Experiments in the Detection of Upper Limb Posture through Kinestetic Strain Sensors

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Abstract

Conductive elastomers are a novel strain-sensing technology which can be embedded unobtrusively into a garment's fabric. A prototype was realized to simultaneously measure the strains at multiple points of a shirt covering the thorax and upper limb. This paper describes preliminary experiments with machine learning techniques, employed to analyse the strain measures in order to reliably reconstruct upper-limb posture. The scope of the application is to detect execution, correctness and progress of physical exercises performed as part of neurological rehabilitation therapy.

1 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).

2 Background and setting

Recently, a novel type of sensor, based on conductive elastomers (CE) smeared on fabric, has been proposed [7]. 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 [5] 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 [2]. 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 [8]. The garment is able to detect body postures taken by patients while performing prescribed exercises for physical rehabilitation after discharge by the rehab clinic.

3 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

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Figure 1. Sensing stripes (thick line) and connecting wires (thin) are CE elastomer printed on fabric. Inner layer shown.

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 (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 [1]. 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. Application of pre-processing to multi-sensor data is under study.

4 Methodology

After the garment is worn (figure 1), one subject was 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.

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) [9]. The term "attribute" comes from the machine-learning

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

Table 1. Causes of uncertainty in CE sensors

literature, and in the following will be used interchangeably with the terms "sensor" and "channel".

The exercise protocol, does not only foresee a *correct* execution, but also a series of *incorrect* compensatory postures, which the patient should avoid while exercising. The goal of the system is to both to discriminate progress along the correct execution path, and warn in case one of the improper positions is attained. The scope is therefore to build a rehabilitation *biofeedback* through visualization of the exercise's correctness and progress.

As discussed above, class labels, or target postures, belong to 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 $m = 3$.

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 is highly nonlinear, hard to compute, and, luckily, unnecessary since classification models can be built in the untransformed space. Generation of visual feedback is also allowed in the untransformed sensor space, since a simplified, symbolic representation of exercise progress is desired, not an actual 3D limb reconstruction.

4.1 Challenges to generalization

Several sources of "noise" are known to bias readings from CE sensors in this setting (see Table 1). 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

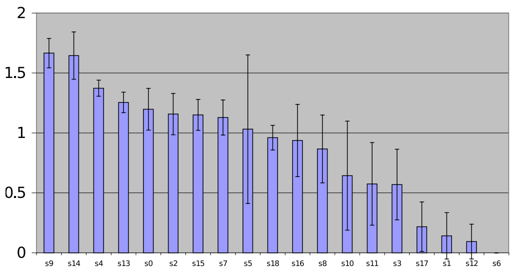

Figure 2. Upper limb adduction: information gain of 19 CE sensors and their standard deviation along four acquisition runs.

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 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.

5 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.

5.1 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 2 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* 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 conforting with respect to the quality of the garment and the appropriateness of the classification approach.

5.2 Classification

Different classification algorithms were compared with the help of Weka software [9]. 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 3 yielded the best results. The most effective algorithm proved consistently to be logistic regression.

The value of k statistic in 10-fold cross-validation was taken as the measure of the correctness of classification. Kappa is equals one when all of the instances are classified correctly, and zero when the number of hits is as large as it would be expected from a random classifier.

In order to implement a prototype for realtime classification, a single model was built with all of the runs available for one specific subject merged together, in order to generalize as far as possible all available data for a given person. This resulted in a subject-specific training set including data from four runs, each having ten repetitions of an upper-limb adduction exercise, plus samples of incorrect positions. The resulting model was implemented as a stand-alone application, connected in real time to the data acquisition electronics, and then tested again with respect to fresh test data, collected at runtime. The experiment yielded the confusion matrix shown in table 2.

For the runtime classification test, $k^{(7)} = 0.75$ is obtained weighing equally all of the exercise positions. This figure indicates a good agreement between model's re-

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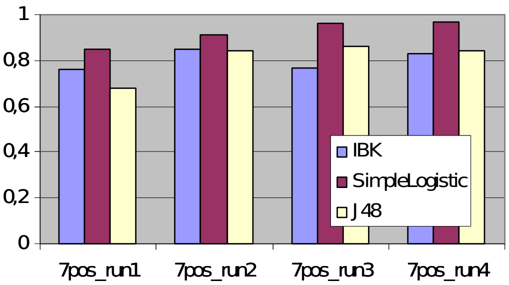

Figure 3. Performance (k value) of three algorithms tested for posture classification, using sensor data from four independent runs.

pos1	pos2	pos3	pos4	err1	err2	err3	
8	0	2	0	0	0	0	pos1
0	10	0	0	0	0	0	pos2
0	0	10	0	0	0	0	pos3
1	0	0	9	0	0	0	pos4
2	0	6	0	2	0	0	err1
0	0	0	4	0	6	0	err2
0	0	0	0	0	0	10	err3

Table 2. Confusion matrix for a logistic classifier in a realtime acquisition session.

sponse and real posture, although there are still a few large off-diagonal counts. If one is only interested in the four steps along the correct execution path, the agreement is much higher: $k^{(4)} = 0.9$.

6 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.

The experiments performed had the purpose of finding a baseline performance indication, therefore sensor data was deliberately not preconditioned. Even so, recognition performance for a realtime classifier seemed 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.

Also, recent tests showed that inter-subject generalization performance is improved when one considers not directly the sensor readings, 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. Discovery of correlations between biometric measures and such systematic offsets is a promising direction for investigation.

Finally, a most exciting improvement over the "static" classifier described here is the recognition of time-dependent *gestures* in wholes. Gesture recognition has been tackled with statistical models, including decoding hidden Markov models [6].

For feedback display of incorrect movements, the definition of an appropriate "distance" will still be necessary, and the information gain criterion described earlier in this work may be a good basis for its formulation.

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