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Posture Classification via Wearable Strain Sensors for Neurological Rehabilitation

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Abstract— **Stroke and other neurological accidents account for a wide fraction of the healthcare costs in industrialised societies. The last step in the chain of recovery from a neurological event often includes motor rehabilitation. While current motion-sensing technologies are inadequate for automated monitoring of rehabilitation exercises at home, conductive elastomers are a novel strain-sensing technology which can be embedded unobtrusively into a garment's fabric. A sensorized garment was realized to simultaneously measure the strains at multiple points of a shirt covering the thorax and upper limb. Supervised learning techniques were employed to analyse the strain measures in order to reconstruct upper-limb posture and provide real-time feedback on exercise progress.**

I. INTRODUCTION

Automatic measurement and recognition of human body postures is a task with several important applications, ranging from the entertainment industry (immersive games), to the animation industry (recording of actors on scenes, and animation of virtual characters), to the clinical application (posture, walk and gait analysis).

Several types of sensors have been developed for posture recognition, which can be broadly classified among body-based systems (e.g. accelerometers, in which the sensing element is fixed on the moving parts of the body), and earth-based (e.g. multiple video cameras which reconstruct three dimensional location of infrared-reflective markers).

II. BACKGROUND AND SETTING

Recently, a novel type of sensor, based on conductive elastomers (CE) smeared on fabric, has been proposed [1]. When sensors are deposited on a garment as stripes, the impedance of each deposited segment varies as a function of the strain to which it is subject.

Advantages of CE sensors over solid-state and other types is their negligible weight and thickness, and the fact that any number of "measuring points" can be let on a garment in a single setup. Laviola [2] has a review in the context of *hand* posture recognition. Gibbs and Asada [3] described a sensing garment of similar spirit, realized with a more traditional sensor technology (elastic wire with sliding contacts).

Rehabilitation after adverse neurological events, including stroke, is known to benefit greatly from early start of physical therapy, both in terms of quality of recovery [4] and cost-effectiveness [5]. The therapy is usually administered in an inpatient setting, few hours a day, by trained therapists under the supervision of clinicians. Facilities for physical rehabilitation are often fully booked, and after patients' discharge there is an interruption in the continuity of care: when at home, neither quantity nor quality of exercises possibly performed by patients, either alone or with the help of caregivers, are followed any longer by professionals.

Availability of elastomer strain sensor technology motivated the realization of a "sensorized sleeve", endowed with multiple CE sensors [6]. The garment is able to detect body postures taken by patients while performing prescribed exercises for physical rehabilitation after discharge by the rehab clinic.

III. DATA ACQUISITION

The problem which will be tackled here is to recover, from the sensor readings, the current position of the body. This will enable us to build systems that are able to detect whether the exercises assigned for rehabilitation are performed, if they are done properly, and for the assigned time. This paper describes the application of a supervised machine-learning approach as an exploratory solution of this task.

Resistance values are sampled via an analogue to digital converter, developed for this task by MyHeart Partner CSEM

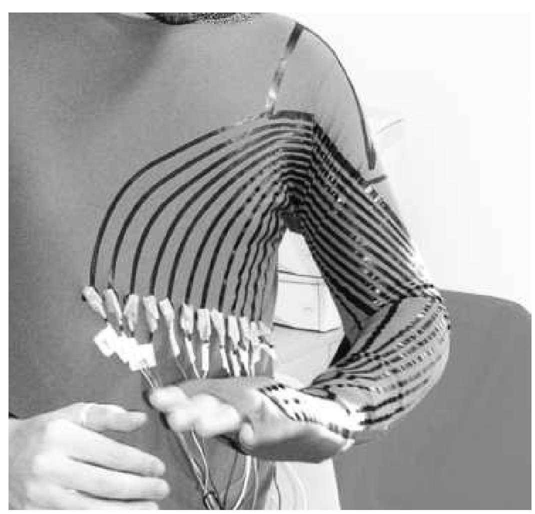

Fig. 1. Sensing stripes (thick line) and connecting wires (thin) are CE elastomer printed on fabric. This is an early, wired prototype.

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Fig. 2. Current garment prototype, with wireless data acquisition electronics. Printed strain sensors are invisible because placed between two layers of Lycra.

(Swiss Center for Electronics and Microtechnology), and streamed at 128 samples/second/channel.

Sensors are realized by printing a single stripe of CE material on the garment fabric before sewing. The stripe's resistance is sampled at several points via connections realized with the same elastomer (Figure 1). Sensors' strain-gauge characteristics have been published in earlier works [7]. The most important nonlinearity in the relationship between resistance and elongation is the presence of a velocity-dependent resistance peak, followed by an exponential tail 3. Application of pre-processing to multi-sensor data is under study.

IV. METHODOLOGY

After the garment is worn (Figure 2), the subject is asked to perform one of several rehabilitation exercises foreseen in the rehabilitation protocol, briefly stopping at chosen intermediate positions. This is done in order to "snapshot" the current sensor readings in a training file along with the corresponding position. Time instants for which readings were acquired are shown as dashed bars in Figure 3.

This simplified setup, therefore, reduces the posture recognition task to a *supervised classification* problem, with 19 numeric attributes as inputs (one for each sensor in the current prototype), and a nominal class label to be predicted as output (the intermediate step along the movement path) [8]. The term "attribute" comes from the machine-learning literature, and in the following will be used interchangeably with the terms "sensor" and "channel".

The exercise protocol foresees both a *correct* execution path and a series of *incorrect* compensatory postures, which the patient should avoid while exercising. Class labels were therefore arranged as a set comprising n intermediate steps taken in the "correct" exercise execution path, and m "incorrect" positions. In the experiments described we have preliminarily fixed $n = 4$ and $m = 3$.

Time scale	Source
$\sim$ ms	Measurement noise
$\sim$ 10 s	Velocity-dependent transients
$\sim 10^2$ s	Sensor repeatability
Days	Displacement after taking off
Months	Long term deterioration
Subject	Body size

TABLE I

CAUSES OF UNCERTAINTY IN CE SENSORS

It is worthwhile noting that in this scheme, posture classification is computed in the space of sensor readings, rather than by comparing angles or other physical parameters. The mapping between sensor readings and physical parameters (e.g. elbow flection angle) is nonlinear and hard to compute. It is however unnecessary, since classification models can be built in the untransformed space. Generation of visual feedback is also possible in the untransformed sensor space, since a simplified, symbolic representation of exercise progress is desired, not an actual 3D limb reconstruction.

A. Challenges to generalization

Several sources of "noise" are known to bias readings from CE sensors in this setting (see Table I). The classification algorithm should be reliable enough to detect postures, as far as possible, even in presence of biases. Performing a subject-dependent "model calibration" is of course undesirable, and unfeasible if it is complex or required too often.

The classification model devised should be *general* enough in order to recognize postures even after the garment is taken off and put back on. To this purpose, the training procedure was arranged as follows: after a subject wears the garment, he cycles several times through the exercise. This is done because there is a strong correlation among samples taken while holding a fixed position. The same correlation is lost after the limb is moved: even if the same position as before is taken, sensor values do not come to exactly the same values as before. Repeating several acquisition cycles during one

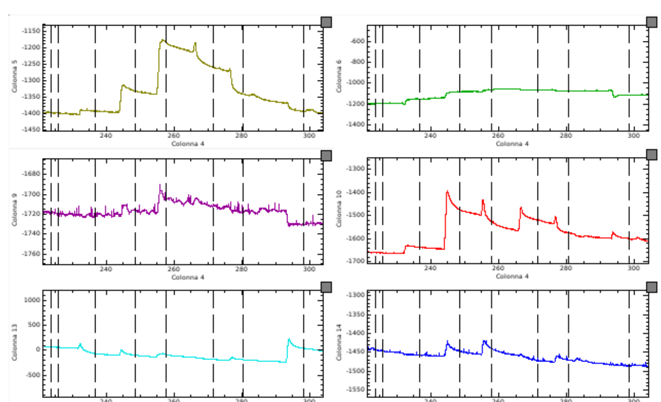

Fig. 3. Resistance values vary with time according with transients and exponential tails. Their values are sampled at specific time instants and readings fed to the classifier. Figure shows six out of 19 total sensors.

training session addresses the generalization with respect to sensor repeatability.

To generalize over sessions, i.e. to account for decorrelation in sensor readings for a chosen posture caused by wearing and un-wearing the garment, we performed multiple *runs*. Runs from four sessions were merged into a larger training set, and used for cross-validation.

V. RESULTS

Before testing actual classification schemes, we performed a preliminary exploration on attributes, in order to discover which sensors contribute most to the detection of specific postures. This task is also known "attribute selection", because can lead to dropping sensors shown to bring no information.

A. Information Content

Several attribute selection schemes have been proposed in the literature. One of them, the *information gain* (IG), is defined as the number of bits of information gained by the knowledge of attribute i, i.e.

$$\mathrm{IG}_i = -\sum_{c\in C} p(c)\log p(c) + \sum_{a\in A} p(a) \sum_{c\in C} p(c|a)\log p(c|a)$$

where A is the set of values taken by attribute i, C is the set of possible class labels, $p(a)$ is the fraction of examples in the training set which for which attribute i has value a, and similar definitions hold for $p(c)$ and $p(c|a)$.

The IG criterion gives a direct indication of which sensors contribute to the knowledge of the class, and which do not. One drawback is that attributes are accounted only separately: a pair of equal attributes will have the same IG, even though they are of course completely redundant (they do not warrant any better classification with respect to having only one). Correlation analysis or other selection schemes can address this problem, if desired.

Figure 4 shows the IG values, in bits, of the 19 sensors (s0 ... s19) as measured in upper limb adduction exercise. Error bars show the standard deviation of IG values across four runs, acquired the same day by the same subject. Once IG is computed, sensors numbers were traced back to their physical location on the garment. Sensors with high IG for this particular exercise, s9 and s14 (IG > 1.5), plus others, are located behind the left shoulder. Sensors 6, 12, 1 and 17 have very low IG, consistently over all runs. This is explained by their placement, since all four are located on the wrist, whose articulation does not come into play in limb adduction. Sensor 5's IG has a high standard deviation, implying that in some sessions it was important, in others it was not; the sensor is located over the chest, and the likely explanation is that its position happens to be at a point of the garment whose tissue becomes wrinkled in this exercise.

The fact that more than half of the sensors have relatively high IG, and that those with low IG are easily explained, is comforting with respect to the quality of the garment and the appropriateness of the classification approach.

B. Classification

Several classification algorithms were compared with the help of Weka software [8]. One model was built for each run, and evaluated against data acquired in the next run, used as an independent test set. Among the classifiers tested, those shown in figure 5 yielded the best results. The most effective algorithm proved consistently to be logistic regression.

A classifier was finally built merging the training data sets available. This resulted in a subject-independent training set, obtained by data from two subjects, over four days. The final set included 905 examples collected in 15 acquisition runs. Between each run and the next, the garment was put off and worn again, in order to generalize over variations possibly introduced by textile displacement. All of the training data was taken on the upper-limb adduction exercise, including four intermediate stops along the correct execution path, and three incorrect compensatory positions.

Table II (upper panel) shows the confusion matrices obtained by the final classifier applying 10-fold cross-validation. The lower panel of same figure was obtained considering not the sensor readings themselves, but rather their deltas with respect to a rest position, which is updated over time. This allows the cancellation of long-term drifts and constant offsets due to the different body structure.

Confusion matrices show that the both classifiers give generally satisfactory performance. The number of incorrectly-classified instances is approximately the same for the two cases, but "severe" errors (confusing a correct posture with an incorrect one, or vice-versa) are less numerous when filtering data with offset subtraction.

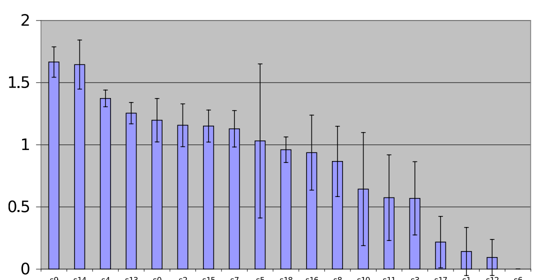

Fig. 4. Upper limb adduction: information gain of 19 CE sensors and their standard deviation along four acquisition runs.

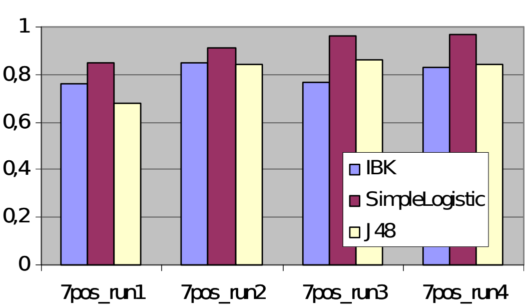

Fig. 5. Performance (k value) of three algorithms tested for posture classification, using sensor data from four independent runs.

pos1	pos2	pos3	pos4	err1	err2	err3	
117	6	4	0	10	2	1	pos1
2	108	13	0	1	1	0	pos2
2	17	90	16	0	0	0	pos3
0	0	13	119	0	8	0	pos4
15	1	1	0	108	0	0	err1
5	0	3	5	4	104	4	err2
0	1	0	1	0	4	119	err3

pos1	pos2	pos3	pos4	err1	err2	err3	
140	0	0	0	0	0	0	pos1
1	111	12	1	0	0	0	pos2
0	15	89	18	0	3	0	pos3
1	0	18	117	0	3	1	pos4
1	0	0	0	114	6	4	err1
1	0	1	6	10	97	10	err2
1	0	0	0	3	13	108	err3

TABLE II

CONFUSION MATRICES FOR POSTURE CLASSIFICATION ON UPPER LIMB ADDUCTION EXERCISE. DATA FED INTO THE MODAL ARE EITHER ABSOLUTE SENSOR READINGS (UPPER PANEL) OR OFFSETS MEASURED WITH RESPECT TO REST POSITION (LOWER).

VI. CONCLUSIONS

This paper described how the problem of posture recognition from n strain sensor readings has been tackled via supervised learning techniques. The treatment involved simplifying the correct and incorrect execution patterns of a given exercise, in order to build a series of basic postures, to be recognized separately by a classifier working in the n-dimensional sensor space.

Recognition performance seems high enough to warrant for its use. There is however room for improvements. One obvious change is to incorporate a priori knowledge of the sensors' characteristics (e.g., transients) into a pre-processing stage. Experiments performed had the purpose of finding a baseline performance indication, therefore sensor data was deliberately not preconditioned (apart from an offset subtraction).

The supervised learning approach allowed us to extract a measure of the information content carried by each sensor. This criterion is useful independently from the gesture recognition scheme which will be employed. It also offers a quantitative indication of the parts of the garment which have a role in recognition of different exercises, and this may be useful for redesign of the sensor layout, if more accuracy is desired.

The current direction for our research is the recognition of time-dependent *gestures* as wholes. Gesture recognition has been tackled with statistical models, including decoding hidden Markov models [9]. The selection of sensors to be considered will still be necessary, and the information gain criterion described in this work may be a good basis for its formulation.

Fusion of data with measurements obtained from other technologies is a promising direction of research which is also being pursued. We are considering multi-sensor data fusion strategies both for calibration (e.g. stereophotogrammetry), and for real-time, on-body usage (e.g. unobtrusive MEMS attitude sensors).

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