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A tool for the real-time evaluation of ECG signal quality and activity: Application to submaximal treadmill test in horses

M. Nardelli[a,*], A. Lanata[a], G. Valenza[a], M. Felici[b], P. Baragli[b], E.P. Scilingo[a]

[a] Department of Information Engineering & Research Centre E. Piaggio, University of Pisa, Via G. Caruso 16, Pisa, Italy
[b] Department of Veterinary Sciences, University of Pisa, Pisa, Italy

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ABSTRACT

This work describes a novel signal quality index (SQI), i.e. *higher-order-statistics-SQI (hosSQI)*, for the real-time evaluation of electrocardiogram (ECG) recording quality. The *hosSQI* formula combines two already known SQIs, kurtosis (*kSQI*) and skewness (*sSQI*), exploiting the related properties to improve their performance.

We validated *hosSQI* using 1000 human pre-labelled twelve-lead ECGs and compared its performance with the state-of-the-art indexes in the literature. Our index outperformed four existing indexes (kSQI, sSQI, basSQI, iorSQI), reaching an accuracy up to 90.38% in the signal quality discrimination. Afterwards, we employed these indexes to compare signal quality of ECGs acquired by two different monitoring systems (red-dot and textile electrode based), in unfavourable conditions in terms of motion artifacts, adhesion and mechanical firmness of electrodes. The existing four SQIs and *hosSQI* were updated each second, using equine ECGs recorded during submaximal treadmill test. Wilcoxon nonparametric statistical test showed that all the SQIs were significantly higher for textile than for red-dot electrodes. A pattern recognition algorithm was implemented to test a real-time discrimination of three activity conditions (walk, trot, and gallop) based on the SQIs. Given that *hosSQI* values computed for red-dot were under the acceptability threshold in more than 63% of signals, we used only the textile data. We employed a C-Support Vector Classification and we found the highest accuracy value in the discrimination of walk and gallop (84.91%). Even if these results are preliminary, we proposed a promising tool for the real-time assessment of ECG signal quality and physical activity, also during intense exercise.

1. Introduction

A real-time evaluation of physiological signal quality, e.g., electrocardiogram (ECG), is essential at the present time, in which wearable sensors allow continuous monitoring during daily activities. Detection of low signal quality in real-time would avoid losing data and time in acquiring unusable signals. Especially in clinical monitoring, this practice would lead to greater confidence for both patients and doctors in using telemedicine devices. The use of these wireless ECG acquisition systems has recently also extended to the physiological monitoring of the animals, in particular horses involved in competitions. In this context, the acquisition of good quality signals is compromised not only by the lack of awareness of the subject, but also by the amount of motion artifacts recorded during the strong physical activity to which the horses are subjected. Horses have always been involved in both professional or pleasure riding activities, but their speed and sheer size made the monitoring of physiological signals more difficult with respect to other species. The introduction of treadmill exercise test allowed assessing horse's response, in terms of autonomic nervous system (ANS), at different levels of physical activity, in controlled conditions (e.g., velocity, running surface, environment) [1]. This test improves the clinical assessment of horse's physical conditions, especially when the animal is not able to reach the desired performance level in conditions of high exercise workload. As a matter of fact, current research findings showed how much the functional evaluation of poor performance is of strong importance during exercise practice [2–4].

A gradual submaximal treadmill test can be also performed in order to make an efficient heart disease diagnosis. In fact, moderate or severe heart pathologies can be diagnosed in standing horses, but in case of subtle rhythm disturbances or exercise-induced problems the suggested way consists in exercise testing [5]. In some clinical cases, cardiac dysrhythmias are difficult to be detected, because

* Corresponding author.
E-mail address: m.nardelli@ing.unipi.it (M. Nardelli).

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even if they could be present during or after a physical exercise, they are not associated to the presence of a severe cardiac disease [6]. For this purpose and considering the athletic target of horses, between standardized exercise testing, the treadmill exercise test has become an important tool for cardiovascular diagnosis [7,8]. However, it requires a continuous monitoring of cardiac signals, which is crucial to detect pathologies that may degrade performance [9] and/or because of unexpected collapse or death [3].

As it can be easily expected, due to the high amount of motion artifacts during hard exercise, the ECG signal becomes hardly to be acquired with a sufficient quality for further analysis. Specifically in such conditions, it is difficult to preserve the adherence between the electrodes and the horse's skin. In the last decades, wearable monitoring systems have been continuously improved in terms of stability, subject comfort, and robustness against motion artifacts [10]. The innovative smart textiles for physiological signal acquisition combine conductive yarn (made of stainless steel fibers) with elastane [11]. These systems have been successfully applied to human monitoring during hospitalization and every-day life [12,13]. In order to address issues regarding horse performances, McGreevy et al. envisioned the use of smart textiles in equestrian contexts, offering a simple link between horse trainer practise and exercise physiology of horses [14].

We here propose a novel real-time signal quality index (SQI) and an evaluation performance comparison with the most used quality indexes for ECG in real-time. Two different acquisition systems, i.e. red-dot and textile electrodes, have been simultaneously applied to five horses during gradual treadmill test [15]. The experimental protocol consisted in four different sessions with increasing velocity, from walk to gallop. Since we have already demonstrated that textile electrodes are more reliable and robust than the Ag-AgCl ones, using ECGs acquired from horses at rest [10,16], here we investigate in real-time if the textiles remain more accurate in ECG signal acquisition also when motion artifact is supposed to be as high as possible (e.g., during gallop). Of note, considering velocity and physical efforts reached by horses in the experiment, a reliable real-time signal quality estimation is essential to identify the limit conditions in which they can be monitored, avoiding to achieve erroneous results and acquire corrupted signals. A real-time index leads to achieve good ECG recordings in tele-health applications, making the operators able to stop the acquisition when the signal quality is insufficient to provide the expected information about the physical condition of the horse.

Therefore, we propose a novel index, the *higher-order-statistics-SQI* (*hosSQI*), which uses the third and fourth statistical moments of the ECG. This index is a synthesis of information coming from kurtosis SQI (*kSQI*) and skewness SQI (*sSQI*), allowing to categorize the ECG quality into three classes (or levels), which are derived from the statistical properties of the signal: good (G), acceptable (A), or unacceptable (U). Moreover, we evaluated whether the new index provided more information than other existing SQIs, through validation on a collection of 1000 human twelve-lead ECGs, gathered from PhysioNet/CINC 2011 Challenge [17,18]. Revising the plethora of developed ECG SQIs [19–25], we selected four SQIs to be included in the comparison, considering their reliability in ultra-short series analysis for real-time applications. Obviously, we compared our *hosSQI* with the two SQIs from which it derives: *kSQI* and *sSQI* [26–31]. Then, we selected other two indexes based on the study of ECG power spectral density (PSD), specifically the relative power of the ECG in the baseline (*basSQI*) and the in-band to out-of-band spectral power ratio within the QRS complex (*iorSQI*) [22,26,32]. According to the literature, these indexes are particularly sensitive to activity-related artifacts and were already employed to compare different ECG acquisition systems [33,32].

Afterwards, we computed statistical analysis between the values of the five SQIs extracted from equine ECGs for investigating the presence of significant differences between the two acquisition systems in the different phases of the experimental protocol. Furthermore, a pattern recognition algorithm has been applied to the best acquisition system for discriminating the three physical activity conditions during the treadmill test (walk, trot, and gallop), using the real-time quality indexes. Specifically, the pattern recognition algorithm consisted a Leave-One-Subject-Out (LOSO) procedure, based on a support vector machine (SVM), specifically the type called C-SVC. A feature selection based on the study of the Jensen-Shannon (*JS*) divergence was also performed in order to detect the most discriminant SQIs.

2. Methods

2.1. ECG signal quality indexes (SQI)

In this study we implemented four quality indexes already used in the literature [26,22,27]:

- relative power of the ECG in the baseline (basSQI)
- in-band to out-of-band spectral power ratio within the QRS complex (iorSQI)
- kurtosis signal-quality-index (*kSQI*)
- skewness signal-quality-index (*sSQI*) and the novel SQI, based on *kSQI* and *sSQI*:
- higher-order-statistics-signal-quality-index (*hosSQI*)

The *basSQI* metric quantifies the ratio between the power in the band [1, 40] Hz and in the band [0, 40] Hz, using the following equation:

$$basSQI = \frac{\int_{1\,\mathrm{Hz}}^{40\,\mathrm{Hz}} P(f)df}{\int_{0\,\mathrm{Hz}}^{40\,\mathrm{Hz}} P(f)df} \tag{1}$$

where *P*(*f*) is the ECG power spectrum. A low *basSQI* means an abnormal situation where the power within the band [0, 40] Hz is high with respect to the power in [1, 40] Hz interval, more specifically the power within the remaining band [0, 1] Hz results to be higher than the power in [1, 40] Hz which contains the greatest part of the power spectral components of ECG signal. This condition is likely to be caused by an abnormal shift in the baseline [22,26].

The *iorSQI* represents the ratio between the power of the ECG signal inside the QRS complex band ([5–40] Hz) and the power out of this band [32]. Considering that the sampling rate was 250 Hz, *iorSQI* is defined as:

$$iorSQI = \frac{\int_{5\,\mathrm{Hz}}^{40\,\mathrm{Hz}} P(f)df}{\int_{0\,\mathrm{Hz}}^{125\,\mathrm{Hz}} P(f)df - \int_{5\,\mathrm{Hz}}^{40\,\mathrm{Hz}} P(f)df} \tag{2}$$

kSQI is the kurtosis value (fourth moment) of the ECG signal and it is calculated as follows:

$$kSQI = \mathbb{E}\left\{X - \mu\right\}^4 / \sigma^4 \tag{3}$$

where *X* is the signal (in this case it is the ECG), μ is the average value of *X*, σ is its standard deviation, and $\mathbb{E}\left\{X - \mu\right\}$ is the expected value of $(X - \mu)$.

sSQI is the skewness of the ECG signal (the third statistical moment), and it is computed following the formula:

$$sSQI = \mathbb{E}\left\{X - \mu\right\}^3 / \sigma^3 \tag{4}$$

2.2. Higher-order-statistics-SQI (hosSQI)

As previously said, *hosSQI* is derived from two indexes already used in the literature: *kSQI* and *sSQI*.

These two indexes are the third (*kSQI*) and the fourth (*sSQI*) statistical moments, and are used to characterize a signal distribution, also evaluating the level of non-gaussianity, in case of correlated signals. In the case of normal symmetric distributions, the values $kSQI = 3$ and $sSQI = 0$ are found. Specifically, when $-0.5 < sSQI < 0.5$ the distribution is close to being symmetrical, but the ranges $0.5 \leq sSQI \leq 1$ and $-1 \leq sSQI \leq -0.5$ indicate a moderately skewed distribution. A rule of thumb recognizes the values of skewness of a Gaussian distribution in the range $[-0.8, 0.8]$. Concerning the kurtosis, a good-quality ECG signal has a kSQI generally higher than 5, as previously demonstrated in [28,29].

We here propose *hosSQI*, based on the preceding considerations about *sSQI* and *kSQI*. This novel index check the ECG signal quality, combining the information given by the *kSQI* and *sSQI*. It was computed as follows:

$$hosSQI = \left|sSQI\right| \times \frac{kSQI}{5} \tag{5}$$

Moreover, we identified three thresholds of the signal quality:

- Good (G): $hosSQI > 0.8$
- Acceptable (A): $0.5 < hosSQI \leq 0.8$
- Unacceptable (U): $hosSQI \leq 0.5$

2.3. Human ECG signals: PhysioNet/CINC 2011 Challenge

We used ECG human signals provided by PhysioNet/CINC 2011 Challenge [34,17,18]. Data consisted in 1000 twelve-lead ECGs, each lasting 10 s, with standard bandwidth comprised in the range 0.05-100 Hz. Each ECG was recorded at a sampling rate of 500 Hz, 16 bits per sample. A group of 23 volunteers manually annotated the signals with varying amounts of expertise in ECG analysis, in blinded fashion for grading and interpretation: 2 cardiologists, 5 ECG analysts, 5 annotators with previous experience reading ECGs, 1 non-cardiologist physician, and 10 volunteers who had never read ECGs previously [18].

Each annotator was asked to give an assessment of each ECG, by attributing one of five following possible labels to it:

- A: a very good recording, with no visible artifact;
- B: a good recording with some artifacts or low level of noise, but with all leads recorded well;
- C: an adequate recording without missing data;
- D: a poor recording in terms of artifact and noise, or a good recording with missing leads;
- F: an unacceptable recording.

Each grade represented an overall measure of quality, considering 10 seconds and 12 channels. The following numerical scores were assigned to each letter: $A = 0.95$, $B = 0.85$, $C = 0.75$, $D = 0.6$ and $F = 0$. Then, the average of all the scores was computed for each ECG, and two labels were assigned: acceptable (if the average grade among the annotators was greater than or equal to 0.7, and no more than one was *F*), unacceptable (if the average grade was less than 0.7), or indeterminate (if the average grade is 0.70 or more, but two or more grades were *F*). The sum of acceptable and unacceptable records was 998: 775 records labelled as acceptable, 223 labelled as unacceptable. Two ECGs were labelled as indeterminate and were not considered in this study.

To validate *hosSQI*, we extracted its values from all the 12 leads of the 1000 ECG signals, together with the values of the other four SQIs we described in Section 2.1.

2.4. Treadmill test in horses: recruitment, experimental protocol and acquisition set-up

Five horses took part in the experiment. They were 5 standardbred female horses, their age was in the range 3–6 years (with a median age of 5 years), and their weight was between 504 and 569 kg (median 537 kg). They were all fed with concentrate and *ad libitum* hay and water, and they presented a median body condition score equals to 3.5 points. All the horses involved in the experiment were considered healthy, in terms of lameness, cardiac conditions, and blood work. None of the horses included in the protocol was pregnant during tests. The protocol was approved by the Ethical Committee of the University of Pisa (p. n 0010135/2018).

A training period lasting eight weeks preceded the experiment. During the training, horses familiarized with treadmill test exercises. After the training procedure, they underwent a standardized exercise test (SET) to achieve a submaximal activity level on a treadmill (SATO 2, Stockholm, Sweden). The exercise protocol consisted in the following four phases: a walk session at a velocity of 1.7 m/s, two trot sessions at increasing velocity of 3.5 m/s and 5.5 m/s (Trot1 and Trot2, respectively), and a gallop session at a velocity of 9.5 m/s. All the four sessions lasted 3 min.

During the experiment, the horses were equipped with systems to measure their ECG. Two identical ECG recording systems (Biopac, California, USA) were used simultaneously, one was connected to two traditional Ag/AgCl electrodes (3M, Saint Paul, Minnesota) while the other was connected to two smart textile electrodes (Smartex Srl, Navacchio, Pisa, Italy). The textile-based system consisted in an elastic belt fastened around the horse chest. The two red-dot electrodes were positioned closed to the textile ones, in the well-known modified base-apex configuration [35].

The systems were connected to a mobile device allowed for controlling the remote storage using a secure digital (SD) card, through a wireless connection.

The treadmill desk was located in a stall with a dimension of 4×4 m, where the acquisition was performed.

2.5. Statistical analysis and pattern recognition

For each protocol session and for each subject, we extracted the values of the five SQIs (*kSQI*, *sSQI*, *hosSQI*, *iorSQI*, *basSQI*), calculated over the first 10 seconds and then updated each second. Given the non-gaussianity of data, we used the Wilcoxon nonparametric statistical test to compare the two ECG acquisition systems. The Wilcoxon paired test was applied using the two vectors (one for each acquisition system i.e. textile and red-dot) made up of the SQIs extracted during all the experiment, considering ten horses.

The same pattern recognition algorithm was implemented using both human and horse ECG data. In the first case the aim was to discern acceptable from unacceptable signals, according to their SQIs. In the second case, we used the pattern recognition to discriminate the activity condition of horses in real-time, using the SQIs updated each second. Specifically we employed a C-SVC with a radial-basis kernel function, using a LOSO procedure [36]. Moreover, a feature selection procedure was applied on the training set. This procedure was based on the computation of the *JS*-divergence to measure the distance between the probability distributions of the two classes (acceptable vs. unacceptable) [37,38]. The *JS*-divergence is the symmetrical version of the Kullback-Leibler (K-L) divergence (called also relative entropy), which measure the dissimilarity between $p(x)$ and $q(x)$ distributions, as follows:

$$D_{KL(p\|q)} = \sum_{x} p(x) \log \frac{p(x)}{q(x)} \tag{6}$$

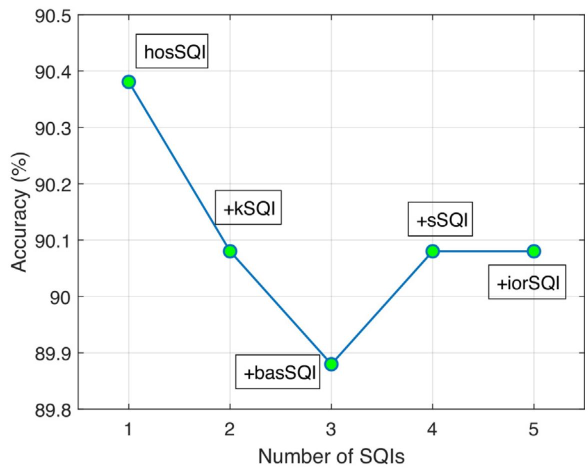

Fig. 1. Percentage of accuracy reached in the recognition of human ECG labels as a function of the number of SQIs used as input of the classifier.

The JS-divergence is computed from D_{KL} using the equation:

$$JS_{div}(p, q) = \sqrt{1/2(D_{KL}(p\|q))^2 + 1/2(D_{KL}(q\|p))^2} \quad (7)$$

The feature which had the maximum JS_{div} between the two classes in the training-set was considered the most discriminant and was used as first input of the classifier. Then one feature was added at each time, following a descendant order in the JS_{div} values.

3. Results

3.1. Accuracy of hosSQI in the discrimination of acceptable/unacceptable human ECG signals

The average of the values found in the 12 leads was computed for each index, in order to provide an overall SQI for each ECG and to compare it to the label (acceptable/unacceptable) assigned in the Physionet repository. Therefore we obtained for each ECG signal five SQIs, and we used these indexes as input of the C-SVC [39], in a Leave-One-Out (LOO) procedure. In Fig. 1 we show the percentage values of accuracy reached in the recognition of human ECG signal labels, calculated as the ratio between the number of successes and total number of signals. The accuracy of the pattern recognition algorithm is presented as a function of the number of SQIs which were selected using the JS-divergence method described in Section 2.5. Following this feature selection, the SQIs were added as inputs of the classifier starting from the most discriminant, as follows: *hosSQI*, *kSQI*, *basSQI*, *sSQI*, and *iorSQI*. The highest value of accuracy was obtained using only the here proposed *hosSQI*, with a percentage of successes of 90.38%.

Table 1
Percentage values of signals found to have a good (G), acceptable (A) or unacceptable (U) *hosSQI*, calculated for each session of the protocol. Values are median and median absolute deviation (MAD) computed for all the horses. R-D = red-dot electrodes, TEX = textile electrodes.

		U (%)	A (%)	G (%)
Walk	R-D	75.58 ± 25.98	7.06 ± 4.94	14.12 ± 23.36
	TEX	0.88 ± 7.33	1.17 ± 4.33	96.18 ± 10.71
Trot 1	R-D	63.33 ± 30.89	8.61 ± 10.33	8.61 ± 31.18
	TEX	0.28 ± 5.94	1.11 ± 7.00	98.06 ± 12.56
Trot 2	R-D	80.83 ± 24.13	12.22 ± 10.94	2.78 ± 18.94
	TEX	0.00 ± 11.38	6.11 ± 8.13	90.86 ± 16.56
Gallop	R-D	84.72 ± 27.64	13.61 ± 9.02	0.00 ± 22.6
	TEX	6.67 ± 9.44	20.83 ± 22.51	68.06 ± 31.11

3.2. Real-time equine ECG quality analysis

In Fig. 2 the trends of the five SQIs are reported as a function of time, throughout the experimental protocol. It is worthwhile noting that the higher SQIs value, the better signal performance. Moreover, the values of all indexes were higher for the textile electrodes than the red-dot ones, in all the protocol sessions. This leads to affirm that textile electrodes can be considered more robust against the movement artifacts. The trends of the statistical moment indexes, *kSQI*, *sSQI* and *hosSQI* showed a decrease of their values during the treadmill protocol, especially in Trot 2 and Gallop sessions.

Concerning the two SQIs computed in the frequency domain, i.e. *basSQI* and *iorSQI*, both exhibit higher values with textile electrodes showing a stable trend for all sessions except for *basSQI* which increases in the last two sessions with red-dot electrodes.

Furthermore, in Table 1 we reported the percentages of ECG signals found to belong to the three classes of acceptance (i.e. U, A, G) in each session, using the here proposed *hosSQI*. The values shown are median percentage values among all the acquisitions, computed with respect to the whole duration of the specific session (which was of 180 s).

The results of Wilcoxon statistical test considering the whole experimental protocol is shown in Fig. 3. For all the SQIs we found a *p*-value lower than 10^{-10}, with a significant decrease in the signal quality estimation for the red-dot electrodes.

Finally, we applied the pattern recognition algorithm to discern the three levels of horse activity: walk, trot, and gallop when the textile monitoring system used, as it is resulted to be more robust from the previous experiments. The SQIs of Trot1 and Trot2 sections were averaged in order to consider a single section of trot. Table 2 reports on the results of pattern recognition algorithm applied to the ECG signals acquired by means of the textile electrode based system. *hosSQI* was selected as the most discriminant feature in the recognition of walk compared to trot and gallop, and the related peaks of accuracy in those cases were 73.47% and 84.91%. When we used our algorithm to discern trot and gallop we reached an

Table 2
Results of C-SVC classifier in the discrimination of horse activity conditions using SQIs values extracted from ECG signals acquired through textile electrodes. Bold indicates the peak of accuracy percentage and the related selected inputs. The accuracy value reported for each case is referred to a number of inputs from 1 to 5, adding at each time a SQI from the most discriminant to the least discriminant, according to their JS_{div}.

Textile electrode based system					
W vs. T		W vs. G		T vs. G	
SQIs	Acc. (%)	SQIs	Acc. (%)	SQIs	Acc. (%)
hosSQI	64.24	*hosSQI*	79.00	basSQI	69.71
hosSQI, kSQI	63.79	*hosSQI*, kSQI	78.79	basSQI, *hosSQI*	73.82
hosSQI, kSQI, sSQI	73.26	*hosSQI*, kSQI, sSQI	78.65	**basSQI**, *hosSQI*, kSQI	**73.91**
hosSQI, **kSQI, sSQI, basSQI**	**73.47**	*hosSQI*, kSQI, sSQI, basSQI	82.26	basSQI, *hosSQI*, kSQI, sSQI	72.26
hosSQI, kSQI, sSQI, basSQI, iorSQI	68.06	*hosSQI*, **kSQI, sSQI, basSQI, iorSQI**	**84.91**	basSQI, *hosSQI*, kSQI, sSQI, iorSQI	73.50

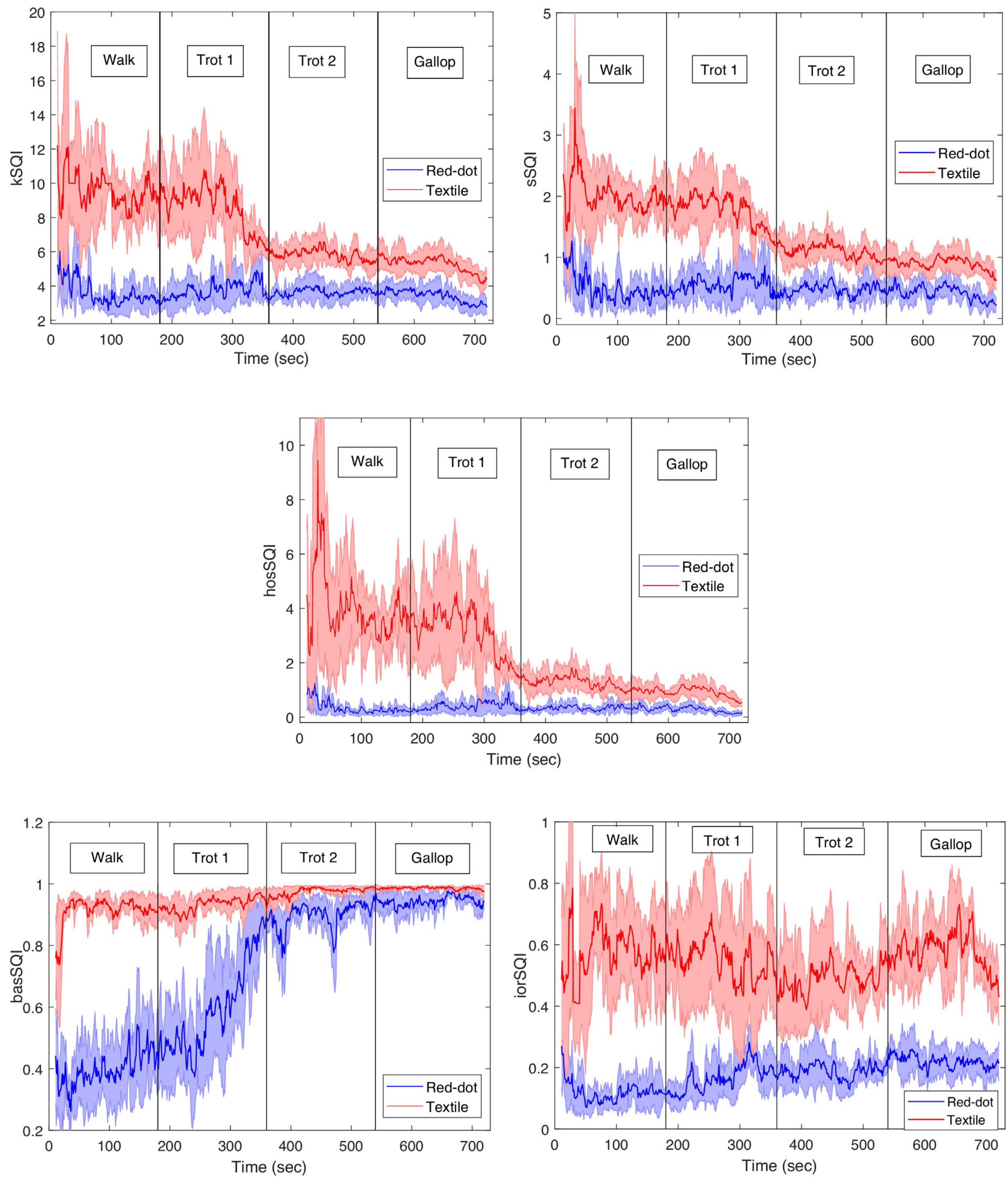

Fig. 2. Median values of SQIs related to red-dot and textile electrode-based acquisition systems. Values are updated each second.

accuracy of 73.91%, with *basSQI*, *hosSQI*, and *kSQI* as inputs. In the three-class recognition problem we obtained a lower percentage of discrimination of the second class (i.e. trot) than the others, however the overall accuracy expressed by the confusion matrix (see Table 3) is greater than 62.7%.

4. Discussion

We proposed a novel tool for real-time monitoring of physiological signals and physical activity of horses during hard exercise, based on a novel ECG quality index. A good quality of equine ECG

Table 3
Confusion matrix related to the application of LOSO C-SVC classifier in the discrimination of the three activity conditions using textile electrode signals.

Textile	Walk	Trot	Gallop
Walk	**65.7059**	27.1765	7.1176
Trot	28.2353	**47.2941**	24.4706
Gallop	12.3529	12.4706	**75.1765**

Note: For each class (walk, trot, and gallop), bold values represent the percentage of instances for which the predicted label is equal to the true label.

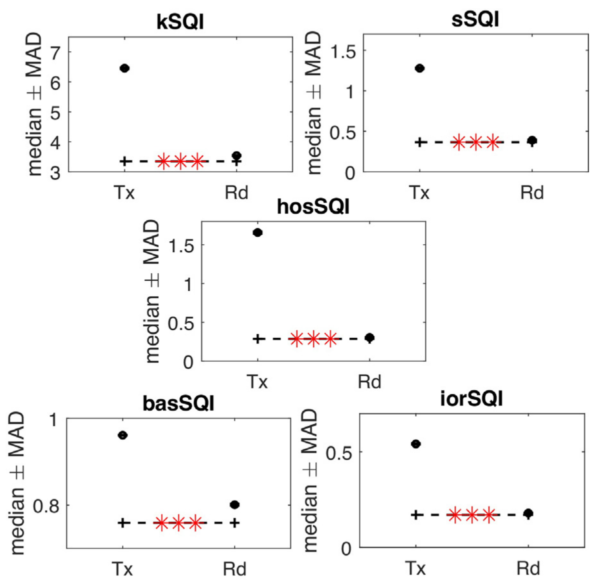

Fig. 3. Results of Wilcoxon statistical concerning the values of the five SQI, in all the experiment.

monitoring may improve the diagnosis of peculiar cardiac disturbances, which are evident only during hard physical activity, and evaluate the athletic performances. Furthermore, ECG signal is fundamental for estimating Heart Rate Variability (HRV) during exercise, which can provide several indexes of ANS regulation and cardiovascular wellbeing [40–42]. A monitoring system able to acquire and store ECGs and to notify the presence of too many movement artifacts or electrode adherence problem, can become a new tool for training practices. The better quality of the ECG trace obtained through textile electrodes has already been investigated in a previous study, concerning horses at resting state but free to move in box [10]. Here instead, we investigated the results obtained using five SQIs, four already known in the literature (*kSQI*, *sSQI*, *basSQI*, *iorSQI*) and one novel here proposed, *hosSQI*, during a huge amount of movements.

First of all, we validated the novel index using 1000 human ECG signals gathered from PhbysioNet/CINC 2011 Challenge [17,18]. The novel index *hosSQI* outperformed the other SQIs when a C-SVC was applied to discriminate the pre-labeled ECG signals, reaching an accuracy up to 90.38%. On the other hand, equine ECG were recorded by means of two ECG acquisition systems for horse monitoring during hard exercise. As physical exercise test, we used the gradual submaximal treadmill, considering four sessions: Walk1, Trot1, Trot2, and Gallop (speed went from 1.7 m/s to 9.5 m/s). Ten acquisitions have been performed. The two acquisition systems were standard red-dot electrodes and a wearable textile system, used and validated simultaneously along the experimental protocol.

The ECG signals acquired by using the two systems showed very different values of SQIs, and in all the cases the textiles presented higher quality than red-dot (see Fig. 2). Wilcoxon statistical test also provided significant results for all the SQIs, when the two systems are compared (see Fig. 3). However, even if this result was coherent over all the SQIs, we can suggest that the most reliable SQIs were the statistical moment indexes, which presented a decreasing trend for both the systems going from the beginning to the end of the acquisition. The decreasing values of *kSQI*, *sSQI*, *hosSQI* can be attributed to the growing amount of movement artifacts when the ride velocity increased. Moreover, the novel index *hosSQI*, combining the information taken from *kSQI* and *sSQI*, is able to assign a label to the acquired signal at each second. As shown in Table 1, these labels can be divided into three ECG quality classes (good, acceptable, or unacceptable), which allow a gradual marker about the real-time decreasing quality of the signals.

Finally, we investigated if the SQIs used in this study were able to automatically discriminate the activities of horses among three classes: walk, trot, and gallop employing a pattern recognition algorithm, based on a C-SVC classifier with a LOSO procedure. A feature selection procedure allowed to investigate the most discriminant SQIs by strategically choosing the input of the classifier. More specifically, for each subject under test we selected an increasing number of features (SQIs), used as input to the classifier, on the basis of the *JS*-divergence (see Table 2). The algorithm reached an accuracy always greater than 73% in the discrimination of two activity conditions (see Table 2). In two out of three cases, the new index *hosSQI* was selected as the most discriminant feature, and it was always present within the input set corresponding to the best performance.

Given that the PSD-based indexes showed an unreliable ECG quality index trend during hard exercise protocol, we suggest that the SQIs based on the study of statistical moments are the most promising indexes for a reliable real-time analysis of ECG quality and activity recognition during physical exercise. The development of an automatic decision support system based on our *hosSQI* could provide real-time information about physical health and performance of horses. The integration of the proposed tool into textile electrode based platform could provide real-time indication about horse activity, based on ECG signals of good quality which can be stored and used for further analyses.

The achieved results are preliminary since the low number of the involved subjects. Certainly, future work should be addressed to involve a higher number of subjects, and also should be applied to real races rather than using treadmill. Importantly, the performance of our index in human monitoring during physical activity should be investigated and validated. In fact, the new SQI presented here opens new possibilities of research toward good-quality real-time monitoring in several fields of application like human-horse interaction during activity condition, especially in emotion transfer between species and affective computing [43–45].

Conflicts of interest

The authors declare no conflicts of interest.

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