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Statistically Rigorous Human Movement Onset Detection with the Maximal Information Redundancy Criterion

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Abstract—**Stroke patients have a decreased ability in performing activity of daily living (ADL) tasks such as in "drinking a glass of water", "lifting a bag", "turning a key" and so on. Sensorimotor force and torque measurements from patients performing these standardized ADL tasks are hypothesized to give quantitative information about the recovery process. Parts of the force/torque measurements contain useful information, when related to the initiation of the movement during ADL tasks. Here we address the challenging problem of automatically extracting the movement initiation from these force/torque measurements. We will adopt a machine learning approach which relies on the statistically rigorous Maximal Information Redundancy (MIR) criterion. This assumes that movement initiation parts of the signals are characterized by an increased redundancy in the signal. A thorough evaluation of the criterion shows that the accuracy of the criterion in movement onset detection is close to that of clinical experts.**

I. Introduction

The quantitative measurement of motor and other neurological functions is a problem, which neurologists and rehabilitation specialists have been dealing with since many years. Clinicians developed for that reason many ways of evaluating sensorimotor skills; however most of these evaluation methods such as the various rating scales of different neurological deficits are purely qualitative and highly subjective. A classical problem is the assessment of hand/finger dexterity in stroke patients. Reaching for and manipulating a perceived object is a basic and obvious sensorimotor skill, which apparently dissolve in no time after a brain insult. Whatever real life task one has in mind, most of them can be conceptualized as starting with the transport phase of the hand toward the target followed by a final approach phase under visual guidance and action of grasping, finished by the retrieval of the object [1]. However, these components are not strictly separated, but are overlapping and interacting in a complex manner. This complexity depends both on cognitive factors, such as the subject's degree of certainty about the accuracy of hand transport, and some lower-level factors responsible for maintaining synergy between preshaping and transport components [2].

It is evident that stroke patients have serious problems with the execution of an important number of tasks related to daily life activities. Brain damage caused by embolic or hemorrhagic infarction disrupts the sensorimotor organization that integrates the information from varies cortical and subcortical areas [3], [4]. In some cases the consequences of the damage are limited and can be clinically appreciated as disturbed, jerky movements. Then, a kinematical analysis is feasible and leads to an understanding of the disrupted control. However, a complete unilateral paralysis followed by the return of nearly invisible movements a few weeks after stroke is a customary course of events. Under these conditions kinematical analysis at task level is unfeasible. Therefore, the introduction of new assessment techniques of arm and hand functionality in a clinical, neurophysiological context is of utmost importance to improve the understanding of the recovery of the stroke patients in this stage.

As the emphasis in stroke rehabilitation is on the improvement of 'function', the new quantitative measurement tool should be based on the Activity of Daily Living (ADL) tasks. These tasks are thoroughly described in textbooks for physical and occupational therapists [5], [6]. Within this scope the ALLADIN project a measuring instrument was developed that records the very low forces and torques produced by stroke patients during attempts of performing ADL tasks under isometric constrains[1]. The basic hypothesis is that features extracted from the movement preparation and initiation under these conditions are determinants for the functional recovery after stroke and reflect the important neural control parameters related to brain plasticity. The assumption is that the extracted features contain special characteristics guaranteeing a correct performance of a particular functional task. Consequently, it can be concluded that the time window around the

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movement onset is of particular interest for the understanding of particular neurological conditions [7] and mechanisms of recovery in stroke. Moreover it can be underpinned by the fact that forces and torques developed around that point of interest seem to coincide with the movement-related brain potential (MRP). This MRP is an electroencephalogram component with three subcomponents related to self-initiated movements. One component is the ‘Bereitschaftspotential’, a slowly rising negative component, starting up to two seconds before movement onset; a second represents the steeper increase in negativity starting at 500 to 300 ms before movement onset and a third is the motor potential self appearing around movement onset and peaking shortly thereafter [8]. Brain lesions have a differential effect on the subcomponents of the MRP, depending on the lesion site and the time that elapsed since the lesion occurred [9]. For the time being, it is unclear whether plastic changes resulting in a partial compensation of impaired motor functions also underlie the alterations in isometric force/torque measurements observed in the hand and fingers of stroke patients during the patient's ‘attempts’ of executing functional tasks such as picking up or moving objects.

Given the muscle weakness at the early stage after stroke, it is difficult to identify the onset of the voluntary component related to the task to be performed, and to extract the onset of the voluntary action from the weak and often noisy force/torque signals. Hence, it is imperative to learn more about what kind of information the signals contain around the movement onset time. A reliable method for onset detection would open new perspectives for studying the changing characteristics of internal forward models required for performing functional tasks after stroke. These forward models have been proven to be of paramount importance for an adequate sensorimotor control of functional movements [10].

II. Methodology

A. Force and Torque Measurements

The defined ADL tasks need to be representative for daily living. In total six tasks were considered in this research: “drinking a glass of water”, “picking up a spoon”, “turning a key”, “lifting a bag”, “reaching for a bottle” and “bringing a bottle to the opposite side”. Eight torque and force sensors are positioned on body parts that are relevant for performing ADL tasks. The sensors are placed on the thumb, the index, the middle finger, the arm, the foot, the big toe, the seat and the back. Each sensor is capable of measuring 3 forces and 3 torques in X, Y and Z direction. Before the experiments start, the patient is positioned in a mechatronic platform [11]. The signals are sampled at 100 Hz.

B. Detection Hypothesis

It is hypothesized that, when the patient starts the movement, the signals become more redundant. Before movement initiation the signals consist of small ‘involuntary’ movements. These signals typically contain low redundancy, meaning that from past measurement samples it is hard to predict future samples. However, when a patient intends to perform a task, the voluntary movements are planned and tend to follow a smooth trajectory. This makes the signal more redundant from the movement initiation on. Hence, it is plausible that continuous monitoring of the redundancy in the signals informs us about the movement initiation.

In order to proceed in a statistically rigorous way, we need a mathematical model, which is able of modeling these temporal correlations between contiguous samples from the signals.

C. Maximal Information Redundancy Criterion

We propose to use a log-likelihood ratio test (LRT) where we test for 2 alternative hypotheses: hypothesis H_1 which assumes that the movement initiation is present, and hypothesis H_0 which assumes the absence of movement initiation. Mathematically this log-likelihood ratio test can be written as:

$$L(y_j^k) = \ln \frac{p(y_j, y_{j+1}, ..., y_k \mid H_1)}{p(y_j, y_{j+1}, ..., y_k \mid H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma, \tag{1}$$

and where hypothesis H_1 is chosen when the log-likelihood exceeds γ and H_0 otherwise. The threshold γ can be found by constraining the probability of false alarms:

$$P_{FA} = \int_{\left\{(\mathbf{y}_j^k:\, L(\mathbf{y}_j^k) > \gamma)\right\}} p(y_j, y_{j+1}, ..., y_k \mid H_0) = \alpha \,. \tag{2}$$

This criterion is well-known as the Neyman-Pearson criterion [12]. In this particular context of signal processing, the y_j, y_{j+1}, … y_k are considered as subsequent samples from a time series. H_1 is the hypothesis that the signal of interest (the movement initiation) is present from sample j to k. H_0 is the hypothesis that the movement initiation is not present at all. We assume that the probability density functions, ‘PDF’s’ in (1) can be parameterized by $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_0$ for H_1 and H_0 respectively. Then the LRT in (1) assumes that parameter vectors $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_0$ are known. When these parameter vectors are unknown, they need to be estimated and (1) then becomes a generalized log-likelihood ratio test (GLRT):

$$GL(y_j^k) = \ln \frac{p(y_j, y_{j+1}, ..., y_k; \hat{\boldsymbol{\theta}}_1 \mid H_1)}{p(y_j, y_{j+1}, ..., y_k; \hat{\boldsymbol{\theta}}_0 \mid H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \,. \tag{3}$$

Here $\hat{\boldsymbol{\theta}}_1$ and $\hat{\boldsymbol{\theta}}_0$ are the maximum likelihood estimates of the unknown $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_0$ parameter vectors. For H_1 we use an autoregressive model (AR), an extensively used mathematical model, which is able of taking temporal correlations into account:

$$y_n = \sum_{i=1}^{p} a_i y_{n-i} + \varepsilon_n, \qquad (4)$$

where ε_n is the innovation process, consisting of i.i.d. (identical and independently distributed) samples, p is the model order and a_i are the regression coefficients. For H_0 we assume i.i.d. y_j, ..., y_k samples to model the lack of redundancy in the signal when there is no movement initiation. This leads (3) to:

$$GL(y_j^k) = \ln \frac{p(y_j, y_{j+1},..., y_k; \hat{a}_1,..,\hat{a}_p, \hat{\sigma}_1 \mid H_{AR})}{p(y_j, y_{j+1},..., y_k; \hat{\sigma}_0 \mid H_{i.i.d.})} \underset{H_{i.i.d.}}{\overset{H_{AR}}{\gtrless}} \gamma, \qquad (5)$$

here $\hat{a}_1$, ...$\hat{a}_p$ are autoregressive parameters estimated from time samples y_j, …y_k. Parameter $\hat{\sigma}_1$ is the estimated standard deviation of the i.i.d. ε_n innovation process. Parameter $\hat{\sigma}_0$ is the estimated standard deviation from i.i.d. y_j, ..., y_k samples. Finally, performing a change in variables, (5) can be written as:

$$\ln \frac{P(\varepsilon_j, \varepsilon_{j+1},..., \varepsilon_k; \hat{a}_1,..,\hat{a}_p, \hat{\sigma}_1 \mid H_{i.i.d.\varepsilon})}{p(y_j, y_{j+1},..., y_k; \hat{\sigma}_0 \mid H_{i.i.d.})} \underset{H_{i.i.d.}}{\overset{H_{i.i.d.\varepsilon}}{\gtrless}} \gamma, \qquad (6)$$

For the motivation in going from (5) to (6), see [13]. Note that we did not make any assumptions about the distribution (except for being i.i.d.) of the ε_n process in H_1 and the y_j, … , y_k samples in H_0. Finally, it can be proven [13] that (6) is asymptotically equivalent with:

$$\begin{aligned} &\approx (k-j+1)(H_G(y) - H_G(\varepsilon) - J(y) + J(\varepsilon)) \underset{H_{i.i.d.}}{\overset{H_{i.i.d.\varepsilon}}{\gtrless}} \gamma \\ &= (k-j+1)\left(R_G(y) - J(y) + J(\varepsilon)\right) \end{aligned} \qquad (7)$$

This states that the log-likelihood ratio can be written asymptotically as a difference in Gaussian entropies, $H_G(y)$ and $H_G(\varepsilon)$ corrected with the negentropies $J(y)$ and $J(\varepsilon)$. $R_G(y)$ is the marginal information redundancy [14] under assumption of Gaussianity:

$$R_G(y) = H_G(y) - H_G(\varepsilon) = \frac{1}{2} \ln \frac{\hat{\sigma}_0^2}{\hat{\sigma}_1^2} \underset{H_{i.i.d.}}{\overset{H_{i.i.d.\varepsilon}}{\gtrless}} \gamma \qquad (8)$$

This can be interpreted as follows: if we would have assumed Gaussian distributed y and ε variables then the distance to Gaussianity (the negentropies $J(y)$ and $J(\varepsilon)$ in (7)) would be zero, this would lead to (8) as a well known model selection criterion. Here we use our more general maximal information redundancy criterion in (7). The maximal refers to the fact that for when the LHS in (7) is maximal for the (k-j+1) interval within a time series, we have the minimal probability of false alarms from (2). However, in general we don't need to take the maximum and use a predefined γ.

We approximate the negentropy in (7) from [15]:

$$J(y) = k_1 \left(E\left\{ y \exp(-\frac{y^2}{2}) \right\} \right)^2 + k_2 \left(E\left\{ |y| - \sqrt{\frac{2}{\pi}} \right\} \right)^2, \qquad (9)$$

where k_1 and k_2 are constants and E is the expectation operator. Equation (9) estimates the distance to Gaussianity by estimating symmetry (first term) and bimodality (second term).

Finally, we note that many researchers have proposed entropy criteria heuristically. However, (7) shows the very interesting result that for mode detection of AR models, it is an asymptotically optimal result, because it can be proven it is asymptotically equivalent with a log-likelihood ratio test (see [13] for a proof).

III. VALIDATION

Finally, we perform an extensive validation of our criterion on onset detection in human movement initiation. The 'ground-truth' is determined by the manual indication of the onset points from the force and torque signals by 5 clinical experts engaged in the ALLADIN project. Figure 1 shows an example of torque signals for the right index in "drinking a glass of water".

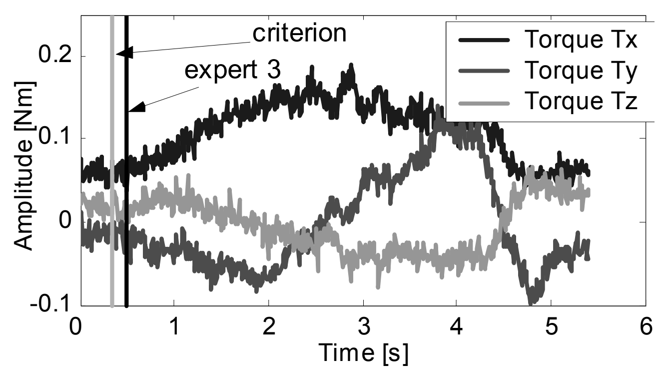

Fig. 1. Movement initiation onset detection. The 3 curves show the torques in X, Y and Z direction over time for 1 sensor attached to the right index. The vertical bars illustrate the decision taken by an expert (right) and by our criterion (left). The 3 torques are combined in 1 decision using a weighted average of the energies in the 3 signals.

We summarize the experimental conditions:

- data from 7 different control subjects and 7 patients performing ADL tasks were obtained, in order to show the generality of our approach over different subjects (both patients and control subjects),

- a total of 96 ADL tasks were performed, approximately evenly distributed over the 14 subjects,
- an about equal mixture of the 6 different ADL tasks were performed (see section II. A.), in order to show the generality of our approach over different tasks,
- in each ADL task, 8 sensors were attached to the body, hence this results in a total of 96*8 = 768 initiation points to be detected both for the force and the torque measurements,
- each expert was asked to indicate the onset points independently from each other expert,
- we kept the parameters of the *maximal information redundancy* criterion (7) constant over all decisions:
    - the window length (k-j+1) was set equal to 30,
    - H_1 was chosen as the AR(2) hypothesis,
    - H_0 was chosen as the i.i.d. hypothesis,
    - γ in (3) was set equal to 10^2.

Note that these parameters were not optimized. They were selected based on the comparison of some empirical results of the application of the *maximal information redundancy* criterion with the results of some experts, based on a few measurements. One global onset point is determined by combining the onsets for the X, Y and Z directions: a weighted average of signal energies for the onsets from the 3 directions is taken to find the global onset. In order to validate the criterion numerically, we compute the inter-expert-expert onset differences:

$$IEE(k,l,m) = E(k,m) - E(l,m), \text{ with } k < l, \quad 1 \le k \le 5, \; 1 \le l \le 5 \text{ and } 1 \le \text{m} \le 768. \tag{10}$$

E(k,m) is the onset time determined by the k-th expert for the m-th measurement (running over all 96 tasks with 8 sensor measurements each).

The inter-expert-criterion onset differences are computed as:

$$IEC(k,m) = E(k,m) - C(m), \quad 1 \le k \le 5 \text{ and } 1 \le \text{m} \le 768. \tag{11}$$

C(m) is the global onset point determined by the criterion for the m'th measurement. The 'probability of correctness' is then defined as the fraction of IEC values that fall between the p*100% and (1-p)*100% percentile of the IEE values. For p equal to 0.05, the p*100% and (1-p)*100% percentiles of inter-expert-expert onset differences for the forces are equal to: $IEE_{0.05}$ = -056 s and $IEE_{0.95}$ = 1.48 s. This results in a 'probability of correctness' for the force values of poc_{forces} = **0.81** (hence, 81% of the IEC force values are confined between $IEE_{0.05}$ and $IEE_{0.95}$). For the torque values we get:

$IEE_{0.05}$ = -0.61 s and $IEE_{0.95}$ = 1.50 s. This results in a 'probability of correctness' for the torque values of $poc\_{torques}$ **0.79** (hence, 79% of the IEC torque values are confined between $IEE_{0.05}$ and $IEE_{0.95}$).

Given the large diversity of the subjects (and their different strategies to perform an ADL task) and the fact that the parameters of the *maximal information redundancy* criterion were not optimized, these results are satisfying.

IV. Conclusion

We gave a thorough motivation for human movement initiation onset detection. It was shown that the underlying assumptions can be captured by the *maximal information redundancy* criterion. A very thorough evaluation showed that the criterion could approach the decision of experts as close as 0.8 in 'probability of correctness'. The results indicate a further promising future for our *maximal information redundancy* criterion.

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