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SEGMENTATION OF HUMAN MOTION ACCELERATION WITH PROBABILISTIC CLASSIFIER

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Abstract: *This paper describes a method for signal segmentation in human motion analysis. Proposed method uses a probabilistic change point estimator combined with a Trigg's tracking signal for detection of changes in a signal variation and segmentation to the subsections by these change points. Main usage of this method is in fields of sport training or health condition monitoring but it can be also used in technical monitoring.*

Keywords: Signal segmentation, Change point detection, Motion analysis, Trigg's tracking signal.

1. Introduction

Detection of changes in time-series data is frequently solved task in the quality control, statistics and data mining for decades. Besides of alarm triggering, change points can be used for segmentation of acquired data into parts with similar properties.

If the nature of the signal changes significantly at some point in time, this point can be marked as the change point which separates two subsections of the signal, so called signal segments. These segments usually differ in some parameter of their probability distribution. Identifying changes in parameters of the probability distributions of points preceding and following the actual sample is usually called distributional change detection.

In motion analysis, various movement types like walking, running or jumping usually differs in the signal properties. With the use of a segmentation algorithm, data of these individual motions can be selected from the acquired dataset and processed separately.

2. Method

2.1. Probabilistic change point estimator

Let's consider digital signal as the set of realizations of random variable which has a probability density function with the vector of parameters $\boldsymbol{\theta}$. In most technical cases, probability density function follows a normal distribution $N(\mu,\ \sigma^2)$ (Vechet et al., 2010). The vector of parameters consists of two elements – mean and variation – $\boldsymbol{\theta}\ = (\mu, \sigma^2)$.

Finite set of samples $X = \{x_1, x_2, ...\}$ can be separated into K subsets. In the case of change point detection in acceleration, the subsets mainly differ in a variation σ_k^2. Mean value μ_k of each segment is very close to zero, so its changes are not tracked and probability density function is considered symmetric around zero.

The elements of the *k*th segment can be expressed as the realization of the random variable with normal distribution $N(0,\ \sigma_k^2)$. The task is to find the *n*th sample, which separates segments k and k+1. The change occurs, when the preceding points have different probability density function then the followings.

The probability, that point x follows the probability density function with zero mean and variance σ^2 is expressed with a function $p(x,\ \sigma)$ according to equation (1).

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$$p(x, \sigma) = e^{-\frac{x^2}{\sigma^2}} \quad (1)$$

The probability of change L_k for *k*th sample of the signal X can be expressed with the change estimator $\hat{w}(x)$. A logarithmic density ratio is a good estimate of change (Sugiyama, 2015). This estimator is described with equation (2) as a log-ratio of two probabilities – whether sample X_k follows probability density function of the following or preceding samples. Due to the shape of the logarithmic function around zero, this estimator provides sensible detection of small changes but is also prone to be sensitive to outliers.

$$L_k = \ln \frac{p(X_k, \sigma_1)}{p(X_k, \sigma_0)} \quad (2)$$

In this equation, σ_0 represents standard deviation of the preceding points and σ_1 is the standard deviation of the following points. Standard deviations are computed from the finite windows of length $H = 50$.

The value of L_k is close to zero for similar p-values – this refers to the fact, that the preceding and following points have similar statistical parameters. L_k is positive for a higher likelihood of increasing the variation and negative for decreasing. Due to the large variations in scale of L caused by the logarithmic function, simple thresholding cannot be used.

2.2. Change point evaluation with use of the tracking signal

Many statistical quality control techniques are used in a field of economics, technical monitoring, medical applications (Blackwell et al., 1992) and others for decades. One of them is the Trigg's tracking signal, which is widely used especially in forecasting and change detection in processes monitoring. Trigg defined the tracking signal TTS as (Trigg et al., 1967)

$$TTS_n = \frac{SFE_n}{MAD_n} \quad (3)$$

where *SFE* represents exponentially smoothed forecast error. This one is recursively defined with adjustable smoothing parameter α according to equation (4). A decent value of α in this study is 0.2, which provides an acceptable compromise between detection delay and smoothing.

$$SFE_n = \alpha \cdot FE_n + (1 - \alpha) \cdot SFE_{n-1} \quad (4)$$

The probability of change L_k is used as the forecasting error FE_k. Mean absolute deviation (MAD) represents the exponentially smoothed absolute forecast error according to equation (5).

$$MAD_n = \alpha \cdot |FE_n| + (1 - \alpha) \cdot MAD_{n-1} \quad (5)$$

Because of its definition as ration, TTS takes the values of interval $[-1, 1]$. *TTS* zero-crossing is the sign of change in the input signal. For consecutive segments, which parameters are changing monotonously, the tracking signal will approach the theoretical minimum or maximum. This is the main disadvantage, which makes monotonous changes detection very difficult, even impossible.

2.3. Change point detection in acceleration

The proposed method was used for a segmentation of a human motion acceleration measured with the inertial MEMS sensor. Because of the character of human motion, the signal segments differ mainly in variance and changes in mean value of acceleration are insignificant. This property can be even amplified with the use of acceleration derivation – the jerk $j(t)$ – instead of acceleration. Because of discrete nature of the signal, jerk is obtained with numerical derivation according to equation (6).

$$j_n = \frac{\mathrm{a_n} - \mathrm{a_{n-1}}}{\Delta t} \quad (6)$$

3. Results

Fig. 1 displays a forward acceleration of front crawl swimmer. Data were acquired during one swimming pool length using MEMS accelerometer with 100 Hz sample rate. Data were pre-processed and the influence of gravity field was removed.

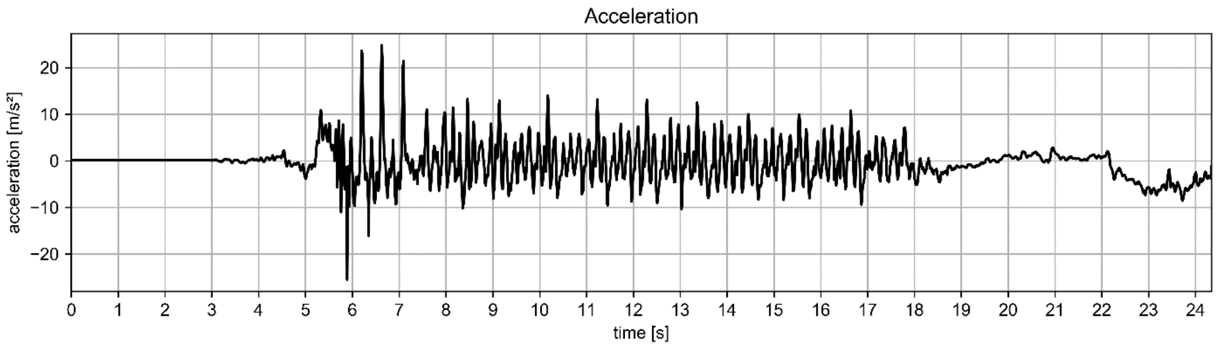

Fig. 1: Forward acceleration of the front crawl swimmer.

The first graph of Fig. 2 shows a jerk obtained as numerical differentiation of the forward acceleration. Jerk was processed by running average filter with a length of 3 samples for outliners removal. The second graph displays the value of change estimation expressed log-ratio *L*. The third graph shows the Trigg's tracking signal with change points marked with blue points.

The criterion of minimal distance between two changes was used for suppressing of false-positive detection. Change point is accepted only if the criterion of minimal distance t = 0.25 s from the preceding point is met.

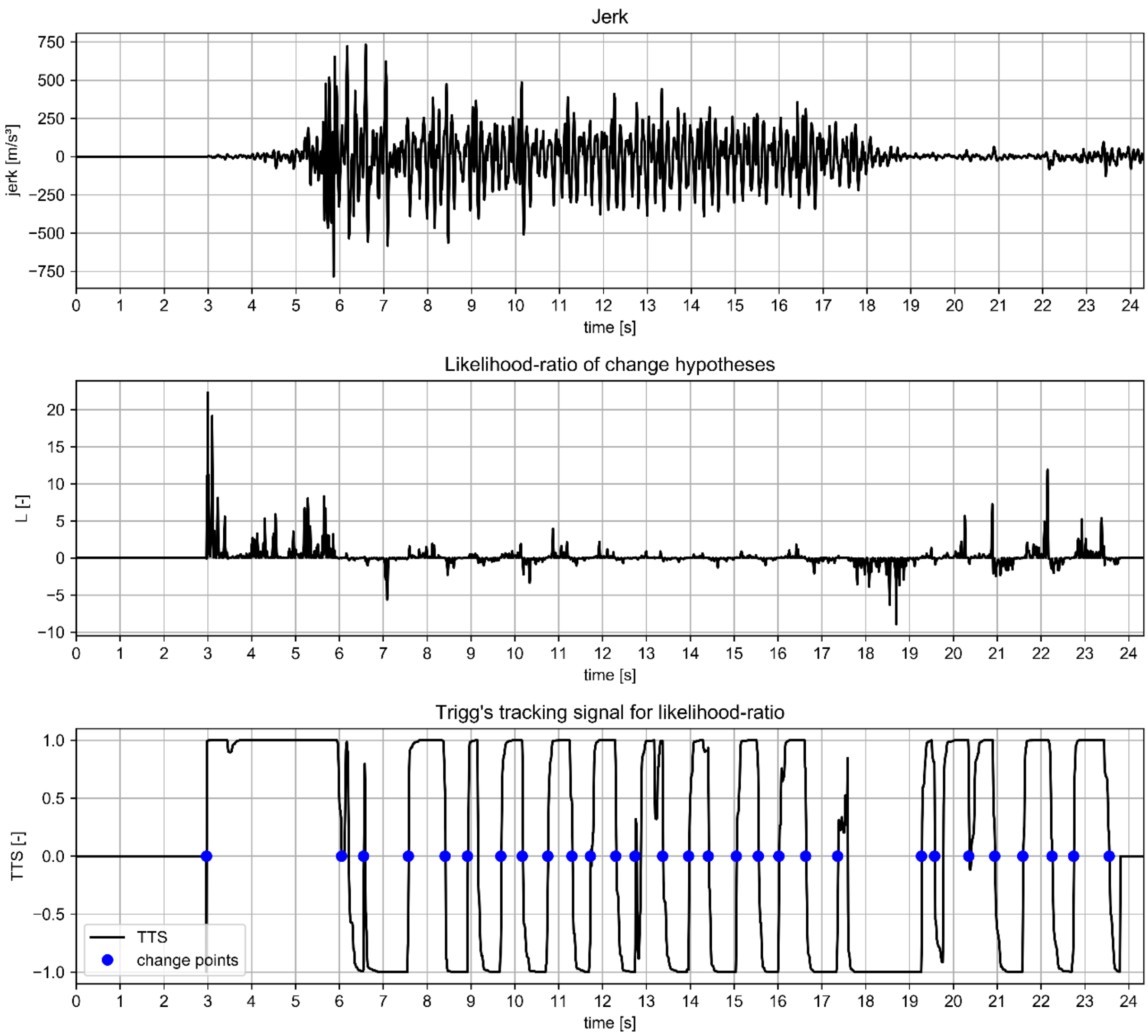

Fig. 2: Jerk obtained as derivation of simmer's forward acceleration, it's log-likelihood of change and Trigg's tracking signal of the log-likelihood. Blue points mark detected change points.

In Fig. 3, the output set of change point is showed. Blue vertical lines separate detected segments, which differs in jerk variation. It can be seen, that signal segments between time 7 – 18 s are in a good match with swimmer's arm strokes. The second graph of the Fig. 3 provides a comparison with an angular velocity measured with gyroscope in perpendicular axis. Change point at time 6.5 s is a typical example of false-positive change detection error. It can be seen, that change in TTS is for this change point very narrow. From the previously described reasons, the algorithm cannot detect consecutive segments with monotonously increasing or decreasing variation.

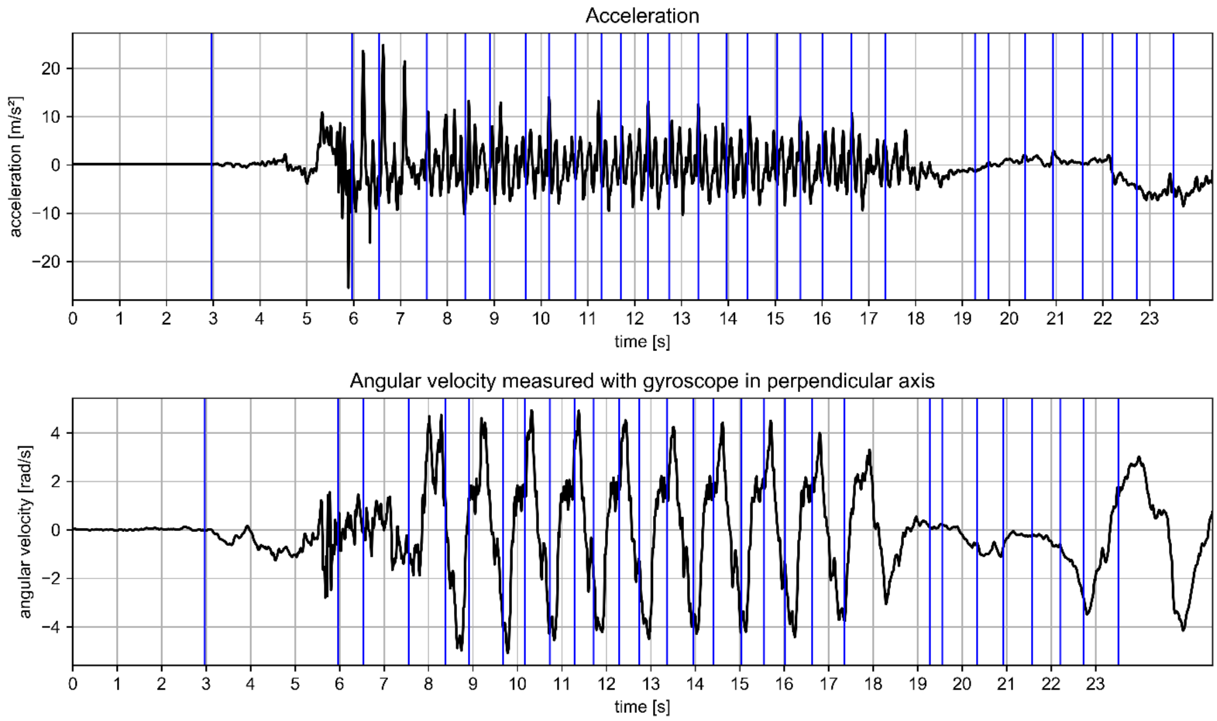

Fig. 3: Acceleration data with marked segments. The lower graph displays the angular velocity measured in perpendicular axis for evaluation of the arm-stroke detection.

4. Conclusions

This paper presented the method for segmentation of human motion acceleration. This method combines probabilistic change estimator with a Trig's tracking signal for change detection in obtained motion data variation. The method was demonstrated on the segmentation of swimmer's acceleration into individual arm strokes. The results show sensitivity of proposed method. For further development, it would be appropriate to eliminate false-positive detections with an use of advanced probabilistic change estimator.

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