

Monitoring Dressing Activity Failures through RFID and Video

A. Matic¹; P. Mehta²; J. M. Rehg²; V. Osmani¹; O. Mayora¹

¹Ubiquitous Interaction Group, CREATE-NET, Trento, Italy;

²Health Systems Institute and GVI Center, School of Interactive Computing, Georgia Institute of Technology, Atlanta, GA, USA

Keywords

Pervasive healthcare, monitoring activities of daily living (ADL), assessing dressing activity

Summary

Background: Monitoring and evaluation of Activities of Daily Living in general, and dressing activity in particular, is an important indicator in the evaluation of the overall cognitive state of patients. In addition, the effectiveness of therapy in patients with motor impairments caused by a stroke, for example, can be measured through long-term monitoring of dressing activity. However, automatic monitoring of dressing activity has not received significant attention in the current literature.

Objectives: Considering the importance of monitoring dressing activity, the main goal of this work was to investigate the possibility of recognizing dressing activities and automatically identifying common failures exhibited by patients suffering from motor or cognitive impairments.

Methods: The system developed for this purpose comprised analysis of RFID (radio frequency identification) tracking and computer

vision processing. Eleven test subjects, not connected to the research, were recruited and asked to perform the dressing task by choosing any combination of clothes without further assistance. Initially the test subjects performed correct dressing and then they were free to choose from a set of dressing failures identified from the current research literature.

Results: The developed system was capable of automatically recognizing common dressing failures. In total, there were four dressing failures observed for upper garments and three failures for lower garments, in addition to recognizing successful dressing. The recognition rate for identified dressing failures was between 80% and 100%.

Conclusions: We developed a robust system to monitor the dressing activity. Given the importance of monitoring the dressing activity as an indicator of both cognitive and motor skills the system allows for the possibility of long term tracking and continuous evaluation of the dressing task. Long term monitoring can be used in rehabilitation and cognitive skills evaluation.

impairing the independence of an individual's life. One of the most common causes is aging. According to the statistics of AoA (Administration of Aging) [2], by 2030 the number of older persons over 65 years is projected to be around 71.5 million only in the US. This is an increase of more than twice in comparison to the year 2000. Also, it is estimated that half of the elderly have some cognitive problems, while half of the elderly over the age of 85 exhibit symptoms that characterize Alzheimer's disease to varying degrees [3]. However, ADL impairments are not necessarily the consequence of an old age; diseases such as stroke or accident-related paralysis affect people of any age, impairing their motor skills and consequently affecting ADL. Therefore, it is important to monitor the performance of ADL of affected persons after an event that has resulted in such impairment. For example, the nursing homes that receive Medicare funds in the US must record and report the ADL performance of patients [4]. Due to the increasing prevalence of the diseases that affect ADL, healthcare institutions are struggling with the increasing care provisioning demand and shortage of specialists and caregivers. Adding to these costs is the requirement for long-term monitoring of patients in order to adjust the course of therapy, follow the progression of disease, or investigate the speed of recovery (e.g. after stroke [5]).

These issues have prompted healthcare institutions to investigate various cost-cutting strategies. In this respect, one promising direction is exploiting the opportunities provided by new information and communication technologies [26]. Arrnrich et al. [24] emphasized the importance of pervasive, continuous and reliable long-term monitoring systems, providing a direction for the future research. Significant results have been obtained in the development of smart environments for moni-

Correspondence to:

Aleksandar Matic
Ubiquitous Interaction Group
CREATE-NET
via alla Cascata 56/D
38123 Povo, Trento
Italy
E-mail: aleksandar.matic@create-net.org

Methods Inf Med 2011; 50: ■-■

doi: 10.3414/ME10-02-0026

received: May 25, 2010

accepted: December 1, 2010

prepublished: ■■■■

1. Introduction

Demographic changes in the developed world and current trends in the developing world are pointing towards a future where the number of elderly will increase significantly. The diseases that increasingly affect this population group are often associated

with impairment of cognitive abilities and increased difficulty in performing the activities of daily living (ADL). ADL is a term that incorporates the basic tasks of everyday life such as eating, bathing, toileting, dressing and other common every-day activities [1]. There are a number of causes that affect the ability to perform ADL, thus

toring hand washing [6, 7], cooking [8], and taking medications [9]. However, the task of monitoring dressing progress and failures, which is a basic daily activity, has not received the attention that it deserves. Walker et al. [5] argue that dressing is a complex skill, important for the successful rehabilitation of stroke patients, and that it should be monitored continuously for many years. This is because there is a correlation between cognitive factors and dressing ability that can provide valuable information about the state of a patient's cognition. Moreover, the assessment of variations in patterns of daily activities, including dressing of elderly, and capturing patterns of change over time, are very important since they can be indicative symptoms of early dementia or can be used to measure the progress of the disease [10].

Typical practices in monitoring dressing activities involve therapists periodically taking notes while the patient performs the dressing steps [11, 12]. This has three considerable disadvantages: i) dressing is a very personal and private activity and carrying it out in front of another person is often uncomfortable and unpleasant; ii) note taking is not only error prone (due to the tiredness of the therapist, for example), it is also subjective, creating difficulties in comparing the notes when different therapists assist the same patient; iii) the presence of therapists can result in inconsistencies between the recorded performance of the activity and performance of the same activity carried out in the patients' usual environment, such as their home. This is because patients and especially the elderly will invest extra effort to carry out the activity correctly, and thus vindicate their independence, as was demonstrated in a study by Brown et al. [13].

In response to these issues, we have addressed the challenges in monitoring the dressing task, thereby enabling support for long-term assessment, through the use of two different technologies, namely computer vision and radio frequency identification (RFID). In our design, the two technologies act in a complimentary manner, addressing the challenge of monitoring different aspects of a dressing task. The challenge relates to the fact that the set of dressing failures exhibited by patients cannot be reliably recognized with a single technol-

ogy working in isolation. The set of most common failures relate to i) putting clothes in an incorrect order (such as t-shirt over a jumper) [14], ii) putting on clothes partially (such as only one sleeve or one trouser leg is in) [5], iii) putting on clothes backwards or the other way around (inner part of a garment is on the outside or when trousers' zipper is on the back) [15], iv) putting on too many layers of clothing and not adjusting garments with the temperature [14] and v) putting on clothes on the wrong part of the body (for example pants instead of shirt) [14]. In conjunction with identifying dressing failures, it is also important to recognize when the correct dressing is performed as well.

A key requirement for a dressing monitoring system is to be unobtrusive, especially with regards to visible and wearable sensors (such as wrist worn devices). This is because wearable devices may influence the dressing activity and also because patients with dementia may tend to remove foreign objects. Therefore, in our system we have aimed to fulfil the requirements for an unobtrusive system, while achieving a high recognition rate both for correct dressing events and dressing failures.

The paper is organized as follows. Section 2 reviews the related work in the domain of smart environments intended for monitoring ADL. Our approach and description of the experiments are provided in Section 3 and 4 respectively. Finally, we discuss the future work and draw the main conclusions.

2. Related Work

The performance of a patient in the dressing task is often studied in medicine. Walker et al. [10] investigate how dressing is affected during the rehabilitation after a stroke. They emphasize the types of failures as important parameters for determining relations between the nature of cognitive impairment and dressing ability. Dressing performance is analyzed very often in patients that suffer from Alzheimer's disease or other types of dementia (e.g. [11, 12]). Feyereisen et al. [11] claim that there is both clinical and theoretical support for the

importance of studying Alzheimer's patients' ability to perform the dressing task, since it is cognitively demanding and organised along a hierarchical plan with some repetitions of the same movement. They confirm that the impairments of dressing are quite common in patients suffering from dementia and they identify critical steps in the dressing task and perform a qualitative analysis of failures depending on the level of disease. Sometimes it is possible to restore dressing independence [16] for Alzheimer patients, which also underlines the importance of monitoring that task. These works, as well as current practices, still rely on therapists to evaluate the patient's performance in person or sometimes subjects are recorded and video is analyzed by specialists (e.g. in [5]).

Numerous previous works have addressed the goal of monitoring ADLs in order to assess the subject's performance or to assist them in accomplishing tasks properly. Cook and Schmitter-Edgecombe [25] assessed the quality of the five activities: telephone use, hand washing, meal preparation, eating and medication use, and cleaning. The approach was tested using data collected from 60 volunteers and the results showed correct labelling and assessing the performed task regarding the completeness and consistency. Cooking, as one of the most common household tasks, is addressed in [8]. This project provides assistance during the cooking process by showing snapshots of recent actions on a display positioned in the kitchen. The system acts as a memory aid and was shown to be helpful when subjects with memory problems were interrupted while performing the task. Wu et al. [17] presented an approach to activity recognition based on object use that minimizes the amount of human-labelled data required for modelling. The combination of vision and RFID technologies is tested in a kitchen scenario and it achieves a recognition rate of 80% in 16 activities with 33 objects. The system described in [7] addresses the problem of recognizing steps in hand washing using video processing, with the main goal of assistance. Applying Hidden Markov Model (HMM)-based approach, an activity recognition rate of 79% is achieved. In their work on MedTracker [9], Hayes et al. developed

an electronic pillbox that continuously monitors the medication-taking process over a certain period.

Previous research in ADL has primarily focused on inferring which activity is carried out at any given time. It has not addressed the evaluation of the performance of an activity.

One of the turning points in the field of inferring ADL is the project described in [4]. It addresses the recognition of 14 everyday activities based on the objects used, employing an RFID reader embedded in a glove while the characteristic objects for these tasks are tagged. The system reports not only the most probable activity but also the quality of performance to a certain extent, such as if a subject is wearing the same clothes each day. Dalton et al. [18] evaluate the accuracy of ADL identification using wireless kinematic sensors depending on their position and on the manner of data processing. For the case of placing sensors on the ankle and hip, recognition rate is 81.2%. The authors report dressing among the recognized activities. Using support vector machines (SVM) and the data acquired from infrared sensors, microphones, door contact sensors, webcams and accelerometers, the design [19] also recognizes when a subject performs dressing/undressing in addition to six other daily activities. Ten ADLs are recognized in [1] using the fusion of RFID and accelerometers.

In the current literature there are no systems capable of monitoring the dressing task in detail, with the aim of distinguishing between the failure modes of this activity and correct dressing. However, there have been several papers in computer vision which concentrate on the problem of person detection. The work described in [16], for example, addresses the problem of estimating body shapes underneath clothing. The authors in [20] study the feature sets required for robust visual object detection, with human detection as a test case. In [21], the authors try to estimate the shape of clothing from images of the clothing. A network of cameras is used to analyze the fit of clothing on a person in [22]. The work presented in [23] is interesting in that it describes a method for segmenting clothes in an image using a set of examples. This method could be used to improve the re-

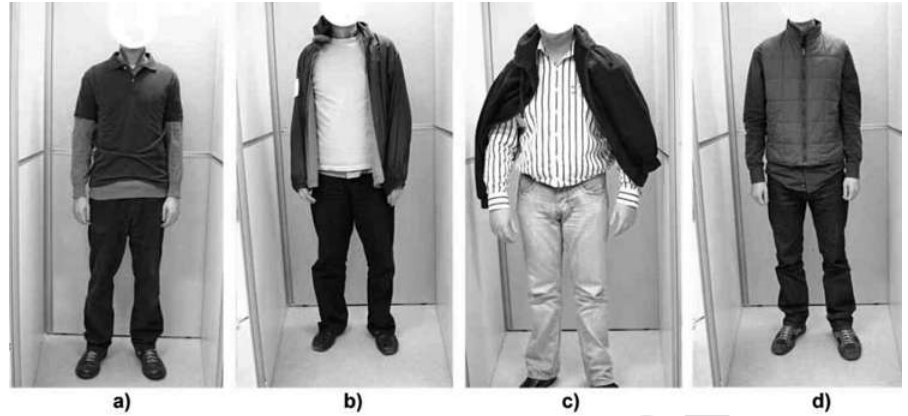


Fig. 1 Common failures in dressing activity (upper garments)

sults of segmentation in our work. In contrast to the aforementioned projects, our system provides the evaluation of the dressing task and it is capable of recognizing dressing failures along with correct dressing.

3. Our Approach

The aim of our project is to non-intrusively recognise the steps involved in a dressing task and evaluate the correctness of dressing activity. The most common dressing failures that occur with patients are described below:

- **Putting on clothes in the wrong order**
Patients with dementia are often confused with regard to the kind of garments that they are wearing; and thus put them in the wrong order, such as t-shirt over a jumper or a jacket (► Fig. 1a).

- **Putting on clothes backwards or other way around**

Another common failure in a dressing task is putting garments on backwards, where the inner part of the garment is on the outside or the other way around, where the front side of the garment is on the back side of the body. The first case, for instance, often arises when patients take off their clothes and try to put them back on again (► Figs. 1b, 2c).

- **Putting on clothes only partially**

Stroke patients, in particular, have difficulties with putting the clothes on properly. The failure is exhibited through failing to put the paretic hand or leg through the correct sleeve or trouser leg. In that way, they end up with a garment only partially worn (► Figs. 1c, 2a, 2b).

- **The number of layers of clothing is not appropriate for the temperature**
Judgment of warm and cold weather is

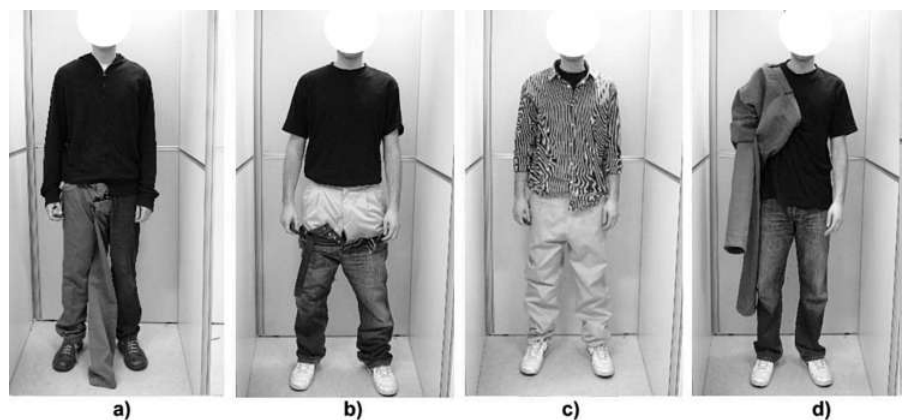


Fig. 2 Common failures in dressing activity (lower garments)

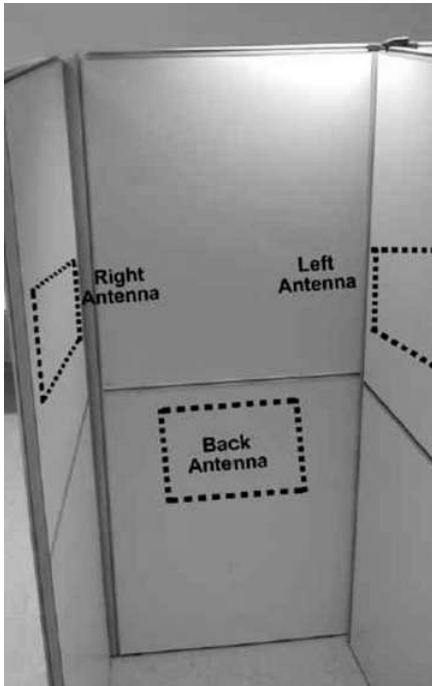


Fig. 3 Dressing booth denoting the position of hidden RFID antennas

impaired in dementia patients. As a consequence, these patients may put on too many or too few layers of clothing (► Fig. 1d – e.g. indoor temperature).

- **Putting on clothes on the wrong part of the body**

Patients may get confused as to which part of the body a garment should be put on, thus attempting to put a cloth on the wrong part of the body (► Fig. 2d).

The above failures are visually illustrated by experimental examples shown in ► Figures 1 and 2. Note that Figures 2a and 2b show putting pants on partially while having another set of pants on. This was done to



Fig. 4 RFID tags used in our experiments

preserve the privacy of participants in our experiments. In terms of experiments, this will be equivalent to the case of putting on pants on bare skin (since no human observer will be present).

Vision or RFID working in isolation can be used to detect specific types of failures but have proven to be insufficient to recognize all of the failures reliably. Therefore, we fuse the information from vision with information coming from RFID tags in order to detect a failure and identify its type.

3.1 Experimental Setup

Our setup is illustrated in ► Figure 3. The dressing booth had dimensions of 1m by 1m and in our experiments its size was large enough to allow ample space for all the maneuvers necessary to perform dressing in a natural manner, as evidenced by the subjects that took part in the experiments. Two RFID antennas are positioned on each of the side walls and one on the back wall, 140 cm and 90 cm from the ground, respectively. A video camera positioned at the entrance of the dressing booth recorded image sequences as the dressing activity was taking place. The subject's face was automatically blurred, to address privacy concerns.

Upper garments are tagged inside on the shoulders and on the lower part of the back. We chose the lower part of the back for two reasons; first, to avoid possible interference between adjacent antennas and second, to increase the recognition rate of correct dressing since the back of garments cannot be checked by the vision system, due to the camera position. Lower garments, such as pants were tagged on front side near the zipper and on the back side below the belt. In the sections that follow, we provide a description of the RFID and the vision setup.

3.2 Monitoring of Dressing Activity with RFID

Given the wide variety of RFID tags, which come in a wide range of shapes and sizes, we could easily identify ones that are small, non-intrusive, and almost invisible to our

subjects (► Fig. 4). In our experiments, we have used an RFID system that works on 13.56 MHz with passive tags (► Fig. 4) and antennas with a reading range of approximately 30 cm. RFID antennas and associated hardware were hidden behind the dressing booth, thus our setup was free of observable sensors to allow as natural behavior as possible.

While some patients will dress correctly, others attempting the dressing activity will exhibit a number of failures. Individual failure categories along with the correct dressing are described below.

3.2.1 Upper Garments

3.2.1.1 Putting on a Garment Correctly

The mechanism for recognizing the dressing steps is based on detecting the tags attached to the shoulders and the back, once they are in the range of corresponding antennas (► Fig. 3). When a person is facing the entrance of the dressing booth and a garment is put on properly, the right shoulder tag, left shoulder tag and bag tag should be detected on the right, left and back antennas respectively. The back tag and only one shoulder tag are enough to detect that the garment is put on properly. However, as expected, we found from the experiments that tagging both shoulders instead of one improves the probabilities of detection of correct dressing.

3.2.1.2 Getting the Order of Garments Wrong

Once we recognise that the garment is put on, it becomes easy to follow the sequence of events to determine the order in which the garments are put on and to infer an eventual failure in the ordering, such as putting a t-shirt over a jumper.

3.2.1.3 Not Adjusting Clothes to Weather Conditions

At the end of the task, the system is aware of which garments have been put on, which in conjunction with the information of weather conditions and simple reasoning, can provide appropriate recommendations if the number of layers is not adjusted properly.

3.2.1.4 Putting on Garments Backwards

Such event is recognized via the RFID system in similar manner to the recognition of correct dressing: the back tag is recognized with back antenna, left shoulder tag with right antenna and right shoulder tag with left antenna when the subject is facing the entrance of the changing room.

3.2.2 Lower Garments

3.2.2.1 Putting on Lower Garments Correctly

Lower garments were tagged on the front and the back side at the same height as the back antenna used to detect back tags of upper garments. When the video system detects the change in the colour of a lower garment (the video algorithm to achieve this is described later) the RFID recognises their orientation by checking if the back tag is in the range of back antenna in the dressing booth. Once the two conditions are satisfied the event is reported as correct dressing.

3.2.2.2 Putting on Lower Garments the Other Way Around

As above, once the video detects the change of lower garments but RFID identifies the front tag in the range of the back antenna, the event is categorized as dressing failure.

3.2.2.3 Too Many Layers Put on

Once the system recognises when a single garment is put on, it is able to follow the sequence of putting on multiple garments. This failure is reported when two (or more) tags corresponding to lower garments are detected in the range of the back antenna at the same time, while video reports the top garment. Our assumption is that having two layers of pants on is considered too many layers; however, clearly this will depend on other factors such as the weather and current season when considering long underwear for example.

The final decision is made when both RFID and Video confirm the aforementioned events. This is done in order to avoid false positives/negatives that may occur due to the limitations of both technologies when working in isolation. Table II presents the system's reports based on what RFID

and video identify at the same time. For example, putting on pants correctly, other way around or having one or more pants below could look very similar, judging only by appearance. So video reports all these events as correct dressing. In these cases, depending on RFID readings the final report is made. The failures related to putting lower garments on the wrong part of the body or putting on garments partially are addressed solely through video processing which will be described in Section D.

3.3 Bayesian Network Model

In order to infer the dressing steps from RFID readings, we developed a simple Bayesian Network model. Nodes "Left", "Back" and "Right" correspond to the RFID antennas as positioned in the changing room. "Left" and "Right" nodes can take "Left tag", "Right Tag" and "Not Detected" states while the node "Back" takes the following states: "Back Tag Detected – Upper Garment", "Back Tag Detected – Lower Garment", "Front Tag Detected – Lower Garment" and "No Tag Detected". This means that the side antennas ignore the readings of back tags and the back antenna ignores the readings of the shoulder tags. In this manner we can filter unintended readings that are not relevant to the dressing task, such as readings captured when a subject is moving inside the changing room or while the subject is holding a garment. "Final State" node decides whether the garment is correctly put on, incorrectly put on or that the garment has not been put on. The probabilities of taking each of these states depend on the states of parental nodes and they are adjusted from training evidence.

Video image recordings provided the ground truth and were taken periodically from the beginning up to the end of the dressing task.

Within the scope of our problem, the most significant limitation of RFID is that it cannot detect a dressing failure when a garment is put on partially (such as a shirt pulled on the neck only) or on the wrong part of the body. This is due to the fact that our RFID antennas cannot compute the distance of the tag from the antenna, thus unable to spatially localise the tag within

required granularity. Therefore, recognising the failure of partially worn clothes is identified with vision processing.

Using RFID technology introduces additional challenges in terms of tagging all of the garments with two or three tags. Depending on the number of garments, this might be a laborious task. However, it needs to be done only once because plastic RFID tags can be used which are water proof and therefore can be washed embedded in the clothes.

3.4 Vision Processing to Identify Type of Failure

In order to address the limitations of RFID, we use clustering of colours and their comparison to detect if a dressing failure has occurred. We take as input a pair of images, one from when the subject comes to the dressing booth in our lab and the other after the dressing activity has completed. As a pre-processing step, we perform clustering of each image on the basis of the colour of clothes and try to identify whether the cluster belongs to the top of the body or the bottom, or to the background. Next, we use a rule-based inference system that performs matching of these colour clusters, and their spatial positions, if needed, to identify if there is a dressing failure or not. This pre-processing is explained next and shown in ► Figure 5.

First, we perform background subtraction to isolate the person from the image. This is done by simply averaging the background images and subtracting them from the image with the foreground. Then, thresholding is performed to obtain a mask for the foreground image. All pixel values lying outside the mask area are made white. Next, we obtain a feature vector containing the RGB values of the colours and their weighed spatial coordinates for input to the k-means clustering algorithm. The number of clusters k is incrementally checked to see if it lies in 3 to 8 by choosing a threshold empirically over which the sum of differences (between the points and clusters) should not lie. Once k-means algorithm is performed, we get an image that is labelled with the different cluster values corresponding to each pixel. This serves as input

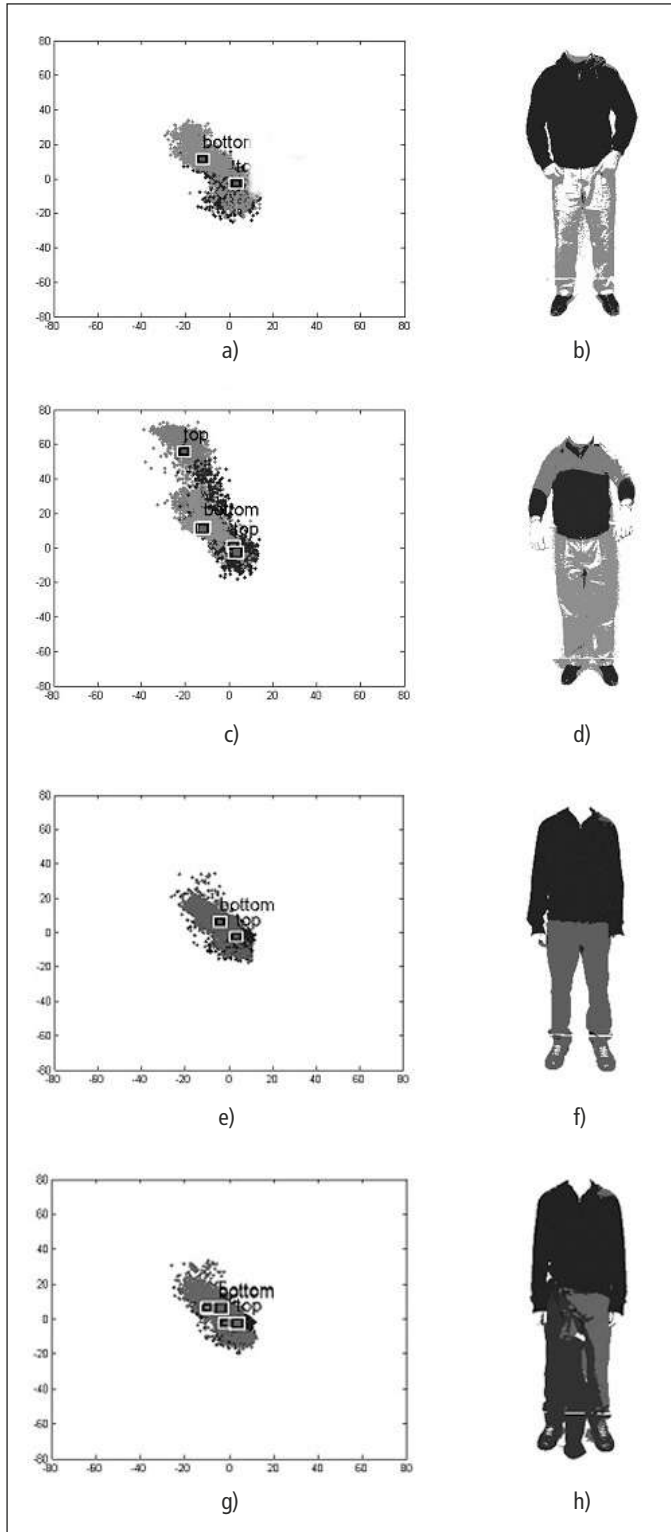


Fig. 5 (a, e) Plot showing color clusters corresponding to before image. (b, f) Image labelled with cluster value and color corresponding to centroids for before image. (c, g) Plot showing colour clusters corresponding to after image. (d, h) Image labelled with cluster value and colour corresponding to centroids for after image

bottom part. If the count in one part for that label value is negligible as compared to the count in the other part, then it is assumed that cluster belongs to the other part with the higher count. Now that we know whether a particular cluster label corresponds to the top or the bottom of the image, we can easily separate the two. We store the count value of each cluster label as well as the part that it corresponds to.

$$K_{match,2}^{before} = \arg \min_k \|C_2^{before} - C_k^{after}\| \quad (1)$$

We match the values of the centroids from the before and after image on the basis of their Euclidean distances, as shown in ▶ Equation 1. The points which have the closest distance between them are said to form a match. A series of empirical checks are then performed on the matched clusters and also with the unmatched clusters. The following list summarizes them.

i) For each group of pixels, if all the centroids match, we check if they have a similar count and whether they belong to the same part. If so, then we conclude that the dressing activity is correct.

ii) For some groups of pixels, if their centroids match but their counts differ by a large amount, then this is classified as a partial dressing failure. A real world analogy to this would be wearing an unzipped jacket initially, so that you can see some parts of the colour of the t-shirt underneath but largely the jacket colour and then, wearing the jacket partially, as a result of which the t-shirt colour is more visible.

iii) For some groups of pixels, if their centroids are unmatched in both the before and after cases, but they are similar in count and belong to the same part, we can say that one colour completely replaces another colour afterwards. This is possible in number of cases – if a new layer is worn on top of the already existing layer and it completely hides the one underneath it, or just the opposite- a layer, which completely hid the layer underneath, is not worn now. It is also possible that such layers of clothes are just worn out of order.

iv) If the centroid for a group of pixels remains unmatched in the before image, we check to see if the number of pixels belong-

to the spatial analysis phase. We define a horizontal line through the middle of the image to differentiate between the top and the bottom parts of the image. In order to determine uniquely which cluster corre-

sponds to what part, the following approach is used: i) Clusters corresponding to the white color are background clusters and ii) count of a label is used to resolve the conflict of whether it belongs to the top or

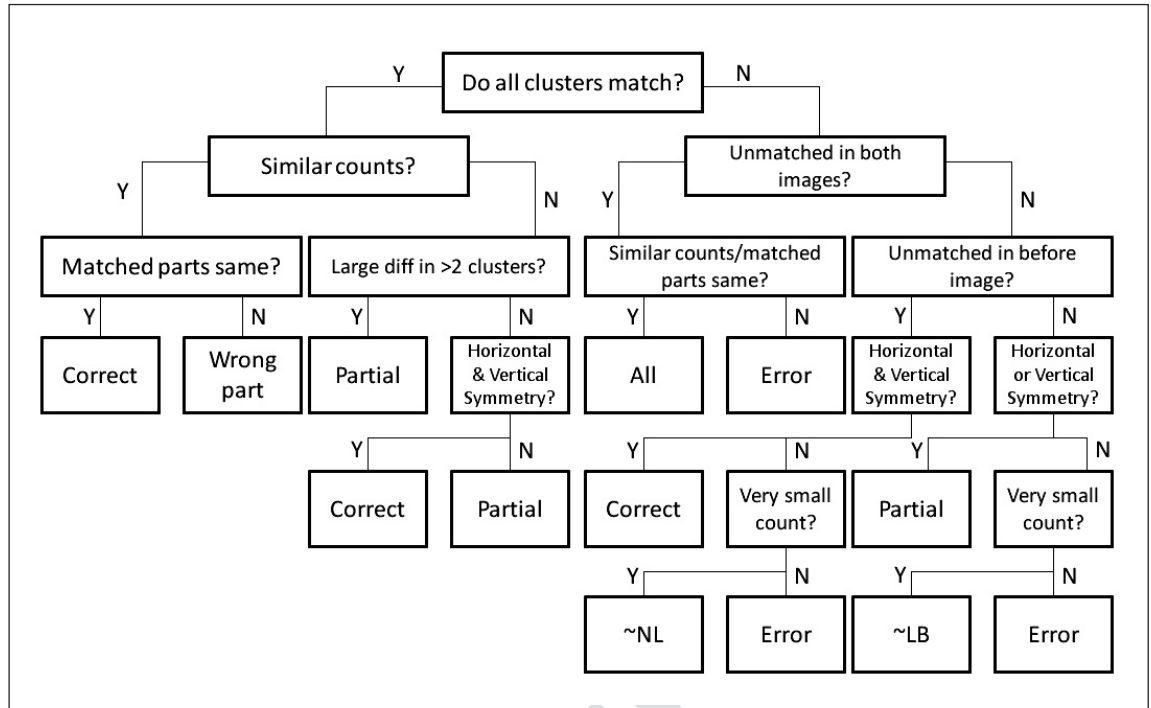


Fig. 6 Decision tree depicting inference system for cluster color comparison

ing to that group is much less. This would be the case when some headgear which contributes a small amount of a different colour is worn initially but is not worn later on. This would also be the case when a shorter outerwear is worn on top of a longer innerwear in the earlier case and then later on the order of wearing them is reversed. Thus, we can conclude from these tests that a layer is either left behind or it is out of order, that is, a new layer has not been added.

v) In case the unmatched group of pixels from the earlier image has a sizable count, we check their spatial position. If the dominant colour that is matched in both the before and after images has horizontal and vertical symmetry, this can be classified as correct dressing. This case can be visualized as a person wearing a partly zipped jacket initially, as a result of which we can see a sizeable portion of the inner garment and then later on, he zips up the jacket completely and hence, hides the colour of the inner garment.

vi) If there are unmatched clusters in the after image, we check spatially whether they have horizontal or vertical symmetry. If any of these checks fail, it is easy to conclude that a new garment is being worn but partially.

vii) If, however, the count of the unmatched cluster dominates the count of the matched cluster from the same part, we can assume that a new layer has been added that partly hides the older layer or there is a change in the order of the clothes worn.

► Figure 6 illustrates the various steps of the rule-based inference system. Due to the constraints on the vision system, it is sometimes not possible to exactly show that a failure is present; rather it is easier to show that a particular failure is not present in the input pair. As a result, the leaves of the decision tree in case of incorrect dressing say that the failure is ‘Not a new layer’ (~NL) or ‘Not left behind a layer’ (~LB) or All, which indicates that either there could be a new layer or a layer could have been left behind or the layers are out of order.

Table 1 System’s reports for lower garments

Video	RFID	Report:
Correct dressing	Back tag	Correct dressing
Correct dressing	Front tag	Other way around
Correct dressing	Two or more tags	Too many layers
Partial dressing	Not relevant	Partial dressing
Wrong part of the body	Not relevant	Wrong part of the body

4. Experimental Results

In Sections 1 and 2 we present the results when both parts of the system are tested in isolation using only upper garments. The Section C shows the results for lower garments, for which the monitoring is only realized in the fusion, and the fusion results for upper garments.

4.1 RFID

The RFID design was tested using a t-shirt and jumper tagged on both shoulders and back, winter jacket tagged on left shoulder and back and light jacket tagged on right shoulder and back. As expected, correct dressing of single garment was inferred

Table 2 RFID results

Event Type	Correct Dressing	Wrong Order	Backwards	Unrecognized
Correct Dressing	83.9%	0%	0%	16.1%
Wrong Order	0%	80%	0%	20%
Backwards	0%	0%	83.3%	16.7%
Unrecognized	0%	0%	0%	–

Table 3 Vision results

Event Type	Correct Dressing	Partial Dressing	Wrong Dressing
Correct Dressing	73%	9%	18%
Partial Dressing	0%	100%	0%
Wrong Dressing	14%	0%	86%

10–20% more reliably for three-tagged garments, namely a t-shirt and a jumper in comparison to the light and the winter jackets that had only two tags.

We recruited 11 participants (ten males and one female, of ages between 28 and 40 years) that were not connected to this research study. Overall, 52 activity trials were performed. The participants were asked to choose any combination of clothes they wanted and to perform the dressing task without further instructions; as they would do at home. Initially they performed correct dressing. Then, they were asked to perform two out of three failures (putting on the garments the inside out, in the wrong order or putting garments partially), which were described by the researchers. As noted previously, the RFID system was unable to address the failure of partially putting on a garment; hence fusion is needed.

► Table 1 shows the results of experiments for the RFID system. The last column represents the situations in which the system reported “unrecognized event” when the subjects have put garments in a correct way, backwards or incorrect order.

Table 4 Wrong Dressing results

Event Type	All	~ NL	~ LB
All	100%	0%	0%
~ NL	0%	100%	0%
~ LB	0%	0%	100%

These false negatives were the consequence of missing two tags at the same time. On the other hand, detecting two or three tags on the corresponding antennas at the same moment is unlikely to happen when a garment is not put on (such as when a subject is holding a garment inside the dressing booth), which is confirmed by the absence of false positives in our experiments (last row in ► Table 2).

4.2 Vision

The following table, ► Table 3, shows the confusion matrix generated when testing images for 1) Correct Dressing, 2) Partial Dressing Failure, 3) Wrong Dressing. ► Table 4 is a breakdown of the different cases related to Wrong Dressing.

We have used 30 image pairs for verifying our algorithm. The survey of images brings forth the following limitations in the method used. The background subtraction algorithm is very naïve, and can fail when the clothing is similar in color to the background. It is also sometimes difficult to distinguish between clusters of two colors when they are proximal in value and spatial position. Moreover, garments with multiple colors or having complex patterns will make it difficult to perform matching and failure detection. Clothes with various color patterns will generate almost as many clusters as each individual color in both before and after cases. Although we have not

tested this hypothesis experimentally, we believe that this should not affect the matching algorithm. The results of colour clustering may be affected by the surrounding lighting variations, as a result of which the spatial position ($\langle x, y \rangle$ coordinates) of the color pixel are also considered for clustering. Also, since exact color match is not required, color clusters closest to each other are considered while matching instead of looking for an exact match.

4.3 Fusion of RFID and Vision Processing

► Table 5 presents the confusion matrix for the fusion of RFID and vision observations when monitoring dressing of upper garments is addressed while ► Table 6 shows the results for lower garments. Recognition of the case of putting garments on backwards or other way around cannot be done without RFID, while the failure of putting on the garment partially or on wrong part of the body can only be detected through vision processing. This was the motivation for the joint development and integration of the two systems. The results for correct dressing and wrong order detection for upper garments further illustrate the complementary nature of the two systems. The fusion provides 10% higher recognition rate for inferring the wrong order of dressing in comparison to the RFID system working in isolation, where the overall improvement increases from 83.9% (RFID) and 73% (Vision) to 93.5%.

5. Conclusion

We have demonstrated that the fusion of RFID and vision processing systems can reliably detect a number of common failures in dressing experienced by patients with various impairments. Some of the failures can only be identified with one of the two systems, thus making the fusion a requirement, while for the failures that both systems are capable of recognizing, the experimental results showed an appreciable improvement in the recognition rate. As a result, we achieved a robust system to monitor the dressing activity. The system pro-

Table 5
Fusion results (upper garments)

Event Type	Correct Dressing	Wrong Order Dressing	Backwards Dressing	Partial Dressing	Un-recognized
Correct Dressing	93.5%	0%	0%	0%	6.5%
Wrong Order Dressing	0%	90%	0%	0%	10%
Backwards Dressing	0%	0%	83.3%	0%	16.7%
Partial Dressing	0%	0%	0%	100%	0%
Unrecognized	0%	0%	0%	0%	–

vides a platform to provide assistance to patients experiencing dressing difficulties. For example, it can warn a subject about dressing failures through voice feedback. In addition, it allows for the possibility of long term tracking of eventual changes in dressing performance, which can be used as indicators in the evaluation of the overall cognitive state.

The fusion of RFID and the video analysis proved to be an effective solution for monitoring activities of daily living such as the case of our system for recognition of dressing steps or the design for monitoring kitchen activities [17]. In the future work, we will investigate other potential domains of monitoring everyday behaviour where our system can be successfully applied.

Acknowledgments

The research was funded by the Autonomous Province of Trento, Call for proposal Major Projects 2006 (project ACube). A portion of this research was supported in part by NSF Award 0916687. Authors would like to thank volunteers for their time in participating in our experiments.

Table 6
Fusion results (lower garments)

Event Type	Correct Dressing	Other way around	Partial dressing	Wrong part of the body	Un-recognized
Correct Dressing	80%	0%	0%	0%	20%
Wrong Order Dressing	0%	70%	0%	0%	30%
Backwards Dressing	0%	0%	100%	0%	0%
Partial Dressing	0%	0%	0%	100%	0%
Unrecognized	0%	0%	0%	0%	–

References

- Stikic M, Huynh T, Laerhoven KV, Schiele B. ADL Recognition Based on the Combination of RFID and Accelerometer Sensing. *PervasiveHealth 2008. Proceedings of the 2nd International Conference on Pervasive Computing Technologies for Healthcare*; 2008.
- www.aoa.gov (Internet). Administration of Aging; (cited 2009 November 9).
- Morris M, Lundell J, Dishman E, Needham B. New Perspectives on Ubiquitous Computing from Ethnographic Study of Elders with Cognitive Decline. *UbiComp'03: Proceedings of the 5th International Conference on Ubiquitous Computing*; 2003.
- Philipose M, Fishkin K, Perkowitz M, Petterson D, Fox D, Kautz H, et al. Inferring Activities from Interactions with Objects. *Proceedings of the 2nd International Conference on Pervasive Computing*; 2004.
- Walker CM, Sunderland A, Sharma J, Walker MF. The impact of cognitive impairment on upper body dressing difficulties after stroke: a video analysis of patterns of recovery. *J Neurol Neurosurg Psychiatry* 2004; 75: 43–48.
- Peters C, Wachsmuth S, Hoey J. Learning to recognise behaviours of persons with dementia using multiple cues in an HMM-based approach. *Proceedings of the 2nd International Conference on Pervasive Technologies Related to Assistive Environments*; 2009.
- Mihailidis A, Carmichael B, Boger J. The Use of Computer Vision in an Intelligent Environment to Support Aging-in-Place, Safety, and Independence in the Home. *IEEE Transactions on Information Technology in Biomedicine* 2004; 8 (3): 238–247.
- Mynatt ED, Melenhorst AS, Fisk AD, Rogers WA. *Aware Technologies for Aging in Place: Understanding User needs and Attitudes. Proceedings of the 2nd International Conference on Pervasive Computing*; 2004.
- Hayes TL, Hunt JM, Adami A, Kaye JA. An Electronic Pillbox for Continuous Monitoring of Medication Adherence. *Proceedings of the 28th IEEE EMBS Annual International Conference*; New York City, USA; 2006.
- Kaye J. Home based technologies: A new paradigm for conducting dementia prevention trials. *Alzheimer's&Dementia, The journal of the Alzheimer's Association*. 2008; 4 (1 Suppl 1): S60–66.
- Feyerisen P, Gendron M, Seron X. Disorders of Everyday Actions in Subjects Suffering from Senile Dementia of Alzheimer's Type: An Analysis of Dressing Performance. *Neuropsychological Rehabilitation* 1999; 9 (2): 169–188.
- Namazi K. Dressing independently: A closet modification model for Alzheimer's disease patients. *American Journal of Alzheimer's Disease and Other Dementias* 1992; 7 (1): 22–28.
- Brown C, Moore WP, Hemman D, Yunek A. Influence if instrumental activities of daily living assessment method on judgements of independence. *American Journal of Occupational Therapy* 1996; 50 (3): 202–206.
- Alzheimer's Australia. An Australian Government Initiative. *Dressing – Caring for someone with dementia*; 2005.
- Lyketsos CG, Rabins PV. *Dementia Care Guidelines for Families*, Division of Geriatric Psychiatry and Neuropsychiatry The Johns Hopkins University; 2006.
- Balan AO, Black MJ. The Naked Truth: Estimating Body Shape Under Clothing. *Proceedings of the 10th European Conference on Computer Vision*; 2008.
- Wu J, Osuuntogun A, Choudhury T, Philipose M, Reh G. A Scalable Approach to Activity Recognition based on Object Use. *ICCV 2007: Proceedings of the 11th IEEE International Conference on Computer Vision*; 2007.
- Dalton AF, Morgan F, Loughin GO. A preliminary study of using wireless kinematic sensors to identify basic Activities of Daily Living. *Proceedings of the*

- 30th Annual International IEEE EMBS Conference, Vancouver, British Columbia, Canada; 2008.
19. Fleury A, Noury N, Vacher M. Supervised Classification of Activities of Daily Living in Health Smart Homes using SVM. Proceedings of the 31st Annual International Conference of the IEEE EMBS, Minneapolis, Minnesota, USA; 2009.
 20. Dalal N, Triggs B. Histograms of Oriented Gradients for Human Detection. Proceedings of the International Conference on Computer Vision & Pattern Recognition; 2005. pp 886–893.
 21. Lobay A, Forsyth DA. Recovering Shape and Irradiance Maps from rich dense texture fields. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition; 2004.
 22. Zhang W, Beggole J, Chu M, Liu JJ, Yee N. Real-time clothes comparison based on multi-view vision. Proceedings of the 2nd ACM/IEEE International Conference on Distributed Smart Cameras; 2008.
 23. Gallagher A, Chen T. Clothing Cosegmentation for Recognizing People. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2008.
 24. Arnrich B, Mayora O, Bardram J, Troster G. Pervasive Healthcare: Paving the Way for a Pervasive, User-centered and Preventive Healthcare Model. *Methods Inf Med* 2010; 49 (1): 67–73.
 25. Cook DJ, Schmitter-Edgecombe M. Assessing the Quality of Activities in a Smart Environment. *Methods Inf Med* 2009; 48 (5): 480–485.
 26. Koch S, Marscholke M, Wolf KH, Plischke M, Haux R. On Health-enabling and Ambient-assistive Technologies. *Methods Inf Med* 2008; 28 (1): 29–37.