Geometric approach to biomedical signal processing: ballistocardiografic monitoring of vital functions

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***Abstract*—**We present a new mathematical technique of biomedical data processing, based on the knowledge of differential geometry of curves. The efficiency of the method is demonstrated using real and simulated ballistocardiographic data. The basic vital functions - heart and respiration rates - have been extracted from the data measured by a special bed equipped with mechanical sensors. Simulated data are used to show the robustness of the method with respect to possible very low signal-to-noise ratio.

***Keywords*—**Ballistocardiography, Differential geometry, Vital functions.

I. Introduction

THE main objective of the present study is to introduce a new mathematical method of biomedical signal processing, based on the differential geometry of curves. It has been shown recently that the novel application of mathematical approach, commonly used in some completely different disciplines, to the biomedical signal processing can bring some really new, and sometimes surprising, insights to the information extraction from the data and its interpretation. As an example we mention the application of random matrix theory - a common tool in quantum chaos domain - for the human EEG analysis, [1], see also [2]. The differential geometry is a very versatile tool covering wide range of applications e.g. in physics, such as general theory of relativity, quantum waveguides theory, etc. However, its usage for the biomedical signal processing was, up to our knowledge, reported for the first time quite recently in 2008, [3]. Since 2008, several papers concerning the geometric approach applied to so-called ballistocardiography have been published.

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The brief review of these results is provided in Section III of the paper.

Ballistocardiographic signal represents the mechanical recoil of the human body caused by the cardiac and respiratory activity. Another aim of the paper is to show that geometric approach to the human ballistocardiographic signal enables an unobtrusive detection of useful physiological information. It covers the heartbeat and respiration monitoring and provides an estimation of the pulse wave velocity along the abdominal aorta.

Ballistocardiography has a long tradition. It has been studied for decades using various types of measuring devices. It was demonstrated in many clinical studies that the signal contains valuable information about the state of the cardiovascular system. However the variability and complexity of the signal hindered its usage in the routine clinical praxis - see [4] and [5] for a review.

The complexity of the ballistocardiographic signal distinguishes it from the commonly used ECG (electrocardiography) which measures the electric activity of the heart. While ECG is easily reproducible the measured mechanical signal is more challenging. Even if the person is quietly resting the body motions caused by the cardiac activity interfere with the breathing and with the motion of viscera. Moreover the heart activity excites various mechanical resonances that are not directly related to the cardiovascular process and depend on the immediate condition of the body tissues and of the underlying bed. An additional problem is related to the contact between the body and the measuring sensor.

The ballistocardiographic measurement is done unobtrusively, i.e. the sensors are implemented in the bed and are invisible for the patient. Moreover the patient is free to take any position he wants (provided he rests quietly). This means that there is not a standard mechanical force transfer between the body and the sensor. So the measured signal depends substantially on the posture of the body. And last but not least are also problems caused by the vibration of the ground (external noise) [6]. Particularly in higher floors it can influence the measurement substantially. As summary: a clear and repetitive pattern known from the ECG signal (the QRS complex) is usually missing in the ballistocardiographic signal.

On the other hand the mechanical monitoring has also certain advantages. ECG represents solely the electrical control signal. What really matters is however the related mechanical activity of heart muscle and the propagation of the pulse wave along the arterial tree. The heart contraction can be displayed by echography which is however time consuming and requires experienced personnel. The ballistocardiographic data can supply similar information. Their advantage is that they enable a low cost and continuous monitoring. And the motion activity and/or the sleep evaluation of the person can be obtained into the bargain, [7]. The technological improvement of the mechanical sensors enables nowadays to integrate them into a standard bed. So it is not a surprise that we can recently observe an renewed interest in this field.

There are several attempts to use the mechanical sensors in an bed to monitor the human vital functions. Some of them are based on the weight measurement that represents a standard part of modern intensive care bed. Another solution of interest could be easily portable and of potential use in any standard bed. By a portable equipment we mean simple enclosure that can be placed below the bed mattress and being able to register and evaluate the ballistocardiographic signal. The drawback of such a portable equipment is that the obtained data are usually of lower quality than data obtained on an intensive care bed with special construction and equipment. This means that the mathematical algorithm analyzing the data from the portable ballistocardiographic equipment has to be particularly robust and stable. Such algorithm based on geometrical properties of the signal has been developed and is described below.

II. Signal analysis

As already mentioned even in the ideal case without external noise there is already a variability of the ballistocardiographic signal due to the insuppressible interference between the cardiac and respiratory motions. Therefore to cut the signal into epochs related to the particular heartbeats is, in contrast to ECG, not straightforward. Several methods were developed for this purpose. One of them use the machine learning [8], [9]. Another method improves the signal by using multiple sensors imbedded into the bed mattress and measuring the pressure changes on various places [10] etc. We will use the fact that the real ballistocardiographic signal is by its nature three dimensional object since it reflects the body recoil in the longitudinal, lateral and in the dorso-ventral directions [11], [12]. The clue is however not contained merely in the three dimensional character of the data but also in the method we use to uncover the underlying processes - our analysis will be purely geometrical. We will not treat the measured data as several separated time series but we will describe them as the coordinate projections of a certain object - the signal curve. As far as we know this approach is new and has been not reported or used before, with the exception of our recent papers, [3], [13] – [17]. The clinical tests performed up to this day show that it enables the unobtrusive monitoring of the vital functions regardless on the particular sensor system construction.

The ballistocardigraphic process is a mechanical image of the momentum changes due to the heart muscle contraction and the pulse propagation along the main arterial branches. It has therefore similar geometrical transformation properties as the measured body. When the signal is measured in a fixed reference frame (related with the bed) and the body turns round, the measured ballistocardiographic signal curve rotates as well [18]. The process itself remains however unchanged and so the transformed signal curve describes the same hemodynamics. (The influence of gravity or of other external forces is neglected for simplicity.) Note that the measured signals - i.e. the particular projections of the signal curve to the coordinate system - may change drastically when the body turns. The geometric properties of the signal curve remain however invariable. The gravity slightly changes this picture. It has been for instance demonstrated, that during a parabolic flight, which withdraw the gravity influence, the signal curve of a vector cardiogram undergoes an additive scaling - see [19].

Based on the above arguments we can now formulate the main approach to the ballistocardiographic vital functions monitoring. We will not analyze the measured time series themselves. We will also not study the particular signal curve (i.e. a geometric object, whose coordinate projections are the measured data). The crucial issue we will discuss are the equivalence classes of the signal curves, i.e. classes of curves that are equivalent under the similarity transform, i.e. under rotation and translation.

From the mathematical point of view, we will exploit the invariant curve description based on the concept of moving coordinate frame, [20]. At a given point of the curve the local coordinate frame is defined in such a way that one of its axes is tangential to the curve, the second axis represents the normal, the third is the binormal, etc. As the point moves along the curve the coordinate system changes as well. The signal (and hence also the final signal curve) is naturally measured in (parametrized by) time. Geometrically this is, however, not the optimal description since such a parametrization is not related to the curve geometry. A natural parameter is the arc length, i.e. the length measured along the signal curve. What is understood under the notion “arc length” depends on the transformation under which the invariance is defined. Here we look for a curve description that is invariant under the Euclidean transformation - so “arc length” means simply its Euclidean length. A similar theory can be, however, constructed also for the affine group -see [21].

A. Geometric Invariants

To construct the Euclidean geometric invariants let us consider a smooth and regular n-dimensional time parameterized curve $c(t)$, i.e. the smooth mapping $c : [0, T] \to \mathbf{R}^n$ with T being the length of the measured interval, such that the standard n-dimensional Euclidean space norm of its derivative

$$\|c'(t)\| = \sqrt{\sum_{j=1}^{n} \left(c_j'(t)\right)^2} \neq 0 \text{ for all } t \in [0,T]. \quad (1)$$

The functions c_j denote the curve projections to fixed reference frame.

The Euclidean arc length is defined by

$$s(t) = \int_0^t \left\| c'(\tau) \right\| d\tau \ . \qquad (2)$$

Function s is obviously increasing, thus there exists its inverse. Writing $\bar{c}(s) = c(t(s)),$ where $t(s)$ is the inverse of $s(t)$ we obtain reparameterization $\bar{c}$ of the curve c called arc length or unit speed (since clearly $\left\| \bar{c}'(s) \right\| = 1$) parametrization. Since both curves c and $\bar{c}$ belong to the same equivalence class, i.e. they describe the same geometric object, we will omit the bar hereafter. If it would be necessary, we will distinguish both mappings by writing t or s as the function argument.

Although the following construction can be made for any parametrization, we will use the arc length, since the following formulae are simpler for this case. Let us assume that the derivatives $c'(s)$, $c''(s)$, …, $c^{(n-1)}$ are linearly independent for each s. Then there exists for each parameter s an orthogonal frame $(E_1(s),\ldots,E_n(s))$ of n-dimensional unit vectors such that the k-th derivative $c^{(k)}(s)$ of the curve $c(s)$ can be expressed as a linear combination of its first k vectors $(E_1,\ldots,E_k)$, $1 \le k \le n-1$. So the vector $E_1(s)$ is just the derivative of the curve with respect to the arc length s: $E_1(s) = c'(s)$. Next vectors $E_2(s),\ldots,E_{n-1}(s)$ can be obtained by the Gramm-Schmidt orthogonalization of the first $n - 1$ derivatives of $c(s)$. The last vector is simply the unit vector perpendicular to $(E_1(s),\ldots,E_{n-1}(s))$ completing a right-handed frame. The family $(E_1(s),\ldots,E_n(s))$ is called the distinguished Frenet frame.

The further geometric invariants (called usually Cartan curvatures) κ_i, $i = 1, \ldots, n - 1$, describing uniquely the curve c (up to the similarity transform) are defined by the Frenet-Serret formulae as

$$\kappa_i(s) = E_i'(s) \cdot E_{i+1}(s). \qquad (3)$$

Roughly speaking: the curvatures κ_i characterize the local changes of the coordinate system related with the curve. It is worth to notify that there are exactly $(n - 1)$ curvatures describing the n-dimensional curve. One dimension seems to be missing. This is due to the fact, that the curvatures describe the object invariantly, i.e. independently on its rotation and translation. The missing dimension describes the exact position of the curve in the space whereas the internal geometry of the curve is given by the $(n - 1)$ functions κ_i.

Our main assumption is that haemodynamical events like the heart contraction or the scattering of the pulse wave on an arterial bifurcation express themselves in the intrinsic geometry of the signal curve and are contained in the functions κ_i. In practice it turns out that to recognize the main cardiac and pulse wave events it is enough to investigate the signal arc length and first curvature κ_1 only.

B. Arc Length and the Monitoring of the Vita Functions

Let us calculate the Euclidean arc length (2) for a nontrivial signal (i.e. a signal that is not constant in all channels). For large t the function $s(t)$ is approximately linearly increasing with time: $s(t) \approx at$ at with a being a constant depending mainly on the signal variance. We will assume for simplicity the variance to be constant, i.e. that the signal strength and the background noise do not change during the measurement. Subtracting the linear increase we define a new function $M(t) = s(t) - at$ which display the local changes of the arc length. The processes (respiratory or the cardiac activity) that are reflected in the ballistocardiographic signal change the geometry of the signal curve. They lead to local changes of the arc length that are finally displayed as a quasiperiodic behavior of the monitoring function $M(t)$. The point is that the arc length is not very sensitive to the detailed shape of the signal. This solves the problem related to the ballistocardiographic signal variability. Although the signal shape of a resting person changes in the dependence on the instant interference between the cardiac activity and breathing the arc length grow is less sensitive. We will use the function $M(t)$ as the starting point for the ballistocardiographic vital functions monitor.

To be precise let us define the running average of the arc length over a time period Δ,

$$\bar{s}(t,\Delta) = \frac{1}{\Delta} \int_{t-\Delta/2}^{t+\Delta/2} s(\tau) d\tau \qquad (4)$$

and the monitoring function $M(t)$ as

$$M(t,\Delta) = s(t) - \bar{s}(t,\Delta). \qquad (5)$$

The interval Δ used in the above definition depends on the underlying physiological process and equals to 4 seconds for breading or to 1 second for the cardiac activity respectively. In the ideal case of a resting person and a small background noise the function $M(t, \Delta)$ behaves quasiperiodically. The time elapsed between two subsequent heart beats (Δ = 1s) or between two breaths (Δ = 4s) is simply obtained as the distance between two subsequent maxima (or minima) of the function $M(t, \Delta)$.

The body motion and/or the external influence (for instance the building vibrations) may lead to the appearance of additive and spurious maxima, which are not related to the physiological process of interest. The quasiperiodic character of monitoring function remains, however, untouched since those perturbations are mainly of a random nature. The mean time elapsed between two subsequent heart beats is in this case obtained using the autocorrelation function.

C. Cartan Curvatures and Pulse Wave Velocity

Mechanical events like a heart contraction or a scattering of the pulse wave on an arterial bifurcation lead to recoils and can be registered by mechanical sensors. It might be difficult to observe this response just by inspecting the individual time series. But such events change the geometry of the total signal curve. Hence they will be visible as a changeover of its invariants.

It was demonstrated that the scattering of the pulse wave on the aortic arch as well as its scattering on the abdominal bifurcation appear as clear maxima in the first Cartan curvature. The time lag between these two events (two

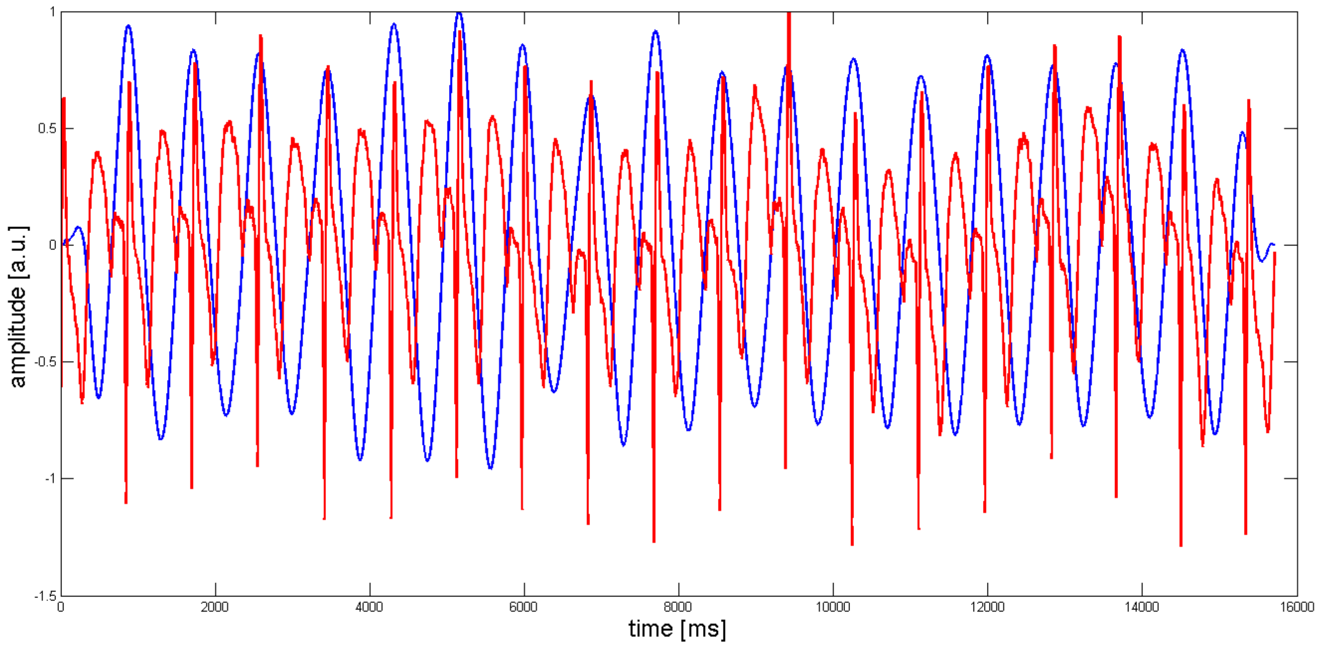

Figure 1: Comparison of the monitoring function (blue) and the ECG signal (red) in one volunteer.

maxima) is inversely proportional to the pulse wave velocity.

III. Summary of Published Results

Our above described geometrical approach to ballistocardiographic signal analysis has been used for several experiments. The paper [3] (see also [13]) deals with the experiment of the volunteers reclining quietly on the stiff bed mounted on the top of standard Bertec force plate, model 4060A, equipped with the strain gage transducers. The pulse wave velocity on the aorta was estimated using the first Cartan curvature.

The data measured by a prototype of a ballistocardiographic bed with four three-axes strain gauge transducers embedded in its legs were analyzed in [14]. The pulse wave velocity as well as heart beat variability were evaluated. The results were compared with the pulse wave velocity measured by applanation tonometry (see [22]) and RR intervals measured by standard ECG, respectively.

IV. Experimental Setup

The data obtained by the automatic weighing system integrated into the intensive care bed “Multicare” produced by Linet, Ltd. manufacturer are studied. The four weighing sensors are placed in the four corners of the loading surface of the bed. A volunteer was asked to lie quietly in the supine position on the bed. Signals from all four sensors were digitalized with AD converter and stored to the computer hard disc. The above described mathematical method has been implemented on the computer as a Matlab script.

The geometric approach has been tested on a group of 10 healthy volunteers (7 male and 3 female) of the age varying from 28 to 56. Each measurement lasted for four minutes. The ECG signal was measured simultaneously for comparison.

V. Artificial Data

We emulated the ballistocardiographic signals that were similar to measured signal recordings. Several Gaussian waveforms (with different means, standard deviations and amplitudes) were chosen to emulate the mechanical response of the cardiovascular system. Variability between trials as well as the quasiperiodic character of the data were achieved by varying the parameters of Gaussian waveforms. The white background was added to the signal. The SNR of emulated data was varied from 1 dB to -10 dB. .

VI. Results

It appeared that the integrated weighing sensors were not sufficiently precise to estimate the pulse wave velocity. Their precision was, however, perfectly sufficient to obtain the information about the vital functions, in particular heart beat and respiratory frequency with the beat-to-beat precision.

The above described monitoring function was calculated and the heart rate and respiratory frequency was evaluated for each measured subject. The heart beat was then compared to the RR intervals obtained from the standard one-channel ECG recordings.

The typical example of the monitoring function in comparison with the ECG signal is depicted in Fig 1. One can easily check the clear coincidence of the ECG R waves with the peaks of the monitoring function.

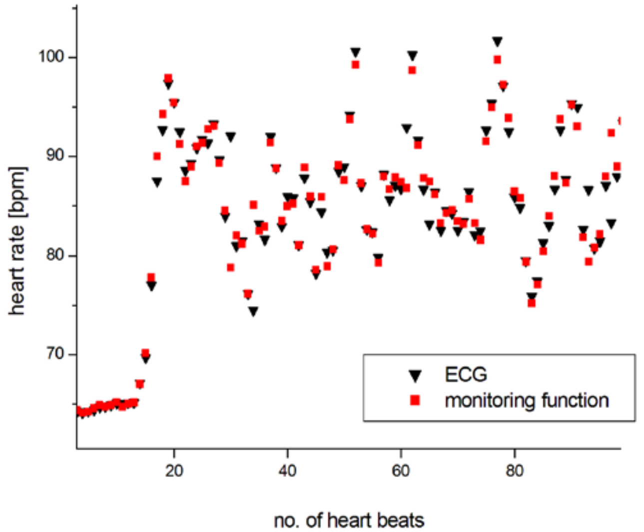

Figure 2: Heart rate in beat to beat precision obtained by geometric approach and ECG.

Figure 2 shows the example of the heart rate (in the unit of beat per minute) evaluated by ECG RR intervals and by our method.

The respiration was also obtained from slower variations of the monitoring function, see Fig 3.

In all measured volunteers we have found the difference between heart rate measured by the monitoring function and ECG was less than 10%.

The analysis of the artificial ballistocardiographic data has proven the robustness of the technique with respect to low signal-to-noise ratio. It may seem surprisingly, since naturally the calculation of derivatives increases noise power. However the above described smoothing procedure (running average) is really powerful.

We have not observed any significant difference in the monitoring function while signal-to-noise ratio was varied. As an example we present a comparison of a one particular emulated signal depicted together with a monitoring function for two different values of signal-to-noise ratio. While the noise of the signal itself is really obvious, the monitoring function remains nearly unchanged, see Fig. 4.

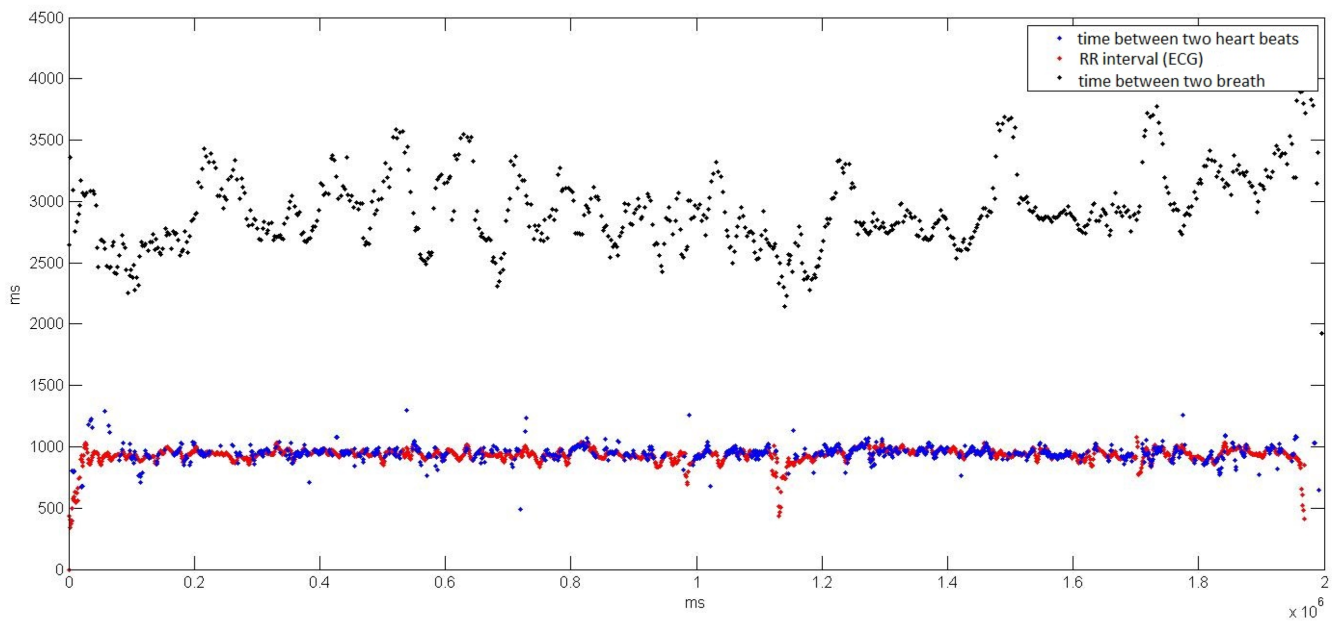

Figure 3: Time intervals between two following heart beats obtained by geometric approach and ECG together with the time interval between two subsequent inhalations.

VII. Conclusions

Rather recent method of the biomedical signal processing based on differential geometry was presented. Its efficiency and the robustness was confirmed on the data measured by the weighing sensors integrated in the intensive care medical bed as well as on the emulated data. The open question remains the possibility of the usage of the geometric approach to analyze some other biomedical signals.

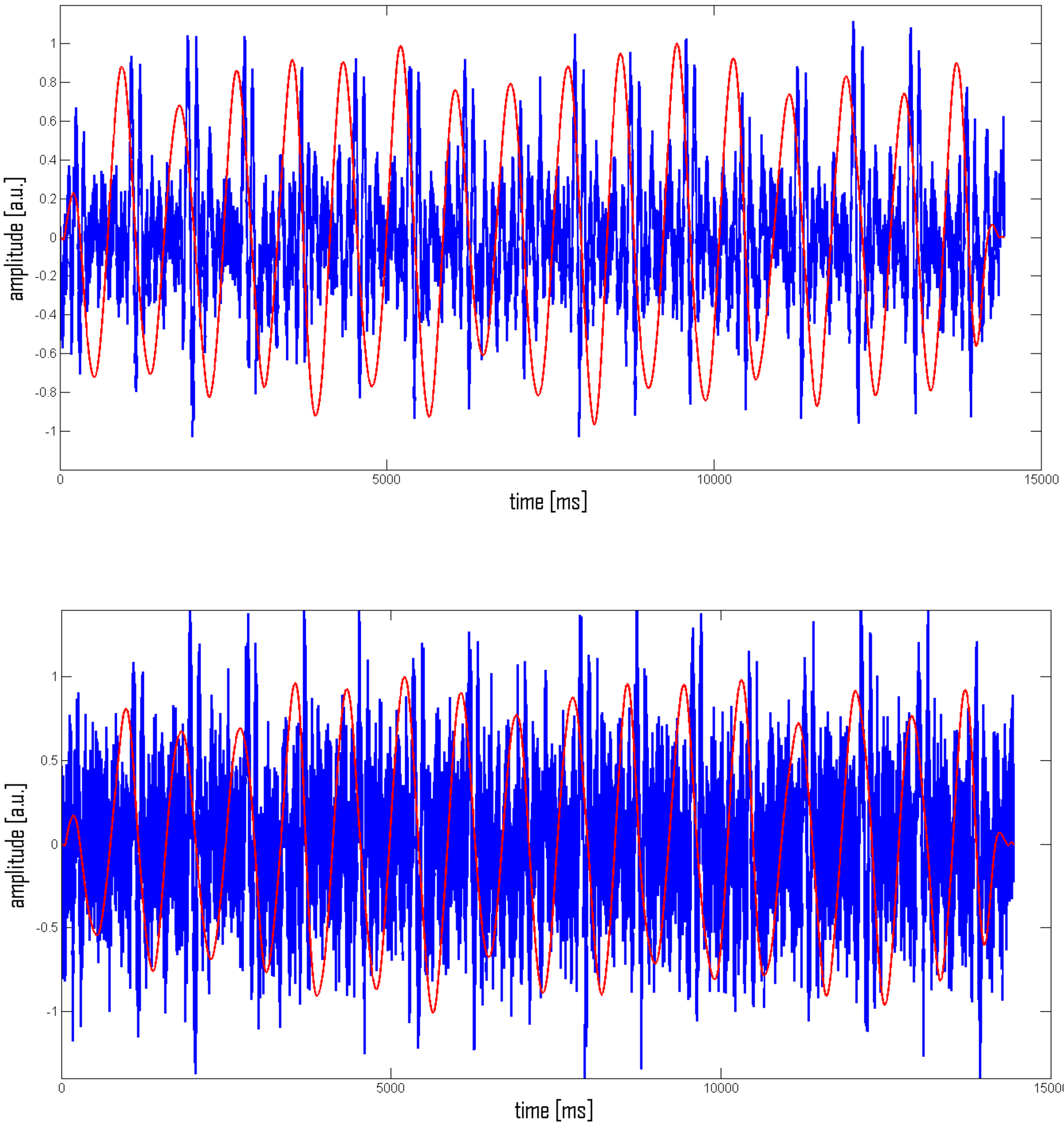

Figure 4: Comparison of the signal from one particular artificial balilistocardiographic channel (blue) with the monitoring function (red). The signal-to-noise ratio in the upper part is 1, while in the lower part -10.

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