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RESEARCH ARTICLE

Validation of a Wearable System for Respiratory Rate Monitoring in Dogs

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ABSTRACT One of the most relevant physiological parameters in dogs is respiratory rate (RR). The aim of this paper is to present a novel wearable system that allows to accurately estimate RR in dogs, and to compare it to a gold standard in static conditions. Data from 12 dogs were acquired while the animals were anesthetized and attached to a vital signs monitor. The experimental setup consisted of three Inertial Measurement Units (IMUs) applied on the dog, and a video camera filming the RR value shown on the monitor. The range of RR values analyzed in the study is 0 to 29 breaths per minute, read by the vital signs monitor. The mean RMSE for the data acquisitions is 1.68 breaths per minute. The values of the filtering parameters that allow to obtain the best performance depend on the specific acquisition. This result demonstrates that adaptive filtering is a viable method for the application. Future developments include tests on a larger dataset, and trials on dogs in unconstrained environments and during movement.

INDEX TERMS Dogs, respiratory monitoring, veterinary medicine, wearables.

I. INTRODUCTION

One of the most relevant physiological and clinical parameters in dogs is respiratory rate (RR), which is expressed in breaths per minute (bpm) and generally ranges between 18 and 25 at rest [1]. If the animal is healthy, breathing activity is accomplished efficiently and effectively by the synchronized activity of ribcage muscles, diaphragm, and abdominal muscles, in a complex anatomic geometry further complicated by the extreme variability of the canine morphology and size. Dog's size is classified into 5 classes (toy, small, medium, large, and giant), with body adult weight ranging from the 1 kg Chihuahua to the 115 kg St. Bernard [2]. Based on the chest morphology, dogs can be further classified in deep, oval or barrel chested [3], [4]. In presence of respiratory diseases, the animal either minimizes its activity or compensates by altering its breathing pattern. For this reason, many animals effectively hide their illness until critically low levels of lung reserve remain [5].

The gold standard measurement of RR in dogs is the vital signs monitor when the dog is under anesthesia or mechanically ventilated, and the manual count of breaths in all other settings. However, most vital signs monitors used in the clinical practice are designed for use on humans, and parameters are manually tuned by veterinarians to best fit each dog. This is a strong limitation of such technologies, together with their invasiveness and the suitability of use only in specific cases. Manual counting of breaths, on the other hand, is less invasive but prone to errors and highly dependent on the ability of the operator (veterinarian, nurse, owner) in this specific procedure and further influenced by the neuroendocrine effects of the hospital-related stress, similarly to the so-called white-coat syndrome.

For this reason, wearable devices represent an opportunity to overcome these limitations, as they are suitable for

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prolonged use in unconstrained environments. Pet wearables are a market segment of increasing interest and are mostly used to track activity and location [6]. Another possible application of wearables in the veterinary field is the remote monitoring, or telemonitoring [7], of the animal's physiological parameters in ambulatory settings or outside the clinical environment. In the last years, sleeping RR has gained a huge role in the chronic in-house management of dogs affected by mitral valve disease, being pulmonary edema the direct consequence of the disease and the specific target of the chronic pharmacological therapy [8], [9].

A wearable system to perform RR measurement objectively, automatically, non-invasively, and continuously in unconstrained environments would provide an opportunity of better diagnosis, follow-up, and health status monitoring in pathological conditions, and of early screening on apparently healthy animals [10]. There are examples in the literature and on the market of wearable devices designed for RR monitoring in dogs, one of which is the Dolittle monitor, a heart failure management platform for pets by the South Korean company Zentry inc. [11]. This platform is based on a wearable belt that is placed around a dog's (or cat's) chest wall to detect vital signs, among which RR. However, there are no published studies assessing the performances of this product. The lack of published validation studies does not allow to rely on such devices in the clinical practice.

Other techniques that have been proposed are generally derived from human techniques [7], [12], such as in the case of respiratory inductance plethysmography [13]. There are several others types of sensors or garments [14] used in humans that exploit chest wall movements to derive the respiratory signal: resistance-based sensors [15], [16], capacitance-based sensors [17], [18], electrical impedance tomography [19], inertial measurement units (IMUs) [20], and fiber optic sensors [21], [22].

The aim of this paper is to present a novel wearable system based on IMUs that allows to accurately estimate RR in dogs, and to provide validation data that compare the novel system to a gold standard in static conditions. One of the intended final uses of this wearable system is the monitoring of RR in dogs during sleep, thus the validation in static conditions. To the best of our knowledge, no other systems for RR monitoring in dogs based on IMUs have been validated in the literature.

II. MATERIALS AND METHODS

Data from 12 different dogs were acquired during surgical interventions while the animals were anesthetized and attached to a monitor of vital signs, among which RR. The dogs were client-owned dogs with naturally occurring diseases that required general anesthesia and intubation.

Each data acquisition lasted around 15 minutes, and the number of acquisitions per dog varied depending on the performed surgery (two acquisitions on dog 1, four acquisitions on dog 2, one acquisition on all other dogs). The total number of available acquisitions was 16, but 2 of them were excluded due to technical malfunctioning, once of the gold standard, and once of the system to be validated. The characteristics of the dogs whose data were analyzed are reported in Table 1.

Finally, three additional data acquisitions were performed on three awake small dogs (a Pug, a Dachshund, and a Pinscher), which had limited room for movement, to test whether this configuration would work in presence of movement artifacts. In the case of these acquisitions on awake dogs, the gold standard was not available, therefore the filtering was applied by choosing optimal parameters by visual inspection of the traces.

The experiment was approved by the Bioethics Committee of the University of Perugia (approval number 25/2022). Before enrollment of a dog, the owner signed an informed consent form.

The experimental setup consisted of three Inertial Measurement Units (IMUs) applied on the dog, a smartphone to collect real-time data from the IMUs, and a video camera filming the RR value shown on the monitor.

The monitors used were of different commercial brands, but all had a refresh frequency of 1 Hz; RR data were then transcribed and compared to the values read by the IMUs.

The IMU-based units used in this work have been described in previous works on humans [23], [24], [25], [26], and in a granted patent [27]. All units are based on the nRF52832 microcontroller by Nordic Semiconductor, chosen because of its ability to exploit the ANT protocol. The IMU used is the ICM-20948 by TDK InvenSense, which embeds a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer, has a voltage operating range of 1.71 V to 3.6 V, and exploits the I^2C interface for external sensors.

The IMU-based system is composed of three units: one is placed on the thorax, one on the abdomen, and one in a region which is not subject to respiratory movements, in the case of this work the back. The third IMU is also called reference. The IMUs are attached to the dog by means of a 5 cm width traditional adhesive plaster with textile backing (Leukoplast®), as shown in Fig. 1.

The signals from the thoracic and abdominal units contain the respiratory signal but also unwanted noise such as changes in postures. The unit on the back, *i.e.*, the reference unit, contains only the signal related to the body movements but is not affected by respiratory activity. The sampling rate of the IMUs is 40 Hz and quaternions are computed at this frequency on each of the three IMUs. A quaternion is represented by four elements:

$$\boldsymbol{q} = q_0 + \boldsymbol{i}q_1 + \boldsymbol{j}q_2 + \boldsymbol{k}q_3$$

where q_0, q_1, q_2, and q_3 are real numbers, and $\boldsymbol{i}$, $\boldsymbol{j}$, and $\boldsymbol{k}$ are mutually orthogonal imaginary unit vectors. Rotation quaternions, which are the ones used in this algorithm,

TABLE 1. Characteristics of the dogs enrolled in the study.

Dog identifier	Breed	Age	Sex	Weight [kg]	Procedure
D1	Mongrel	4 years	M	6.6	Imaging
D2	German shepherd	8 months	F	26.7	Imaging
D3	Yorkshire Terrier	10 years	M	9	Dental debridement
D4	Boxer	7 years	M	35	Orthopedic
D5	Corso Dog	1 years	F	27,7	Entropion correction
D6	Corso Dog	1 years	M	34	Entropion correction
D7	Dalmatian	4 years	M	25	Imaging
D8	German Shepherd	6 years	M	21,2	Orthopedic
D9	Mongrel	9 years	F	26,5	Imaging
D10	Setter Gordon	9 years	F	24,5	Ectropion correction

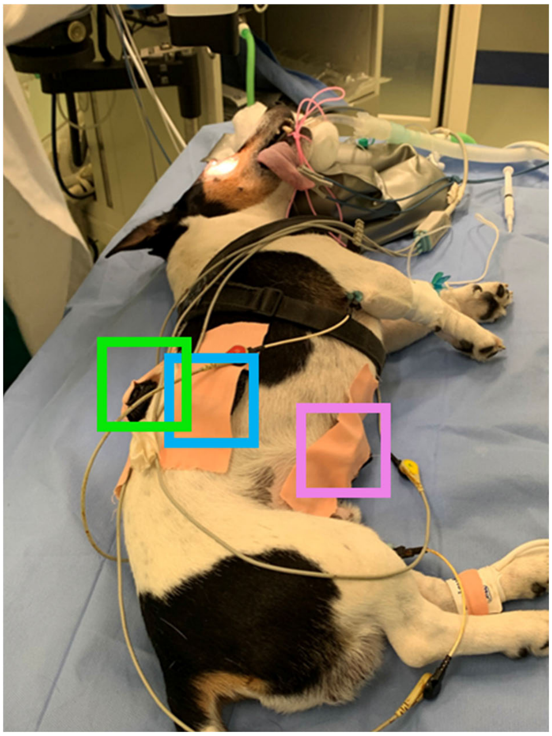

FIGURE 1. The three IMUs placed on a patient. The thoracic IMU is highlighted in light blue, the abdominal IMU in pink, and the reference one in green.

represent rotations in three dimensions, and solve the problem of gimbal lock characterizing the Euler representation of orientation [28]. Quaternions are computed with the algorithm developed by Madgwick et al. [29].

One quaternion out of four is then sent by means of the ANT transmission protocol to a smartphone app with a simple user interface that can be operated by trained personnel. Thus, the actual sampling rate is 10 Hz. The algorithm used to process the signals coming from the IMUs is a modified version of the one used for human subjects, described by Cesareo et al. [30].

After the data were sent to the smartphone and saved in a Google Firebase cloud, the signals from the three IMU-based units were processed together with a dedicated script developed using the Python programming language. All the signal processing (pre-processing, dimension reduction, spectrum analysis, and processing) is performed with the same script, and the different steps of the script are summarized in Fig. 2.

In the pre-processing phase, the thoracic and abdominal quaternions were referred to the reference quaternion and filtered with a moving average on 97 samples. The number of samples is the same as in the algorithm for humans [24]. Two new traces containing the quaternions relative to the reference were thus obtained.

With the aim of reducing the dimension of the dataset, the Principal Component Analysis (PCA) was performed on the two obtained traces, *i.e.*, the quaternion describing the movement of the thorax with respect to the reference and the quaternion describing the movement of the abdomen with respect to the reference. The first component, which is the one with the greatest amount of explained variance, was computed for both the thorax and the abdomen. This component was considered the respiratory signal and formed the basis for the spectrum analysis.

This yields two traces, one describing the thoracic movements (thoracic trace, or 'TH'), and one describing the abdominal movements (abdominal trace, or 'ABD'). The total movement is given by the sum of the two traces (total trace, or 'TOT'). All three were used for comparison with the gold standard, and for each data acquisition the best one was chosen.

The generated signals were filtered with a Savitzky-Golay Finite Impulse Response (FIR) smoothing filter of the 3rd order with a window length of 29 samples, which was experimentally determined to retrieve better results that the length of 31 samples used for humans [24]. There was always a minimum threshold frequency ($f_{SG,min}$) to avoid centering the spectrum around 0 Hz. $f_{SG,min}$ was different for each data acquisition and was chosen with the criterion of minimization of the Root Mean Square Error (RMSE). The use of a low threshold helped in the identification of the power spectral density (PSD) peak related to the RR and did not consider very low frequency peaks, often caused by movement artifacts.

Subsequently, the PSD estimate was computed employing the Welch's method, with the Hamming window type, 300 samples as window size, and 50 or 100 samples of overlap. Also these parameters were chosen to be the same as in the human algorithm [24]. The number of samples of overlap is one of the fine-tuned parameters of the algorithm. The PSD maximum in the interval between the computed

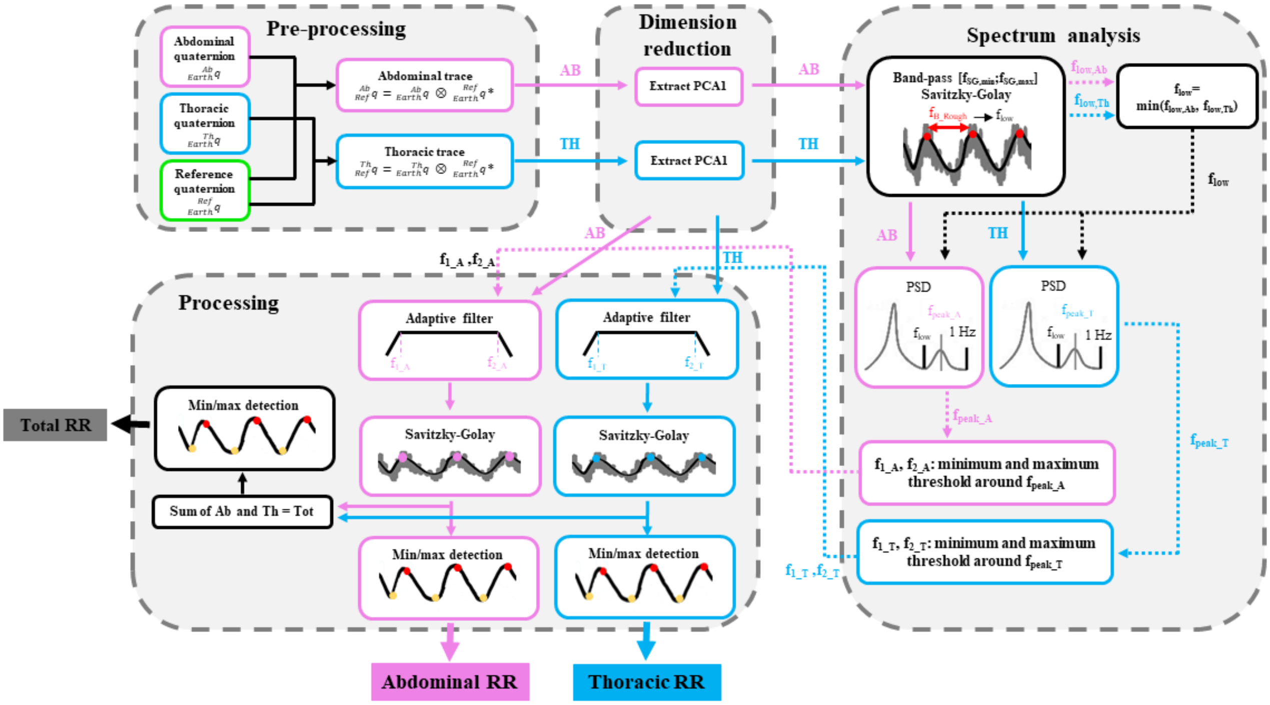

FIGURE 2. Schematic representation of the Python signal processing algorithm. Operations referred to the thoracic unit or trace are highlighted in light blue, those referred to the abdominal unit or trace are highlighted in pink, and those referred to the reference unit are highlighted in green.

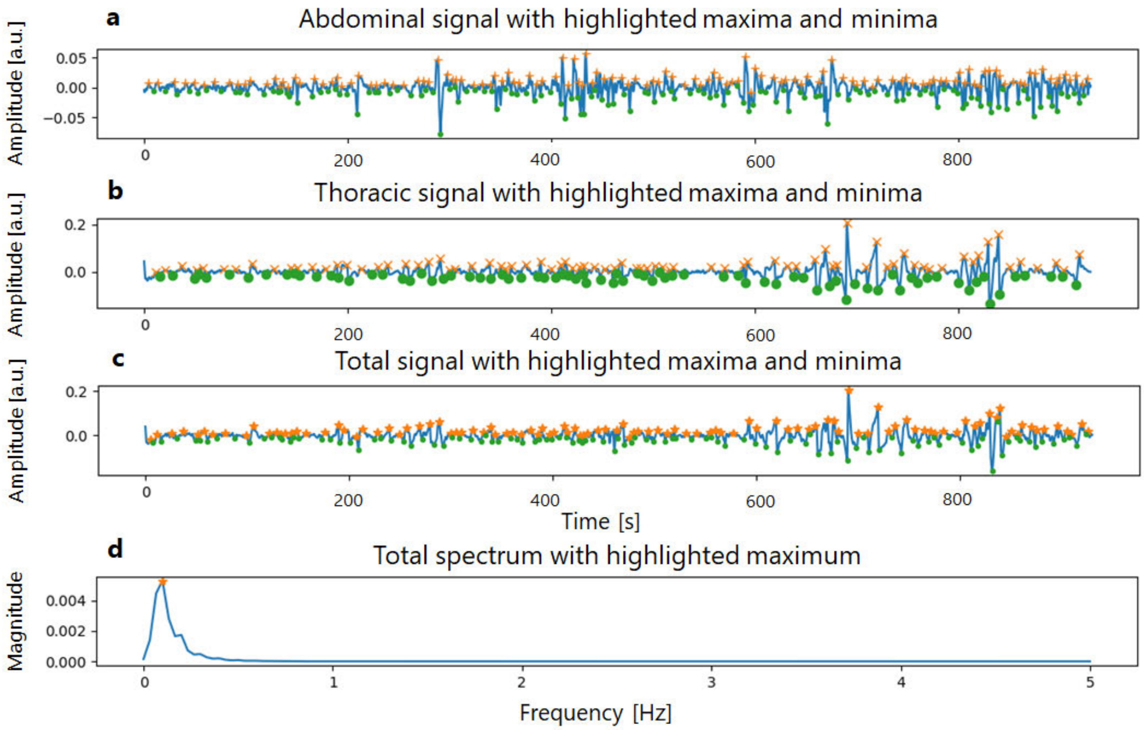

FIGURE 3. a) Abdominal signal with highlighted maxima and minima; b) Thoracic signal with highlighted maxima and minima; c) Total signal with highlighted maxima and minima; d) Total spectrum of the respiratory trace, around 0.1 Hz (~ 6 bpm).

low threshold and a maximum (0.7 Hz) was identified (f_{peak}) and used to build the adaptive band-pass filter settings (centered in f_{peak}). Then, a parametric tuning based on the f_{peak} value was performed. The parameters that were changed are the window length in terms of samples for the 3rd order Savitzky-Golay filter and the minimum peak distance. Afterwards, filtered signals were further smoothed through the application of another 3rd order Savitzky–Golay FIR filter, to optimize subsequent detection of maxima and minima point, which were identified applying the parameters

TABLE 2. RMSE values for all data acquisitions.

Dog identifier	Acquisition identifier	Best RMSE [bpm]	Trace	$f_{SG,min}$ [Hz]	Overlap	Prominence	Cutoff Butterworth [Hz]
D1	A1	1.77	TOT	0.06	100	Automated	0.05
	A2	2.17	TOT	0.03	100	Automated	0.04
D2	A3	1.02	ABD	0.01	50	Automated	0.03
	A4	1.16	TOT	0.04	50	Automated	0.04
	A5	0.45	TOT	0.01	100	Automated	0.01
	A6	1.39	TH	0.01	100	Automated	0.02
D3	A7	2.99	TOT	0.27	50	Automated	0.04
D4	A8	1.28	TOT	0.02	100	Automated	0.01
D5	A9	1.12	TOT	0.03	50	0.001	0.01
D6	A10	3.02	TOT	0.09	100	Automated	0.01
D7	A11	2.01	TOT	0.09	100	0.001	0.03
D8	A12	4.11	TOT	0.12	100	0.005	0.08
D9	A13	0.45	TH	0.02	50	Automated	0.11
D10	A14	1.65	TH	0.01	100	0.005	0.03
All	Mean	1.68		0.06	n.a.	n.a.	0.04

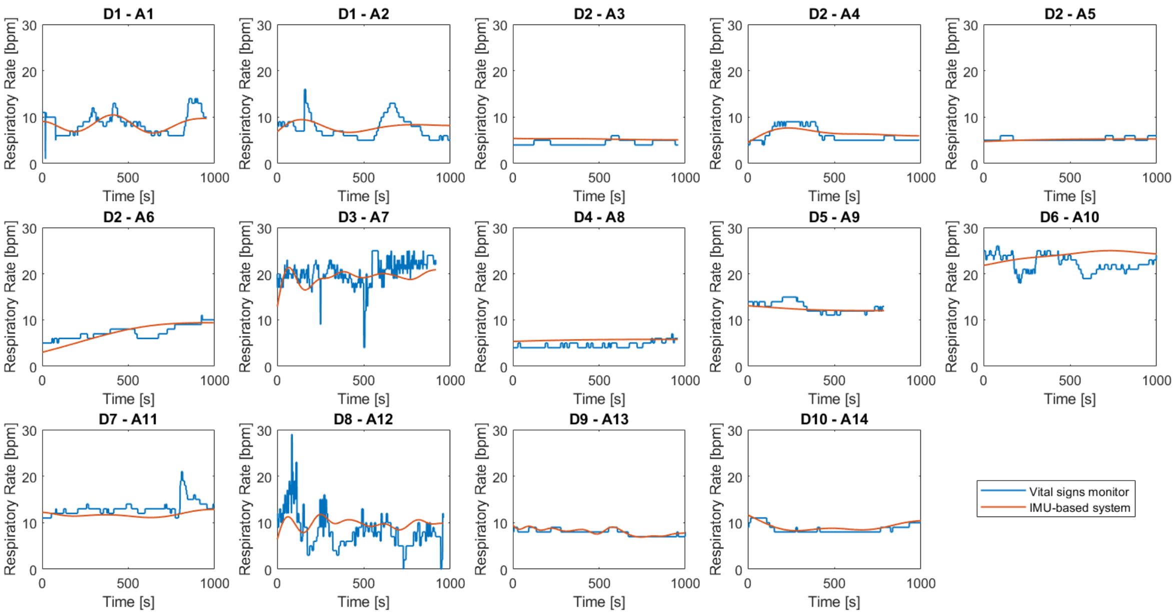

FIGURE 4. Comparison between monitor and IMU-based system data for all dogs and all data acquisitions.

previously set. Another parameter that was fine-tuned during this trial was the prominence of the peaks to be considered as a different breath; this parameter measures how much a peak stands out with respect to the surrounding signal. The values varied between what was determined by the algorithm, 0.001 and 0.005. The latter values were experimentally selected to obtain the best correspondence whenever the algorithm would automatically select values that were too high to detect small peaks.

This algorithm allowed to obtain an array of breath-to-breath RR data. This array was filtered with a 4^{th} order low-pass Butterworth filter with a cutoff frequency varying between 0.01 and 0.20 and the data were compared to the ones obtained by the monitor. As it was stated before, the specific trace (ABD, TH, TOT) and some of the filtering parameters ($f_{SG,min}$, samples of overlap, prominence, Butterworth cutoff frequency) were chosen for each data acquisition to minimize the RMSE with respect to the monitor.

III. RESULTS

An example of respiratory traces obtained on dogs during anesthesia is reported in Fig. 3. Three traces are obtained for each data acquisition: one for the thorax in Fig. 3b (thoracic unit with respect to the reference), one for the abdomen in Fig. 3a (abdominal unit with respect to the reference), and a total one in Fig.3c. Maxima and minima were successfully identified by the algorithm. Fig. 3d represents the spectrum of the total trace for its complete duration, and the peak corresponds to the RR content (around 6 bpm for most occurrences). The RMSE error of this acquisition with respect to the monitor is 1.77 bpm.

Complete RMSE values for all 14 data acquisitions are reported in Table 2, together with the fine-tuning parameters used for the specific acquisitions. The range of RR values analyzed in the study is 0 to 29 breaths per minute, read by the vital signs monitor. As it is reported in the table, the mean RMSE for the acquisitions is 1.68 bpm. The specific

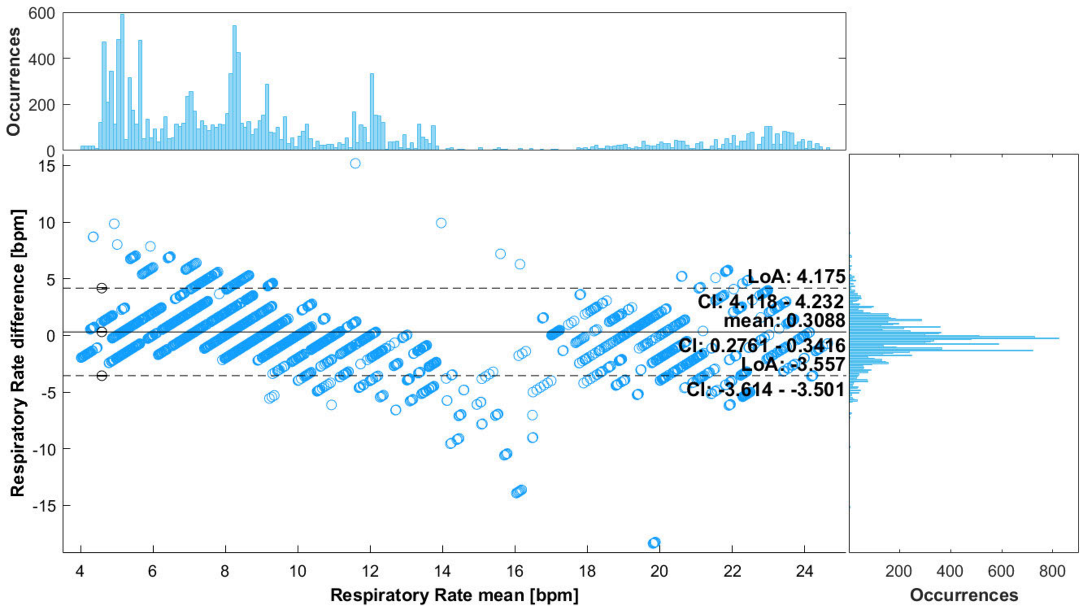

FIGURE 5. Bland-Altman plot comparing the RR values from the monitor and from the IMU-based system. The histograms on the right and on the top represent the occurrences of the differences and of the means, respectively.

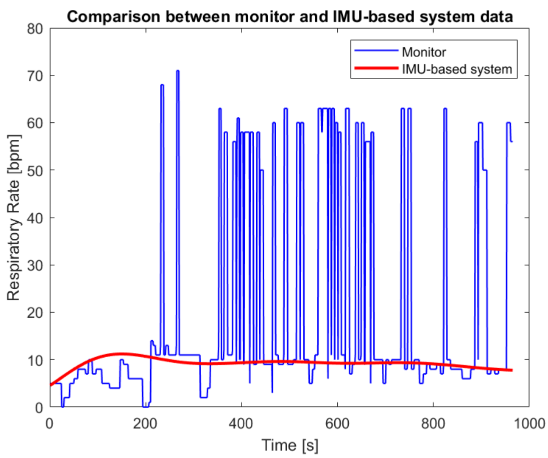

FIGURE 6. Values of RR read by the monitor in the case of the dog which had technical issues with the gold standard.

trace and the value of the parameters that allow to obtain the best performance depends on the dog. This result shows that adaptive filtering can be used for the application. Fig. 4 shows the comparison between the RR derived from the best trace and the values shown on the monitor after filtering of the breath-to-breath RR values for all dogs and all acquisitions. It can be noted from the figure that data showed by the monitor in some cases present sudden, stepwise changes in RR.

The IMU-based system follows the trend smoothly. For instance, in D1 – A1, which is the same that is reported in Fig. 3, the monitor presents an anomalous drop at the beginning of the data acquisition, probably due to a malfunctioning, while the behavior of the wearable system is more stable. There are also cases in which the IMU-based system does not perform well when compared to the gold standard, for example in the case of D6 – A10 and D8-A12.

Fig. 5 reports the Bland-Altman plot comparing the two measurement systems. The difference is computed as monitor data minus IMU-based system data. The mean difference is 0.31 bpm, so the IMU-based system slightly underestimates the monitor data. It must be noted, however, that RR values provided by the IMU-based system have two decimals, while RR values from the monitor are integers. The lower and upper Limits of Agreement (LoA) are 4.17 bpm and −3.50 bpm respectively, therefore 95% of the data are in that range of agreement as per the Bland-Altman plot definition [31]. The histogram of the distribution of the differences shows that the density is very high around a difference of 0 bpm. The histogram of the means shows that, while most detected frequencies were lower than 15 bpm, also higher values of RR were evaluated during the protocol.

Also, we report one of the cases when there was a technical malfunctioning. Specifically, we report the values read by the vital signs monitor in the case of the dog that had a technical malfunctioning of the gold standard. As it can be seen in Fig. 6, values quickly oscillate between values around 10, which was the actual RR, and values around 60. An estimation of the values from the IMU-based system, on the other hand, appears more in line with the observed RR values. It was not possible, however, to evaluate the accuracy of the IMU-based system in this specific case. In this dog, the most likely explanation of the vital signs monitor malfunctioning is that the values around 60 represent the heart rate. In fact, in the presence of a bradypnoea or normopnoea together with a significant cardiac stroke, it can happen that the heart itself with its action (dilation and contraction) can compress and dilate the lung synchronously with the cardiac

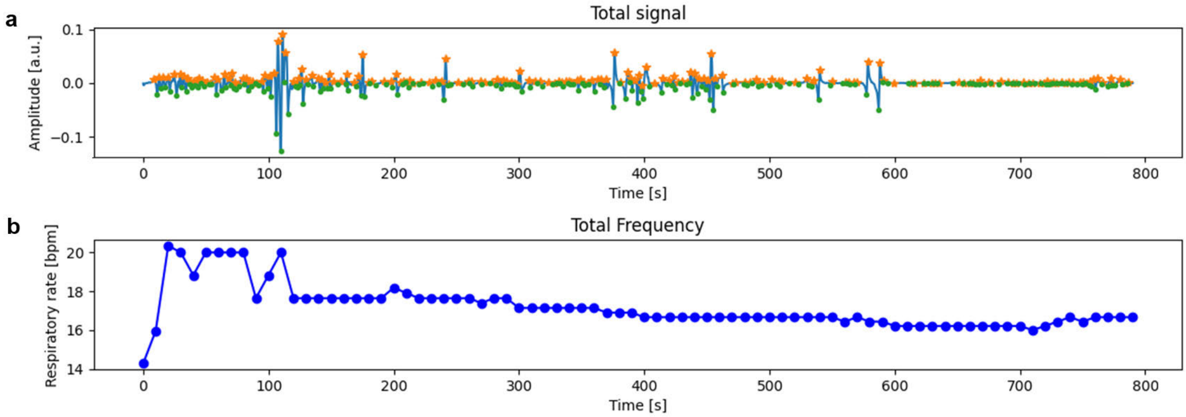

FIGURE 7. **a) Total signal of an awake Pug with highlighted maxima and minima; b) Total frequency of an awake Pug during the data acquisition.**

actions during the respiratory resting phase. All this, also visible graphically on the vital signs monitor, causes the exit and entry of air through the capnometry probe which is interpreted as a spontaneous respiratory act but is instead a cardiac artefact.

Finally, the results of the data acquisition performed on the awake Pug are reported in Fig. 7. Specifically, Fig. 7a reports the total trace, and Fig. 7b shows the variations of RR over time. This trace was filtered with a $f_{SG,min}$ of 0.15 Hz, an overlap of 100 samples, an automated prominence value, and no further Butterworth filter on the obtained RR. After the first seconds of adjustment, the values observed in this condition are compatible with what is known in the literature. The two other dogs, *i.e.*, the Pinscher and the Dachshund, had similar median values of RR: 17.91 bpm (Pinscher, thoracic trace, $f_{SG,min} = 0.20$ Hz) and 18.75 bpm (Dachshund, abdominal trace, $f_{SG,min} = 0.20$ Hz).

IV. DISCUSSION

Respiratory rate is a vital parameter that is often counted manually in human and veterinary applications. As this physiological signal can be an early detector of deterioration of several pathologies, collecting RR data continuously, inside, and outside of clinical settings, would enhance the clinicians' knowledge of the health status of a patient. Wearable devices represent an opportunity to perform RR measurements in a low-cost, unobtrusive way, and to obtain new insights on this vital sign.

A situation in which monitoring of RR is particularly relevant is during sleep, particularly in dogs affected by mitral valve disease [8], [9], which is the rationale behind the validation of the proposed configuration in static conditions. This paper reported data acquisitions during anesthesia because in such setting the gold standard measurement is also available, and our goal was to assess the feasibility and validity of RR measurements in dogs by means of a wearable system. The frequencies detected by the gold standard were generally lower than 15 bpm, which is like the previously reported median respiratory rate in healthy sleeping dogs [9]. It must be noted that most instrumentation used in veterinary hospitals is designed for human medicine and used on animals as well, so algorithms are not fine-tuned for dogs, and even less so for the different breeds and sizes. An example of this was seen in Fig. 6, where the IMU-based device we presented seemed to work better than the gold standard.

IMUs were applied to the dogs in a non-invasive way, with no pain or discomfort that we were aware of even after removal. The RMSE and LoA can be considered satisfactory. In particular, the configuration that we have presented, which allows to obtain a signal with two degrees of freedom (thoracic signal and abdominal signal), is advantageous to consider the different types of chest wall movements that can be predominant in dogs of heterogeneous sizes and breeds. Another advantage of this configuration with three IMUs is the possibility of localizing with greater detail the affected areas in case of pathological respiratory patterns [32]. The best number and positioning of IMUs for respiratory monitoring is still a topic of research and study in human beings [33], however our configuration proved to be effective in detecting the respiratory rate in dogs during this experiment.

Given the static nature of the experimental setup, the obtained results are probably positively affected by the lack of movement during anesthesia, but negatively affected by the small datasets. In fact, the lack of movement is reflected in the absence of movement artifacts apart from the movements impressed upon the dog by the surgeon. Tests during anesthesia on a larger dataset will allow to refine the signal processing algorithm. In fact, now the algorithm depends on a fine-tuning of the signal processing parameters, but this can be overcome by determining fixed threshold once the dataset is large enough to determine which parameters are on average the best performing. Additionally, machine-learning based methods can be employed to automatically select the best filtering parameters given the characteristics of the signal.

Preliminary results in Fig. 7 show that it was possible to retrieve reasonable values of RR also when the dog was awake. Consequently, trials on dogs in unconstrained environments, such as during movement, are needed to provide the real-life data that are not available as of today. Monitoring dogs in real-life scenario is indeed the aim of future works with this wearable system, now that preliminary data show it is feasible to monitor RR in dogs with this technology. In a real-life dynamic scenario, the reference IMU unit can be used to filter out movements that are related to the whole body but not to respiratory activity. Furthermore, information on the dog's activity is of interest *per se*, so the same sensor network can be used for multiple purposes [34]. In this type of application, the IMU sensors can be embedded in the dog's harness, a site where other sensors have been embedded in previous works [35].

The flexibility of the sensor platform allows the integration with other wearable and portable devices for the simultaneous acquisition of other physiological parameters. A possible future development is the integration with a wearable ECG sensor [36]. The work by Grosso et al. [37] proposes the integration of a commercially available respiratory signal band with an ECG on dogs with sinus arrythmia; this type of integration provides relevant clinical information. Also, integration with portable or wearable environmental monitors [38] could provide information on the air quality surrounding the dog, with benefits for the animal itself as well as the owner, in the framework of the so-called 'One Health' [39].

V. CONCLUSION

This paper presents an innovative wearable body sensor network that can be used to successfully monitor RR in dogs. The monitor consists in three IMU-based devices placed on the thorax, on the abdomen, and on a reference point, *i.e.*, on the back of the dog. The novelty of the presented system lies in its complete wearability, potential integration into a harness, and usability by dog owners during daily life. The validation demonstrates that this solution is usable during sleep, which is the most similar conditions to the presented validation. Furthermore, preliminary results on the awake dogs show that this system can be successfully employed also in presence of movement artifacts.

Future developments of the study include tests during anesthesia on a larger dataset to perfect the signal processing algorithm, and trials on dogs in unconstrained environments and during movement.

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