the smart sensors into a collared golf shirt with three buttons, Figure 2(a). The IR LED is integrated into the front of the shirt (Figure 2(b) and (d)). To identify the four possible dressing states, three stainless-steel conductive fibers were stitched into the shirt: one at the back and one on each of the sleeves (Figure 2(c) and (e)). The fiber was also stitched around each buttonhole (Figure 2(f)). A copper wire was stitched around the buttons, and a copper film was attached to the back of the buttons (Figure 2(g)). The conductive fibers are directly connected to a microprocessor (ESPRESSIF ESP32-WROOM-32D) that receives the sensor readings and performs the classification. For this particular clothing item, the detection of the four dressing states follows the conditions presented in Table I.

![Figure 2](image-url)

Figure 2. The system implemented on a collared shirt, showing (a) the front of the shirt, (b) an IR image of the LED light, (c) the electrodes on the back and the sleeves, (d) a close-up of the LED attached to the fabric, (e) a close-up of the conductive wire used as electrodes, (f) the conductive thread sewed around the buttonhole, and (g) the button with copper wire and copper film.
V. Experiments

To determine the performance of the Clothing Perception System, we performed: 1) tests on each sensor individually, and then 2) had participants wear the shirt in different configurations for the four different dressing states.

A. Individual Sensor Testing

1) Capacitive Sensor

The capacitive sensors made from stainless-steel thread are defined as follows based on their location: “Back” where the sensor is on the back of the shirt, and “Left” and “Right” for the sensors on the individual sleeves. These sensors can be used to identify all four possible dressing states (correct, partial, inverted, and backwards) as outlined in Table 1. To demonstrate the response of the capacitive stainless-steel thread capacitive sensor, tests were conducted by inserting an arm through both the right and left sleeve with the stainless-steel thread sewn in. We also tested the sensor sewn in the back by putting the shirt on. This procedure is to mimic the contact with the skin when the user is wearing the shirt. The response time of the three capacitive sensors was determined to be 10 ms, which is acceptable for our proposed application. As the results are similar, we present the average number of cycles using the sensor in the right sleeve, Figure 3, to discuss in more detail. In particular, without any skin contact, the average number of cycles is approximately 23 with a standard deviation of 0.72 cycles and a lower limit of 18 charging cycles. This lower limit is used as the minimum threshold to represent the non-contact scenario. As seen in Figure 3, there is a visible drop in the number of cycles when the sensor is in contact with the skin (16 cycles) which is more than 10 standard deviations from the non-contact value.

2) Contact Switches

To evaluate the contact switches on the three buttons of the shirt, they were fastened and unfastened correctly in sequence from button 1 to button 3 and then from button 3 to button 1, respectively. The results are presented in Figure 4. When the three buttons were correctly fastened into buttonhole 1, buttonhole 2, and buttonhole 3, a 3.3V signal can be observed at each of these buttonholes. When they were unbuttoned, and no longer in buttonhole 3, buttonhole 2 and buttonhole 1, the output voltage dropped back to 0V as the short circuit was no longer present.

Lastly, a test was conducted where the buttons and buttonholes were also mismatched. To check if a button was mismatched (i.e., button 1 in hole 3), the 3.3V input was applied sequentially to each button. If the hole did not correspond to the button with the applied voltage, then there was a mismatch. The button mismatch was detected in all trials.

3) RGB-D sensor

To determine if the IR LED could be detected, we placed the shirt at 10 cm distance increments from the Kinetec sensor in order to measure the detected blob radius. Figure 5 shows the change in radius (in pixels) of the white blob detected by the IR camera of the Kinetec sensor. The maximum distance at which the LED is still visible was determined to be 110cm.

B. Wearing the Shirt Tests

Once the individual sensors were tested, we conducted experiments with all integrated sensors for the four states to determine the performance of the Clothing Perception System during the dressing activity. Four participants were asked to wear the shirt in the following six different configurations: (i) correctly; (ii) partial, with the right arm not through the sleeve and all buttons unfastened, (iii) backwards, and (iv) inverted. Each configuration had 4 trials.

The Kinetec sensor was placed 100 cm away from each participant as shown in Figure 6. This enabled the RGB-D sensor to detect both the user skeleton and the IR LED, and was within the detection range for the IR LED.

The results for all participants for the four configurations are presented in Figures 7-10 as boxplots. Figure 7 shows the sensory information for the correctly worn dressing state. As can be seen in Figure 7(a), the output from all three capacitive sensors was below the threshold of 18 cycles, when they were touching the skin of all participants in all trials. In Figure 7(b) all three contact switches had an output of 3.3V as they were fastened correctly by all participants in all trials. The mean radius of the IR LED was 1.5 pixels (σ = 0.1), Figure 7(c).

Figure 8 shows the sensory information for the partially worn dressing state. As shown in Figure 8(a), the outputs of the back and left capacitive sensors are below the threshold, as they were touching the skin of all participants in all trials,
however, the right capacitive sensor’s output is above the threshold, as that sleeve was not used in this state. In Figure 8(b), the three contact switches had outputs of 0V as they were not fastened by all participants in all trials. Figure 8(c) shows that the mean radius of the IR LED was 1.5 pixels ($\sigma = 0.19$).

The results for the worn backwards dressing state are shown in Figure 9. In Figure 9(a), the outputs of the left and right capacitive sensors were below the threshold, as they were touching the skin of the four participants, however the distribution of the back capacitive sensor was above the threshold. The back capacitive sensor did not touch the skin of any of the participants as the high collar of the shirt was touching the participants’ chins and preventing the sensor to touch the skin on their chest. Figure 9(b) presents the 0V output of all three contact switches as they were not fastened. In Figure 9(c), the IR LED was not detected and therefore its detected radius was 0 pixels.

Figure 10 shows the sensory information for all the sensors for the worn inverted state. In Figure 10(a), the outputs of all three capacitive sensors were above the threshold as none of them were touching skin. Figure 10(b) shows the output value of 0V for the contact switches as the buttons were not fastened. In Figure 10(c), the IR LED was not detected and thus its radius was 0 pixels.

Figures 11-14 show the sensory output over time during an entire dressing activity of a single participant for each of the four configurations. Figure 11 shows the sensory outputs for the correctly worn dressing state. At first, the participant puts the shirt on with torso and left arm in. This action was completed at time A, where the values for both the Back and Left capacitive sensors were below the threshold of 18 cycles. After that, the participant put the right arm through the right sleeve. This action was completed at time B, where the value for the Right sensor dropped to below the threshold. Then, the participant started buttoning the three buttons correctly, which were buttoned at times C, D and E, respectively. At time F, the LED was detected with a mean radius of 1.5 pixels. After time F, the system determined that the shirt was worn correctly based on the sensory information.

Figure 12 presents the sensory outputs during a trial for the partially worn dressing state. The participant put on the shirt without putting the right arm through the sleeve. This action finished at time A, where the values for both the Back and Left capacitive sensors dropped below the threshold. After time B, the LED was detected with a mean radius of 1.4 pixels, and the system determined that the shirt was worn partially.

Figure 13 shows the outputs during a trial for the worn backwards dressing state. First, when the user put the shirt on backwards, finishing the action at time A, the capacitive sensors in both sleeves dropped below the threshold. At time B, no LED was detected. After time B, the system detected that the shirt was worn backwards.

A trial demonstrating the inverted dressing state is shown in Figure 14. The participant finished putting on the shirt at time A, where the output of the capacitive sensors dropped from the initial values but were still higher than the threshold value. At time B, the IR LED was not detected as it was facing towards the body of the participant. After time B, the system correctly classified the shirt as being inverted.

VI. CONCLUSIONS

The novel Clothing Perception System for dressing presented in this paper uniquely combines smart clothing and an RGB-D sensor to detect dressing different dressing states. Contact switches and capacitive sensors were developed and integrated along with an IR LED into a shirt for proof-of-concept testing. Experimental results showed that the system was successfully able to repeatedly detect the four target dressing states (correctly worn, partially worn, backwards and inverted). Our future work will consist of implementing the system with our assistive robot.
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Figure 11. Sensory outputs for the Worn Correctly Dressing State.

Figure 12. Sensory outputs for the Worn Partially Dressing State.

Figure 13. Sensory outputs for the Worn Backwards Dressing State.

Figure 14. Sensors outputs for the Worn Inverted Dressing State.

REFERENCES


