Автоматизация научных исследований в машинном обучении

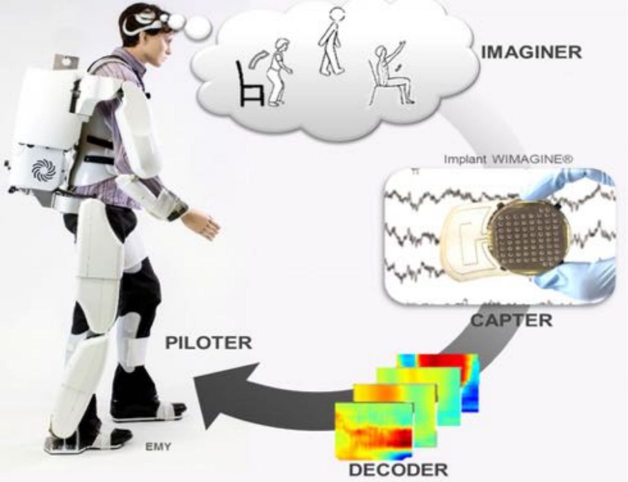
Вадим Викторович Стрижов

Московский физико-технический институт

Осенний семестр 2018

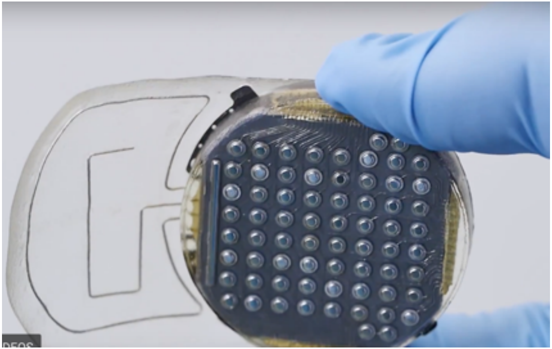
The BCI project

aims to develop compensating systems that will help people with a severe motor control disability recover mobility.



www.clinatec.fr

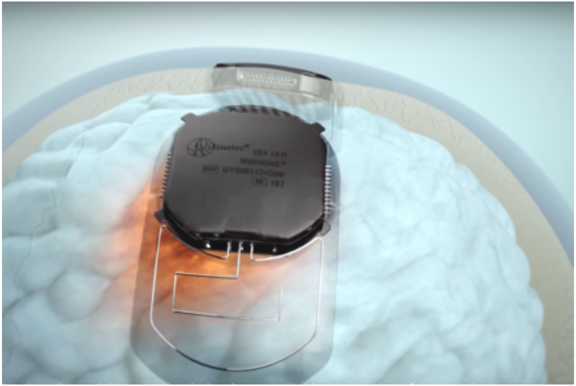
Implant WIMAGINE to measure ECoG



records ElectroCorticoGrams, has remote power supply, and wireless data transfer system.

WIMAGINE: Wireless 64-Channel ECoG Recording Implant for Long Term Clinical Applications Mestais, G. Charvet, F. Sauter-Starace, M. Foerster, D. Ratel, and AL. Benabid IEEE Trans Neural Syst Rehabil Eng. 2015 Jan;23(1):10-21. www.clinatec.fr

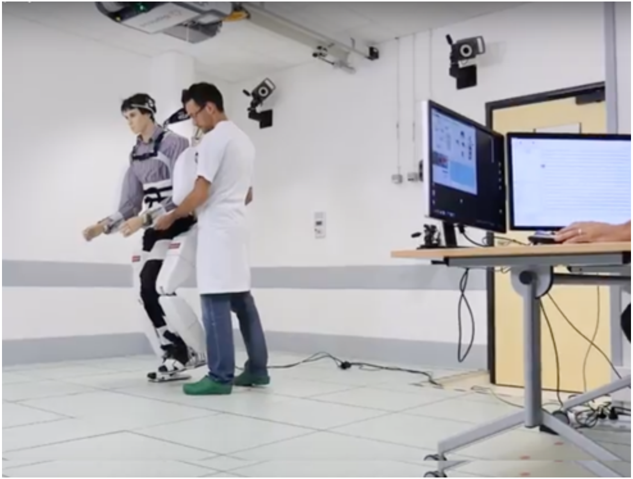
Implant WIMAGINE to measure ECoG



detects the electrical activity in the motor cortex with "minimally-invasive implantation in the cranium and, over the long term, to measure ElectroCorticoGrams thanks to an array of <u>electrodes in contact with the d</u>ura mater."

Eliseyev, A., and Aksenova, T. Stable and artifact-resistant decoding of 3D hand trajectories from ECoG signals using the generalized additive model // J. Neural Eng.(2014) 11, 066005. www.clinatec.fr

The BCI project

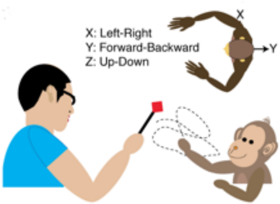


"The subject placed inside the exoskeleton can drive it by imagining movements as if they were making the movement themself."

www.clinatec.fr

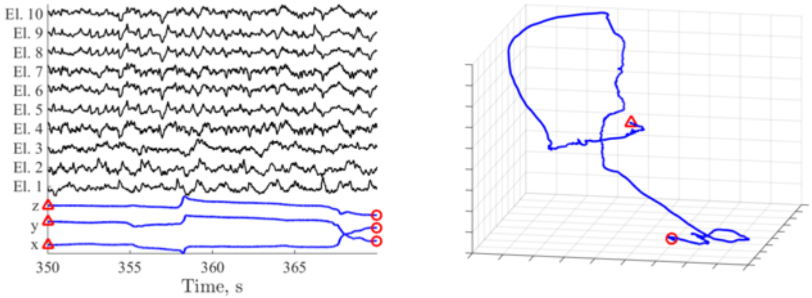
Neurotycho data, foodtracking task

A monkey is tracking food rewards with the hand contralateral to the implant side. The experimenter demonstrated foods at random locations at a distance of 20 cm for the monkey at random time intervals 3-4 times per minute, and the monkey grasped the foods



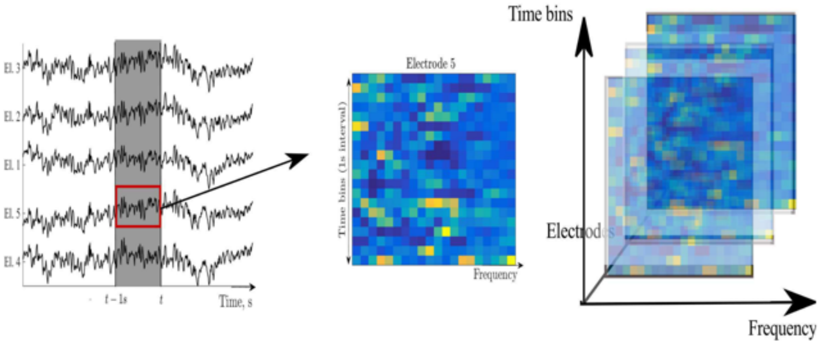
- Subdural (32 electrodes): 2 monkeys, 3 and 5 records, taken within 7 months.
- Each record measures about 1000 seconds with ECoG and motion data (wrists, elbows and shouders) sampled at 1KHz and 120Hz, respectively.

ECoG and corresponding physical motion



Extracts (350–370s) from voltage and wrist position time series for monkey A and 3D wrist trajectory for the same extract.

The feature construction procedure



For each electrode a one-second long historical interval $[t_m - \Delta t, t_m]$ undergoes wavelet transformation and thus obtains feature description in spectral-temporal domain. Merging spectral-temporal feature matrices for all electrodes, one obtains 3D feature description X_m for the time point t_m.

Problem statement: movement prediction

Inputs: multivariate time series $\mathbf{s}(t) \in \mathbb{R}^{N_{\text{ch}}}$ — voltage measurements for each channel $1, \dots, N_{\text{ch}}$.
Targets: multivariate time series $\mathbf{y}(t) \in \mathbb{R}^3$ with 3D limb coordinates.

The goal us to reconstruct $\mathbf{y}(t)$ from $\mathbf{s}(t), \dots \mathbf{s}(t - \Delta t)$.

The time series are converted to the data sample $(\underline{\mathbf{D}}, \mathbf{Y})$:

$$\underline{\mathbf{D}} \in \mathbb{R}^{T \times F \times N_{\text{ch}} \times M}, \; D_{(m,:,:,:)} = \underline{\mathbf{X}}_m, \quad \mathbf{Y} = [\mathbf{y}_1^{\mathsf{T}}, \dots, \mathbf{y}_M^{\mathsf{T}}]^{\mathsf{T}},$$

such that $\mathbf{y}_m = \mathbf{y}(t_m)$ and $\underline{\mathbf{X}}_m \in \mathbb{R}^{T \times F \times N_{\text{ch}}}$ is a three-way matrix, which stores time-frequency features extracted from the time series $[s_n(t_m - \Delta t), \dots, s_n(t_m))]$ along all channels n, $n = 1, \dots, N_{\text{ch}}$.

The reconstructed trajectory $\hat{\mathbf{Y}}$ approximates the real $\mathbf{Y}$ as a linear combination of features:

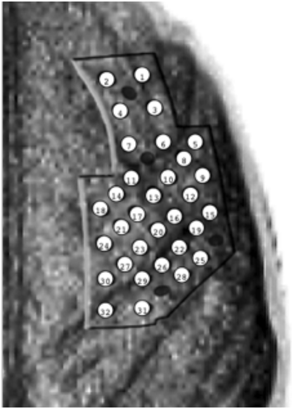
$$\hat{\mathbf{y}}_m = \text{vec}\big(\underline{\mathbf{X}}_m\big)^{\mathsf{T}} \hat{\mathbf{w}},$$

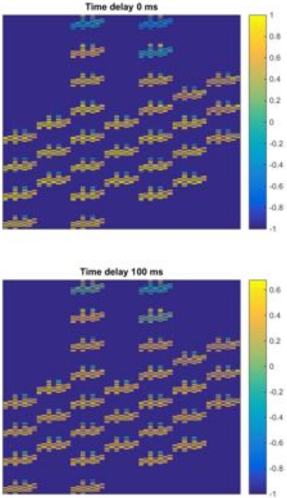
where the weight vector $\hat{\mathbf{w}} \in \mathbb{R}^{T \cdot F \cdot N_{\text{ch}} \times 3}$ minimize the squared sum of residues:

$$\hat{\mathbf{w}} = \arg\min_{\mathbf{w}} ||\hat{\mathbf{Y}} - \mathbf{Y}||_2^2.$$

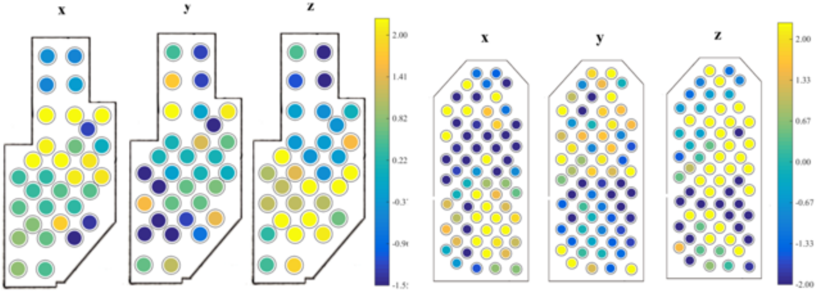
Feature extraction: time-domain features

Correlations between channels in time domain:





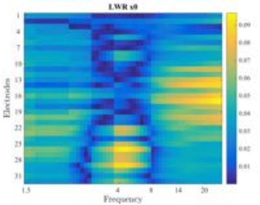
Cross-correlation between ECoG and target time series

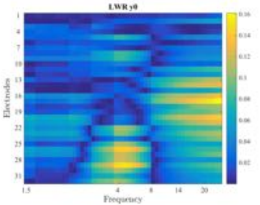


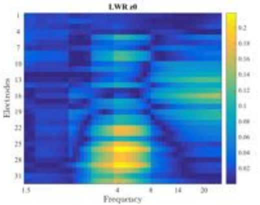
Absolute values of cross-correlation between ECoG and target time series (wrist positions) in time domain for monkeys A (32 electrodes) and K1 (64 electrodes).

Problem statement: feature selection

Absolute values of cross-correlation between ECoG and target time series in (left wrist) frequency domain. No time delay $\tau = 0$.

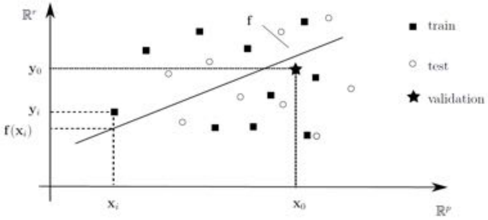






The auto-regressive design matrix for the multivariate target

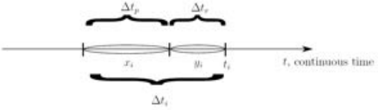
Forecast is a mapping from p-dimensional objects space to r-dimensional answers space.



Projection to Latent Structures (PLS)

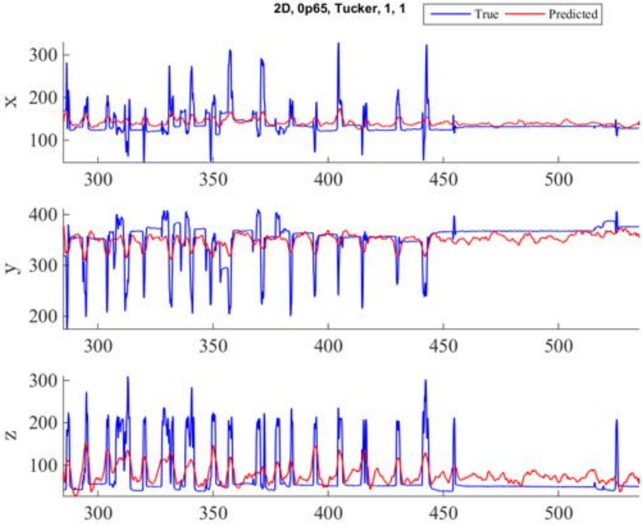
$$
\begin{aligned}
\mathbf{X} &= \mathbf{T}\mathbf{P}^{\mathsf{T}} + \mathbf{E}, \quad \mathbf{P}^{\mathsf{T}}\mathbf{P} = \mathbf{I}_N, \\
\mathbf{Y} &= \mathbf{U}\mathbf{Q}^{\mathsf{T}} + \mathbf{F}, \quad \mathbf{Q}^{\mathsf{T}}\mathbf{Q} = \mathbf{I}_N, \\
\hat{\mathbf{Y}} &= \hat{\mathbf{T}}\mathrm{diag}(\beta)\mathbf{Q}^{\mathsf{T}} = \mathbf{X}\mathbf{W}.
\end{aligned}
$$

$$
\mathbf{X}^* = \left[\begin{array}{c|c} \underset{1\times n}{\mathbf{x}} & \underset{1\times r}{\mathbf{y}} \\ \hline \underset{m\times n}{\mathbf{X}} & \underset{m\times r}{\mathbf{Y}} \end{array}\right]
$$

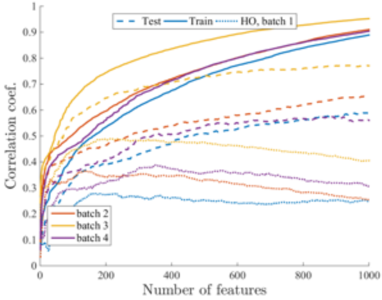


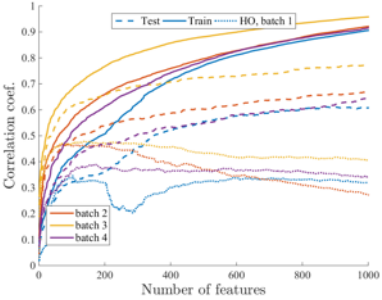
Example of forecast (2D)

50 best (according to M-QPFS) features. Predicted trajectories are smoothed by 2.5s window.



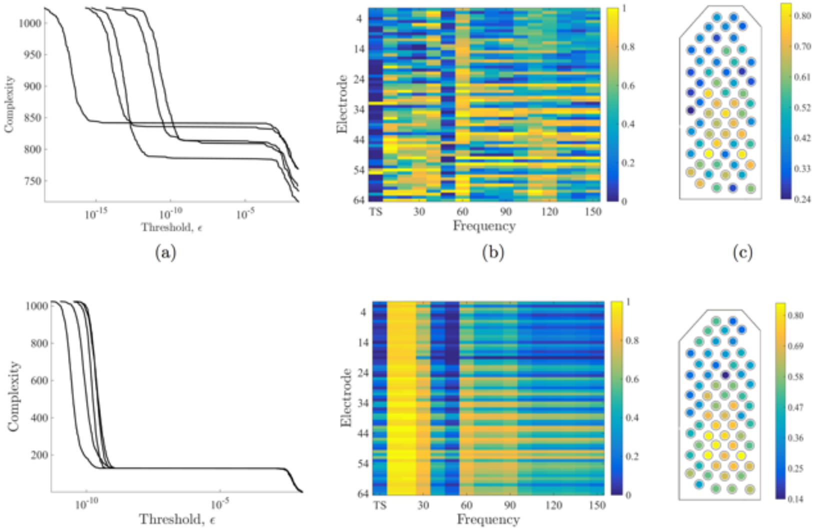
The forecasting quality measures





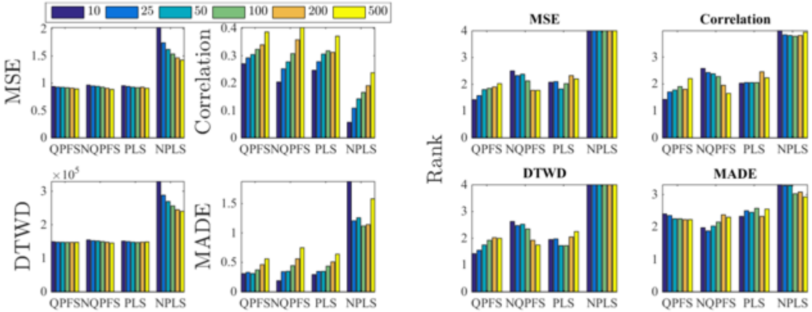
Forecasting quality measures as correlation coefficient between the original wrist trajectory and the reconstructed trajectory. Unfolded QPFS (left) and Multi-way QPFS (right).

Complexity and threshold value



Evaluation of electrode-frequency pairs importance. Importance is measured as feature rank, averaged over cross-validation splits. Electrode ranks, averaged over frequencies.

Average values of all quality criteria to compare algorithms



Average values of all quality criteria for the compared algorithms (left). Average rankings of the compared algorithms, the lesser the better (right).

Three characteristic time spans

- An elementary movement
- A motion
- An action
- ...
- The lifespan

Complex action: workers construct a rack

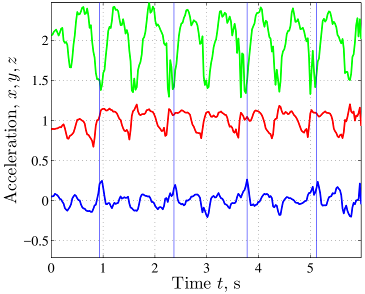
Complex action: workers construct a rack

Complex action: workers construct a rack

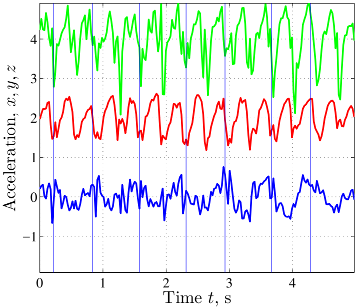
3D-projection of acceleration time series to spatial axis

$$\mathbf{x} = \{acc_x(t); acc_y(t); acc_z(t)\}_{t=1}^{n} \mapsto \mathbf{y} \in \mathbb{R}^S.$$

Slow walking



Jogging



Local models for deep learning neural network

Model $\mathbf{f} = \mathbf{a}(\mathbf{h}_N(\ldots \mathbf{h}_1(\mathbf{x})))(\mathbf{w})$ contains local approximation models $\mathbf{h}_k$ autoencoder $\mathbf{a}$ and softmax classifier

$$\mathbf{f}(\mathbf{w}, \mathbf{x}) = \frac{\exp(\mathbf{a}(\mathbf{x}))}{\sum_j \exp(a_j(\mathbf{x}))}, \qquad \mathbf{a}(\mathbf{x}) = \mathbf{W}_2^{\mathsf{T}} \mathbf{tanh}(\mathbf{W}_1^{\mathsf{T}} \mathbf{x}),$$

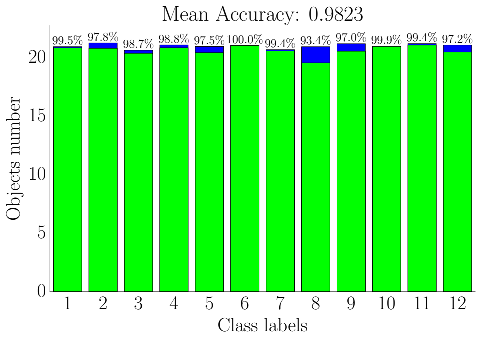
where w minimizes the error function.

Feature generation, the local approximation models $\mathbf{h}_k$:

- parameters of SSA approximation of the time series $\mathbf{x}$,
- FFT of $\mathbf{x}$,
- parameters of polynomial/spline approximation,
- self-modeling regression SeMoR,
- distance to centroids,
- time-alignment

could reduce complexity this model down to complexity of logistic regression and boost the classification quality.

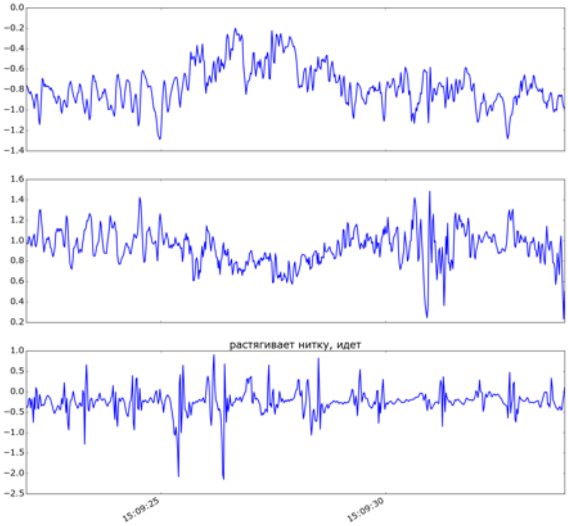
Performance of the human physical activities classification



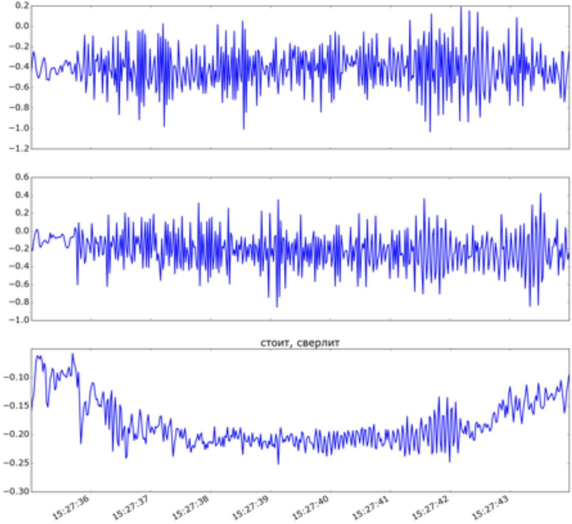
1) walk forward
2) walk left
3) walk right
4) go upstairs
5) go downstairs
6) run forward
7) jump up and down
8) sit and fidget
9) stand
10) sleep
11) elevator up
12) elevator down

Ignatov A.D., Strijov V.V. Human activity recognition using quasiperiodic time series collected from a single triaxial accelerometer // Multimedia Tools and Applications, 2015, 17.05.2015 : 1-14.

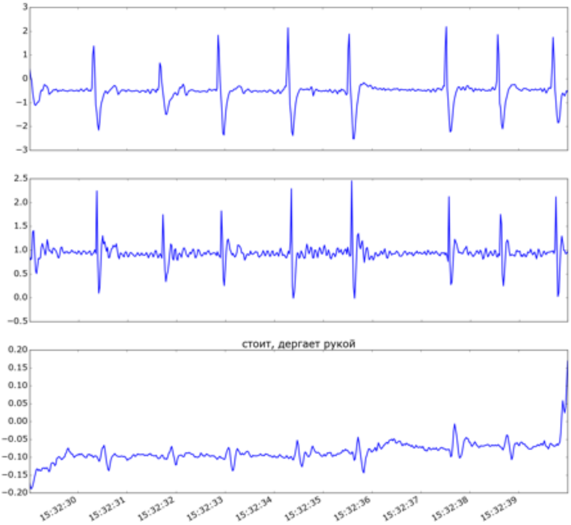
Complex movement: the worker stretches a string while walking



Complex movement: the worker is drilling while standing



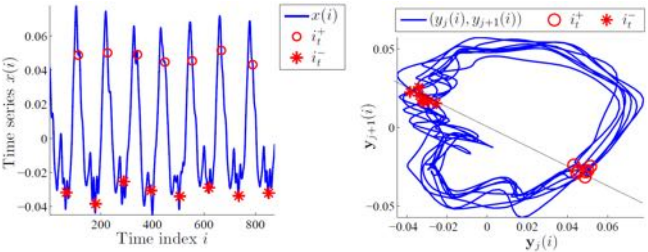
Complex movement: the worker is twitching his hand



Human gate detection with time series segmentation

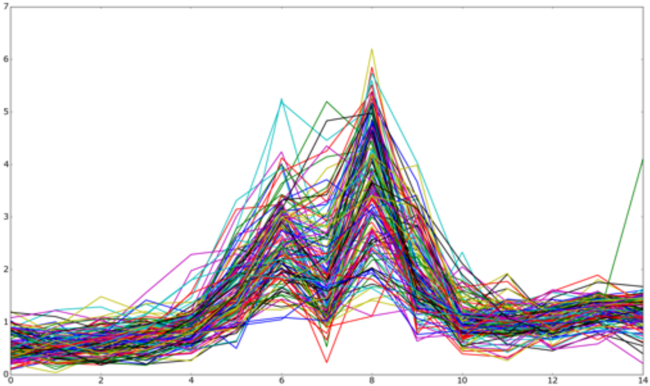
Find dissection of the trajectory of principal components $\mathbf{y}_j = \mathbf{H}\mathbf{v}_j$, where $\mathbf{H}$ is the Hankel matrix and $\mathbf{v}_j$ are its eigenvectors:

$$\frac{1}{N}\mathbf{H}^{\mathsf{T}}\mathbf{H} = \mathbf{V}\boldsymbol{\Lambda}\mathbf{V}^{\mathsf{T}}, \quad \Lambda = \mathrm{diag}(\lambda_1, \ldots, \lambda_N).$$

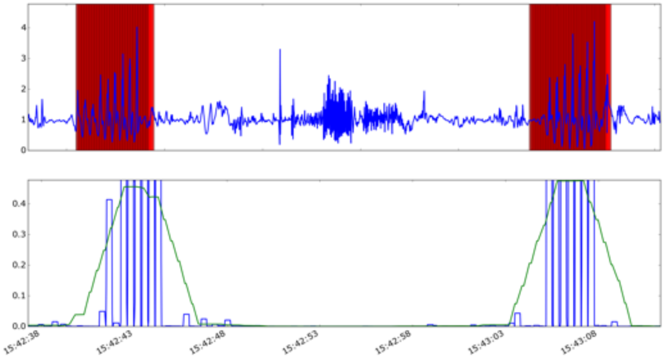


Motrenko A.P., Strijov V.V. Extracting fundamental periods to segment human motion time series // IEEE Journal of Biomedical and Health Informatics, 2016, 20(6) : 1466 - 1476.

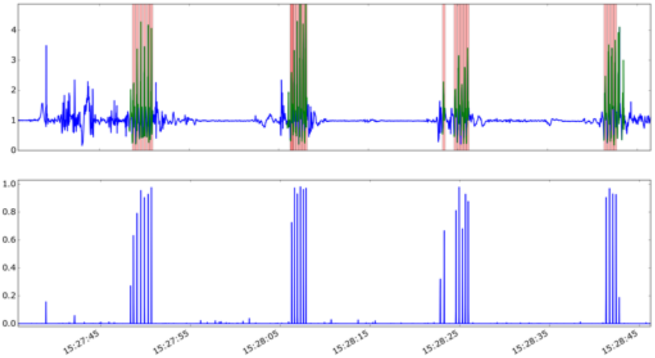
The hammer clogs a dowel, elementary movements



The hammer clogs a dowel, the movements join a motion



The motion "to clog dowel"



The motion and its neighborhood to discover an action