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Influence of a Loose-Fitting Sensing Garment on Posture Recognition in Rehabilitation

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Abstract— **Several smart sensing garments have been proposed for postural and movement rehabilitation. Existing systems require a tight-fitting of the garment at body segments and precise sensor positioning. In this work, we analyzed errors of a loose-fitting sensing garment on the automatic recognition of 21 postures, relevant in shoulder and elbow-rehabilitation. The recognition performance of garment-attached acceleration sensors and additional skin-attached references was compared to discuss challenges in a garment-based classification of postures. The analysis was done with one fixed-size shirt worn by seven participants of varying body proportions. The classification accuracy using data from garment-integrated sensors was on average 13% lower compared to that of skin-attached reference sensors. This relation remained constant even after selecting an optimal input feature set. For garment-attached sensors, we observed that the loss in classification accuracy decreased, if the body dimension increased. Moreover, the alignment error of individual postures was analyzed, to identify movements and postures that are particularly affected by garment fitting aspects. Contrarily, we showed that 14 of the 21 rehabilitation-relevant postures result in a low sensor alignment error. We believe that these results indicate critical design aspects for the deployment of comfortable garments in movement rehabilitation and should be considered in garment and posture selection.**

I. INTRODUCTION

Novel technical solutions to embed miniaturized sensors and electronics into textiles open a vast spectrum of applications in sports, rehabilitation and personal assistance. In particular, smart garments have a broad potential in activity monitoring of postures and movements in everyday life situations.

A wide number of sensing modalities has been proposed to monitor postures. Several approaches used textile integrated strain sensors [1][2], relying upon the hypothesis, that different postures result in distinguishable elongation patterns. Tognetti et al. [1] investigated a conductive elastomer that shows piezoresistive properties when deformed. The material was applied in a special layout to shoulder, elbow and wrist regions of an upper limb garment for posture classification. Mattmann et al. [2] analyzed a novel elongation-sensitive yarn and classified upper body postures with a tight fitting suit, called Backmanager. Dunne et al. [3] developed a garment-integrated optical fiber for monitoring seated spinal postures. In this work, we follow the approach of Van Laerhoven et al. [4], who demonstrated that on-body acceleration sensing units can be used for a classification of body postures. In order to track motion of body segments, acceleration sensors

have been complemented by gyroscopes and magnetic field sensors in inertial measurement units and integrated, e.g. in the tight-fitting Moven system [5]. Size and power consumption of inertial measurement units still limit their seamless garment integration.

State of the art systems require an accurate positioning of the sensing elements on the body, consequently, tight-fitting garments are used. However, in many practical applications a tight-fitting garment is not feasible. These garments are less accepted by intended wearers, e.g. attaching a tight-fitted garment poses a physical challenge for patients in movement rehabilitation. Moreover, tight-fitting garments require a manual adjustment of the sensor positions to ensure effective operation, and hence expert supervision. The shift to more comfortable everyday garments remains a challenging research, since a fix sensor position in relation to the body cannot be guaranteed. For these systems measurement reliability deteriorates and requires additional adaptivity. We believe, however, that non-tight garments are feasible for particular applications if the trade-offs between fitting and introduced inaccuracies are understood.

In this paper we make the first step towards this goal by analyzing the effect of a smart garment (the SMASH system) on the recognition of postures in rehabilitation. Miniaturized sensor platforms allow us to compare the recognition of skin- and garment-attached sensors in concurrent measurements, without influencing another. We selected seven wearers of different body sizes to vary the garment fitting and quantify the general effect of the garment on posture recognition performance. We analyze 21 shoulder- and elbow-postures individually to identify posture groups that are particularly affected by sensor shifts in non-tight garments.

II. SMASH GARMENT SYSTEM

In this work, we used the Smart Shirt (SMASH) for analysis. The SMASH is a posture and movement sensing platform, integrated into a non-tightened upper body garment [6]. It was designed to sense and process data on-body and, moreover, to provide appropriate real-time feedback for movement rehabilitation or sports coaching.

SMASH is implemented in a hierarchical and scaleable system architecture. Sensing and processing tasks are efficiently distributed locally and logically onto different processing

Fig. 1. SMASH system (inner side) with the Konnex and three Gateways (marked with a circle). The fourth Gateway is hidden.

units. A central system control unit (*Konnex*) is connected to four sensor *Gateways*, using a wired *system bus*. Together they form a static body area network, which is fully integrated on the inner-side of the garment (Figure 1). Each of the four Gateways provides standardized interfaces to a maximum of 127 peripheral sensing platforms (*Terminals*), that can be arbitrarily placed over the body. Figure 2 shows a 3D-acceleration Terminal as it was used in this work. A detailed description of the system is provided in [6].

A main design aspect for the SMASH system was to keep the garment comfortable to exploit the potential benefits of wearable assistants [7]. For textile integration, electronic modules of the core system were miniaturized and glued to the inner-side of the shirt using silicone gel (Acetoxysilane). The gel covers all modules of the core system and protects them from environmental stress, shocks, vibration, electrical shorts and wearer's sweat (see Figure 2). After five times of washing, a separate textile-glued Gateway-module stood functional.

In contrast to other garment-based data acquisition platforms that are similar in design [8], the SMASH system is enabled to perform an on-body sample-wise real-time classification using a Nearest Centroid Classifier. In this work, we configured the system to send gathered data to an outer PC for offline analysis, using an integrated Bluetooth module.
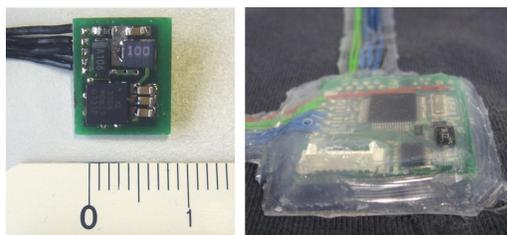

Fig. 2. Left: acceleration sensing Terminal (8mm by 10mm). Right: Gateway encapsulated with silicone.

III. EXPERIMENTAL PROCEDURE

Seven healthy individuals (3 female, 4 male), aged between 20 and 35 years with body heights, between 160 cm and 190 cm were considered in the study. The participants adopted 21 postures that were grouped in 13 exercises that are relevant for shoulder- and elbow-joint rehabilitation. The complete exercise set was repeated three times. Figure 3 depicts all postures during execution. Before each exercise, the upcoming postures were explained and shown to the participants on pictures. An experiment observer annotated the conducted postures. Each exercise began with a neutral position, standing upright, arms relaxed (see Figure 3, posture 1). Besides its function to prepare for the next exercise, the neutral position was also intended to restore the garment's natural alignment on the body. The garment alignment was not otherwise purposeful manipulated.

Garment- and skin-attached acceleration sensors were placed congruently for a comparison of their classification performance. One pair of sensors was located at the right wrist, a second pair on the right upper arm. Figure 4 shows the two sensor pairs and their respective positioning. All acceleration data were recorded with a sample frequency of 16 Hz.

IV. GARMENT-RELATED POSTURE CLASSIFICATION ERROR

Fig. 4. Upper plot: placement of acceleration sensors on right lower and upper arm. Lower plot: skin- and garment-attached acceleration sensors at the right wrist (sensor-positions marked with circles).

To quantify the effect of SMASH on posture recognition, classification performances of garment- and skin-attached acceleration sensors were compared. We used a Nearest Centroid Classifier algorithm as it is implemented in the SMASH. To avoid inter-individual variations, in a first step, training and testing of the classification algorithm was done for each participant separately. A three-fold cross-validation scheme was applied to include two repetitions of the exercises for the algorithm training and test the classification performance on the left out exercise repetition. Each repetition was used once for testing. Normalized accuracy was computed as

Fig. 3. Exercise postures performed with the SMASH system.

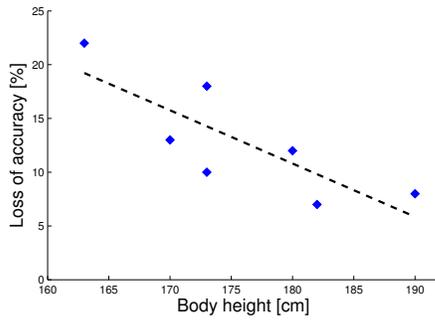| Participant	1	2	3	4	5	6	7	mean
a_{Skin} [%]	90	87	92	85	91	96	74	88
$a_{Garment}$ [%]	78	77	70	78	78	78	66	75
$e_{Accuracy}$ [%]	12	10	22	7	13	18	8	13

Fig. 5. Loss of accuracy $e_{Accuracy}$ in relation to body height.

$a_N = 1/C \sum_{i=1}^{C} \frac{Recognized_i}{Relevant_i}$, where C is the total number of postures. $Recognized_i$ and $Relevant_i$ are the number of correctly identified and the total number of postures from type i respectively.

The classification resulted in a mean normalized accuracy of 75% for the garment-attached sensors and 88% for the skin-attached reference sensors. Table I summarizes the participant-specific classification performances, where a_{Skin} and $a_{Garment}$ are the skin- and garment-based classification accuracy. The results confirmed that the orientation of the garment-attached sensors was changed in relation to the body during the execution of exercises. Results achieved with the reference sensors are independent of the garment or participant's proportions, they reflect variability in the posture's execution and limits in posture discrimination.

We found no consistent relation between the classification accuracy and participant's physical proportions. However, as an intuitive metric we calculated the participant-specific loss of accuracy $e_{Accuracy} = a_{Skin} - a_{Garment}$ (see Table I). The alignment error of garment-attached sensors led to a mean loss

of accuracy $e_{Accuracy}$ of $\sim 13\%$. Figure 5 depicts the loss of accuracy in relation to body height. $e_{Accuracy}$ increased to $\sim 22\%$ for a participant with a body height of $163\,cm$, where the garment sleeve showed clear wrinkles at the wrist-sensor. For tall participants the shirt tended to become tighter, resulting in less degree of freedom for the garment sensors. Hence, the loss of accuracy decreased.

Moreover, we investigated whether a systematic selection of the sensor features would improve the classification performance. Our hypothesis was that variance in the garment-attached sensors was introduced by certain acceleration axes. The optimal feature subset was determined for the dataset of each participant using a complete search wrapper approach. A small increase in garment-based accuracy was observed for removing one acceleration axis (accuracy improved by +4%). However, for all feature subsets the loss of accuracy remained more than 10% (see Fig. 6).
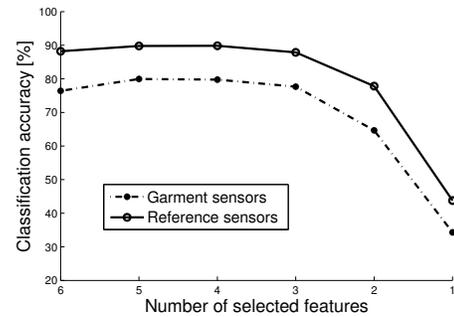

Fig. 6. Classification accuracy using sensor selection.

V. POSTURE-RELATED ERRORS

In this section, we analyze how the individual postures affect the orientation error of garment-attached acceleration sensors. This analysis can identify postures, that benefit from a tight-fitting garment, e.g. to improve recognition performance. In order to remove body proportion dependent influences, we considered the exercise data from one participant that fit perfectly into the garment after the manufacturer's sizing guide. We investigated the sensor alignment error by using the absolute angular deviation e_{Angle} between gravity vectors of skin and garment sensors ($\vec{v}_{Skin}, \vec{v}_{Garment}$). The gravity vectors were computed from the raw acceleration axes, with

$\vec{v}_{Skin} = \{s_x, s_y, s_z\}$ and $\vec{v}_{Garment} = \{g_x, g_y, g_z\}$, respectively. The angular deviation e_{Angle} was calculated using Eq. 1.

$$e_{Angle} = \left| \arccos \left(\frac{\vec{v}_{Skin} \cdot \vec{v}_{Garment}}{|\vec{v}_{Skin}| \cdot |\vec{v}_{Garment}|} \right) \right| \quad (1)$$

Figure 7 shows the angular deviation for all exercise repetitions of postures 2–21 for the wrist sensors. The box indicates lower quartile, median, and upper quartile of angular deviation. The whiskers lines extending from the boxed area indicate the extent of remaining values. The first neutral posture (posture 1) is not shown, since the angular deviation was reset before each exercise.
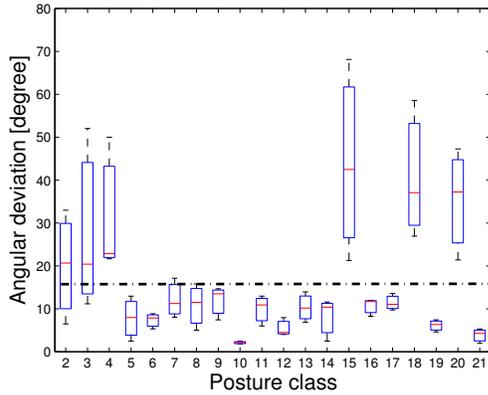

Fig. 7. Angular deviation of postures 2–21 for one participant with perfect fitting. The threshold divides two error groups.

The individual postures showed a spread of $3°$ to $70°$ in angular deviation. To qualitatively categorize postures (compare to Fig. 3) into two error-groups, we introduced a threshold at $15°$ (shown in Fig. 7). An angular deviation below the threshold was observed for 14 postures (5–14, 16, 17, 19, 21). Postures resulting in large angular deviation were categorized as follows:

(1) Straight arm abductions: In postures 2–4 the straight arm was moved upwards at the side or frontal from the body and resulted in a large angular deviation ($10° \leq e_{Angle} \leq 55°$). The elbow was not bent as for postures 8–10, that showed a relative small error ($3° \leq e_{Angle} \leq 14°$).

(2) Rotations of the lower arm: The large angular deviation ($e_{Angle} \cong 42°$) of posture 15 is a result of the non-tightened sleeve wristbands. Consequently, the sleeves did not follow arm rotations to supination.

(3) Combined postures: Postures 18 and 20 showed large alignment errors ($23° \leq e_{Angle} \leq 58°$). Both postures required movement sequences that contain elements, similar to postures 4 and 15. Especially the lower arm rotation raised the angular deviation, as detailed for posture 15 above.

Depending on the application and required measurement accuracy, the identified postures with large alignment errors should be measured using tight-fitting garments.

VI. CONCLUSION

In this work we analyzed the influence of a smart garment on the posture recognition performance used for shoulder- and elbow rehabilitation. Our direct comparison of skin- and garment-attached acceleration sensors showed an average loss in system accuracy of 13%. These differences could not be improved by an optimized sensor selection. We concluded that the garment affects all sensor features in the selected postures. The loss of accuracy decreased with increasing body dimensions. To this end, for the largest individual in our investigation, the SMASH performed almost as tight-fitting garment.

We further evaluated posture groups that are particularly affected by errors introduced by our garment-attached sensors. We found three groups and showed that 14 of the 21 postures resulted in a sensor orientation error of less than $15°$. The postures that were particularly affected included straight arm abductions and rotations of the lower arm. These effects could be explained from the orientation change of garment sensors relatively to the body and, if desired, could be reduced by using tightened garments.

We believe that our work is a first vital attempt to analyze and quantify the garment effect on posture recognition. This recognition is highly relevant in movement rehabilitation. With the help of smart garments, initial rehabilitation support assistants be realized that focus their feedback on less affected postures.

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