Smart Monitoring of User's Health at Home: Performance Evaluation and Signal Processing of a Wearable Sensor for the Measurement of Heart Rate and Breathing Rate

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Abstract: Nowadays, the monitoring of users' health status is possible by means of smart sensing devices at low-cost and with high measuring capabilities. Wearable devices are able to acquire multiple physiological and physical waveforms and are equipped with on-board algorithms to process these signals and extract the required quantities. However, the performance of such processing techniques should be evaluated and compared to different approaches, e.g. processing of the raw waveforms acquired. In this paper, the authors have performed a metrological characterization of a commercial wearable monitoring device for the continuous acquisition of physiological quantities (e.g. Heart Rate - HR and Breathing Rate - BR) and raw waveforms (e.g. Electrocardiogram - ECG). The aim of this work is to compare the performance of the on-board processing algorithms for the calculation of HR and BR with a novel approach applied to the raw signals. Results show that the HR values provided by the device are accurate enough (±2.1 and ±2.8 bpm in static and dynamic tests), without the need of additional processing. On the contrary, the implementation of the dedicated processing technique for breathing waveform allows to compute accurate BR values (±2.1 bpm with respect to standard equipment).

1 INTRODUCTION

The improvement of people's safety and the control of their health conditions represent the primary challenges about Smart Home (Sixsmith A. and Sixsmith J., 2000) and Smart Cities (Revel et al., 2014). The Italian project Health@Home: Smart Communities for citizens' wellness (H@H) aims to reach such goal through the integration of domotic and biomedical devices in Smart residential environments (Abascal, 2004), (Demiris et al., 2006).

Nowadays, acquiring physical (Catal et al., 2015), (Bayat et al., 2014), (Abdallah et al., 2015) and physiological (Pantelopoulos and Bourbakis, 2010), (Parvaneh et al., 2014), (van Andel et al., 2015) signals from a person is a quite easy task, thanks to the rapid growth of low-cost Information and Communications Technologies (ICT). Wearable sensors are able to measure even more physiological waveforms (e.g. ECG) in real-time and are equipped with on-board algorithms, in order to extract the most interesting values (e.g. HR, BR, etc.), without the need of additional processing. However, it is fundamental to provide a metrological characterization of such devices, especially if they will be adopted for health care assistance, e.g. the remote monitoring of chronic patients in outpatients settings (Appelboom et al., 2014), (Lowe and Olaighin, 2014).

Several commercially available systems are described in literature, with details about their performances and accuracy estimation through dedicated tests (Kristiansen et al., 2011), (Parak et al., 2015), (Vanderlei et al., 2008). One example is the BioHarness^{TM} 3.0 (BH3) sensing device, which allows the user to simultaneously measure five physiological and physical quantities (HR, BR, Acceleration, Activity level and Posture). Specific information about validity and reliability of the proposed device are discussed in (Johnstone et al., 2012a), (Johnstone et al., 2012b), through dedicated laboratory tests. Results from field-based tests, i.e. discontinuous incremental walk-jog-run protocol as described in (Johnstone et al., 2012c), suggest that the accuracy of the collected data decreases with the entity of movement (high uncertainty for treadmill

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speed > 6 m/s). The good performance of such equipment makes possible to apply it in several field of applications, e.g. the continuous monitoring of sportsmen's functional state in the conditions of natural activity (Runova et al., 2012). Other recent researches underlines the potentials of using this tool in outpatient settings (Deepika et al., 2015), (Angarita et al., 2015), (Bakhchina et al., 2014), emergency department triage (Bianchi et al., 2013), or as a support tool in the prevention of abnormal events, e.g. fall detection (Hemalatha and Vaidehi, 2013), (Sannino et al., 2015). Differently from other wearable devices, BH3 is able to acquire and store both raw physiological waveforms (e.g. ECG and Breathing) and the computed quantities after a dedicated processing (HR, BR).

The aim of this work is to improve the accuracy assessment of the BH3, by comparing its performances in the measure of physiological quantities (HR, BR) with gold standard techniques (ECG and respiration belt). In particular, the focus has been not only in the comparison of the values computed on-board by the device, but also the ones to be derived through a dedicated processing of the raw signals acquired. So, this analysis would allow to better understand if the values computed by BH3 are accurate enough without the need of additional processing or, if needed, to identify the best algorithm to apply to raw signals.

2 MATERIALS AND METHODS

BH3 is a compact physiological monitoring module, attached to a lightweight Smart Fabric strap or garment which incorporates ECG and Breathing detection sensors. This version has been tuned up with respect to the previous models, in order to improve its usability and acceptance, e.g. by older people (Ehmen et al., 2012). The device is directly worn on the skin (Figure 1) of the participant via an elasticated strap positioned around the chest (50g, 50mm width). The monitoring device (weight 18g, 28x7mm), which attaches to the left of the chest strap, can act as both transmitter and data logger. The internal memory makes it possible to store up to 500 hours of acquisition and the battery life has been improved respect to previous versions, up to 35 hours in logging mode. Five quantities are measured simultaneously, time stamped and exportable to Excel.

Electrocardiographic raw signal is acquired through electrode sensors, housed within the chest strap and sampled at 250 Hz.

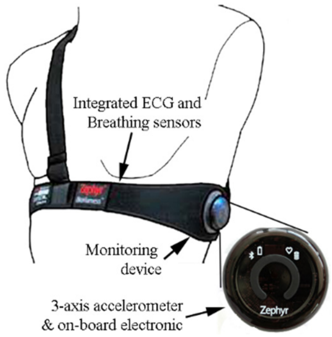

Figure 1: BH3 multi-parametric device.

Breathing waveform is collected using a capacitive pressure sensor (25 Hz) that detects the circumference expansion and contraction of the torso. An embedded algorithm uses the pressure change to create a sinusoidal waveform. Aberrant pressure changes are filtered to remove unwanted noise, and the gain for the waveform is automatically centred at zero (Bianchi et al., 2013). Tri-axial accelerometer signal is acquired by using piezoelectric technology (i.e. cantilever beam set up, sampled at 100 Hz). It is based on a micro electro-mechanical accelerometer sensor with a capacitive measurement scheme and is sensitive along the three orthogonal axes (vertical (x), sagittal (z) and lateral (y)) (Johnstone et al., 2012a). Acceleration data is measured in gravitational force (g) in a range of -3 to +3 g on each single axis, or as Vector Magnitude Units (VMU), which is an integrated value over the previous one second epoch:

$$VMU = \sqrt{A_X^2 + A_y^2 + A_z^2}$$

Finally, the posture of the subject is monitored by using similar piezoelectric technology. Acting as an inclinometer, data is reported in angular degrees, ranges between -180° and +180°, monitoring how far the device is "off the vertical" (Johnstone et al., 2012a). In addition to the acquisition of the raw waveforms, the device is able to perform embedded processing to compute the instantaneous values, e.g. HR, BR, posture, with an output frequency of 1Hz. These data are stored in a formatted Excel file and can also be transmitted by BH3 through wireless communication protocol (i.e. Bluetooth SPP 2.1). Figure 2 shows a dedicated GUI for Windows to monitor in real-time the subject's physiological quantities. In this work, the BH3 has been analysed to provide the accuracy estimation for the physiological quantities. In particular, a novel processing technique has been applied to the raw waveforms to extract Heart and Breathing Rate (Section 2.3) and the computed values have been compared to the ones obtained by signals acquired from standard instrumentation.

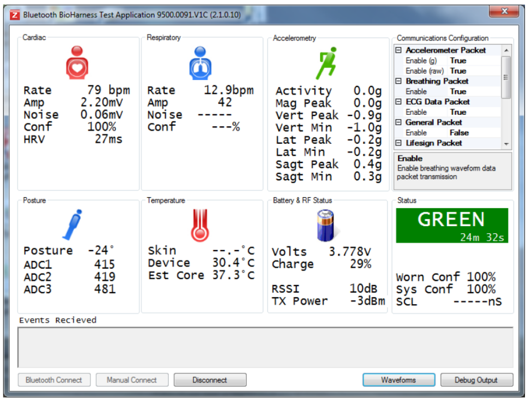

Figure 2: Zephyr GUI to monitor real-time subject health status.

In addition, a similar analysis has been conducted for the values provided by the system through on-board processing. The measurement campaign has been conducted for both HR and BR during rest conditions. Moreover, given the importance of Heart Rate, a dynamic test has also been performed, in order to quantify the loss of accuracy of the device due to the movement of the subject (e.g. while the user is performing daily life routines). This aspect is extremely important because traditional instrumentation (i.e. ECG) are not suitable for these kind of applications (e.g. continuous monitoring of HR and Heart Rate variability within daily activities, indoor and outdoor) because of the need of a continuous power supply and the discomfort for the user caused by the cables.

2.1 Heart Rate Test Procedure

The HR test procedure has consisted of two trials. The first part of the work has interested the accuracy evaluation of the quantities computed from BH3 (i.e. instantaneous values and HR from the raw waveforms) during rest condition. As for gold standard measurement, a 3-lead ECG has been acquired simultaneously by means of an ADInstruments board (model ML865 PowerLab 4/25T), with a sampling frequency of 1 kHz and an uncertainty of ±1 bpm.

Figure 3 shows the setup for the test performed. In particular, it has consisted of:

- Personal computer to collect and process the data offline;
- Acquisition board from ADInsruments for the ECG acquisition (reference system);
- Electrode sensors for the ECG signal acquisition;
- BioHarness 3.0, placed on the chest of the subject and then connected to PC with a proprietary cradle (data upload for post-processing).

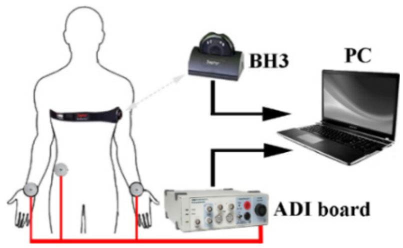

Figure 3: Measurement setup for Heart Rate test procedure (rest condition).

Table 1: Participants for the HR rest tests procedure.

Subject	M/F	Age [years]	Weight [kg]	Height [m]	BMI [kg/m²]
1	F	20	55	1.62	21.0
2	F	23	47	1.66	17.1
3	M	23	92	1.81	28.1
4	F	23	48	1.55	20.0
5	M	26	72	1.83	21.5
6	F	23	63	1.64	23.4
7	F	23	47	1.66	17.1
8	F	26	53	1.66	19.2
9	F	21	52	1.64	19.3
10	F	22	70	1.70	24.2
11	F	23	58	1.72	19.6
12	F	23	59	1.62	22.5
13	M	23	74	1.73	24.7
14	F	23	55	1.65	20.2
15	M	24	71	1.72	24.0
16	M	24	71	1.82	21.4
17	M	28	80	1.80	24.7
18	M	23	63	1.72	21.3
19	F	28	64	1.78	20.2
20	F	21	42	1.50	18.7
Mean		23	61.8	1.69	21.4
STD		3.1	12.4	0.09	2.7

Twenty healthy participants (Table 1) have been recruited for this trial. They have been asked to sit quietly and breathe normally, while their ECG has been acquired. Five records of one minute each have been recorded from both the BH3 and standard ECG. During the second trial, the subjects have performed a motion test, which has been implemented to quantify how motion alters the performance of the sensors. In this case, four healthy participants (2 males and 2 females, age 25.5±2.5 years, weight 63.5±11.7 kg, height 1.74±0.06 m, BMI 20.77±2.74 kg/m^2) have performed a continuous walking exercise in laboratory using a commercial treadmill. In detail, the HR motion test procedure has consisted of:

- 5 minutes of initial rest;
- 5 minutes of a gradual speed increasing from 4

km/h to 6 km/h
- 5 minutes of a walking period with a speed of 6 km/h;
- 5 minutes of a gradual speed decreasing from 6 km/h to 4 km/h;
- 5 minutes of final rest.

The measurement setup for the motion tests has been the same for the rest condition, with the only difference related to the position of the electrode sensors of the standard ECG (placed in the chest of the subject). In this case, it has been possible to reduce the motion artefacts of the gold standard during the walking experiment.

2.2 Breathing Rate Test Procedure

A preliminary Breathing Rate test procedure has been implemented with the use of a metronome application for Android devices (available online at https://play.google.com/store/apps/details?id=com.gismart.metronomefree&hl=it), in order to force the participants to produce a standardized breathing waveform. The BH3 has been applied to the subject in order to acquire both its breathing waveform, sampled at 25 Hz, and the instantaneous BR values, (1 Hz). Five healthy participants (3 males and 2 females, age 26.2±1.5 years, weight 66.4±10.7 kg, height 1.80±0.1 m, BMI 21.2±2.4 kg/m^2) have been recruited for the breathing test. A standard respiratory belt from ADInstruments (model MLT1132), based on the extensometer principle, has been used as gold standard.

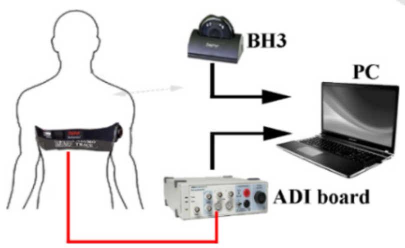

Figure 4: Measurement setup for the breathing tests.

As shown in Figure 4, both the belts have been placed on the subject chest and acquired simultaneously. Two different timings for the metronome have been defined, following the frequency of a medium (25 bpm) and a high breathing (40 bpm), and two records of 90s for each timing have been acquired.

Differently from the HR tests, the instantaneous BR value provided by BH3 has not been compared to the reference value, because the length of the test has been too short to make the stabilization of the value

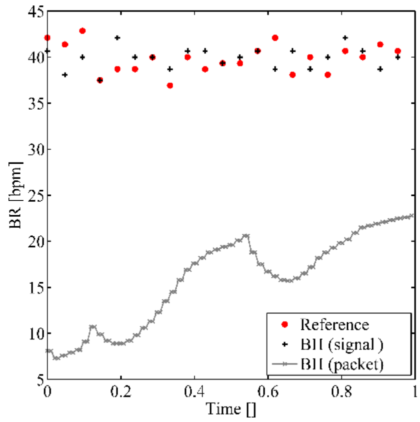

Figure 5: BR values computed within a trial (truncated 90 s of signal). The short period of the trial does not allow to have a stable value for the instantaneous BR computed by BH3, even if it is possible to obtain the correct BR from the raw signal.

provided possible. In fact, the instantaneous values computed by BH3 (referred in Figure 5 as BH - packet) have not become stable yet (a decreasing offset is observed within the short time of the trials). This is because the value provided by the sensor is calculated after the application of a moving average window, so several minutes are needed before performing such test in order to reach a stable value. Basing on this observation, the performance analysis has been conducted only between the BR computed by post-processing BH3 raw waveforms (referred in Figure 6 as BH - signal) and the quantities computed from the reference breathing signals. The next section illustrates the signal processing techniques performed for all the tests conducted.

2.3 Signals Processing

The application of a processing algorithm is needed to compute the physiological parameters from the raw waveforms (ECG, Breathing) of both gold standard and BH3. In literature there are several approaches to gather HR values from ECG signals (Pan and Tompkins, 1985), (Josko, 2007).

In this work, the approach described previously by authors in (Cosoli et al., 2015) has been applied for both rest and motion tests, in order to compute the HR values for both the gold standard and the BH3 raw signals. The algorithm is based on the computation of the slope of the signal, which makes the extraction of relevant features possible, according to the morphology of the signal (Hu et al., 2014). In particular, the approach has been used to identify the R peaks in the ECG waveforms and so calculate the HR, according to the equation:

$$HR = \frac{60}{R_i - R_{i-1}}$$

Before applying the cited procedure, the following pre-processing steps have been applied, in order to reduce the noise and issues related to movement artefacts from the raw signals (Figure 6):

1) Synchronization of both signals (reference ECG, BH3 waveform) and resampling (250 Hz);
2) Mean removal;
3) Filtering (Butterworth 3rd order band pass filter – 0.5÷30 Hz);
4) Normalization with the maximum absolute value of the waveform.

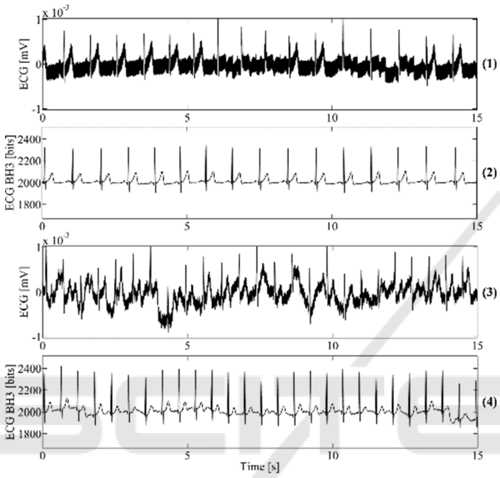

Figure 6: ECG signals acquired during the dynamic trial for both sensing devices. (1, 2): raw ECG waveform from gold standard technique and wearable sensor during rest condition; (3, 4): raw signals acquired during a walking condition (6 km/h) with treadmill.

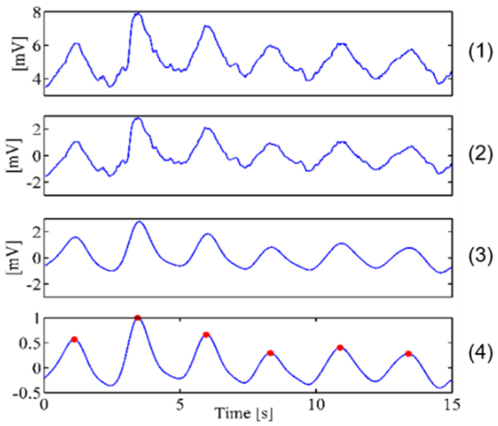

Figure 7: Processing steps for breathing waveform within a test (25 bpm). 1) Synchronization and resampling (25Hz); 2) Mean removal; 3) Filtering; 4) Normalization and peaks identification.

The conditioned signal has then been divided in windows of 30 s, where an average HR value has been computed. As for the Breathing waveform, the signal pre-processing procedure has been the same (the steps are summarized in Figure 7), except for the application of a different filter (Butterworth 3rd order band-pass filter, 0.5÷1 Hz). In addition, the algorithm for the feature identification (Hu et al., 2014) has been tuned, in order to locate the maximum of each sinusoidal waveform and calculate BR consequently.

3 RESULTS

Figure 8 shows the correlation between the HR values computed from BH3 raw signals (y-axis) and the ones from the gold standard (x-axis). A Matlab routine based on Minimum Volume Ellipsoid (MVE) has been implemented to remove the outliers (red points) (Riani et al., 2012).

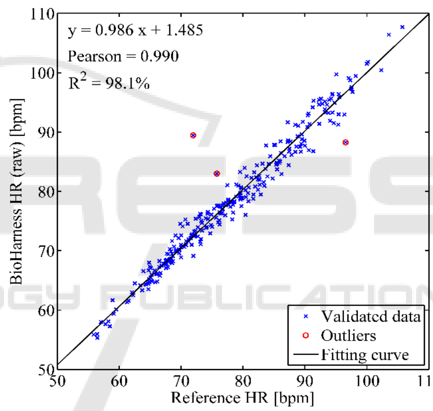

Figure 8: Linear correlation between the HR values of the BH3 raw ECG and the HR values of the standard ECG for the rest condition of 20 participants.

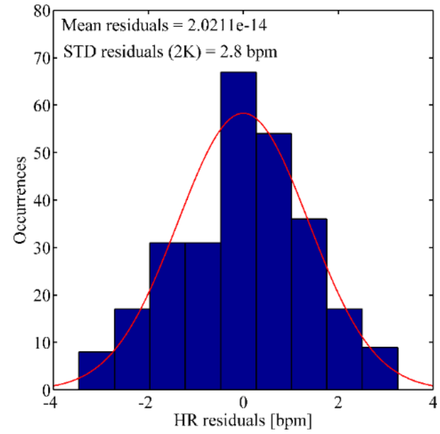

Figure 9: Uncertainty estimation for the HR values of the BH3 raw ECG for the rest condition.

Then, a residual analysis has been performed to verify the Gaussian distribution and to calculate the final accuracy of the measurement. For example, Figure 9 shows a deviation of ±2.8 bpm (coverage factor k=2). If combining this result with the uncertainty of the gold standard (±1.0 bpm) a final accuracy of ±3.0 bpm is obtained.

The same analysis has been conducted for all the tests performed. In particular, the four cases reported in Table 2 are related to:

1) the HR computed from the BH3 raw signal during the rest condition;
2) the HR values provided (on-board processing) for the rest condition;
3) the HR computed from the BH3 raw signal during the motion test;
4) the HR values provided (on-board processing) for the motion test.

Table 2: Results of the tests conducted. R^2 = coefficient of determination. STD = standard deviation of residuals.

Case	Sensitivity []	Bias [bpm]	R^2 []	STD (2σ) [bpm]	Combined STD [bpm]
1	0.986	1.485	98.1	±2.8	±3.0
2	1.008	-0.247	99.1	±1.9	±2.1
3	0.820	15.05	81.7	±5.4	±5.5
4	0.992	1.044	99.0	±2.6	±2.8

If looking at Table 2, it can be observed that the uncertainty of HR measurement increases with the level of activity performed and similar results have been found in the state of the art (STD = ±6 bpm from 0 to 12km/h in (Johnstone et al., 2012a)).

Besides, it can also be noted that the HR values computed from BH3 with a proper internal processing (case 2 and 4) are more accurate than the ones obtained by processing the raw ECG and Breathing signals (case 1 and 3). This suggests that the on-board algorithms are robust enough to provide a good measurement, even in presence of motion artefacts (improvement of accuracy from ±5.5 to ±2.8 bpm). As concerning Breathing Rate, the computed BR values are highly correlated (R^2 = 98.3%) to the ones of gold standard instrumentation (Figure 10), with a deviation of ±2.1 bpm (Figure 11).

These results are in agreement with the ones discussed in (Johnstone et al., 2012a), where an accuracy < ±3.0 bpm has been found. Within these trials, it hasn't been possible to assess the accuracy for the instantaneous BR values due to short time of the acquisition. This suggests that future experiments are needed to quantify clearly the time needed to the measurement to become stable and reliable.

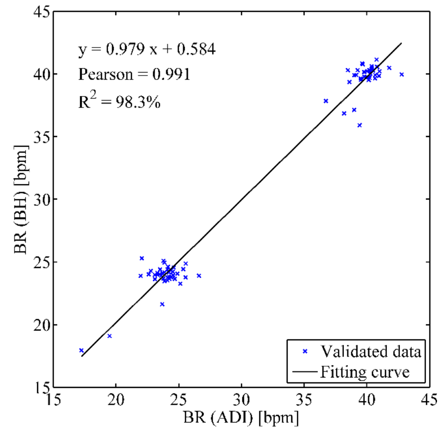

Figure 10: Linear correlation between the BR values of the BH3 raw signal and the BR values of the respiratory belt for the frequency of a slow breathing (25 bpm) and a high breathing (40 bpm) of five participants.

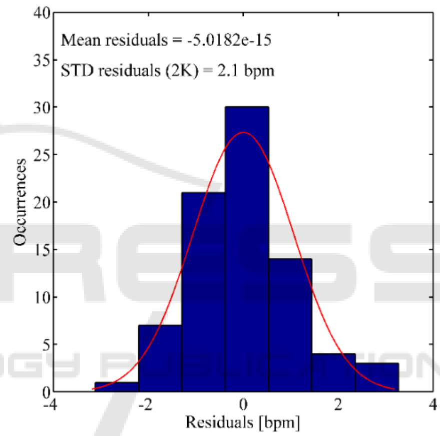

Figure 11: Uncertainty estimation for the BR values of the BH3 raw signal within the tests performed.

4 CONCLUSIONS

Wearable devices are even low at low-cost and with high computing capabilities, allowing them to measure different physiological signals and extract useful quantities (e.g. HR, BR). However, it is fundamental to provide metrological characterization of such measurements and, if needed, to identify the best processing technique to get reliable values.

The aim of this work is to evaluate the accuracy of the BioHarness 3.0 commercial device in the monitoring of physiological parameters.

The experiments conducted for Heart Rate have demonstrated that the values computed on-board by the device are accurate (deviation of ±2.1 bpm for the static condition and ±2.8 bpm concerning the test with the treadmill) and no further processing of the raw signals is required.

On the contrary, during the tests conducted for the Breathing Rate, it has been observed that the BR values computed require several minutes to become stable. However, the proposed signal processing of the breathing waveform allows to compute BR values, which are strongly correlated (R^2 = 98.3%) to the gold standard and with a deviation of ±2.1 bpm.

Future works will be focused on a deeper analysis of the breathing signal coming from the BH3. Particular attention will be paid on the identification of the time interval needed for the instantaneous BR value to become stable.

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