

# Effects of different automatic filters on the analysis of heart rate variability with Kubios HRV software

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Received: 09.09.2016

Accepted: 21.12.2016

## Summary

**Background and objective:** Heart rate variability (HRV) can provide useful information on different physiological situations. The aim of this study was to analyse heart rate variability (HRV) indices following the application of different filters included in a widely used analysis program.

**Material and method:** 30 measurements were recorded of the heart rate signal of professional footballers. HRV was recorded in a sitting position, early morning and fasting. The HR monitor Firstbeat Bodyguard recorded HR data for 10 minutes during every measurement and Kubios® software imported and analysed all RR intervals. Each recording was analysed without a filter (none) and subsequently with each of the five different filters (very low=0.45 sec. low=0.35 sec. medium=0.25 sec. strong=0.15 sec. very strong=0.05 sec). The variables analysed pertained to time domain (standard deviation of RR intervals (SDNN), the square root of the mean of the squares of the differences between adjacent RR intervals (rMSSD) and the number of pairs of adjacent RR intervals that differ by over 50ms in the whole recording, divided by the total number of RR intervals and expressed as a percentage (pNN50)); frequency domain (high frequency HF, low frequency LF, very low frequency VLF, both in terms of power and peak frequency); the diameters of the Poincaré plot (SD1 and SD2); as well as the internal complexity of the signal, Detrended Fluctuation Analysis ( $\alpha_1$  and  $\alpha_2$ ) and approximate and sample entropy (ApEn and SampEn).

**Results:** A significant difference was only found for rMSSD, pNN50, LF power and HF power and SD1 when comparing the analysis of the no filter recording with the very strong filter.

**Conclusion:** The filtering system provided by the Kubios® software to treat the artefacts did not affect the values of the HRV indices analysed, except when the "very strong" filter was applied.

**Key words:**  
Heart rate variability. Filter system. Kubios®.

## Efecto de los diferentes filtros automáticos en el análisis de la variabilidad de la frecuencia cardiaca con el software Kubios HRV

### Resumen

**Introducción y objetivo:** La Variabilidad de la Frecuencia Cardiaca (VFC) puede proporcionar información útil sobre diferentes situaciones fisiológicas. El objetivo de este estudio fue analizar los índices de variabilidad de la frecuencia cardiaca (VFC) tras la aplicación de diferentes filtros incluidos en un programa de análisis utilizado.

**Material y método:** Se registraron 30 mediciones de la señal del ritmo cardíaco, pertenecientes a futbolistas profesionales. La VFC se registró en una posición sentada, por la mañana y en ayunas. Se realizó un registro de 10 min de duración con el monitor de ritmo cardíaco Firstbeat Bodyguard y todos las series de intervalos RR fue importada y analizada con el software Kubios®. Cada serie de tiempo se analizó sin un filtro (ninguno) y posteriormente con cada uno de los cinco filtros diferentes (Muy bajo = 0,45 seg. Bajo = 0,35 seg. Medio = 0,25 seg. Fuerte = 0,15 seg. = Muy fuerte 0,05 seg). Las variables analizadas pertenecen al dominio de tiempo (desviación estándar de los intervalos RR (SDNN), la raíz cuadrada de la media de los cuadrados de las diferencias entre intervalos adyacentes RR (rMSSD) y el número de pares de intervalos RR adyacentes que difieren en más de 50 ms en toda la grabación, dividido por el número total de intervalos RR y expresada como un porcentaje (pNN50)); al dominio de la frecuencia (HF: alta frecuencia, LF: baja frecuencia y VLF: muy baja frecuencia, tanto en términos de potencia y la frecuencia de pico); los diámetros del gráfico de Poincaré (SD1 y SD2); así como la complejidad interna de la señal, con el análisis de la fluctuaciones sin tendencias ( $\alpha_1$  y  $\alpha_2$ ) y entropía aproximada y muestral (ApEn y SampEn).

**Resultados:** Se encontró sólo diferencia significativa en rMSSD, pNN50, HF y LF en términos de potencia y SD1 cuando se compararon los registros al aplicar el filtro muy fuerte con sin filtro.

**Conclusión:** El sistema de filtrado proporcionada por el software Kubios® para tratar los artefactos no afectó a los valores de los índices de VFC analizados, excepto cuando se aplicó el filtro "muy fuerte".

**Palabras clave:**  
Variabilidad de la frecuencia cardiaca. Sistema de filtro. Kubios®.

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## Introduction

Heart rate variability (HRV) is the variation that occurs in the series of time interval measured between two consecutive heartbeats (RR interval)<sup>1,2</sup>. HRV is a non-invasive method that enables us to evaluate the interaction between the sympathetic and parasympathetic nervous system, reflecting the heart's capacity to adapt to changing physiological conditions. In fact, a lower HRV indicates a predominance of sympathetic activity and an augmented HRV indicates a predominance of parasympathetic activity on the sino-auricular (SA) node<sup>1</sup>.

HRV has been widely studied in cardiac patients<sup>1,3-6</sup> as well as athletes<sup>7,8</sup>, among other areas. Different devices have been used for this purpose, from a holter to different heart rate monitors. In many cases, however, it is hard to get a good HRV measurement owing to the appearance of artefacts in the signal. This could be caused by technical factors (including missed beats) or by the appearance of ectopic beats. Technical causes can pertain to poor placement of the electrodes during measurement or to the movement of the subject during the test, particularly during long recordings or when the subject is asleep. Ectopic beats can be normal and relatively common in healthy subjects<sup>1,9</sup>.

For some authors, the presence of ectopic beats can modify the values of the HRV indices by up to 50% of the final results<sup>9</sup>. Hence, artefacts in the signal must be treated following HRV measurement in order to obtain suitable results<sup>10,11</sup>. Many methods and algorithms for editing or correcting dubious R-R intervals have been developed and evaluated. Some of the common artifact correction and editing techniques involve deletion, interpolation of degree zero, interpolation of degree one (linear interpolation), and cubic spline interpolation. Interpolation methods replace the non-normal R-R intervals with new interpolated R-R intervals. Unlike the deletion method, interpolation methods preserve the initial number of samples. Most interpolation methods can be considered to serve as low-pass filters with different filtering capacities. Interpolation of degree zero substitutes the abnormal R-R intervals with an average value that is computed from the neighbouring normal R-R intervals. In interpolation of degree one, called linear interpolation, a straight line is fitted over the abnormal R-R intervals to obtain new values. One popular spline interpolation method is a cubic spline interpolation, where smooth curves are estimated through a number of data points by fitting a third degree polynomial. It has been recommended to use interpolation methods when R-R interval time series contain occasional ectopic beats and artefacts. This especially concerns the power spectrum HR variability analysis<sup>12</sup>. In addition, several other methods have been proposed for artefact correction such as comparing and merging method<sup>13</sup>, the predictive autocorrelation method<sup>14</sup>, non-linear predictive interpolation<sup>15</sup>, exclusion of R-R interval segments with divergent duration<sup>16,17</sup>, impulse rejection<sup>18</sup>, the integral pulse frequency model<sup>19,20</sup>, the sliding window average filter<sup>21</sup>, non-linear filtering combined with wavelet based trend removal<sup>22</sup>, and threshold filtering also with wavelet based trend removal<sup>23</sup>.

Some studies have compared the impact of editing methods on the results of HRV analysis<sup>8,14,15,24-27</sup>. However, although these studies yield different results depending on the type of study, the message was the same: filtering methods affect HRV analysis. The differences between the results could be attributable to the type of study population used, the

length of the R-R interval time series, the editing method, the number of samples edited, etc.

Furthermore, there is an increasingly widespread use of commercial software that by default previously filters the signal without the user knowing exactly what has been done, or in the best case scenario, software that allows the user to apply different types of filter discretely. Anyway, automatic filters that exclude some intervals from the original RR sequence should not replace manual editing because they are known to behave unsatisfactorily and to have undesirable effects leading potentially to errors.

Moreover, in commercial software that offer the possibility of choosing different filter levels, this choice is subjective by the examiner. Therefore, given a specific number of artifacts, we do not know if the result would be the same if the time series is subjected to a type of filter or other. This is what happens to Kubios, one of the commercial programs more often are being used in recent times in the analysis of HRV. It offers five levels of filtering that users will choose based on their inspection of the track.

The aim of this study was to analyse HRV indices for a group of athletes in all the domains following the application of different filters included in a commonly used analysis software.

## Material and method

### Study samples

30 heart rate signal recordings were analysed, belonging to high level professional athletes (aged  $25.22 \pm 3.41$  years old; weight  $74.42 \pm 7.31$  Kg; height  $178.85 \pm 7.83$  cm). The Local Ethics Board approved the study, which followed all the principles set out in the Declaration of Helsinki. All subjects signed an informed written consent to participate in this study.

### Method

HRV was recorded along 10 minutes in a sitting position, early morning and fasting. The subjects were seated for 10 minutes before recording to explain the conditions. They were asked to remain in the same position without speaking during the recording time.

The HR monitor Firstbeat Bodyguard (Firstbeat Technologies; Jyväskylä, Finland) recorded HR data for 10 minutes during each recording. This two channel monitor acquires RR intervals with 1 ms resolution and a sampling rate of 256 Hz. Firstbeat Uploader (Firstbeat Technologies; Jyväskylä, Finland) software downloaded the data from the devices to the computer and Kubios® software<sup>28</sup> (Kubios HRV. 2.1, Biosignal Analysis and Medical Imaging Group, Kuopio, Finland) imported and analysed all RR series. Following the manufacturer's instructions in order to avoid the interference of artefacts, the time series were manually checked for artefacts before the analysis<sup>28,29</sup>.

Kubios® (Finland) is a widely used free software for HRV analysis and it includes artefact correction options that can be used to correct artefacts from a corrupted RR interval series<sup>28,29</sup>. The user can select between very low, low, medium, strong, and very strong correction levels. In addition, a custom level in seconds can be set. The different correction levels define thresholds (very low=0.45 sec, low=0.35 sec,

medium=0.25 sec, strong=0.15 sec, very strong=0.05 sec) for detecting RR intervals differing “abnormally” from the local average RR interval. For example, the “medium” correction level will identify all RR intervals that are larger/smaller than 0.25 seconds compared to the local average. Furthermore, the above correction thresholds are for 60 beats/min heart rate; for higher heart rates the thresholds are smaller (because the variability is expected to decrease when HR increases). The corrections to be made on the RR series are displayed on the RR interval axis. A piecewise cubic spline interpolation method is used in the corrections<sup>28</sup>.

Each recording was analysed without a filter (none) and then subsequently with each of the five different filters (very low, low, medium, strong and very strong).

The variables analysed were: in the time domain<sup>1</sup>, the standard deviation of RR intervals (SDNN), the square root of the mean of the squares of the differences between adjacent RR intervals (rMSSD) and the number of pairs of adjacent RR intervals that differ by over 50ms in the whole recording, divided by the total number of RR intervals and expressed as a percentage (pNN50). In the frequency domain<sup>1</sup>, high frequency (HF: 0.15-0.4 Hz), along with low frequency (LF: 0.04-0.15 Hz) and very low frequency (VLF: 0.0033-0.04 Hz) oscillations were analysed both in terms of power (ms<sup>2</sup>) and peak frequency (Hz). In terms of the Poincaré graph<sup>30</sup>, the longitudinal (SD2) and transversal (SD1)<sup>31</sup> axes were analysed. To study the complex structure of the signal, two tools were used. Firstly, a Detrended Fluctuation Analysis (DFA)<sup>32,33</sup> was conducted, measuring the correlation between data at different time scales through short and long term fluctuations that are characterised by slopes  $\alpha_1$  and  $\alpha_2$ , respectively. And secondly, the irregularity of the signal was measured by means of approximate entropy (ApEn)<sup>34</sup> and sample entropy (SampEn)<sup>35</sup>.

## Statistical analysis

A descriptive study was carried out of all the variables, determining their average values and standard deviation. The normality of distributions was assessed with the Shapiro-Wilk test. The contrast of hypothesis was carried out with the test of Kruskal-Wallis for the non-normal variables (VLF, LF and HF, both in Hz and ms<sup>2</sup>) and a repeated measures ANOVA was used with the normal variables. The Bonferroni test was done as a test post-hoc and the significance threshold was set at  $p < 0.05$ .

## Results

Table 1 shows the average values and standard deviations for the measurements taken with each of the filters (none; very low; low; medium; strong and very strong) for each of the HRV parameters analysed. Significant differences were only found for RMSSD, pNN50, power LF, power HF and SD1 when comparing the measurement taken without a filter to the very strong filter.

Table 2 shows the filter with which the first change is detected in each domain: Time Domain, Frequency Domain, Poincaré plot and Nonlinear values. Most subjects present changes with very low filter and no subject showed the first change with the VS filter. In other words,

no subject reached the very strong filter without the record showed a change in some variable.

## Discussion

The main contribution made by this paper was that the use of a filtering system provided by the Kubios® software for the treatment of artefacts did not affect the values of the HRV indices when they are analysed in group, with the exception of when the “very strong” filter was applied. The variables obtained by means of non-linear analysis methods were not even altered by the strongest filter on the signal filtering system of this software.

In an ideal situation, HRV analysis is conducted with a series of RR intervals including only pure SA beats (NN interval). However, the series of RR intervals obtained on the basis of ECG recordings in ambulatory measurements or portable devices within the world of sport (heart rate monitors) are in most cases imperfect, so they are not without artefacts. However, when working with cardiac patients there can also be added alterations caused by cardiac arrhythmia that can be present in up to 90-95% of patients with acute myocardial infarction<sup>12</sup>. Hence the importance of editing the RR series before analysing it, a task that is often missed when working quickly with commercial software. It is common engineering practice to resample the time series as well as the use of several smoothing models<sup>36,37</sup>. For Buchheit<sup>9</sup>, the presence of a single ectopic beat during a 5-min recording can modify HRV indices by up to 50% and for Thuraishingham<sup>22</sup> ectopic beats cause erroneously high values in the standard deviation of the R-R intervals (SDNN). Ectopic beats can be common events, especially among patients with cardiovascular disease, but they can also be present in healthy subjects<sup>12</sup>. In addition to physiological artefacts, there can also be errors attributable to technical aspects when taking measurements or the software used to detect R-R artefacts. For example, the detection algorithm can be faulty if the R-R interval detection threshold is too low or too high. Therefore, artefacts and ectopic beats represent a problem that must be taken into account when measuring HRV since they could impact the reliability of the result. However, in general there is very little information about the filters used by different analysis software and the equations they apply.

This study found no significant modifications in the HRV measurements regardless of the filtering level used, with the exception of the very strong filter on the variables mentioned previously. This might be due to the use of measurements taken from top athletes, who present high variability that is probably less sensitive to the interpolations made for the filter. As for the changes observed when comparing the gross signal (no filter) with the very strong filter level, this could be due to the fact that the threshold established for this filtering level (0.05 s) is so demanding that what it actually does it intensely smoothes the signal that alters the results for some indices in the time and frequency domains, although without affecting the complex structure of the signal as demonstrated by the absence of changes in the non-linear parameters.

As can be seen in Table 1, the rMSSD is the only variable that apparently shows a progressive decrease of the mean values as the filtering intensity increases, although the difference is not significant until using the VS filter. All other variables have apparently stable mean values until reaching the VS filter where they show a large change that

**Table 1. Average and standard deviation for each measurement and each of the filters.**

	Filter	None	Very low	Low	Medium	Strong	Very strong
SDNN (ms)	Average	135.81	136.79	133.05	131.06	121.41	98.76
	SD	55.83	56.30	54.47	51.39	48.54	38.51
RMSSD (ms)	Average	96.98	90.55	84.44	76.09	59.90	25.76 (*)
	SD	56.42	49.70	43.63	36.13	23.43	4.96
pNN50 (%)	Average	39.50	39.96	39.83	39.01	33.91	5.53 (*)
	SD	22.33	22.07	22.04	21.51	18.05	3.12
VLF (Hz)	Average	0.01	0.01	0.01	0.01	0.01	0.01
	SD	0.01	0.01	0.01	0.01	0.01	0.00
LF (Hz)	Average	0.07	0.08	0.07	0.09	0.07	0.06
	SD	0.02	0.02	0.02	0.09	0.02	0.01
HF (Hz)	Average	0.20	0.20	0.20	0.20	0.19	0.25
	SD	0.05	0.05	0.05	0.05	0.04	0.38
VLF (ms <sup>2</sup> )	Average	9,964.63	11,059.90	10,888.94	11,356.78	10,109.38	8,024.69
	SD	8,282.29	10,324.11	10,256.56	11,414.19	10,009.39	7,119.34
LF (ms <sup>2</sup> )	Average	5,968.57	5,802.70	5,491.25	4,793.61	3,458.68	987.40(*)
	SD	4,625.82	4,265.79	3,935.40	2,998.78	2,037.96	389.75
HF (ms <sup>2</sup> )	Average	2,853.30	2,585.98	2,304.20	1,829.54	1,023.63	117.95(*)
	SD	3,060.02	2,641.39	2,228.81	1,604.62	753.70	60.34
SD1	Average	69.24	64.10	59.76	53.85	40.62	18.23(*)
	SD	39.89	35.19	30.89	25.58	17.81	3.52
SD2	Average	178.12	181.55	179.56	176.73	165.69	138.11
	SD	70.82	73.31	72.95	69.32	67.95	54.75
DFA alpha 1	Average	1.19	1.22	1.25	1.27	1.31	1.55
	SD	0.25	0.23	0.21	0.19	0.19	0.11
DFA alpha 2	Average	0.99	1.00	1.00	0.99	1.07	1.26
	SD	0.10	0.10	0.10	0.20	0.11	0.14
ApEn	Average	1.15	1.16	1.16	1.16	1.14	0.82
	SD	0.10	0.10	0.10	0.10	0.12	0.18
SampEn	Average	1.29	1.30	1.31	1.32	1.29	0.80
	SD	0.26	0.26	0.27	0.28	0.28	0.22

Average values and standard deviation for each measurement and each of the filters (none; very low; low; medium; strong; very strong) for each of the HRV parameters analysed. (\*)  $p < 0.001$ . ApEn, approximate entropy; SampEn, sample entropy; DFA, detrended fluctuation analysis; HF, high frequency; LF, low frequency; pNN50, number of pairs of adjacent RR intervals that differ by over 50ms in the whole recording, divided by the total number of RR intervals and expressed as a percentage; rMSSD: square root of the mean of the squares of the differences between adjacent RR intervals; SDNN: standard deviation of RR intervals; SD1: transversal diameter; SD2: longitudinal diameter; VLF: very low frequency.

in some variables becomes statistically significant. Although in each individual record a progressive reduction of HRV can be observed from the filter that causes the first change (Table 2), in a group analysis no significant change is evident until reaching the VS filter because each record corrects its artifacts with a different level of filtering, but none of them reaches the VS filter.

These results have an interesting application for those studies of athletes in which these variables are analyzed in group<sup>38</sup>.

Sitting position is not standard for HRV analysis, although it is commonly used for short records in sports population<sup>6,38</sup>. However, this can be neglected in this study since this is only data acquisition for further technical analysis.

The duration of recordings (10 minutes) is in accordance with the guidelines of the Task Force<sup>1</sup> which states that in studies researching HRV, the duration of recording is dictated by the nature of each investigation. In this case, our preoccupation was to provide enough data for nonlinear analysis and according to Pincus<sup>34</sup> N for ApEn should be between 100

and 900 data (for  $m=2$ ). A 10 min recording contains about 600 data. For SampEn and DFA the N needed is similar<sup>39,40</sup>.

## Conclusions

In conclusion, there are no significant differences between the results obtained by subjecting a series of data taken from top athletes to the different filters provided by Kubios® software, except the strongest one.

## Acknowledgment

This study has been conducted within the framework of the Research Project with reference TEC2013-48439-C4-4-R, which is part of the State Research, Development and Innovation Programme for the Challenges of Society and funded by the Spanish Ministry of Economics and Competitiveness.

**Table 2. Filter that produced the first change.**

Subject	Time domain	Frequency domain	Poincaré plot	Nonlinear variables	Total
1	VL	VL	VL	VL	VL
2	M	M	M	M	M
3	VL	VL	VL	VL	VL
4	VL	VL	VL	VL	VL
5	M	L	L	M	L
6	M	M	M	M	M
7	S	S	S	S	S
8	VL	VL	VL	VL	VL
9	VL	VL	VL	VL	VL
10	M	M	M	M	M
11	VL	VL	VL	VL	VL
12	VL	VL	VL	VL	VL
13	S	M	M	M	M
14	L	M	L	L	L
15	S	S	S	S	S
16	S	S	S	S	S
17	L	L	L	L	L
18	M	M	M	M	M
19	S	S	S	M	M
20	L	VL	L	VL	VL
21	VL	VL	VL	VL	VL
22	M	M	M	M	M
23	VL	VL	VL	VL	VL
24	VL	VL	VL	VL	VL
25	VL	VL	VL	VL	VL
26	VL	VL	VL	VL	VL
27	L	L	VL	VL	VL
28	VL	VL	VL	VL	VL
29	VL	VL	VL	VL	VL
30	VL	VL	L	VL	VL

Filter with which the first change is detected in Time Domain, Frequency Domain, Poincaré plot and Nonlinear variables (VL: very low; L: low; M: medium; S: strong). No subject showed the first change with the VS filter. The last column ("Total") shows the first filter with which the first change is observed in any variables.

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