Classification of Involuntary Hand Movements

Aki Härmä
Philips Research, Eindhoven, The Netherlands

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Abstract: Involuntary movements of arms and legs reflect neural and metabolic processes in the human body. In this paper the focus is on the properties of physiological tremor, shivering, and tremors caused by physical fatigue measured in fingers of a subject. Three different signal modeling paradigms are compared in the paper using accelerometer data. It is first demonstrated that the data can be modeled as a nearly stationary low-order AR process. Next, it is shown that the different data types can be classified using long-term feature distributions in a naive Bayes classifier. Finally, a comparable performance is obtained when the signal is modeled as a Markov process emitting small prototypical movements or jerks.

1 INTRODUCTION

Involuntary movements are common in all animals and typical symptoms in fever, Parkinson's disease, diabetes, and many other medical conditions. The movements may originate from many different processes in the body. Therefore, one may assume that the classification of the movements could be used to get information about the medical state of a patient. Typical diagnostic tools are various types of tests (Watts et al., 2011), electromyography (Palmes et al., 2010), and movement sensors (Wyatt, 1968; Ackmann et al., 1977) such as accelerometers which are used in the current paper.

The muscular system is organized largely as pairs of antagonist muscles. In normal operation the muscular system is excited by many different processes and even the basic control of a steady posture is the result of active stochastic excitation of individual muscle bundles and feedback via the sensory system. Computational neuromusculoskeletal models (Zhang et al., 2009; Yao et al., 2012) show that the system has an inherent tendency to oscillate. A consequence of this continuous activity is *physiological tremor* which is present in all organisms with a muscular system. In this paper the focus is on physiological tremor, shivering, and tremors caused by muscle fatigue.

A lowered body temperature triggers the thermoregulatory system to activate muscles to produce extra heat and this leads to shivering of the body. The actual mechanism of shivering is not well understood but it is considered to be driven by bursts of neural activity from the rostral ventromedial medulla in the brain through the sympathetic nervous system (Morrison and Nakamura, 2011). Sung *et al* (Sung et al., 2004) demonstrated that the shivering can be detected from an accelerometer attached to the body and the classification of movement patterns can be used to get a rough estimate of the core body temperature. Physical stress in muscles causes fatigue which often leads to tremors. These movements are often associated with metabolic processes in the motor cells in the muscles themselves (Ebenbichler et al., 2000).

In signal analysis and classification the goal is to identify the underlying process behind the observed data. In many areas, e.g., speech processing, signal models that are based on functional models of the process have been found successful. Detailed neuromusculoskeletal models of hand movements have been introduced, e.g., in (Akamatsu et al., 1988; Zhang et al., 2009; Yao et al., 2012), but they do not have an invertible signal model and they also contain parameters that are typically not available and therefore do not directly lead to a practical signal analysis methodology. The problem of the modeling of involuntary hand movements for classification is a central topic of this paper and an area where little systematic work from signal modeling perspective has been done in the past. Physiological tremors, shivering and tremors caused by muscle fatigue seem to have different origins which makes them interesting for this study. In fact, the current author is not aware of a previous comparison of those three common types of movements in the same experimental setting.

Härmä A..
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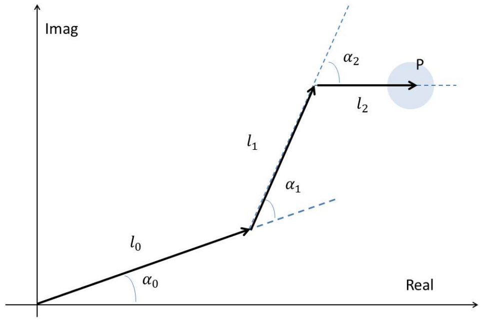

Figure 1: Simplified model of the arm, hand, and finger in a plane.

The three basic signal modeling paradigms are source-filter modeling, distribution models, and sequential models. We start with short discussion on kinematic modeling of hand movement and introduce the experimental data collected for this paper. Next, for each of the three modeling paradigms we define and motivate the methodology, and provide results of the experiments with the data. Finally, the paper is concluded by a discussion on the results and recommendations for future work in the analysis of involuntary hand movements.

2 SIGNAL MODELS

A simplified geometric model of arm and hand in a complex 2D plane is illustrated in Fig. 1. With the origin in the root of the arm, the position of the tip of the finger, P, can be expressed by

$$p(t) = \sum_{j=0}^{J-1} l_j e^{-i\Sigma_k^j(\alpha_k(t))} \tag{1}$$

where J is the number of joints and l_j and α_j are the bone lengths and joint angles, respectively. The joint angles change due to the contractions of the muscles connected over the joint which are caused by neural excitation in the muscle bundles. The movement of the hand (and the captured signal from an accelerometer) is therefore driven by multiple *neural source signals*. The arrival times of individual impulses in different muscles are probably uncorrelated but the signals may still have some long-term correlations. The model does not contain the effects of inertia, elasticity of the muscles, and the neural feedback.

The *minimum jerk model* by Flash and Hogan (Flash and Hogan, 1985) is a simplified model for the kinematics of a short linear movement of a hand from a rest at the position x_0 to full stop at x_f in time t_f. The position as a function of time is given by

$$x(t) = x_0 + (x_0 - x_f)(15\tau^4 - 6\tau^5 - 10\tau^3) \tag{2}$$

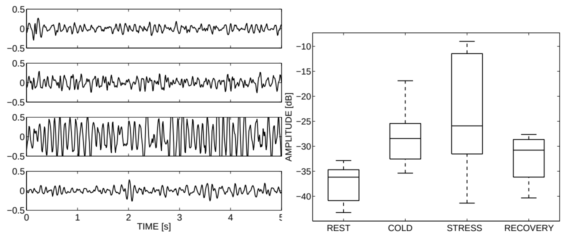

Figure 2: Left: Fragments of *rest, cold, stress,* and *recovery*, from top to bottom, respectively. Right: median and quartile RMS values of signals over all data.

where $\tau = t/t_f$. For the purpose of this paper one may notice that the measured acceleration $h(t)$ corresponds to the second derivative of the function and it is given by

$$h(t) = \frac{d^2x(t)}{dt^2} = \left(\frac{180t^2}{t_f^4} - \frac{120t^3}{t_f^5} - \frac{60t}{t_f^3}\right)(x_0 - x_f) \tag{3}$$

The model has no biometric parameters like bone lengths or masses which would be difficult to acquire. Assuming that the movements in three directions are independent it can be directly extended to 3D accelerometer data.

3 EXPERIMENTAL DATA

The goal of the experiment was to compare the three different signal modeling paradigms with realistic data. The data set was collected using a 3-axis accelerometer (Xsens MTx) which was attached on the back of the middle and ring finger of the subject using an elastic band. The data was captured at the sampling rate of 100 Hz. The physiological tremors were measured in an office room with the subject sitting and resting the elbow on the corner of a desk. Next, the subject went outdoors without a coat (temperature was around 0°C) and stood there for 2-4 minutes until the subject was clearly shivering or wanted to stop the experiment. Next, after a short rest and warming, the subject held a 1-3kg weight in the hand arm extended to the front until the subject felt the fatigue in the arm and/or could not hold the weight anymore. After the period of physical stress the subject was resting until the perceived fatigue disappeared. The data was consequently segmented to four parts: *rest, cold, stress,* and *recovery*. Five healthy male subjects participated in the data collection. Waveforms from the different classes are illustrated in Fig. 2. A dominant frequency component around 10Hz can be often found but there are large individual differences.

The accelerometer signals were preprocessed by a steep high-pass filter with a cutoff at 2Hz to remove the effects of slow hand movements and gravity from the data.

4 SOURCE-FILTER MODEL

One may consider $h(t)$ in (3) as the impulse response of the system from a single neural impulse to the observed accelerometer data. As a *source-filter model* it may be written in the following form:

$$a(t) = \sum_{k=0}^{\infty} \sum_{m=1}^{M} h_m(k,t) e_m(t-k) \quad (4)$$

where M is the number of muscles contributing to the movements, $h_m(k,t)$ is the time-varying kinematic impulse response from an mth muscle (or j th joint in the geometric model) to the accelerometer signal, and $e_m(t)$ is the *neural source signal* (Vinjamuri et al., 2009) exciting the muscle. This is a linear approximation which assumes that the effects of the muscles are independent. In the case of small movements the linearization and independence assumption can be considered justifiable.

Low-order autoregressive models have been used earlier in the spectrum analysis of hand tremors (Zhang and Chu, 2005; Becker et al., 2008; Kucukelbir et al., 2009). Several authors, e.g., (Gantert et al., 1992) have used measures based on the predictability of phase space trajectories (e.g., Lyapunov exponents) to model tremors. In (Vinjamuri et al., 2009) the signals from multiple accelerometers were modeled as convolutive mixtures of a neural source signals that are exciting the muscles. They used independent component analysis to extract the hypothetical neural source signals. The assumed signal model each sensor was therefore similar to (4).

The signal model (4) has multiple source signals which each have a different impulse response which makes the modeling problem very difficult. Let us assume that the excitation is *sparse* such that at a movement is predominantly caused by one neural source signal or a muscle. In this case, the model of (4) could be approximated by a time-varying autoregressive model given by

$$a(t) = \sum_{k=0}^{\infty} h(k,t) e(t-k) \quad (5)$$

where $h(k,t)$ is a time-varying impulse response switching between the different input terminals of the neural source signal. The sparsity assumption has no obvious biomechanical evidence but it is a plausible assumption at least for single rapid jerks.

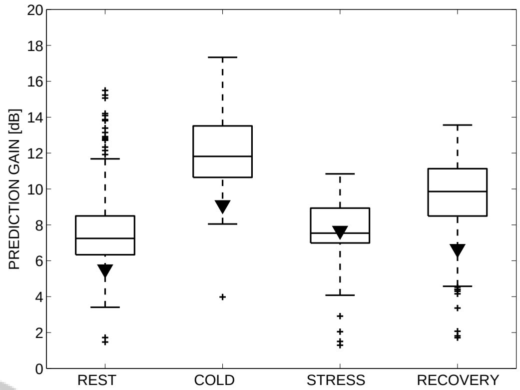

Figure 3: Prediction gain values averaged over all subject and data. The G_p values of the stationary AR model are shown by triangles.

In this paper the time-varying AR system is modeled using the time-varying autoregressive (TVAR) method by Grenier (Grenier, 1983). It is essentially similar to Burg's lattice algorithm (AR) but replaces stationary reflection coefficients by sums of time-varying basis functions (in this case, sigmoids). The time-varying reflection coefficients of the estimated Grenier's model represent the kinematic impulse responses and the prediction residual signal $e(t)$ models the neural excitation. The performance of the source-filter model can be characterized by the prediction gain given by $G_p = 20\log_{10}(E[|a(t)|^2]/E[|e(t)|^2])$. The prediction gain values of the 8th order Grenier's model estimated in 10s frames averaged over all subjects are shown in Fig. 3. Shivering seems to give the largest median G_p value and there is clear difference to the stress condition. Fig. 2 shows that the RMS values of those conditions do not differ significantly. The difference between rest and cold conditions however may be related to the difference in RMS values. Shivering seems to be more predictable than tremors caused by stress. The TVAR model gives consistently a 2-4dB advantage over the static Burg AR model (triangles) in other than the stress condition. Additional experiments demonstrated that the G_p in both AR and TVAR does not increase when the model order is higher that 6. Therefore, one may conclude that data can be modeled as a mildly time-varying low-order AR process and especially the stress condition seems to differ in predictability and time-variability from the other conditions.

5 DISTRIBUTION MODELING

It is common to assume that underlying process is ergodic such that the long-term statistics of features computed from the data are similar over time and in different subjects. For example, in (Jakubowski et al., 2002) the higher-order statistics features computed from accelerometer data were used in a feed-forward neural network to classify successfully physiological, Parkinson's, and essential tremor data.

In early experimentation with multiple algorithm candidates the naive Bayes classifier turned out to be one of the most efficient methods for this type of data. A set of F time- and frequency domain features were computed in one second frames of acceleration data. The naive Bayes model assumes that individual features are conditionally independent random variables within each class, see (Murphy, 2012). The distribution $p_f(x|c)$ of the feature f values within each class c is estimated from the training data. For the unknown input feature vector $\underline{x}$ the likelihood value for each class c are given by

$$p(\underline{x}|c) = \prod_{f=0}^{F-1} p_f(x|c) \tag{6}$$

and choose the class that gives the maximum value. This is a probabilistic signal model that characterizes the long-term statistics of the features computed from the signal.

The following features were computed in two second segments from the data: normalized signal variance, ratio between maximum and mean absolute values, maximum frequency, prediction gain G_p, and the first four cepstrum coefficients computed on a near-logarithmic frequency scale. The naive Bayes classifier was trained using the data from the four classes. The experiment was performed using repeated leave-one-out cross-validation so that the model was tested always using the data from one subject who was not included in the training data. The accumulated sensitivity and specificity percentages over all four classes were 80 and 70%, respectively. The largest number of classification errors was between rest and recovery periods which suggest that most subjects recovered very quickly.

6 SEQUENTIAL MODELS

The kinematic model above suggests that the movement data consists of a sequence of individual events, jerks and spasms. The proposed signal model corresponding to J such jerks is given by

$$a(t) = \sum_{j}^{J} h_j(t - t_j) \tag{7}$$

where $h_j(t)$ is the function of (3) defined in the interval $[0, t_f(j)]$ and zero otherwise. The length of the interval $t_f(j)$ (as well as x_0 and x_f) depends on j but it is likely that there are often similar recurring jerks in the data so that the data can be approximated effectively by a limited *alphabet* of prototypical jerks. Therefore, one may approximate the signal model (6) by a system that produces a sequence of timed indexes of prototypical movements from a fixed vocabulary. For this type of data it is natural to use hidden Markov models (HMM), conditional random fields (CRF), or other graphical models. Sung *et al* (Sung et al., 2004) used the HMM in the method for the analysis of shivering. Their results were promising but they did not give a clear motivation why shivering was considered as a Markov process. The discrete HMM model models state transitions in a *hidden* state machine where only the *emissions* of this state machine at each state transition are observable. One may associate the emissions with the individual movements in the accelerometer data and the hidden state machine with the underlying processes in the body.

A practical way to create the vocabulary of movements, or jerks, is to initialize a codebook of candidate functions and then search for a limited vocabulary of J jerk patterns that has the best match with the data. This was performed using a matching pursuit search with functions of the Flash-Hogan model (3) which are characterized by the duration t_f and the excursion x_f, respectively. The matching criteria is the Euclidean distance between the accelerometer data segment represented by a zero-mean vector $\mathbf{a}(t)$ and a movement vector $\mathbf{h}(x_f, t_f)$ of (3), where t is the time index corresponding to the first element of the vector and length of the vector is the same as the length of $\mathbf{h}(x_f, t_f)$. In order to compare different candidate functions the value is convenient to convert in to a score value in range $[0, 1]$. This is given by

$$s(t, x_f, t_f) = \max(0, 1 - |\mathbf{a}(t) - \mathbf{h}(x_f, t_f)|^2 / |\mathbf{a}(t)|^2). \tag{8}$$

For example, Figure 4 shows examples of average score values for different types of movement data in one subject. One can pick a number of local maxima from each figure as the most typical cases of movements in the data characterized by the excursion x_f and the duration t_f. This was repeated for the entire data set and then a subset of Flash-Hogan functions was determined by searching the maxima within each local connected region in the obtained figure. The accelerometer data is converted to a sequence of prototype indices so that in each short time segment the prototype vector that gives the maximum score is selected. The parameter values for eight common jerk patters were selected from the data. In the experiments the winning prototype giving the highest score was selected in non-overlapping segments of 100ms

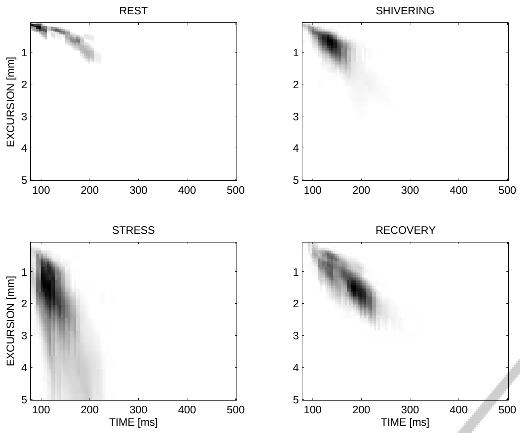

Figure 4: Average score values for the data from one subject (black color - score 1.0).

leads to a data rate of 10 prototype indices per second. The training and cross-validation of the HMM were performed in the same way as in Section 5. The model had 12 hidden states and the model for tested for each 4 second episode.

The accumulated results of multiple cross-validations show that the sensitivity and specificity of the HMM model in the four-class classification problem are 75% and 75%, respectively, and the largest errors are again in the correct classification of the recovery phase.

7 DISCUSSION

The topic of the paper is automatic classification of physiological tremor, shivering, and tremors caused by physical stress. Three different experiments were reported. First, it was demonstrated that the accelerometer data can be modeled as a low-order time-varying autoregressive process and that there are differences between the data types in the prediction gain values. Next, the experiment with a naive Bayes classifier showed that the different data types can be classified based on long-term statistics. Finally, similar classification performance was obtained by modeling movements as a Markov process of small prototypic movements.

All modeling approaches seem motivated and are effective but the error rates were relatively high in all classification experiments, in particular, in the recovery and resting data.

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