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EGLĖ BUTKEVIČIŪTĖ

ECG SIGNAL ANALYSIS FOR THE MODELLING OF TRAINING PROCESS AND FATIGUE EVALUATION

Summary of Doctoral Dissertation
Natural Sciences, Informatics (N 009)

2021, Kaunas

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EKG SIGNALŲ ANALIZĖ TRENIRUOČIŲ PROCESO MODELIAVIMUI IR NUOVARGIO VERTINIMO METODIKOS SUDARYMUI

Daktaro disertacijos santrauka
Gamtos mokslai, informatika (N 009)

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INTRODUCTION

Relevance of the work

Smart technologies become more and more popular among people of different ages. Cloud-based technologies that are constantly improving allow majority services to be offered remotely. In order to monitor the health condition in gyms, clinics, working places or even at home, various apps are useful for those who have specific health conditions, are athletes or beginners in sport activities, elderly people and others. Electronic remote-control systems can sometimes replace ordinary health monitoring methods. People search for information on the Internet about their health condition, possible treatment methods, recommendations and share their experiences with each other. Health monitoring systems often require additional devices. Even though their demand is growing rapidly, every device and application needs to meet today's standards and be user friendly for everyone.

In medicine, biological signals are recorded when a person is in a stationary condition to make sure that the noise of the signal is minimal. However, it is hard to get a signal during activity without any noise that appears with breathing, muscle contractions, poor signal transmit channel or interruptions, blinks and other disturbances. Scientists from Lithuania and abroad apply numerous signal filtering methods without damaging the main signal characteristics in time or frequency scale. Even though signal recording in stationary condition is still widely used in diagnostics, they have limitations when it comes to the evaluation of interactions between different human organism systems and dynamic changes in daily activities.

If a person performs physical or mental exercises, multiple systems work in parallel: cardiovascular, muscular, neural and others. Heart rate variability and electrocardiogram parameter dynamical change analysis are becoming more and more popular because scientists are trying to find out how multiple human parts interact together as a single complex system. These researches are often based on ECG signal analysis; they show uninterruptable immediate heart rate variability, which is a response to different physiological or pathological states. Even though it may seem that ECG signal registration in movement is not a complex task, the signals are contaminated with various noises. The obtained noise is non-stationary and depends on the intensity of a particular exercise. That is why ordinary filtering methods fail in signal processing without damage to basic signal characteristics. The proposed filtering algorithm is able to adapt to the level of appearing noise in different work load (performing exercises with different intensity) and maintain the most important ECG parameter values that are essential for the health evaluation and monitoring.

Furthermore, the investigation of heart rate variability is important as well in physical or mental fatigue detection process. Physical fatigue is of very high importance for athletes and employees who work intensively. Even though athletes have a low risk of heart disease, the unnoticed symptoms can cause permanent heart injuries in a long-term. For this reason, people doing sports often have an interest in new technologies that allow monitoring health conditions or training intensity in real time. Meanwhile, office workers suffer from mental fatigue, which may end up in a chronic disorder and cause long-term consequences. When not noticed in time, the fatigue may result in disability at work. In this research, the main ECG signal parameters were estimated for physical and mental fatigue evaluation by using HRV analysis and machine learning methods.

The main analysis in this work is made on the ECG signals. However, the effectiveness of the proposed noise filtering algorithms has been shown as well for electroencephalograms. The suggested methodology for different types of fatigue detection can be applied in various mobile applications and be used in daily life activities. This could serve as a preventive tool to reduce the risk of injuries, reduce the number of deaths from cardiovascular disorders, detect primary symptoms of fatigue and increase the efficiency at work.

The object of the research is ECG signals that are recorded multiple times per day (morning/evening) during different exercises of various intensity.

The aim of the work is to pre-process electrocardiogram signals, analyse their variations, use the obtained results in training intensity management model and fatigue recognition process.

The main objectives of this research are as follows:

- Review literature about electrocardiogram signal, essential parameters for health evaluation process and parameter estimation algorithms;
- Review literature about high and low frequency filters, select and improve methods for movement contaminated ECG signal processing;
- Conduct ECG signal parameter search algorithm improvement by adding T wave detection algorithm;
- Create a methodology for physical and mental fatigue detection and evaluation.

Methods, software and experimental tools:

- CardioScout Multi device was used for the ECG signals recording and transmission to mobile device (with 500 s^{-1} frequency);
- In this research, for filtering algorithm comparison, clear (without noise) ECG signals were generated using CMRR 2.0 simulator;

- All signal processing, parameter estimation and fatigue identification algorithms were initialised using MATLAB_R2015b mathematical and statistical packages.

For the defence:

- Novel movement artefact filtering algorithm for ECG signal processing, evaluating filtering parameter changes that depend on the movements made and intensity of the training.
- Improved ECG parameter estimation algorithm with T wave amplitude and interval values detection.
- Modified monitoring system for training intensity to make sure that signal processing and feedback are given in real time.
- Novel fatigue recognition methodology that allows to detect and evaluate physical and mental or general fatigue.

Scientific novelty and significance

- Algorithms suitable for the filtering of ECG signal that were recorded during the exercise were improved according to the main characteristics of the signal, without the negative impact on the accuracy of it.
- A novel methodology using HRV analysis is proposed and applied for the physical fatigue recognition. Additionally, beans plot diagrams that were used were improved for the better understanding and easier comparison of data distribution.
- ECG signal parameter estimation algorithm was arranged by adding T wave amplitude and interval values detection. The characteristics that allow detecting instant signal changes in signal classification process were suggested. This methodology is applied for human health evaluation and monitoring processes.

Approval or the results

The majority of the results of this dissertation were presented in 5 scientific publications. Two were published in the list of the Institute for Science Information (ISI) as the main list of publications with citing indexes. The topics of this dissertation were presented in 6 international conferences. Signal filtering methods were initialised in three projects that are related to this research.

Scope and structure of the dissertation

This doctoral dissertation consists of an introduction, 4 main chapters, conclusions, references and a list of publications. The work volume is 114 pages. There are 55 figures, 26 tables and a list of 181 cited references.

1. LITERATURE REVIEW

1.1. ECG signal and parameter estimation methods

The electrocardiogram is the recording of electrical signals of the heart using electrodes placed on the skin surface. Generally, there are 12 different recordings with different placements on the skin. The most popular and explored is V5 derivation (the example is shown in Figure 1).

The recorded biological signals such as electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG) usually are contaminated with various noises from the environment. Numerous methods have been created and applied for digital signal processing and filtering, such as moving average (MA), exponential smoothing or linear Fourier transformation (Gazi, 2016). Although chaotic signals generally are not predicted, the similarities in particular parts of biological signal can be noticed. This can be interpreted as the mean, and the variance of the signal remains almost stationary (Meškauskas, 2017). The main purpose of signal filtering algorithms is to divide the components into informative and undesirable noise.

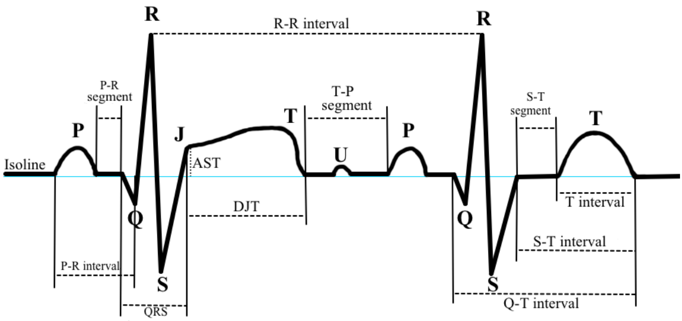

Figure 1. ECG parameters of V5 derivation

There are many different ECG signal parameters (see Figure 1) that could describe different heart pathologies or alert about possible diseases. Numerous articles have been published to help identify the illness or monitor health condition. R–R intervals and QRS complexes are essential parameters for medical diagnostics. Scientists have developed various methods for ECG parameter wave detection and parameter estimation. In 1985, scientists J. Pan and W. Tompkins suggested an algorithm that was based on signal filtering to reveal the frequencies that were induced by the fast heart depolarisation process. They assumed that other frequencies are noise and should be removed. Later, in 2006, scientists J. H. Choi and H. K. Jung proposed a non-supervised learning algorithm that detects action potentials and signal features for the classifiers. This method was based on multiresolution Teager energy operator (MTEO) detection algorithm and its improvement by reducing complexity with sample size implementation (Choi et al., 2006).

In medicine and diagnostics, not only direct ECG parameter values are essential. Heart rate variability (HRV) is obtained from R–R intervals and is very popular in scientific works related to heart behaviour. The HRV analysis is based on R–R interval estimation. Generally, HRV parameters can be divided into two main parts: time domain and frequency domain (Germán-Salló & Germán-Salló, 2016).

Time domain analysis. The methods from this category treat the R–R interval sequence as an unordered set of intervals (in some cases, pairs of intervals) and employ various techniques to express the variance of these data. If RR is defined as adjacent cardio cycles, the time domain HRV parameters ($\overline{RR}$, *SDRR*, *SDSD*, *RMSSD*, *CV*) can be calculated as follows:

$$\overline{RR} = \frac{1}{N}\sum_{n=1}^{N} RR_n, \tag{1}$$

$$SDRR = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(RR_n - \overline{RR})^2}, \tag{2}$$

$$SDSD = \sqrt{\frac{1}{N}\sum_{n=1}^{N}[(RR_n - RR_{n+1}) - (\overline{RR} - RR_{n+1})]^2}, \tag{3}$$

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(RR_{n+1} - RR_n)^2}, \tag{4}$$

$$CV = \frac{SDRR}{\overline{RR}} \cdot 100\%. \tag{5}$$

Even though all these measurements of short-term variation estimate high frequency variations, the correlation between these parameters is high, and nonlinear dynamic remains undervalued (Yaghoobi Karimui & Azadi, 2017).

Frequency domain analysis. The analysis of power spectral density provides information about how the power of the ordered R–R intervals is distributed as a function of frequency. The HRV power spectral density analysis describes two distinct peaks: low-frequency band (LF: in humans 0.04–0.15 Hz) and high frequency band (HF: in humans 0.15–0.4 Hz). Generally, HF fluctuations associate to vagal system modulations, and LF fluctuations are jointly mediated by sympathetic and vagal systems together with the baroreflex mechanism (Camm &

Lu, 2018). Usually, for the better comparison and result interpretation, the frequency domain parameters are normalised in the following way:

$$LF_{norm} = \frac{LF}{LF + HF}, \qquad HF_{norm} = \frac{HF}{LF + HF}. \tag{6}$$

Nonlinear analysis. The methods to measure the nonlinearity in HRV try to quantify the structure and complexity of R–R interval time series. The methods of HRV dynamic analysis are based on chaos or nonlinear system theory. The mechanisms involved in cardiovascular regulation are likely to interact between each other in a nonlinear manner (Castaño et al., 2019). The most essential indices that describe heart dynamic nonlinearity are detrended fluctuation analysis (DFA), Lyapunov exponents, correlation dimensions and others (Muduli & Mukherjee, 2017). For the nonlinear HRV analysis, the Poincare method was selected.

1.2. Methods for signal processing

In order to obtain a full representation of the signal, the smoothing process should be applied (insignificant noise that appeared in the recording process should be removed, and the fluctuations of the signal should be discarded). The algorithms for signal processing can be divided into two groups: working in the scale of time domain and in the scale of the frequency domain. The first group operates directly to the original signal values while other extracts the spectrum of the signal at first and then filters the frequency domain values. Although linear filtering methods such as Wiener filter or singular value decomposition (SVD) (Ziani et al., 2018) are easily described and applied, the effectiveness of these methods reduces if the signal has sharp angles or impulses. Furthermore, in reality recorded signals are non-stationary and fluctuate in time.

Universal methods such as Butterworth filter (Jagtap & Uplane, 2012) are widely used in medicine and diagnostic by Lithuanian scientists (Marozas et al., 2011) and worldwide. They work effectively in high and low frequency noise reduction for different types of signal processing. However, the delays that appear in signal reconstruction process may affect the final result (Tsuzuki & Ogihara, 2018).

The biological signals that are recorded in movement are more contaminated by noise compared to those that are recorded in a stationary condition. The main issue for movement contaminated signals is non-stationary low frequency noise trend. That is why ordinary filtering methods for signal processing become insufficient. One of the most popular algorithms for ECG trend removal is moving average (MA) filter. If there are insignificant amplitude fluctuations, the algorithm eliminates the deviations and transforms the signal in respect to the isoline. This method can be described with the following formula:

$$y(n) = \frac{1}{2N+1} \sum_{i=-N}^{N} x(n+i)\,; \qquad (7)$$

where $x(n)$ and $y(n)$ are input and output signals; N is the sample size. Filtered $z(n)$ signal is found as follows:

$$z(n) = x(n) - y(n). \qquad (8)$$

The scientist Ivan W. Selesnick together with his colleagues in 2014 suggested using a low pass filter and denoising of variance at the same time. Their method is called Baseline Estimation and Denoising with Sparsity (BEADS) (Ning et al., 2014). As a low frequency filter, they selected linear and nonlinear filtering method that is called multiscale wavelet algorithm and improved it by adding sparsity based partial layers between spectrum and peaks. However, this method has many filtering parameters such as normalised cut-off frequency, asymmetry coefficient and others.

1.3. Classification methods for health evaluation

Advanced technologies such as social media, smart phones and computers, portable devices allow to collect big data about various mental or physical health disorders. One of the most rapidly growing technical fields is computer science and statistics with artificial intelligence and data science. Effective algorithms for big data processing are based on machine learning (ML) methodology.

ML can be divided into three main parts: supervised learning (for example, SVM, KNN, NB, DT), unsupervised learning (for example, NN, clustering) and semi-supervised learning (for example, semi-supervised SVM, general learning, mixed models) (Bi et al., 2019). Supervised learning is based on the labelled data analysis. Meanwhile, unsupervised learning learns from unlabelled data and extracts similar patterns. Finally, semi-supervised learning contains data with and without labels because in some cases, there is not enough labelled data that is needed for the classification or prognosis.

The measurement of predictive performance usually is based on the analysis of data in the confusion matrix (Bowes et al., 2014). This matrix reports how the model of prediction classifies different fault categories compared to their actual classification (predicted versus observed). Four data types after the classification process can be described, as it is presented in Table 1.

Table 1. ML elements after prediction has been made

Name	Shorthand	Description
True negative	TN	Item is predicted as correct, but it is faulty
True positive	TP	Item is predicted as correct, and it is correct
False positive	FP	Item predicted as faulty, but it is correct
False negative	FN	Item predicted as faulty, and it is faulty

For the better understanding how well the selected method predicts (in general case), additional measurements can be found. Common statistics are $accuracy$ and $F1$ score that are estimated using the following formulas:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}; \tag{9}$$

$$F1 = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}. \tag{10}$$

Even though $accuracy$ and $F1$ are widely used in ML analysis, they do not consider the size of each category of the confusion matrix. That is why an additional statistic is measured, which is called Matthews correlation coefficient or MCC. It gains the worst value with $MCC = -1$, and the best value when $MCC = 1$.

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP) \cdot (TP + FN) \cdot (TN + FP) \cdot (TN + FN)}} \tag{11}$$

In 1960, scientist Jacob Cohen revealed that there is a level of algorithm precision when the algorithm is no longer capable to predict correctly, and the answer becomes similar to the guess. This statistic is called $kappa$ and is expressed in the following formula:

$$kappa = \frac{accuracy - d}{1 - d}; \tag{12}$$

where $d = \frac{TP+FN}{TN+TP+FP+FN}$. If $kappa > 0.75$, then $kappa$ is considered perfect, from 0.4 to 0.75 sufficient and when $kappa < 0.4$, it is considered weak (McHugh, 2012).

2. METHODOLOGY

In this chapter, the proposed methods of ECG signal processing are described. Moreover, the algorithms and their improvements are presented with detailed descriptions and pseudo codes. The flow chart of initialised methods is shown in Figure 2.

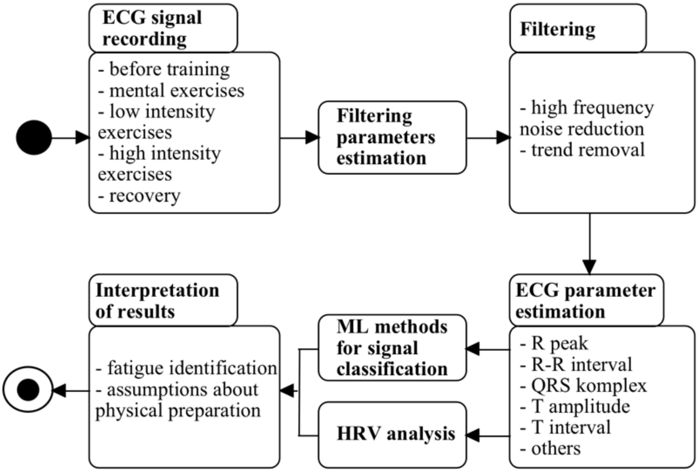

Figure 2. ECG signal processing scheme

2.1. Filtering algorithms

ECG signal recorded in movement can be written in such form:

$$y(n) = x(n) + v(n) + w(n), \qquad n = 1, \dots, N; \tag{13}$$

where x is a low–pass signal without noise, w – stationary white Gaussian noise, v – sparse derivative signal (movement artefact or trend) and N – signal length.

For the data like $y(n)$, two-method combination should be used for denoising. The DWT algorithm was chosen as a high pass filter. Filtering parameter estimation and comparison for this algorithm is described in chapter 3.

Low frequency noise usually is named as trend or movement artefact. While the participant is in a stationary condition (usual in medicine for ECG or EEG signal recordings), ECG signal is located in one horizontal line–isoline (see Figure 1). Discrete N points ECG signal could be written as:

$$[x_1, x_2, \dots, x_N]^T; \tag{14}$$

where T indicates the transpose function of analysed vector or matrix. Usually, the moving average (MA) algorithm is used for trend detection because it does not require additional signal preparation for filtering, does not have many filtering parameters that need to be estimated before computations, works fast and does not require many computational resources. However, it is not suitable for noisy ECG signal processing that is recorded in sudden movement changes, for example, during training session. That is why in this research, the improved BEADS algorithm was chosen for the baseline detection and its removal.

<u>*BEADS algorithm:*</u> this low frequency filter is described by using difference matrixes and cost function minimisation. First order difference $\mathbf{D_1}$ could be expressed in this form:

$$\mathbf{D_1} := \begin{bmatrix} -1 & 1 & & & \\ & -1 & 1 & & \\ & & \ddots & \ddots & \\ & & & -1 & 1 \end{bmatrix}. \tag{15}$$

For N point signal $\boldsymbol{x}$, the first order difference is $\mathbf{D_1}\boldsymbol{x}$, where the size of matrix $\mathbf{D_1}$ is $(N-1)\times N$. Similarly, second order difference matrix with size $(N-2)\times N$ is defined as:

$$\mathbf{D_2} := \begin{bmatrix} -1 & 2 & -1 & & & \\ & -1 & 2 & -1 & & \\ & & \ddots & \ddots & \ddots & \\ & & & -1 & 2 & -1 \end{bmatrix}. \tag{16}$$

In general, k order difference operator with size $(N-k)\times N$ is defined as $\mathbf{D_k}$. For further derivations, the identity matrix $\mathbf{I}$ is defined as zero order difference matrix $\mathbf{D_0} := \mathbf{I}$ $(k=0)$ (size $N \times N$) (Selesnick et al., 2014). In order to find the best solution (minimise cost function $G(\boldsymbol{x})$), the optimization task of three parts should be solved: low frequency noise extraction using a high frequency filter, asymmetric penalty function for negative ECG peaks evaluation and symmetric penalty functions for positive extremums should be defined.

Which penalty function should be used depends on the analysed signal structure. Asymmetry function is used when it is known that the analysed signal $\boldsymbol{x} = [x_1, x_2, \dots, x_N]$ has more positive values than negative and vice versa (as it is in ECG signals). Then, negative and positive signal parts are penalised differently. The $\theta(x,r)$ function is defined as an asymmetric function with asymmetry parameter r:

$$\theta(x,r) = \begin{cases} x, & x \geq 0, \\ -rx, & x < 0. \end{cases} \tag{17}$$

Then, the second order polynomial function $\theta_\varepsilon(x,r)$ can be defined as follows (see full derivation in (Ning et al., 2014)):

$$\theta_\varepsilon(x,r) = \begin{cases} x, & x > \varepsilon; \\ \frac{1+r}{4\varepsilon}x^2 + \frac{1-r}{2}x + \varepsilon\frac{1+r}{4}, & |x| \leq \varepsilon; \\ -rx, & x < -\varepsilon; \end{cases} \tag{18}$$

where $\varepsilon > 0$ is a small constant. The behaviour of new penalty function $\theta_\varepsilon(x,r)$ is similar to $\theta(x,r)$ and is continuously differentiated (Ning et al., 2014).

Using the same definitions, the asymmetric penalty function can be defined as $(N \times N)$ size diagonal matrix $\boldsymbol{\Gamma}(\boldsymbol{v})$ with elements in the main diagonal expressed as follows:

$$[\boldsymbol{\Gamma}(\boldsymbol{v})]_{n,n} = \begin{cases} \dfrac{1+r}{4|v_n|}, & |v_n| \geq \varepsilon \\ \dfrac{1+r}{4\varepsilon}; & |v_n| \leq \varepsilon \end{cases} \tag{19}$$

where $\boldsymbol{v} = [v_1, v_2, \dots, v_N]$. Moreover, the symmetric penalty function can be defined as diagonal matrix $\boldsymbol{\Lambda}(\boldsymbol{v})$ where elements in the main diagonal are expressed in the following form:

$$[\boldsymbol{\Lambda}(\boldsymbol{v})]_{n,n} = \frac{\varphi'(v_n)}{v_n}; \tag{20}$$

where φ is symmetric function and φ' its derivative (see (Selesnick et al., 2014)). The symmetric penalty function is used when filtered signal $\boldsymbol{x}$ and its derivatives $\boldsymbol{D}_i\boldsymbol{x}$ are positive and negative with the same probability. So far defined penalty functions are mostly used to filter extremums. However, the ECG signal as well requires a high pass filter that passes frequencies over higher chosen frequency barrier and leaves the rest part of the signal. High frequency filter can be written as a transfer matrix:

$$\mathbf{H}(z) = \frac{(-z+2-z^{-1})^d}{(-z+2-z^{-1})^d + \alpha(z+2+z^{-1})^d}; \tag{21}$$

where α and d are positive, $d \in \mathbf{Z}$ and defines the order of analysed matrix. The norms of variable $\boldsymbol{x}$ are estimated as follows:

$$\|\boldsymbol{x}\|_1 = \sum_n |x_n|, \qquad \|\boldsymbol{x}\|_2^2 = \sum_n |x_n|^2. \tag{22}$$

Filtering task with all three parts can be written in this form:

$$\hat{\boldsymbol{x}} = arg \min_{\boldsymbol{x}} \left\{ \frac{1}{2}\|\mathbf{H}(\boldsymbol{y}-\boldsymbol{x})\|_2^2 + \lambda_0 \sum_{n=0}^{N-1} \theta(x_n, r) + \sum_{i=1}^{M} \lambda_i \sum_{n=0}^{N_i-1} \varphi([\mathbf{D}_i\boldsymbol{x}]_n) \right\}; \tag{23}$$

where λ_i are regularisation parameters, and *M* indicates the number of symmetric penalty functions that are used in this algorithm. Then, the cost function $G(\boldsymbol{x})$ can be written in this form:

$$G(\boldsymbol{x}) = \frac{1}{2}\|\mathbf{H}(\boldsymbol{y}-\boldsymbol{x})\|_2^2 + \lambda_0 x^T[\boldsymbol{\Gamma}(\boldsymbol{x})]\boldsymbol{x} + \lambda_0 \boldsymbol{b}^T\boldsymbol{x} + \sum_{\mathrm{i}=0}^{\mathrm{M}} \left[\frac{\lambda_{\mathrm{i}}}{2} (\mathbf{D}_{\mathrm{i}}\boldsymbol{x})^{\mathrm{T}} [\boldsymbol{\Lambda}(\mathbf{D}_{\mathrm{i}}\boldsymbol{x})](\mathbf{D}_{\mathrm{i}}\boldsymbol{x}) \right]; \tag{24}$$

where $\mathbf{D}_i$ is the i^{th} order differential operator, and $\boldsymbol{b}$ is a vector of the same values:

$$[\boldsymbol{b}]_n = \frac{1-r}{2}. \tag{25}$$

The minimization of the cost function $G(\boldsymbol{x})$ with respect to $\boldsymbol{x}$ leads to this solution:

$$\widehat{\boldsymbol{x}} = \left(\mathbf{H}^{\mathrm{T}}\mathbf{H} + 2\lambda_0\boldsymbol{\Gamma}(\boldsymbol{x}) + \sum_{\mathrm{i}=0}^{\mathrm{M}} \lambda_{\mathrm{i}}\mathbf{D}_{\mathrm{i}}^{\mathrm{T}}[\boldsymbol{\Lambda}(\mathbf{D}_{\mathrm{i}}\boldsymbol{x})]\mathbf{D}_{\mathrm{i}}\right)^{-1} \mathbf{H}^{\mathbf{T}}\boldsymbol{H}\boldsymbol{y} = \mathbf{A}\mathbf{Q}^{-1}\mathbf{B}^{\mathbf{T}}\mathbf{B}\mathbf{A}^{-1}\boldsymbol{y}; \tag{26}$$

where $\mathbf{Q} = \mathbf{B}^{\mathrm{T}}\mathbf{B} + \mathbf{A}^{\mathrm{T}}\left(\sum_{\mathrm{i}=0}^{\mathrm{M}} \lambda_{\mathrm{i}}\mathbf{D}_{\mathrm{i}}^{\mathrm{T}}[\boldsymbol{\Lambda}(\mathbf{D}_{\mathrm{i}}\boldsymbol{x})]\mathbf{D}_{\mathrm{i}}\right)\mathbf{A}$. A pseudo code of BEADS algorithm is written in Figure 3.

Cost function minimisation of BEADS algorithm

Input: $\boldsymbol{y}$– noisy ECK signal; $\boldsymbol{r} \geq \mathbf{1}$ – asymmetry coefficient, $\mathbf{A}$ and $\mathbf{B}$ – matrixes of filtering coefficients, $\boldsymbol{\lambda_i}$ – regularisation parameters, $\boldsymbol{i} = \mathbf{1}, \dots, \boldsymbol{M}$; $\boldsymbol{\varepsilon}$ – small positive constant.

Output: $\boldsymbol{x}$ – filtered ECK signal, $\boldsymbol{f}$ – value of cost function

BEGIN

$[\boldsymbol{b}]_n = \frac{1-r}{2}$;

$\boldsymbol{d} = \mathbf{B}^T\mathbf{B}\mathbf{A}^{-1}\boldsymbol{y} - \lambda_0\mathbf{A}^T\boldsymbol{b}$;

$\boldsymbol{x} = \boldsymbol{y}$;

while $\boldsymbol{f}$ converge

  if $|\boldsymbol{v_n}| \geq \boldsymbol{\varepsilon}$, tai

    $[\boldsymbol{\Gamma}]_{n,n} = \frac{1+r}{4|x_n|}$;

  if $|\boldsymbol{v_n}| \leq \boldsymbol{\varepsilon}$, tai

    $[\boldsymbol{\Gamma}]_{n,n} = \frac{1+r}{4\varepsilon}$;

  for each *i* from 0 to *M* **do**

    $[\boldsymbol{\Lambda}_i]_{n,n} = \frac{\varphi'([\mathbf{D}_i x]_n)}{[\mathbf{D}_i x]_n}$,

  $\mathbf{M} = 2\lambda_0\boldsymbol{\Gamma}$;

  for each *i* from 0 to *M* **do**

    $\mathbf{M} = \mathbf{M} + \lambda_i\mathbf{D}_i^T\boldsymbol{\Lambda}_i\mathbf{D}_i$;

  $\mathbf{Q} = \mathbf{B}^T\mathbf{B} + \mathbf{A}^T\mathbf{M}\mathbf{A}$;

  $\boldsymbol{x} = \mathbf{A}\mathbf{Q}^{-1}\boldsymbol{d}$;

$\boldsymbol{f} = \boldsymbol{y} - \boldsymbol{x} - \boldsymbol{B}\boldsymbol{A}^{-1}(\boldsymbol{y} - \boldsymbol{x})$;

END

Figure 3. Cost function minimisation of BEADS algorithm

BEADS algorithm recalculates all parameter values as long as the baseline is detected (trend with the smallest errors). A prediction of what parameter values and penalty functions should be used is a complicated task, especially if there is only a little prior information about the analysed signal. ECG signals can be characterised by the QRS complex (see Figure 1) that is an important parameter in medicine and diagnostics. In order to make sure that BEADS algorithm and its filtering parameters are oriented and suitable for ECG signal processing, this method was modified by adding a new algorithm described in Figure 4. The purpose of this algorithm is to find BEADS filtering parameter values that ensure the maximum number of QRS complexes.

```
BEADS filter parameter estimation algorithm
Input: movement – contaminated ECG signal
Output: BEADS filter parameter values
BEGIN
  for each parameter of BEADS filter do
    best_value = 0;
    QRS_maximum = 0;
    for each parameter_value do
      extract low frequency noise from ECG signal using BEADS algorithm
      find R, Q and S peaks;
      j = 1;
      for each i from 1 to max(length(R), length (Q), length(S)) do
        if Q(i) or R(i) or S(i) is empty
          i = i + 1;
        else
          QRS(j) = estimate QRS complex;
          j = j + 1;
        if QRS_maximum < length(QRS)
          QRS_maximum = length(QRS);
          best_value = parameter_value;
END
```

Figure 4. BEADS filter parameter estimation algorithm

The algorithms for QRS complex and other ECG parameters detection are described in subchapter 2.2.

For the high frequency noise reduction, the DWT algorithm was used. Additional filtering parameter estimation analysis is performed in subchapter 3.1.

2.2. Parameter search of ECG signal

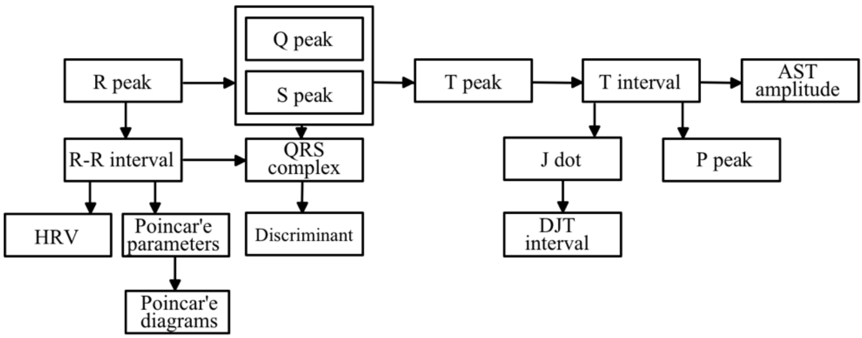

Figure 5. ECG signal parameter estimation sequence

ECG signal parameter search starts with the R peak detection. Then, Q and S peaks can be found or R–R interval estimated. The sequence of all ECG parameter search is presented in Figure 5.

As ECG signals are contaminated with various noises (if recorded in movement), and signal processing should be done in real time; the multiresolution Teager energy operator algorithm was chosen for QRS complex detection. This method and its addition are described in this chapter. The module of peak estimation consists of three parts: signal enhancement, MTEO computation and statistical thresholding (Sedghamiz & Santonocito, 2016).

Signal enhancement. ECG signal is filtered by high pass filter and normalised using low pass filter. Noise reduction algorithms are described in the previous chapter.

MTEO computation. Motor unit action potentials (MUAP) have typically high amplitude and instantaneous frequency. The Teager energy operator (TEO) is time–frequency domain analysis that has been employed in many signal processing applications and is defined as:

$$\omega(x(nT)) = x^2(nT) - x(nT - T)x(nT + T). \tag{27}$$

K–TEO is a multiresolution version of MTEO where $x(nT - T)x(nT + t)$ is replaced with $x(nT - kT)x(nT + kT)$. There, k is an arbitrary parameter that is known as a lag parameter, and *T* is the sampling rate. Furthermore, *k*–TEO can be adjusted to sensitive and more specific frequencies. Therefore, *k*–TEO is an attractive tool due to its effectiveness (compared to the other time–frequency domain methods) and low computational power.

If $x(nT)$ is marked as the original (raw) ECG signal where $n = 1,2, \ldots, N$, and N is the number of signal samples, then *k*–TEO can be defined as:

$$Y_k(nT) = x^2(nT) - x(nT - kT)x(nT + kT); \tag{28}$$

where the choice of *k* depends on the period of analysed spike. Increasing *k* makes the detector less sensitive to the high frequencies and more sensitive to the low frequencies. Finally, the output of MTEO is $t(nT)$ and is expressed as:

$$t(nT) = max\{\hat{Y}_1(nT), \hat{Y}_2(nT), \ldots, \hat{Y}_k(nT)\}; \tag{29}$$

where $\hat{Y}_k(nT)$ is $Y_k(nT)$ after it is smoothed with Hamming window with size $4k + 1$ (Drake & Callaghan, 2006) and normalised using squared variance at scale k.

Statistical thresholding. The purpose of this task is to determine the time when MUAPs appear in $t(nT)$. In this part, a statistical testing method was employed. Two binary hypotheses are defined: $H_0$when MUAP is not present, and H_1 is present:

$$\begin{cases} H_0: t(nT) = G(nT), \\ H_1: t(nT) = s(nT) + G(nT); \end{cases} \tag{30}$$

where $s(nT)$ is the MUAP generated signal, and $G(nT)$ is a random Gaussian noise. The standard deviation $\hat{\sigma}$ of $t(nT)$ can be approximated as the median of its absolute deviation values because median is a random variable and is less sensitive to the outliers than its variance. It can be written as follows:

$$\hat{\sigma} = MEDIANA\{|t(T) - \mu|, \dots, |t(NT) - \mu|\}; \tag{31}$$

where μ is the sample's average value. Furthermore, a close to optimal performance is chosen for the threshold TH_1:

$$TH_1 = \hat{\sigma}\sqrt{2 \ln N}. \tag{32}$$

Therefore, $t(nT)$ is compared to TH_1 and divided into signal segments $t^S(nT)$ and noise $t^G(nT)$:

$$\begin{cases} t^G(nT) \coloneqq \{t(nT) \leq TH_1\} \\ t^S(nT) \coloneqq \dfrac{t(nT)}{t^G(nT)} \end{cases}. \tag{33}$$

Two prior probabilities of the two binary hypotheses ($P(H_0)$ and $P(H_1)$) can be estimated as follows:

$$\begin{aligned} P(H_0) &= \frac{\|t^G(n)\|_1}{N}; \\ P(H_1) &= \frac{\|t^S(n)\|_1}{N} \end{aligned} \tag{34}$$

where $\|.\|_1$ is expressed in the (22) formula. Finally, the decision threshold TH_2 can be written as:

$$TH_2 = \frac{\eta}{2} + \frac{\hat{\sigma}^2}{\eta}\left(C + \ln\frac{P(H_0)}{P(H_1)}\right); \tag{35}$$

where η is the mean of absolute $t(n)$ values, C is selected scaling constant that determines the sensitivity of this method. With previous definitions and testing, a signal with MUAPs is generated:

$$MU(nT) \coloneqq \{t(nT) \geq TH_2\}. \tag{36}$$

The final output of this algorithm is a set of local maxima that indicate ECG signal peaks Q, R, S. A pseudocode of this algorithm adjusted to the QRS complex detection in the ECG signal is shown in Figure 6.

Q, R, S peaks estimation with k – TEO algorithm

Input: ECG – filtered ECK signal; C – constant; ***frequency*** – signal recording frequency
Output: positions of Q, R, S peaks in ECK signal
BEGIN
  $N = \text{length}(ECG)$;
  $L = \mathbf{2} \cdot \boldsymbol{frequency}$;
  for each i from 4 to $N-3$ **do**
    $\boldsymbol{M(1) = \left(ECG(i)\right)^2 - \left(ECG(i-1) \cdot ECG(i+1)\right)}$;
    $\boldsymbol{M(2) = \left(ECG(i)\right)^2 - \left(ECG(i-2) \cdot ECG(i+2)\right)}$;
    $\boldsymbol{M(3) = \left(ECG(i)\right)^2 - \left(ECG(i-3) \cdot ECG(i+3)\right)}$;
    $\boldsymbol{MTEO(i)} = \max(\boldsymbol{M(1)}, \boldsymbol{M(2)}, \boldsymbol{M(3)})$;
    $\boldsymbol{STD} = \text{std}(\boldsymbol{MTEO(1)}, \boldsymbol{MTEO(2)}, \dots, \boldsymbol{MTEO(L)})$;
    $\boldsymbol{TH0 = C \cdot STD} \cdot (2 \ln \boldsymbol{L})^2$;
    $\boldsymbol{TH1 = TH0}$;
  for each i from 4 to $N-3$ **do**
    if $\boldsymbol{MTEO(i-2) < MTEO(i-1)}$ **and** $\boldsymbol{MTEO(i-1) > MTEO(i)}$
      if $\boldsymbol{MTEO(i-1) \geq TH1}$
        $\boldsymbol{MUAP = MTEO(i-1)}$;
        $\boldsymbol{noise = 0,125 \cdot MTEO(i-1) + 0,875 \cdot noise}$;
        $\boldsymbol{TH1 = noise + 0,3 \cdot (MUAP - noise)}$;
    $\boldsymbol{TH2 = C \cdot TH1}$;
    if $\boldsymbol{MTEO(i-1) \geq TH2}$
      $\boldsymbol{RR\_interval(j) = MTEO(i-1)}$;
      $\boldsymbol{j = j + 1}$;
  for each k from 1 to $\boldsymbol{j}$ **do**
    $\boldsymbol{R(k)}$ = R peak detection;
    Q$(\boldsymbol{k})$ = Q peak detection;
    S$(\boldsymbol{k})$ = S peak detection;
END

Figure 6. Q, R, S peaks estimation with k-TEO algorithm

In the V5 derivation of human ECG signal, Q and S peaks gain negative values with respect to isoline. Often, Q peak is obscure and sometimes, even close to zero value. Meanwhile, R or S waves have high deviations from isoline. The QRS complex is a time scale parameter–interval from the beginning of the Q wave to the end of the S wave.

This investigation of ECG signals includes not only R–R and QRS interval search or Q, R, S peak detection. Further analysis includes T wave amplitude and interval values' estimation. T interval starts at the beginning of T wave and ends when T wave reaches isoline again. k-TEO algorithm does not include these parameters' search. That is why additional algorithm was made for the other ECG parameter estimation that is based on the local extremum search (see Figure 7). This method consists of three main parts:

T wave peak estimation. T wave stands between S wave and Q wave peaks and has the highest amplitude value in this interval (see Figure 1). This means that T wave peak can be estimated using (37) this formula:

$$T(n) = \max_{i=S(n):Q(n+1)} \{f(i)\}; \quad (37)$$

where $S(n), Q(n)$ are positions in ECG signal f of S and Q waves, respectively.

Detection start and end position points of the T wave. T wave starts when the ECG signal changes its direction with respect to isoline (starts to increase). The beginning of T wave is a bit further than the end of S wave but does not reach its peak. Although the ECG signal is filtered, it still contains some minor value fluctuations that make additional local minima and maxima. The critical values of $T(n)$ wave can be estimated from this equation:

$$\frac{df(i)}{di} = 0; i \in \big(S(n) + C \cdot fs{:}\, T(n)\big); \quad (38)$$

where C is a constant and fs is recording the frequency of ECG signal. The beginning of T wave is considered to be the position of minimal value of all estimated local extremums:

$$T_{start}(n) = \min_{i=1:N}\{K_i(n)\}; \quad (39)$$

where N is the number of local extremums and K_i is i^{th} extremum value. The end of T wave is estimated similarly. In this case, the extremums are in the interval between the peak of T wave and before the beginning of Q wave.

$$\frac{df(i)}{di} = 0; i \in \big(T(n){:}\, Q(n+1)\big); \quad (40)$$

$$T_{end}(n) = \min_{i=1:N}\{K_i(n)\}. \quad (41)$$

T interval estimation. If the previous steps (that detects T wave start and end position points) are realized correctly, the T interval estimation is an uncomplicated task and can be done using this formula:

$$T_{int}(n) = T_{end}(n) - T_{start}(n). \quad (42)$$

A pseudo-code for T wave detection in presented in Figure 7.

If R peaks, QRS complexes, T intervals are estimated correctly, further parameters can be found (ST, QT, DJT or AST). J point is an inflection point in the interval from the end of S wave to the start of T wave. Usually, the J point position matches the end of S wave or has a completely different position in this interval. In order to find the inflection point J, the equation with second row derivative should be solved:

$$\frac{d^2 f(x)}{dx^2} = 0. \quad (43)$$

T interval estimation algorithm
Input: ECG – filtered ECK signal; C – constant; $\boldsymbol{Q}, \boldsymbol{R}, \boldsymbol{S}$ peaks; ***frequency*** – signal recording frequency
Output: *T_interval*, *T_amplitude*
BEGIN
$\boldsymbol{N}$ = length(S)
for each i from 1 to N **do**
$T\_position(\boldsymbol{i})$ = local extremum in the interval $[\boldsymbol{S}(\boldsymbol{i}) + \boldsymbol{C} \cdot \boldsymbol{frequency}; \boldsymbol{Q}(\boldsymbol{i}+\boldsymbol{1})]$;
$T\_amplitude(\boldsymbol{i}) = \boldsymbol{ECG}(T\_position(\boldsymbol{i}))$;
start_extrema = ECG extrema in the interval $[\boldsymbol{S}(\boldsymbol{i}) + \boldsymbol{2C} \cdot \boldsymbol{frequency}; \boldsymbol{T}(\boldsymbol{i})]$;
end_ekstema = ECG extrema in the interval $[\boldsymbol{T}(\boldsymbol{i}); \boldsymbol{Q}(\boldsymbol{i}+\boldsymbol{1})]$;
start_number = length(*start_extrema*);
end_number = length(*end_extrema*);
if *start_number*= **0**
$T\_start(\boldsymbol{i}) = (\boldsymbol{S}(\boldsymbol{i}) + \boldsymbol{T}(\boldsymbol{i}))/\boldsymbol{2}$;
else
$T\_start(\boldsymbol{i})$ = min(*start_extrema*);
if *end_number*= **0**
$T\_end(\boldsymbol{i}) = (\boldsymbol{T}(\boldsymbol{i}) + \boldsymbol{Q}(\boldsymbol{i}+\boldsymbol{1}))/\boldsymbol{2}$;
else
$T\_end(\boldsymbol{i})$ = min(*end_extrema*);
$T\_interval(\boldsymbol{i}) = T\_end(\boldsymbol{i}) - T\_start(\boldsymbol{i})$;
END

Figure 7. T interval estimation algorithm

DJT interval starts at the J point and ends at the end of T wave. In order to estimate this value, the subtraction (from T wave end position point subtracted J point) should be made. AST parameter is the amplitude distance from isoline to S wave end point. If the human heart is in a good condition, the AST$= 0$. Otherwise, this parameter can gain positive or negative values.

One of the most popular ECG derivative parameters is a discriminant that describes the fluctuation of R–R intervals and QRS complexes. In ECG signal analysis, the selected discriminant estimation method is expressed in this form:

$$D(RR - QRS)_n = (RR_n - QRS_n)^2 + 4(RR_{n-1} - QRS_{n-1})(RR_{n+1} - QRS_{n+1}); \tag{44}$$

where RR is duration between R peaks, n is the cycle number of the heart. This parameter is very sensitive to all changes in ECG signal and is widely used to monitor the health condition of sportsman during the stress tests.

2.3. Signal classification

A classification algorithm is a method that consists of two main parts: primary signal transformation and the classification itself. Primary transformation process is used to gain specific features from the raw signal and reduce its dimension for the better classification results. At the end of this process, a part of ECG signal (or its parameters) is considered as noise and is removed from the further analysis (as non-essential information) (Wei et al., 2018). The classification of ECG signals to different pathologies or health stages is a complicated task that is based on signal structure recognition. Generally, several classification algorithms are used to solve the particular problem (Shao et al., 2018). A similar classification task can be formulated in the fatigue identification process. In this case, the research object is not continuous ECG signal or its fragmentation but different signals that were recorded at different times of the day (in the morning and in the evening). Usually, fatigue appears after intensive physical activity or at the end of the day. Physical fatigue detection is a simpler task because after intensive training session, the heart works faster. Meanwhile, mental fatigue detection is a complicated task because there is no clear difference in ECG signal parameters. The suggested classification process for mental fatigue identification is shown in Figure 8.

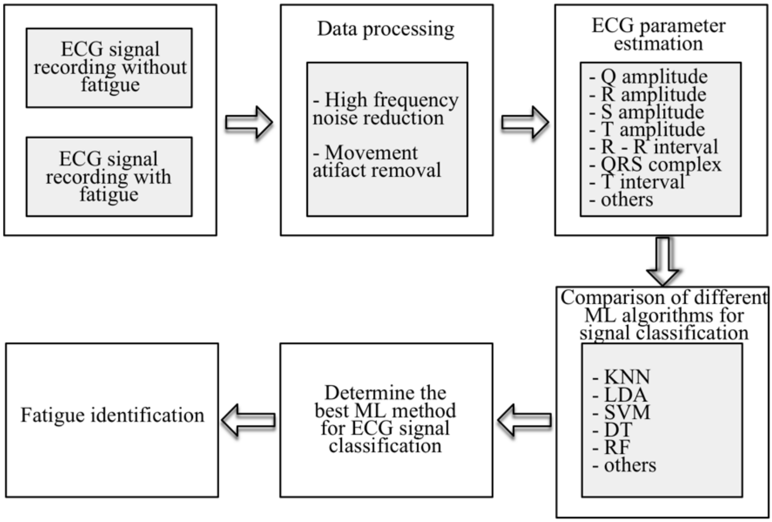

Figure 8. ECG signal classification scheme for fatigue detection

In data science and forecasting, plenty machine learning algorithms have been created, such as k-nearest neighbours (KNN), linear discriminant analysis (LDA), support vector machine (SVM), decision trees (DT), random forest (RF) and others. In this research, a comparison of different methods was made. It appeared that RF classifies signals with the highest accuracy (see subchapter 4.2). This algorithm is based on DT and consists of three main parts:

- Input all data into root nodes for every DT;
- Minimize the Gini coefficient by dividing data into nodes;
- Repeat all steps at each split node until the RMSE in the node falls below a certain value, or the tree reaches a defined depth.

If n is defined as a number of samples in the node t and each node has c classes, then the number of samples belonging to the class i is n_i. The ratio $p(i|t)$ is given by:

$$p(i|t) = \frac{n_i}{n}. \tag{45}$$

Gini coefficient I_G for each node can be defined as (Oeda & Chieda, 2019):

$$I_G(t) = 1 - \sum_{i=1}^{c} p(i|t)^2. \tag{46}$$

The random forest algorithm requires two data sets, i.e., for training and testing. The more data is given, the higher classification accuracy can be reached.

2.4. Modelling of training process

As healthy lifestyle is becoming more popular, people practise sports more often. Biological parameters became the main indicator to avoid heart failure. Furthermore, people that are doing sports professionally aim to improve their physical condition in order to achieve better results. The suggested training session model allows monitoring health condition in real time and warns when the intensity should be reduced or suggests to increase the training intensity.

In this doctoral dissertation, a real time is defined as 10 sec time interval in which the ECG signal is recorded. At each 10 sec, the QRS complex and discriminant are measured, and their values are averaged. The training session process could be described in five parts: duration, heart rate, QRS complex, JT interval and discriminant (D).

Duration. Each training session duration depends on the R–R interval quantity. It is recommended that it should not exceed 1500 R–R intervals.

Heart rate (HR). The lower and upper bounds of heart rate are defined as follows:

$$HR_{low} = \big((220 - A) - HR_b\big) \cdot 0.5 + HR_b, \tag{47}$$

$$HR_{up} = \big((220 - A) - HR_b\big) \cdot 0.85 + HR_b; \tag{48}$$

where HR_{low} is a lower bound of HR and HR_{up} is upper bound, HR_b is HR before training, A is the age of a person (Poderys et al., 2010). If HR reaches a lower value than HR_{low}, then the training intensity should be increased. Moreover, if HR is higher than HR_{up}, then the exercises should be chosen with lower intensity or the training session should be stopped.

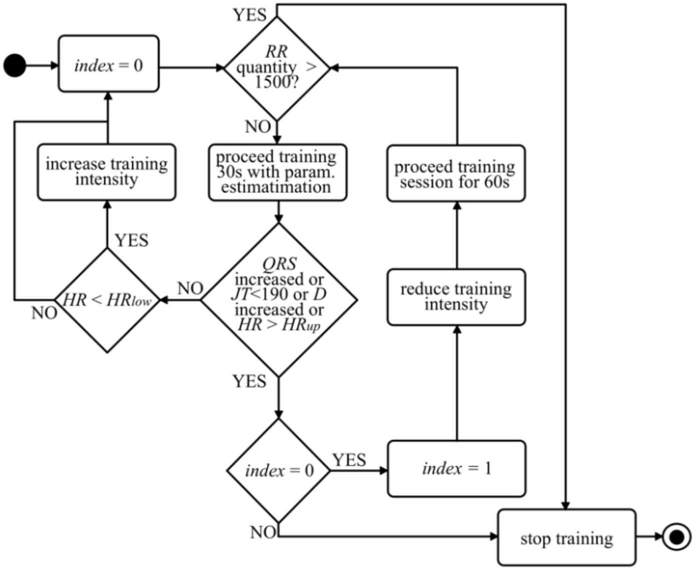

Figure 9. Decision making scheme for the training session

QRS complex. If in 30 sec, QRS increases by 5%, the training intensity should be reduced. For the next 60 sec, the parameter estimation process is suspended. Then, if QRS is still increasing, the training session must be stopped.

JT interval. If JT duration becomes less than 190 msec, the training intensity should be reduced, and the parameter estimation is stopped for the next 60 sec. After that time, if JT still is less than 190 msec, the training session should be stopped.

Discriminant (D). The discriminant monitoring process is similar to the QRS complex: if it increases for 30 sec by 10%, the training intensity should be reduced, and only after 60 sec, it is measured again. If in the next 30 sec it is increasing again, the training session must be stopped.

If ECG signal parameters are stable (QRS and D do not increase) or do not reach critical values, the training intensity should remain the same. Otherwise, it should be increased, decreased, or the training session must be stopped (Gobinath Aroganam, 2019).

The whole rule-based decision-making algorithm is shown in Figure 9. There is a variable named "index" that is a used mark if the critical parameter value were reached for the first or second time. At the beginning of this algorithm, "index" is equal to zero, and before intensity reduction, it gains value 1. Then, the corresponding parameter is not evaluated for 60 sec, and the training session should be stopped if the parameter still indicates a critical health condition.

Otherwise, the variable “index” again is equal to zero, and the participant continuous exercising with lower intensity.

The main purpose of this model is to detect physiological state changes and the best training intensity according to internal and external factors (e.g., as adaptation to different geographical conditions and time difference, remained fatigue, etc.). In the international CareWare project “Electronic Wearable Sport and Health Solutions”, collaborating with scientists from different scientific fields, a mobile app was created that gave feedback about the training intensity in real time. In this application, the health state evaluation is made by using ECG signals and evaluating its parameter values.

3. ECG SIGNAL FILTERING ALGORITHMS

For the algorithms accuracy comparison and filtering parameter estimation, ECG signal was generated using CMRR 2.0 simulator that illustrates clear (without noise) electrocardiogram of a healthy heart. The simulator generates a sinusoid with 150 bpm (beats per minute). The high and low frequency noises were added to this signal, i.e., high frequency – random Gaussian white noise, low frequency – sinusoid. The new ECG signal is transformed as follows:

$$f(t) = 0.3 \cdot \sin(0.9 \cdot \pi \cdot t) + 0.001 \cdot d; \quad (49)$$

where d is a random variable with a standard normal distribution.

3.1. Comparison of filtering algorithms and estimation of parameters

Before BEADS filtering parameter estimation, it is important to make sure that this algorithm is suitable for real time data processing. The run-time of BEADS for N–point data is presented in Figure 10. Fifty different ECG signals were generated and filtered using BEADS method. In this graph, some fluctuations can be seen. In certain cases, the calculations took more than 3 sec. However, the average curve has a linear correlation to the data size. This shows a good asymptotic complexity of the analysed algorithm and appropriate real time data filtering.

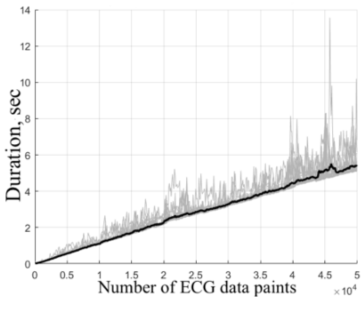

Figure 10. The complexity of the BEADS algorithm in ECG signal filtering

In the high frequency filtering process, a three-level discrete wavelet transform algorithm was chosen where threshold functions are from Daubechies wavelet function family. This method gives the best results at wavelet functions families of “db11” and “db12”. For further analysis, the “db11” has been chosen. The simulated and filtered ECG signals using both methods (BEADS and DWT) are shown in Figure 11.

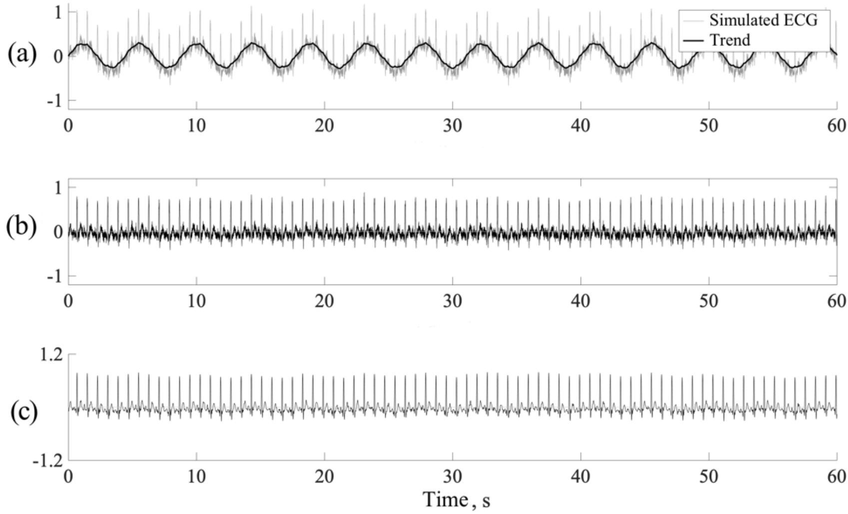

Figure 11. Filtering example for simulated ECG signal: (a) simulated signal and estimated trend with BEADS algorithm, (b) signal without movement artefacts, (c) signal with noise reduction using DWT filter

For the best movement artefact detection, several methods were compared between each other, such as the moving average filter (MA), Butterworth filter, Wiener filter, DWT, etc. The main issue with standard methods is that some parts of ECG signal are smoothed, and the signal loses a certain amplitude parameter value. Methods like Wiener filter are not capable to identify the movement trend precisely, and the signal becomes rambling with respect to isoline. Meanwhile, MA and BEADS may adapt to the analysed signal and extract movement artefact without losing the most important ECG signal characteristics. Even though both algorithms are working precisely, the MA not always manages to adapt to sudden signal changes and precisely transform it on the isoline.

In Figure 12, the comparison of two filtering methods (MA and BEADS) is presented where a participant was doing different exercises. If exercises are not intense and movements are slow and simple (squats and lunge parts (a) and (b)), the movement trend (bolded line) looks similar in both methods. There are some variations, but it should not affect the final classification result. Meanwhile, in part (c), a severe shortage of MA method can be seen when some ECG parameters change their sign together with the amplitude value. The identification and interpretation of these parameters become a complicated task for diagnosis and health evaluation. The major difference between MA and BEADS methods can be seen in part (d) where the ECG signal is more contaminated by noise. In this part, almost all QRS complex falls lower isoline (except R peak). In this way, the T wave interval becomes shorter, and other parameters change their values.

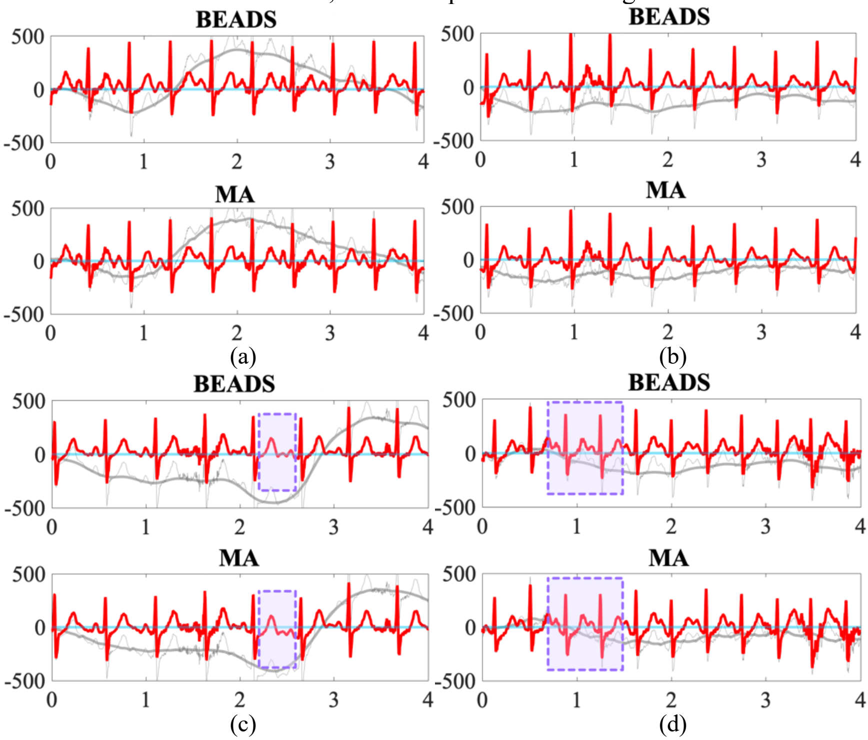

Figure 12. Comparison of MA and BEADS filtering algorithms: (a) squats, (b) lunge, (c) standing up from sitting position, (d) air squats

Table 2. The number of QRS complexes that were found using BEADS and MA algorithms

No.	Type of performed exercise	BEADS, QRS number in 1 min.	MA, QRS number in 1 min.
1	Squats	119	118
2	Lunge	124	124
3	Lunge	138	138
4	Cardio	147	142
5	Cardio	150	147
6	Cardio	153	143

Additional comparison of MA and BEADS methods can be seen in Table 2, where the numbers of QRS complexes are shown. In this table, similar results are presented: when training intensity is high and movements are fast, a lot of information is lost while filtering with MA algorithm. In some cases, even 10 QRS complexes are missing compared to the BEADS filter. Furthermore, it should be noticed that the length of the delay window in MA algorithm was selected 0.5 sec and for reconstruction, 0.25 sec.

3.2. Noisy EEG signal simulation using ECG signal movement artefacts

In this subchapter, the EEG signal is simulated using ECG movement artefacts. This process consists of five parts:

- *Signal recording:* ECG signals were recorded while a series of different physical exercises were performed. The SOA was used to monitor human physiological signals.
- *BEADS filter parameters optimization* using noisy ECG signal as a reference and the number of detected QRS complexes as a fitness function.
- *Movement artefact extraction* from the ECG signal using the modified BEADS filter.
- *Generation of the surrogate movement signals* using Intrinsic Mode Function (IMFs) that has derived from Empirical Mode Decomposition (EMD). Then, it is applied on the EEG signal.
- *Movement artefacts removal* from the noisy EEG signal.

The flow chart of the proposed methodology is shown in Figure 13.

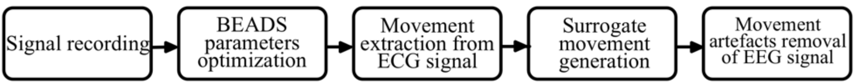

Figure 13. Schematic diagram of applied methods for the EEG signal simulation

For the ECG signal recording, the CardioScout Multi device was selected (sampling frequency 500 s^{-1}). This experiment consists of ten main functional training exercises with two static exercises (plank and side plank), two cardio exercises (star jump and high knee) and six dynamical exercises (dead bug, burpee, lunge, air squat, scatter jump and push up). The duration of each exercise performance was about 1 min. The recorded ECG signals have various amplitudes and fluctuations because they have been affected by different high and low frequency noise.

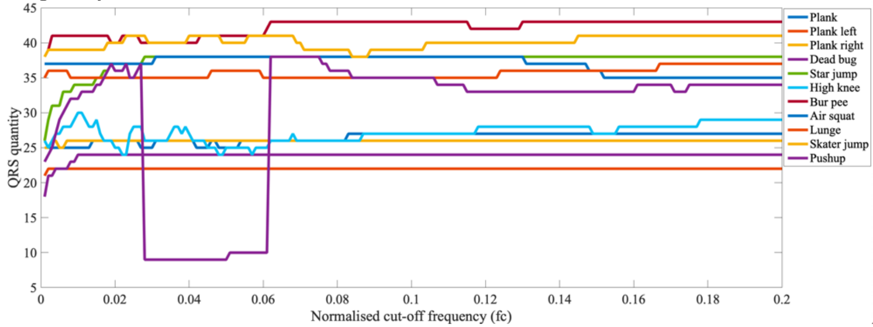

Figure 14. Normalised cut-off frequencies in different physical exercises and QRS complexes detection in noisy ECG signals

Some examples of BEADS filter parameters optimization during different exercises are presented in Figure 14. The most important parameter for filtering is normalised cut-off frequency f_c. Each exercise has its own baseline because different muscles are working. In Figure 14, it can be seen that the best results (highest QRS number) are reached with $f_c < 0.1$. Some exercises are almost stationary (plank, side plank), and their normalised frequency values should be lower than $f_c < 0.02$. Furthermore, cardio exercises (such as high knee or skater jump) have larger trend and are more affected by high and low frequency noise. That is why the QRS detection becomes a complicated task, and f_c fluctuates more. During the ECG signal processing and its trend removal, the QRS detection process is initialized in each step. It is assumed that the higher number of QRS complexes leads to a better filtering result.

Furthermore, it can be noticed that the "dead bug" exercise has a high trend that fluctuates a lot. The example of this exercise and movement signal extraction is presented in Figure 15.

After the ECG signal pre-processing had been completed, and all movement trends had been obtained, the next step was a baseline appliance on the EEG signal. Simulated EEG signals were modelled as a superposition of two main components, i.e., the original EEG signal and surrogate movement signals. This allows to simulate movement contaminated EEG signals and learn or suggest different methods for the EEG signal processing during physical activity.

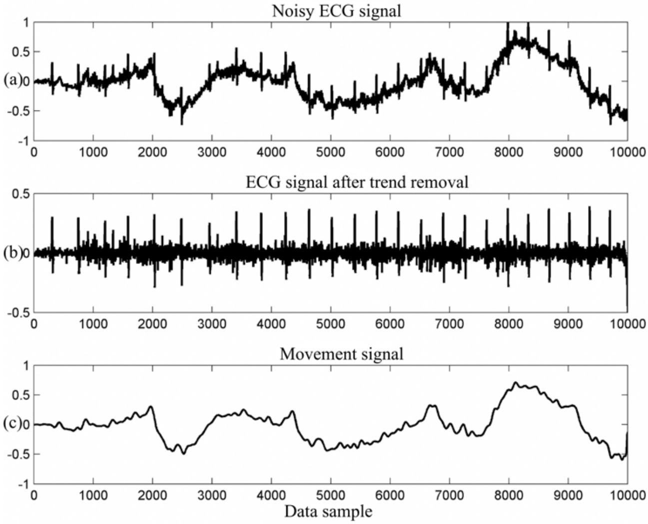

Figure 15. (a) Example of the ECG signal contaminated by movement artefact, (b) detrended ECG signal, (c) signal of extracted movement

The spectral Pearson's correlation was estimated using the spectra of the original and simulated EEG signal (see Table 3). There, $spkor_{sig}$ shows the spectrum correlation of the original and detrended EEG signals. For better comparison, alpha, beta and gamma waves were separated, and their spectrum correlations were calculated as well. $spkor_{alpha}$, $spkor_{beta}$, $spkor_{gamma}$ represents the spectrum correlation between alpha (8–15 Hz), beta (16–31 Hz) and gamma ($\geq$ 32 Hz) waves of the EEG signal. The results represented in Table 3 show that the proposed method does not damage the spectral characteristics of the EEG signal and the denoised signal resemble the original signal. The best correlation was achieved when the participant performed "star jump" and "air squat" exercises. Moreover, higher frequencies lead to lower Pearson correlation. This could have happened at the time of trend removal process because of the corruption of the signal. The higher is the frequency, the bigger corruption is done, because EEG signals mainly have high frequency waves.

Table 3. Correlations of original EEG and filtered EEG signals that were contaminated by movement artefacts

Exercise	$spkor_{sig}$	$spkor_{alpha}$	$spkor_{beta}$	$spkor_{gamma}$	f_c
Plank	0.895	0.908	0.929	0.931	0.083
Side plank (left)	0.900	0.948	0.958	0.962	0.002
Side plank (right)	0.907	0.954	0.963	0.963	0.003
Dead bug	0.923	0.920	0.954	0.963	0.010
Star jump	0.930	0.962	0.974	0.964	0.028
High knee	0.914	0.930	0.969	0.966	0.010
Bur pee	0.902	0.924	0.957	0.950	0.062
Air squat	0.928	0.958	0.972	0.960	0.031
Lunge	0.836	0.849	0.871	0.869	0.167
Skater jump	0.920	0.867	0.942	0.949	0.023
Push up	0.923	0.916	0.960	0.963	0.062

3.3. Conclusions

Stationary recorded ECG signal filtering does not require difficult methods, and it can be done using MA filter or Furje transformation. Generally, the processing of these signals requires only one filtering method for low and high frequency noise reduction. Ordinary ECG filtering methods cannot be reliably used in movement because of two main problems:

1) some methods are not capable to sufficiently reduce the noise and expose basic ECG signal characteristics because of the noise frequency fluctuations.
2) the selected removable frequency interval is too wide and that causes essential information losses about the signal itself.

The majority of simple filtering methods is not considering the time domain delay, or the signal is smoothed to the point that there is no meaning of analysing amplitude parameter values that have been left. During low intensity exercises, MA algorithm works fine and with similar accuracy as BEADS filter. However, if exercises make muscles contract fast and hear is loaded more intensively, MA fails in movement-artefact detection and hardly reconstructs the ECG signal on the isoline. Some parameter values even change its sign (amplitude value).

The fluctuations of high and low frequency noise depend on the exercise type and are not stationary. That is why different algorithms were proposed for those tasks: BEADS algorithm extracts the trend of the particular movement, and DWT method reduces high frequency noise. Even though BEADS algorithm is more complex and requires more computational resources (compared with MA filter), its complexity has a linear correlation to the size of the data that leads to good real time processing results. It has been found that the same filtering methods are appropriate for EEG signal processing and do no damage to the spectral characteristics of the analysed signal.

4. ECG SIGNAL ANALYSIS FOR FATIGUE DETECTION AND EVALUATION

4.1. Fatigue evaluation using HRV analysis

Before HRV analysis and fatigue detection, it is important to filter and correct the R–R intervals sequence. There are mainly two artefact types in R–R interval series, i.e., ectopic beats and missing/misread value. Three artefact detection methods (percentage filer, standard deviation filter, median filter) were applied that form the corrected signal data points with spline interpolation for the detected artefact. Using these filtering methods, the R–R interval data was prepared for linear and non-linear HRV analysis.

Linear heart rate variability parameters can be divided into two main groups: time and frequency scale parameters. In this research, ECG signals were recorded for 60 days (each duration was 60 sec). Two times a day (in the morning and in the evening), 8 exercises were performed (4 with low intensity: squats, lunge, side lunge, stand up from sitting position and 4 with high intensity: high knee, air squats, star jumps, scatter jumps). Each exercise was performed for 15–16 times with 15 sec rest. ECG signals were recorded before and after the training sessions. Four different stages can be defined: A1 in the morning, before exercises; A2 in the morning, after exercises; A3 in the evening, before exercises; A4 in the evening, after exercises. For the recorded ECG signals, R–R intervals were estimated, and HRV parameters were found. Time and frequency scale HRV parameters distribution is shown in Figure 16 where bean plots are presented. In Figure 16, the differences between data distributions of all four stages can be seen: linear HRV time scale parameters differ a lot between stages A1 and A2 or A3 and A4. This means that instant physical fatigue can be recognized from those graphs. However, the detection of mental or general (physiological) fatigue that appears in the evening (between stages A1 and A3) is a more complicated task. There is no big difference in bean plots (data distribution) of those stages. In this research, additional statistics were calculated for stages A1 and A3. From basic linear HRV parameter statistics and data correlation hypothesis, no statistical significance in correlation has been noticed, and $p > 0.05 = \alpha$. This leads to the conclusion that linear HRV analysis is not suitable for the physiological fatigue detection.

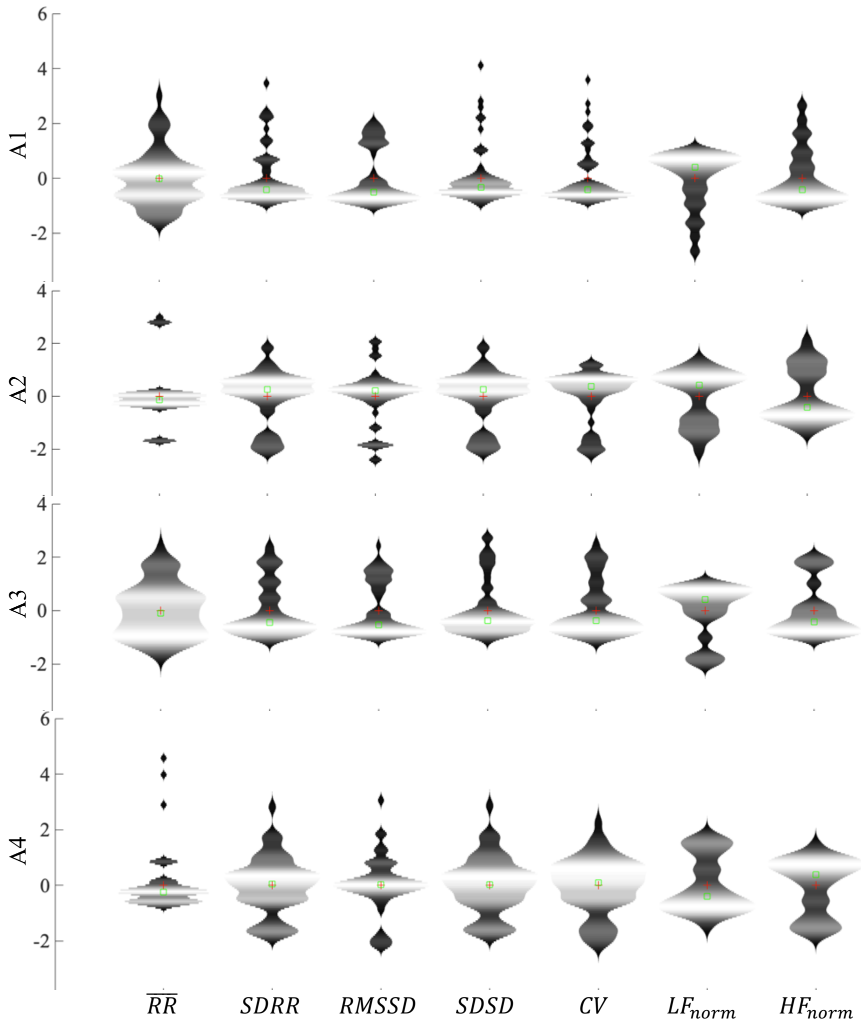

Figure 16. Beans plots of linear HRV parameters in different stages (A1, A2, A3, A4)

Further analysis was performed using a nonlinear HRV method with Poincare plots and parameters. In this research, five different stages were discussed: B1 before training, B2 low intensity exercises, B3 rest time, B4 high intensity training, B5 recovery time. The example of measured Poincare parameters is presented in Table 4. In this table, the heart rate variability changes of different training stages are shown. The estimated parameters are expressed in seconds. In this particular example, the participant performed squats as a low intensity exercise and air squats as a high intensity exercise. In Table 4, the B1 stage illustrates a good heart condition with scattered dots that leads to high heart rate variability. The same tendency can be noticed in stages B3 and B5. However, B2 and B4 show limited HRV. During the resting time, $SDRR$ increased and reached an even better value than it was before training ($SDRR_1 = 0.086 < 0.142 = SDRR_3$). This means that after low intensity training session, HRV returned to the normal condition. However, after the training session (stage B5), $SDRR$ parameter decreased, and HRV hardly returned to the normal condition. This could be described as fatigue.

Table 4. Poincare parameters in different exercises

Stage	Training intensity	$SD1$	$SD2$	$SDRR$	$RMSSD$
B1	Before training	0.010	0.111	0.086	0.015
B2	Low intensity exercise	0.006	0.064	0.087	0.008
B3	Testing time	0.017	0.116	0.142	0.024
B4	High intensity exercise	0.007	0.088	0.078	0.011
B5	Recovery time	0.009	0.131	0.065	0.011

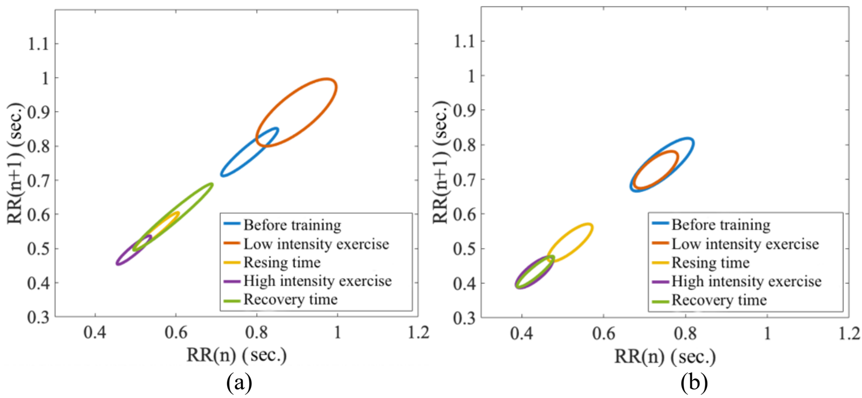

Figure 17. Poincare ellipses examples in different stages: (a) person that was exercising regularly, (b) person that did not have intensive physical activity for a long time

Two examples of Poincare ellipses are shown in Figure 17 where participants have different physical preparation: part (a) is when the participant is doing sports professionally and regularly, part (b) is when the participant did not have any high intense activity for a long time. In Figure 17, it can be seen that the ellipse of stage B2 in part (b) (of the person with no physical preparation) dropped instantly compared to the ellipse in stage B1. It can be stated that for this person, HRV is small and cannot adapt even to the low intensity exercises. Moreover, in three minutes of recovery time, the ellipse of this participant (in part (b)) hardly moved from the position of stage B4 (high intensity exercise). Meanwhile, a person in part (a) had almost full recovery in stage B5 where the ellipse consistently came back to the initial position. Based on these observations, it can be stated that Poincare analysis is a good method for instant fatigue detection and evaluation of human physical preparation. However, linear and nonlinear HRV analysis methods are not sufficient for mental or physiological fatigue detection.

4.2. ECG signal classification for fatigue identification

Even though the HRV analysis is a good tool for physical fatigue detection, the mental or physiological fatigue identification is a more complicated task and requires using more complex methods. In this research, additional ECG parameters were estimated: Q, R, S, T peak amplitude values (marked as *Qa*, *Ra*, *Sa*, *Ta*), QRS complexes (marked as *QRS*) and R–R, T, ST, QT intervals (marked as *RR*, *Tint*, *ST*, *QT*). The example of ECG parameter estimation is shown in Figure 18. For physiological fatigue detection, stages A1 and A3 were analysed (see subchapter 4.1); 8271 measurements have been estimated in 60 days of ECG signal recordings: 4195 belong to stage A1 and 4076 to stage A3. It has been noticed that some ECG signal parameter values overlap. For example, there is no significant difference between stages A1 and A3 in RR interval values. That is why simple and linear methods are not capable to separate these stages and identify fatigue. In this research, machine learning technique was selected to classify the ECG parameters into stages A1 and A3.

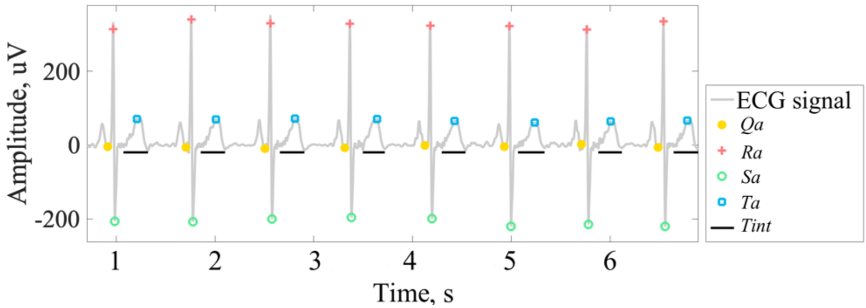

Figure 18. Example of ECG parameter estimation

At the beginning of this research, different ML algorithms were analysed and compared (see Table 5 and Figure 19) with all 9 ECG characteristics. The data set is split into training and validation (70%) and testing (30%) subsets. To all ML methods, 10-fold cross validation was applied to make sure that the model does not overfit the training data. In Figure 19, the validation accuracy results have been presented when 100 calculations were applied. In Table 5, $validation_{accuracy}$, $F1$, MCC were averaged and compared to all analysed ML algorithms.

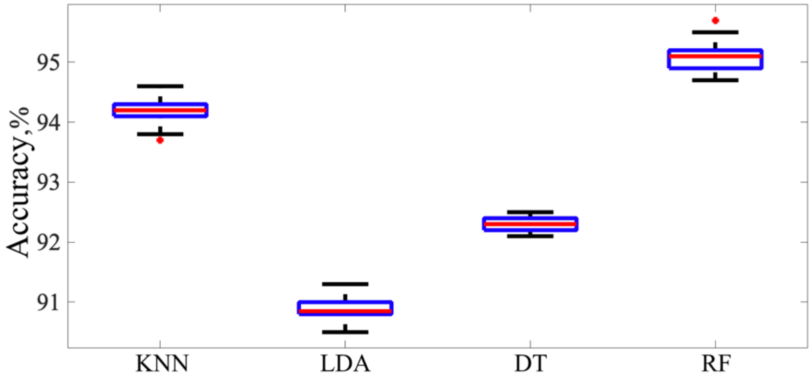

Figure 19. Boxplots of different ML algorithm accuracies

From Table 5 and Figure 19, it can be seen that the best algorithm for physiological fatigue detection is random forest that classifies stages A1 and A3 with higher than 95% accuracy. For all compared ML techniques, different hyperparameter values were analysed. In this research, DT had 100 maximum splits and 9 maximum surrogates in each node. Meanwhile, the selected RF algorithm consists of 30 DT with maximum 20 splits for every tree. Based on these results (see Table 5), RF algorithm was selected for further analysis.

Table 5. The accuracy of different machine learning algorithms

Method	$validation_{accuracy} \cdot 100\%$	$F1$	MCC
KNN	94.19%	0.94	0.87
LDA	76.82%	0.75	0.46
Quadratic SVM	90.89%	0.91	0.82
DT	92.31%	0.92	0.83
RF	**95.08%**	0.95	0.90

RF algorithm consists of different DT in which every node is a condition on a single feature, designed to split dataset into two parts. Similar response values end up in the same data set. Different ECG characteristics (parameters) may have different impact on the classification result. The importance of the feature is computed from how much each feature decreases the entropy in a tree.

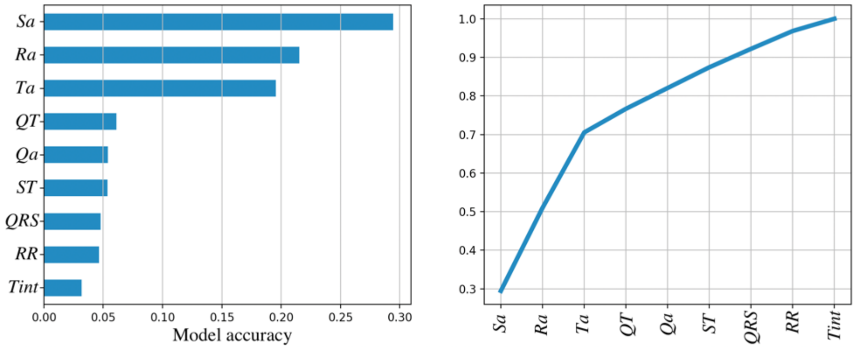

Figure 20. The importance of ECG parameters in stages A1 and A3 classification: (a) ECG parameters and FR accuracy, (b) cumulative accuracy curve for RF model

As it can be seen in Figure 20, if the selected threshold is equal to 0.8, only four ECG parameters (*Sa*, *Ra*, *Ta* and *QT*) are important for A1 and A3 stage classification (fatigue detection). Based on these results, the final RF model is designed using only these four ECG characteristics.

A random forest algorithm has many different hyper parameters, and all should be estimated. For this task, a random search algorithm was selected. It is based on grid search technique (that tries every possible combination) but iterated limited times and randomly selects hyperparameter values. Only the best hyperparameter values are saved that maximize the FR validation accuracy. The final results are shown in Table 6.

Table 6. RF model hyperparameter values

Parameter	Value
"max_depth" ensures that no further splitting will be made if the maximum tree height is reached	7
"min_samples_split" only nodes with equal or higher number of samples could be split	40
"max_features" defines the number of features to be considered while initiating each split	2
"min_samples_leaf" defines the minimum number of samples in every leaf	7
"n_estimators" is the number of decision trees	40
"learning_rate" defines the impact of final result for every newly added tree	0.15

Finally, RF model testing results are presented in Figure 21 where confusion matrix is shown. It can be noticed that true positive (stage A3) and false positive (stage A1) values are predicted with similar accuracy (95% and 94%). The general testing accuracy of this model is 94.5%.

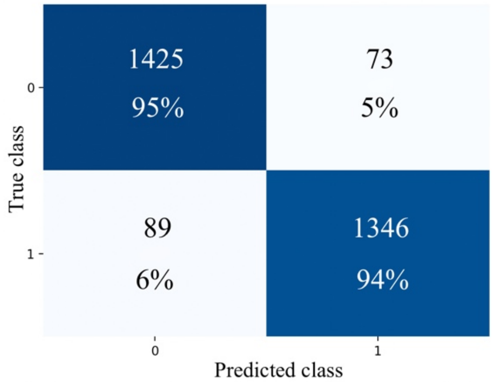

Figure 21. Confusion matrix of stages A1 and A3 classification results

4.3. Conclusions

Signal artefact detection and its correction for the recordings of physiological signals during dynamic activities are important for the analysis and understanding the way human body works. This research presents a novel approach for the analysis of signal artefacts from R–R interval data series.

This research analyses two types of fatigue, i.e., 1) physical fatigue that appears instantly during or after training session, 2) mental fatigue that appears at the end of the day or after intensive work in front of the computer. When a comparison of ECG signals before and after the training session was done, some of the suggested linear HRV parameters exposed instant physical fatigue. No statistical significance was found between the morning/evening estimation of HRV linear parameters.

Nonlinear HRV analysis using Poincare diagrams identifies physical fatigue as well as allows making assumptions about physical preparation of participant's heart for an intensive work load. Observing R–R interval fluctuations in different stages (while performing different exercises) and the shape of the ellipse or position in the $(RR(n), RR(n+1))$ coordinate plane, the exercises can be grouped by intensity. Furthermore, it has been noticed that the more intense is the exercise, the lower $SDRR$ value can be reached (for example, when walking for the first time, $SDRR_{walk} = 0.239$, while in the first "scatter jump" round, $SDRR_{scatter\ jump} = 0.040$).

Whereas the HRV analysis limited to R–R interval analysis and its fluctuations, identifying mental or general fatigue, is a hard task. An additional analysis was made for this purpose where other ECG parameters were estimated:

Q, R, S, T peak amplitude values, QRS complex, R–R interval, T interval, QT and ST. However, using the RF model, only four features (*Sa*, *Ra*, *Ta* and *QT*) appeared to be important for A1 and A3 stage classification task. The final RF model can predict fatigue with higher than 94% accuracy.

CONCLUSIONS

1. ECG signals that are recorded in movement are contaminated by various disturbances such as electrode contact noise, unstable wires and movement artefacts. In this research, it has been found that only one filtering algorithm is not enough to process these signals. A combined filtering method was proposed that consists of two different algorithms, i.e., modified BEADS algorithm for low frequency noise (movement artefacts) removal and DWT for high frequency noise reduction.
2. In this research, a modification of BEADS algorithm was introduced. With this improvement, different BEADS algorithm parameters (such as f_c) can adapt to ECG signal noise and eliminate it. The modification allows to extract low frequency noise without damaging bio-signal time and frequency scale characteristics. During the study, it appeared that similar algorithms (such as moving average filter) distort some ECG signal characteristics (for example, moves T wave above the isoline). In addition, the extracted movement artefact signal from ECG signal is as well used to generate surrogate EEG signals.
3. The ECG parameter search algorithm is based on k-TEO method. It was extended by adding T wave peak and interval detection. The suggested method is appropriate for real time processing. The obtained ECG parameter values are used in HRV analysis and signal classification process.
4. A special training session intensity control model is presented. It helps to avoid heart failure or injury. This model is integrated in Careware mobile app and used together with CardioScout Multi device for athlete training sessions.
5. A new linear and nonlinear HRV analysis methodology is suggested that allows to immediately identify physical fatigue while exercising or just after the training session. In addition, a significant correlation between Poincare ellipse shape or position in coordinates plane and participant training preparation has been noticed.
6. After ML algorithms comparison, the random forest method was selected for physiological fatigue identification. In addition, it appeared that four ECG parameters (*Sa*, *Ra*, *Ta* and *QT*) are the most important in the fatigue classification process. The final RF model can predict physiological fatigue with higher than 94% accuracy.

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EKG SIGNALŲ ANALIZĖ TRENIRUOČIŲ PROCESO MODELIAVIMUI IR NUOVARGIO VERTINIMO METODIKOS SUDARYMUI

Temos aktualumas ir svarba

Išmaniosios technologijos vis populiarėja tarp įvairaus amžiaus žmonių, o tobulėjantys įrenginiai bei besiplėtojanti debesų duomenų saugojimo sistema leidžia daugumą paslaugų vykdyti nuotoliniu būdu.

Sveikatos būklės stebėjimui sporto klubuose, klinikose, darbo vietose ar namuose vis dažniau naudojamos įvairios mobilios aplikacijos, skirtos mėgėjiškai sportuojantiems, atsakingus darbus dirbantiems, vyresnio amžiaus ar specifinių susirgimų turintiems žmonėms, profesionaliems sportininkams ir kt. Elektroninės nuotolinio valdymo sistemos kartais gali pakeisti įprastus sveikatos priežiūros ir stebėsenos metodus. Žmonės vis dažniau ieško informacijos internete apie savo sveikatos būklę, galimus gydymo metodus, rekomendacijas ar dalijasi patirtimi tarpusavyje. Neretai sveikatos stebėjimo sistemoms reikalingi papildomi prietaisai, todėl jų paklausa nuolat auga, tačiau tiek įrenginius, tiek aplikacijas turi būti paprasta naudoti, jie turi būti lengvai suprantami kiekvienam vartotojui. Invaziniai tyrimo metodai tokiu atveju tampa netinkami, todėl elektrinius gyvybinius signalus ir kitus sveikatos duomenis registruojantys neinvaziniai įrenginiai bei juos apdorojanti programinė įranga tampa paklausi.

Medicinoje elektriniai signalai paprastai yra registruojami žmogui esant stacionarioje būsenoje, nes norima minimizuoti galimus išorinius triukšmus. Tačiau registruojant įprastinėje aplinkoje retai pavyksta išvengti triukšmų, kurie gali atsirasti dėl kvėpavimo, raumenų susitraukimų, prastų signalo perdavimo kanalų ar nutrūkimų, nepilno elektrodo sąlyčio su oda, mirkčiojimo ir kitų trikdžių. Lietuvos ir užsienio mokslininkai pritaikė bei išplėtojo daugybę signalų filtravimo algoritmų, kurių dėka įvairūs triukšmai gali būti sumažinami nesugadinant pačio elektrinio signalo charakteristikų. Nors stacionariai registruoti signalai vis dar plačiai naudojami diagnostikoje, jie netinkami įvertinti žmogaus organizmo skirtingų sistemų tarpusavio sąveiką bei kitimo dinamiką kasdienės įprastinės veiklos metu.

Žmogui atliekant fizinius ar protinės veiklos pratimus veikia kelios sistemos, taip pat širdies bei kraujagyslių, raumeninė ir nervų sistemos. Vis populiarėjančiais širdies ritmo variabilumo bei elektrokardiogramų parametrų dinaminių sąsajų tyrimais siekiama rasti sąryšius tarp žmogaus kompleksinės sistemos komponentų. Nors šie tyrimai dažniausiai pagrįsti elektrokardiogramų signalų analize, jie atspindi nepertraukiamus momentinių širdies ritmų svyravimus ir suprantami kaip atsakas į įvairias fiziologines būsenas ar tam tikras patologines būkles, reguliuojamas autonominės nervų sistemos ar kraujotakos. Nors judesio metu elektrokardiogramų registravimas neatrodo sudėtinga užduotis, tačiau patys signalai yra gerokai triukšmingesni nei fiksuoti stacionariomis sąlygomis.

Priklausomai nuo judesio intensyvumo triukšmai tampa nestacionarūs ir standartiniai filtravimo algoritmai nebesugeba signalų apdoroti tinkamai, nepažeisdami svarbiausių charakteristikų. Šiame darbe pasiūlyti elektrinių signalų filtravimo algoritmai geba prisitaikyti prie triukšmo lygio esant skirtingai širdies apkrovai (parenkant skirtingo intensyvumo fizinius pratimus) bei išsaugo pagrindines elektrokardiogramos signalo parametrų reikšmes, reikalingas būklės įvertinimui ir proceso valdymui.

Širdies ritmo variabilumo tyrimai taip pat svarbūs ir fizinio ar fiziologinio nuovargio identifikavimo procese. Fiziologiniu nuovargiu vadinamas bendras nuovargis, apimantis fizinį, protinį ir emocinį žmogaus nuovargį. Fizinis nuovargis ypač aktualus profesionaliai sportuojantiems ar intensyvų atsakingą darbą atliekantiems asmenims. Sportininkai patenka į mažos rizikos grupę dėl tikimybės susirgti širdies ligomis, tačiau, nepastebėjus simptomų laiku, gali atsirasti negrįžtami širdies pažeidimai. Dėl šios priežasties vis daugiau profesionalių sportininkų ir neprofesionaliai sportuojančių žmonių domisi naujausiomis technologijomis, leidžiančiomis stebėti savo sveikatos būklę bei kontroliuoti treniruotės intensyvumą realiu laiku. Tuo tarpu, biuro darbuotojai dažniausiai susiduria su fiziologinio nuovargio problemomis, kurios gali pereiti į lėtinius sveikatos sutrikimus bei turėti ilgalaikių pasekmių. Neretai laiku nepastebėtas nuovargis gali tapti pagrindine nedarbingumo priežastimi. Šio tyrimo metu buvo identifikuojami pagrindiniai elektrokardiogramos parametrai, leidžiantys aptikti fizinį ar fiziologinį nuovargį naudojant širdies ritmo variabilumo analizę ir mašininį mokymą.

Pagrindiniai tyrimai šiame darbe atliekami naudojant elektrokardiogramos signalus, tačiau taip pat parodyta, kad naudoti triukšmų filtravimo algoritmai yra efektyvūs ir kitiems elektriniams signalams. Apdorotiems signalams buvo patobulinti ir pritaikyti elektrokardiogramos parametrų paieškos algoritmai ir, naudojant širdies ritmo variabilumo analizę, parinkti metodai nuovargio vertinimui. Be to, nuovargio identifikavimo metodika ateityje gali būti pritaikyta įvairiose mobiliose aplikacijose ir naudojama darbo metu. Tai leistų sumažinti traumų riziką, mirčių skaičių dėl širdies ir kraujagyslių ligų bei laiku aptikti nuovargio pirmuosius simptomus ir, juos efektyviai pašalinus, padidinti darbingumą.

Tyrimų objektas – elektrokardiogramos signalai, registruoti įvairaus intensyvumo fizinių ir protinių pratimų metu.

Darbo tikslas – apdoroti elektrokardiogramos signalus ir analizuoti jų pokyčius, gautus rezultatus panaudoti treniruočių proceso valdymo modelio ir nuovargio vertinimo metodikos sudarymui.

Darbe sprendžiami uždaviniai:

- Elektrokardiogramos signalus bei jų apdorojimą aprašančios literatūros analizė ir pagrindinių parametrų identifikavimas, siekiant ištirti sveikatos būklės vertinimo parametrus.

- Žemo ir aukšto dažnių triukšmų pašalinimo algoritmų apžvalga bei tinkamų metodų parinkimas ir jų pagerinimas.
- EKG signalo parametrų paieškos metodų papildymas įtraukiant į algoritmą T bangos amplitudines bei intervalines vertes.
- Fiziologinio nuovargio vertinimo metodikos sudarymas, realizavimas bei testavimas realiomis sąlygomis.

Darbui naudojami įrenginiai ir programinės priemonės:

- Elektrokardiogramos registruojamos naudojant CardioScout Multi įrenginį (su registravimo dažniu 500 s^{-1}).
- Algoritmų paklaidoms vertinti generuojami elektrokardiogramų signalai naudojant simuliatorių CMRR 2.0, kuris generuoja sinusoidę su 150 bpm (dūžių per minutę).
- Visi signalų apdorojimo, EKG parametrų paieškos bei nuovargio vertinimo algoritmai realizuoti naudojant MATLAB_R2015b paketo matematinės ir statistinės analizės funkcijas.
- R-R intervalų filtravimo algoritmai realizuoti naudojant Kubios HRV programinį paketą.

Darbo mokslinis naujumas ir praktinė svarba:

- Tyrimo metu buvo parinkta elektrokardiogramos, registruotos judesio metu, filtravimo algoritmai bei patobulinti atsižvelgiant į pagrindines signalo charakteristikas, jų neiškraipant.
- Suformuota širdies ritmo variabilumo vertinimo metodika fiziniam nuovargiui įvertinti, apimanti duomenų analizę, interpretaciją ir vizualizaciją.
- Sudaryta elektrokardiogramos signalo parametrų paieškos metodika, įtraukiant T piko amplitudines ir intervalines reikšmes. Signalų klasifikavimui pasiūlytos charakteristikos, kurios leidžia įvertinti signalo pokyčius. Metodikos taikomos žmogaus sveikatos būklei vertinti ir stebėti bei nuovargiui identifikuoti.
- Individualizuotos treniruotės valdymo rekomendacijos, vertinimui naudojant duomenis, gautus iš nutriukšmintos elektrokardiogramos.

Darbo rezultatų aprobavimas:

Disertacijos tema pateikti 5 moksliniai straipsniai, iš kurių 2 mokslinės informacijos instituto duomenų bazės (ISI) leidiniuose, kurios turi citavimo indeksą. Viena publikacija atspausdinta tarptautinėje, kita nacionalinėje leidyklose. Likusios trys publikacijos pristatytos kitų tarptautinių duomenų bazių recenzuojamuose leidiniuose.

Šiame darbe gauti rezultatai buvo pristatyti 6 tarptautinėse konferencijose. Lietuvoje vykusiose tarptautinėse konferencijose: 2017 metais Druskininkuose „Mathematical modeling and analysis: 22nd international conference“, 2018 metais Druskininkuose „10th international workshop on data analysis methods for software systems“, 2019 metais Kaune „Sportininkų rengimo valdymas ir sportininkų darbingumą lemiantys veiksniai: sporto forumas – tarptautinė mokslinė konferencija, skirta Lietuvos sporto universiteto 85-mečiui paminėti“ ir Vilniuje „Information and software technologies: 25th international conference“. Taip pat disertacijoje aprašyti tyrimai pristatyti 2017 metais Graikijoje, Salonikų mieste, „International conference on biomedical and health informatics“ ir Estijoje, Talino mieste, „Sampling theory and applications 2017: 12th international conference“. Pasidalinta patirtimi bei pristatyti tyrimai Porto universitete Portugalijoje 5 dienų stažuotėje „STSM scientific mission“ tema: „ECG signal filtering, analysis and parameter estimation“, kuri buvo finansuojama European Cooperation in Science and Technology (COST).

Disertacijos darbo rezultatai buvo naudojami struktūrinių fondų projekto „EKG signalo filtravimo ir parametrų skaičiavimo tyrimas“ (inočekiai nr. 01.2.1-MITA-K-824-01-0359) mokslinių tyrimų ir technologinės plėtros įgyvendinimui (2017 09–2018 02). Taip pat plėtojami tyrimai programos EUREKA projekte 11169 „Non-intrusivehuman fatigue assessment (Fatigue)“ (2018 09 01–2021 08 30). Be to, dalis darbe aprašytų metodų prisidėjo prie „CareWare: Electronics Wearable Sport and Health Solutions“ projekto plėtojamų tyrimų.

Darbo apimtis ir struktūra:

Šią daktaro disertaciją sudaro įvadas, 4 pagrindiniai skyriai, išvados, praktinė svarba, literatūros sąrašas ir publikacijų sąrašas. Darbo apimtis yra 114 puslapių, 55 paveikslų, 26 lentelės ir 181cituojamų literatūros šaltinių aprašas.

IŠVADOS

1. Judesio metu registruoti EKG signalai yra triukšmingi dėl atsiradusių įvairių trikdžių (tokių kaip elektrodo sąlyčio su oda, laidų judėjimo ir pan.) ir pačio judesio pobūdžio. Tyrimo metu nustatyta, kad vieno bendro filtravimo algoritmo tokiems signalams apdoroti nepakanka. Šiame darbe pasiūlyta naudoti dviejų metodų derinį: modifikuotą BEADS algoritmą – žemo dažnio triukšmams (judesio artefaktams) pašalinti ir DWT – aukšto dažnio triukšmams sumažinti.
2. Šiame darbe aprašyta BEADS algoritmo modifikacija skirta judesio metu registruotiems EKG signalams filtruoti. Dėl šio patobulinimo, algoritmo parametrai (tokie kaip f_c) geba prisitaikyti prie skirtingų judesio triukšmų ir sėkmingai juos eliminuoja nepažeidžiant pagrindinių signalo parametrų. Tyrimo metu paaiškėjo, kad alternatyvūs algoritmai, tokie kaip slenkančio vidurkio filtras, kai kurias EKG signalo dalis iškraipo (pvz., T banga atsiduria žemiau izolinijos), o tai apsunkina tolesnę EKG parametrų paiešką. Be to, naudojant modifikuotą BEADS algoritmą neiškraipomos pagrindinės biologinių elektrinių signalų (EKG, EEG, EMG) laiko ar dažnių skalių

charakteristikos.

3. Palyginus kelis filtravimo metodus buvo parinktas DWT algoritmas EKG signalo aukšto dažnio triukšmams sumažinti. Naudojant šį algoritmą simuliuotiems EKG signalams su Daubeches „db11“ bangelėmis pašalinami aukšto dažnio triukšmai ir gaunama RMSE paklaida lygi 0,088.
4. EKG parametrų paieškos k – TEO algoritmas papildytas T bangos apskaičiavimu ir rastos kitų EKG parametrų (Ta, $Tint$, QT ar ST) reikšmės. Kadangi šio signalo forma bei parametrų eiliškumas žinomas, papildymai remiasi ekstremumų nustatymu ir nereikalauja didelių skaičiavimo resursų (reikalingų duomenų apdorojimui realiu laiku) bei randa parametrus triukšmingame signale.
5. Atlikus papildomus eksperimentus sudarytas ir aprašytas treniruotės intensyvumo valdymo modelis, leidžiantis sportuojančiam išvengti širdies veiklos sutrikimų, traumų ir pasiekti maksimalių rezultatų (įvertinus QRS, $ŠR$, JT ir kt.). Šis algoritmas įdiegtas į Careware mobilią aplikaciją ir kartu su CardioScout Multi įrenginiu naudojamas profesionaliai sportuojančių žmonių treniruotės metu.
6. Pasiūlyta tiesinė ir netiesinė ŠRV metodika geba identifikuoti fizinį nuovargį treniruotės metu ar po jos. Priklausomai nuo pratimo intensyvumo keičiasi Poincare elipsės forma bei pozicija. Nors sudėtinga išskirti konkrečias parametrų reikšmes, lemiančias nuovargį, tyrimo metu nustatyta, kad Poincare elipsės postūmis žemyn reiškia padidėjusį širdies darbą. Lėtas elipsės atsistatymas į pradinę poziciją gali rodyti stiprų fizinį nuovargį arba prastą fizinį parengtumą.
7. Palyginus įvairius mašininio mokymo metodus ir įvertinus jų tikslumą, pasirinktas atsitiktinio miško algoritmas kaip geriausiai tinkantis fiziologinio nuovargio identifikavimui (tikslumas apie 95 %). Tyrimo metu paaiškėjo, kad geriausiai nuovargį aprašo keturi EKG signalo parametrai: Sa, Ra, Ta, QT. Nustatyta, kad atsitiktinio miško klasifikatorius individualiam nuovargiui identifikuoti susideda iš 40 skirtingų sprendimų medžių, kurių kiekvieno aukštis ne didesnis nei 7.

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